Conditional hypotheses in comparative social science: mixed-method approaches to middle-sized data analysis

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Abstract

This paper discusses under which circumstances and how configurational comparative methods (i.e. QCA) and statistical methods can be combined to provide tests for the ‘quasi’-sufficiency of any given set of combination of causal conditions. When combined, QCA provides the ability to explore causal substitutability (i.e. multiple paths to a given outcome) and the ways in which many multiple causes interact with one another to produce effects, while the statistical elements can provide robust indications of the probable validity of postulated hypotheses. The potential utility of the mixed-method approach for analyzing political phenomena is demonstrated by applying it to cross-national data regarding party positions on European integration and party-based Euroscepticism in Western Europe. The findings show that oppositional stances to European integration are partly associated with non-governmental ideological fringe parties on both the left and right. The empirical example presented in this paper demonstrates that configurational methods can be successfully combined with statistical methods and supplement the QCA-framework by providing statistical tests of ‘almost sufficient’ claims. However, combining QCA with statistical methods can sometimes be problematic in middle-sized data analysis, especially as the latter usually cannot handle limited diversity (i.e. insufficient information) in the data and/or overtly complex relationships (i.e. having a large number of conjunctural conditions or interacting variables).

Keywords: Boolean logit; Euroscepticism; fuzzy sets; mixed-methods; multiplicative interaction models; political parties; quantitative methods; Qualitative Comparative Analysis; QCA

Introduction

An ongoing debate in the comparative social studies research community concerns whether case-oriented or variable-oriented approaches are most suitable for exploring asymmetric or multiple and conjunctural relationships and explaining observed outcomes.\textsuperscript{1} Clark et al (2006) argue that there is usually no need to depart from standard social science practices when assessing ‘asymmetric’ or conditional causal claims, as suggested in recent qualitative methodology literature (e.g. Ragin, 1987, 2000, 2006; Ragin & Pennings, 2005). However, assuming that we accept the epistemological logic of positivist empiricism and a probabilistic view of data analysis, this paper argues that the debate cannot be so easily settled. Both quantitative and qualitative ‘configurational’ approaches have clear strengths and shortcomings, depending on the research context and the data available for analysis. In this paper I address the potential merits of combining these methods in a mixed-methods approach, when moderately large numbers of cases are available for analysis.\textsuperscript{2} I refer here to crisp set (i.e. dichotomous) Qualitative Comparative Analysis (csQCA), multi-value QCA (mvQCA) and fuzzy sets and fuzzy set QCA (fsQCA) as configurational methods/techniques, or simply QCA.

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My main argument is that the approaches are partially substitutable, and neither is intrinsically superior to the other; instead, they are suitable in different research situations. Whether one or the other is most appropriate in a given situation depends mainly on the type of causal mechanisms under consideration, the number of theoretically plausible conditions or factors involved and the number of cases available for analysis. These aspects also have implications for the situations in which a mixed-method approach can be used. Thus, I argue that statistical analysis utilising models capable of taking into account, to varying degrees, causal complexity (e.g. multiple conjunctural causation, substitutability, equifinality etc.) can supplement QCA analysis under certain circumstances. More specifically, this is usually possible when there is sufficient variation in the independent and dependent variables together with sufficient cases under examination to allow the possibility of correlational analyses. By doing this, QCA analysis can benefit from formal statistical tests to evaluate whether certain combinations of causally relevant factors (conditions) are “almost” sufficient to produce a given outcome, in a statistically satisfactory way.

I demonstrate how the two methods can be combined in analyses of data regarding party positions on European integration in Western Europe. More precisely, the government-opposition hypothesis of party-based Euroscepticism and a second hypothesis postulating that Eurosceptic far-left parties are for the most part restricted to countries with social democratic welfare state regimes are tested. The findings support the government-opposition thesis and show that oppositional stances to European integration are clearly associated with ‘politics of opposition’ (i.e. such stances are generally held by parties at the periphery of their political systems) and associated with ideological fringe parties, single issue anti-EU parties, and special issue protest parties that espouse Euroscepticism. In addition, I found partial support for the hypothesis that opposition from the left is most common in countries with social democratic (i.e. Nordic) welfare state regimes. Methodologically, I demonstrate that statistical methods can be combined, in a straightforward manner, with QCA to provide statistical tests for the sufficiency of any given combination of causal conditions.

This paper is organised as follows. The first part presents the two methodological approaches, by discussing and comparing the degrees to which configurational methods and corresponding statistical approaches diverge from, complement or converge with one another in terms of methodological framework and requirements. This part also discusses how these two methodological traditions can be combined to incorporate further probabilistic causal claims into the QCA framework. The second part provides an application of the two methodological approaches, in the examination of common determinants for party-based Euroscepticism in Western Europe. Finally, I conclude and discuss when it is (and is not) appropriate to combine, or use complementarily, these two methodological traditions.

**Two logics of inference or one?**

The relative merits of the two methodological traditions (case-study oriented versus variable-oriented) for testing asymmetric hypotheses and exploring causal complexity is still dividing the comparative social studies research community (see, for instance, Clark et al., 2006; Goertz, 2006; Seawright, 2005). Instead of choosing one over the other, I argue that the two approaches both have strengths and weaknesses, and both can add potentially valuable knowledge regarding complex social phenomena. These two approaches have different underlying mathematical frameworks (set theory vs. non-linear/linear algebra) and slightly differing epistemological foundations. However, although this is probably not a position shared by all, I would argue that at least when the number of observations is fairly high they are quite closely related.

A common goal of the two approaches is to reduce the causal complexity of the observable reality, when this is possible and desirable. Clearly, most social phenomena are neither linear nor additive in nature. There are some cases where additive and linear models can give an adequate, but still (over-)simplified, description of observed reality, but in most instances relationships are complex, non-linear, non-additive, restricted to certain sub-populations, and influenced by diverse interacting factors, nested to varying degrees in time and space. This is stressed in configurational literature as well as in conventional statistical methodology literature, beyond introductory textbooks. Ragin’s (e.g. 1987, 2000, 2005) descriptions of how QCA differs from variable-oriented research have received strong criticism and particularly his descriptions of quantitative, ‘variable-oriented’ research (e.g. Achen, 2005b:29). For instance, Ragin and Rihoux (2004:22) claim that ‘regression analysis seeks to estimate the net, independent effect of each causal variable, considered in analytic isolation from all other causal variables’. Furthermore they argue that ‘rather
than trying to ‘supplant’ existing practices, the usual recommendation offered by QCA advocates is to use multiple approaches (if the data permit), including conventional quantitative analysis, and then to examine the differences that follow from estimating net effects (the goal of conventional quantitative analysis) versus investigating the different combinations of conditions linked to an outcome (the goal of QCA). There is absolutely nothing wrong with methodological triangulation, but rather than ‘estimating net effects’ one should use quantitative methods that are designed to evaluate conditional or asymmetric causal claims. Consequently, there is a need to state clearly that when moving beyond additive linear regression, e.g. when utilising regression models incorporating interaction effects, there is no such thing as a ‘net independent effect’ of a variable. Rather like ‘multiple causation’ in a QCA analysis, an implicit assumption of regression incorporating interaction effects (or Boolean logit/probit procedures) is that a set of conditions all need to be satisfied before an alleged cause is deemed sufficient to produce its effect.

A key distinction that Ragin (1987:64-67) draws between ‘variable-oriented’ and QCA research with regards to conditional causal claims is that the former requires advance knowledge of plausible interactions (or multiple conjunctural relationships) between factors that influence an outcome, i.e. a theoretical explanation of the specific conditional relationships that may be empirically observable, whereas QCA often makes a starting assumption of maximum complexity. The former essentially outlines the recommended textbook approach to statistical investigation of conditional relationships, but does not tell the whole story. Rather, the major difference between ‘variable-oriented’ and QCA research is that the former requires sufficiently large numbers of cases and variation to assess the validity of claiming that an observed relationship is (or is not) a chance finding (i.e. it is based on probability theory), whereas QCA and related techniques use knowledge acquired at the case level, in analyses of a few cases, and ‘frequency cut-off’, ‘consistency cut-off’ and simple statistical tests (of quasi-sufficiency) when there are more cases, to assess the validity of such claims. Where an analyst using QCA examines data using prior knowledge of the cases and theory in an attempt to identify plausible combinations of conditions that lead to an outcome, this does not differ greatly from standard quantitative data analysis. As described in most textbooks on quantitative data analysis, analysts are usually advised to plot and cross-tabulate their data, using theory as well as prior knowledge of the considered cases when trying to construct a model that accurately describes the relationships involved. Graphically examining the data and relying on judgement and prior knowledge of the relationships and the cases considered to decide the plausibility of the nature of a relationship is an acceptable, established practice among variable-oriented researchers. In both approaches, the analyst is basically qualitatively examining the data and then deciding what to do with it and how to interpret it. However, both use of QCA — due to its ‘strong inductive element[s]’ (Ragin 1987:101) — and visually inspecting data in plots and cross-tabulations can lead to erroneous inferences (and make significance tests deceptive), because in both cases one is using knowledge gained from the dataset itself, and hence potentially basing conclusions (or a model) on partly random associations. This is unlikely to be a problem when there are fairly few cases, but more theory-driven research is generally required when dealing with a larger number of cases, since knowledge and understanding of the specific cases (and the processes that lead to a certain outcome in each case) is likely to be limited. Hence, in research settings with many cases, configurational methods resemble quantitative methods in being fundamentally theory-centred.

In studies employing QCA researchers often study the entire population, or try to understand why some outcome happened in a smaller defined population of cases. Is it then possible to make inferences in QCA and quantitative studies using non-randomised samples or when studying the entire population of interest? Of course, users of both QCA and conventional techniques should be sensitive to what constitutes a sample or a population, and the inclusion of additional cases may have effects on the results (but less so if relationships are understood in a probabilistic fashion). However, when studying whole populations, i.e. when there is no sampling involved, this does not make inferential statistics useless (cf. Bollen, 1995). Also, even when using a non-randomised sample it is still possible to draw conclusions about these cases, but more problematic to make out-of-sample inferences.

Further, in both QCA and ‘variable-oriented’ studies it is essential to consider all relevant causal factors that may affect outcomes, hence an assumption (explicit or implicit) underlying both approaches is that no causally relevant conditions or variables have been omitted from the analysis. However, QCA makes even stronger assumptions than statistical methods that there are no omitted causally relevant factors that might contribute to a given outcome. The reason for this is that in a standard regression analysis the error term can,
in principle, capture the effects of omitted relevant causal variables, i.e. provided that the omitted variables are uncorrelated with all the other included predictors (cf. Seawright 2005). However, in a ‘variable-oriented’ approach the solution to the problems posed by omitted variables is not to include as many potentially, but tentatively, causally relevant variables in the model as possible, as this will not necessarily solve the problems associated with ‘confounding variables’. On the contrary, there is always a risk that the introduction of additional variables will increase the bias if these variables are correlated with the omitted variables. The solution can rather be achieved through a careful research design, that is by thinking carefully about which variables and cases should be included in the analysis and thus making the tests more narrow, focused and controlled (Achen, 2005a; Clarke, 2005). These recommendations regarding research design are explicitly covered in the QCA literature.

In addition, there is a dividing (but fading) line between the two research traditions on whether to view causal relationships as inherently deterministic or probabilistic. The idea of a probabilistic, as opposed to a deterministic view of causation, is that rather than regarding causes as inevitably leading to a certain outcome or effects, they simply raise the probability of their occurrence. A probabilistic view of causation is related to arguments that the world itself is non-deterministic, but even if it is deterministic such a view could be advocated simply because reality is too complex, and our knowledge too limited and ‘error-prone’ to provide more than probabilistic accounts of social relationships (e.g. Goldthorpe, 2001; Lieberson, 1992). As argued, for instance, by Lieberson (1992), even if one has an elaborate theory and well-founded explanations supporting a causal link between an observed outcome and a condition (or factor) in a certain population of cases, relationships are still not generally deterministic. While there may be a few social relationships that resemble laws of (social) nature (Taagepera, 2008), this does not imply completely deterministic causality. Even in (natural) science, models include constants derived by empirically inductive processes, as well as measurement errors and unknown parameters (i.e. omitted variables). In social sciences, where our knowledge is (usually) even more limited of the theoretical micro-foundations of certain phenomena than in natural sciences (since humans are less predictable than systems such as microorganisms, gases, molecules, etc.), social science theories provide even poorer explanations of outcomes in (sub-)populations. Therefore, a fully satisfactory investigation of a causal relationship must be based on a probabilistic view, rather than deterministic view, of causality (cf. King, Keohane, & Verba, 1994:57-63). The configurational methods developed by Ragin (1987) were initially based on a deterministic view of causal relationships and received much criticism for that reason (e.g. King, Keohane, & Verba, 1994:89-90). Today, probabilistic reasoning is now a part of most QCA applications (cf. Ragin, 2000; Rihoux, 2006). This is applied in the QCA framework by: using various kinds of simple statistical tests, e.g. uni- and bi-variate ‘quasi-sufficiency’ statistical tests such as the proportion z-tests and binominal proportion tests suggested by Ragin (2000: Ch. 4); applying ‘frequency thresholds’, i.e. only including configurations for which there are more than a specified number of observed cases; or by examining the solution coverage and consistency. However, the criteria that have been proposed in the QCA literature to date are somewhat vague, e.g. Ragin's measures of consistency and coverage. For instance, in 2004 he advocated use of a consistency cut-off point of 0.85 (e.g. for a crisp set including 85 % of the cases with a certain cause or combination of causes that display a given outcome) (Ragin 2004:11). Later (2006:293) he claimed that with ‘observed consistency scores below 0.75, it becomes increasingly difficult on substantive grounds to maintain that a subset relation exists, even a very rough one.’ However, later still (Ragin 2009, 112–115) he argued that a consistency score of 0.70 is ‘relatively low’ or even ‘very low’ and recommended use of a consistency score of 0.80. Thus, these decision rules, as well as the commonly used levels of significance in statistical analysis, are somewhat arbitrary. Using mechanical levels of rejection thresholds in both QCA and statistical analysis (e.g. the conventional 0.05 and 0.01 levels) we are likely to sometimes accept irrelevant patterns or reject important patterns in the data (e.g. Gill 1999). That is, a statistically significant difference is not necessarily an important difference, and a difference that is not statistically significant may be an important difference. Thus, we should not confuse statistical significance with theoretical or substantial differences. Similarly, QCA should not rely too much on fixed consistency scores, but rather try different rejection thresholds that are fairly close to one, to evaluate how these affect the analysis. Both approaches therefore require that we carefully examine and interpret the data using theoretical and substantive knowledge in order to reach conclusions about the relationships we are interested in.

As mentioned above, Ragin has also proposed simple formal statistical tests to assess the ‘quasi-sufficiency’ of conditions, or identification of conditions that are ‘usually sufficient’ (Ragin, 2000:109-116), ‘almost always’ or ‘usually’ necessary (Ragin 2003) in a QCA framework. However, as shown by Seawright (2005)
these tests make untenable assumptions as they only test one of many possible configurations at a time, implicitly assuming that no other causal combinations are relevant for the outcome. In practice, of course, this may not be true: when analyzing relationships

'a single fs/QCA model typically consists of several tests of different causal combinations, and often finds more than one of them to be relevant, [and so] the missing variables assumption ... is especially problematic. Every time two or more causal combinations are found to be relevant in an fs/QCA analysis, the assumption of no missing variables has failed for each combination - unless the combinations found to be relevant are uncorrelated with each other’ (Seawright, 2005: 18-19).

The same problem arises in a regression context when researchers consecutively try to fit several different models to the same data, which complicates interpretation of the results. Therefore, a more appropriate way to test probabilistic claims in the QCA framework, at least when fairly large numbers of cases are available, would be to supplement QCA analysis with appropriate statistical techniques, and thus strengthen attempts to draw causal inferences from observational data.

In this paper I will not consider fuzzy regression models (statistical estimation models designed to handle fuzzy measurements). Nor will I discuss methodological triangulation with QCA and various types of correlation and additive regression analysis (see for example Amenta & Halfmann, 2000; Amenta & Poulsen, 1996; Ebbinghaus & Visser, 1999) or (more recently) cluster analysis (Cooper & Glaesser, 2011). Instead, the following discussion aims to show when configurational techniques can be combined with comparable statistical techniques to provide statistical tests for a certain set of (multiple and conjunctural) conditions.9

Comparing frameworks, requirements and procedures

Configurational comparative methodology can be seen as both an approach, rooted in a case-orientated research tradition, and as a technique, based on the formal logic of Boolean algebra ‘to help researchers represent and synthesise what they have learned about their cases’ (Ragin, 2005:34). Thus, in QCA analyses there are generally ‘two apparently contradictory goals. On the one hand, one seeks to gather in-depth insight in the different cases and capture the complexity of the cases – to gain intimacy with the cases ... [on] the other hand, one still wishes to produce some level of generalisation’ (Rihoux, 2006:680). As a technique QCA can be placed between, and overlaps with, traditional comparative case-study methods (i.e. focusing on a few cases) and variable-oriented methods. Hence, when moving beyond small-N, to medium-N and large-N research situations, QCA could be complemented with statistical methods; as Ragin (1999:1228) notes, at its core QCA ‘is non-statistical, but probabilistic criteria can be incorporated at various points in the procedure’. This is a very good recommendation, to which this paper aims its contribution by discussing some alternative statistical methods that are often equally applicable for studying multiple and conjunctural causal claims. In the literature (e.g. Ragin, 1987, 2000, 2008), QCA is usually (and oddly) contrasted with linear additive statistical models, but the closest statistical equivalents, in their simplest forms, are linear or non-linear (multiplicative) interactive statistical models. In this paper I propose to complement crisp-set QCA by employing interaction terms in logit and probit models (Ai & Norton, 2003) and Boolean probit and logit (Braumoeller, 2003), and fsQCA using (multiplicative) interactive linear regression models.

Configurational and statistical methods: A comparison

In table 1, I provide a comparative summary of the csQCA and fsQCA methods on the one hand and two sets of corresponding statistical methods: interactive (non-linear/linear) regression models and Boolean logit/probit.

The QCA procedure often starts from the assumption of maximum complexity. In cases where empirical complexity is high, several combinations of ‘causal’ conditions (i.e. sets), or paths, might be identified, and in cases where empirical complexity is low a smaller set of causal conditions can be identified. By contrast, statistical methods do not assume maximum complexity in advance, but specify in advance factors that (according to theoretical considerations) are likely to contribute, singly or interactively, to an outcome. These factors are controlled against each other and evaluated through their statistical significance, as well as their individual and/or joint effect on the outcome (cf. Grendstad, 2007:121).
QCA studies combinations of conditions and outcomes that collectively compose sets, in which conditions and outcomes are understood in terms of their presence (or memberships). Thus, the ‘causal logic’ is that, rather than the study of covariation, QCA is the study of set memberships and relationships. Thus, although QCA and statistical methods can often be used to study the same research problem and in many cases probably yield similar results, they are not identical as configurations do not precisely map onto interacting variables and vice-versa. Furthermore, by the way it is designed the QCA technique will often produce solutions where conditions singly or in combinations with other conditions both can lead to a given outcome (equifinality). This differs from most statistical models used in comparative social research which assumes relationships to be additive and/or interactive (multiplicative) in a single causal-effects framework (unifinality).

Nonetheless, even though the deterministic (or veristic) use of QCA (i.e. csQCA, mvQCA and to a lesser extent fsQCA) allows comparative analysis of sets of small to medium numbers of cases, the number of cases included in the analysis still matters. Thus, a common problem with both case-oriented configurational research and variable-oriented research when dealing with medium numbers of cases is the ‘small-N problem’ with too many variables and too few cases (or observations). If QCA is applied to phenomena characterised by many conditions and relatively few cases the results can become excessively complex, with resulting equations containing several different combinations that may each only cover one case, suggesting that such cases each have a unique causal path. Even when solutions are forced to be parsimonious it may not be possible to interpret them in a theoretically meaningful way. In QCA analysis the possible number of logical combinations grows exponentially with increases in conditions, since for a set of \( k \) conditions the number of possible combinations is \( 2^k \). For example, for \( k = 3 \), the total number possible combination is eight while for \( k = 7 \) the total is 128 and a much higher number of different cases would probably be needed to avoid considerable limited diversity (i.e. resulting from a sample size which is small in relation to the number of conditions). As a consequence, the more conditions we include in our model, the more logical remainders, i.e. configurations that are logically possible but not empirically observed, there will be. In addition, including too many conditions in the analysis increases the risk for misspecifications and the total number of combinations of conditions may be difficult to handle. As Grendstad (2007:127) argues, due “to its procedure of an exhaustive configuration of antecedents, QCA’s challenge is not too many cases, but too many variables. Prescriptively, analysts need not abandon QCA when the number of cases is large”.

The statistical methods used here, namely multiple interactive regression models and Boolean logit/probit, require a fairly large number of cases/observations since the scope for detecting weak or moderate relationships is dependent on the sample size.\(^{12}\)

As most quantitatively trained scholars will be aware, in their simplest forms multiple interactive regression models include interaction terms as cross-products of (standardised) independent and/or dummy independent variables. Since it is usually advisable to include all constitutive terms in a model - that is all additive terms and both higher- and lower-order (multiplicative) interaction terms - the number of parameters to be estimated increases rapidly with increases in the number of independent variables involved in the interactions (for discussions about when it is and is not appropriate to include all constitutive terms see Brambor, Clark, & Golder, 2006; Kam & Franzese, 2007). In practice, statistical analysts usually deal with at most two- or three-factor interaction effects, partly because higher-order interaction effects are more difficult to interpret (particularly when the variables involved are not mostly dichotomies), while QCA does not have this limitation. It is also sometimes argued that one weakness of interactive regression models is that the interacting variables in these models are usually (multi)collinear (e.g. Ragin 1987: 68; 2000:72). Collinearity is especially frequent when squared terms of a variable (a predictor that interacts with itself), or two or more continuous interacting variables, are included. To circumvent this “problem” collinearity can often be minimised by “centring” the variables, i.e. subtracting the mean from every value of the variable, resulting in a centred variable with a mean of zero, while the standard deviation stays the same. Both these claims are nonetheless misunderstandings, for several reasons. Firstly, centring variables will often appear to “reduce” collinearity substantially, but centring the interacting variables ‘alters nothing important statistically and nothing at all substantively’, although it is harmless to do so (Kam & Franzese, 2007:4). Most importantly, centring variables does not add any new information to the estimation. Secondly, even when there is high collinearity and this leads to large standard errors for the model parameters, which in turn are signs of low confidence for these estimates, it is essential to remember that these standard errors are correctly large. The
presence of high collinearity together with large standard errors simply means that there is “too little information” in the data to estimate the model parameters precisely (Brambor, Clark, & Golder, 2006; Kam & Franzese, 2007). Again, this is not a problem within a QCA framework.

Analogously to the effects of increases in the number of conditions in QCA, the total number of interaction terms increases markedly with increases in the order of interaction effects. For instance, a 3-factor interaction model involves seven estimated parameters in total, while for a 4-factor model the total number of estimated parameters is 14 (excluding the constant and additional control variables). Since the possibilities of detecting weak or moderate relationships are dependent on the sample size, the limitations of modelling high-order interaction effects are more serious when there are small sample sizes. Consequently, as in QCA-analysis, modelling statistical interaction effects requires larger numbers of cases when there are more possible factors or conditions that may lead to a given outcome. In QCA analysis there will be too many possible solutions for a given outcome if too many conditions or factors are included in a medium-N analysis, i.e. the problem of ‘large-N configurations with small-N cases’, but we are not likely to get meaningful results from statistical modelling with too many interaction terms either. Thus, in both kinds of analyses there is inevitably a trade-off between the numbers of conditions/factors we can reliably investigate and the number of available cases.

However, other statistical methods that are designed to handle conjunctural and multiplicative causal relationships are also available, such as Boolean statistical techniques e.g. Boolean logit/probit and Boolean throb/tribit (Braumoeller, 2003; Braumoeller & Kirpichevsky, 2005; Gordon & Smith, 2004, 2005). The first of these (closely related) techniques will be considered here, Boolean logit and probit, which is specifically designed to incorporate Boolean logic into logit or probit models, thus allowing probability to be directly incorporated into the QCA framework (for a description and detailed discussion of the method, see Braumoeller, 2003). However, this method has shortcomings in demanding rather strict data requirements, and when there are too few observations together with insufficient variation this could result in practice in non-convergence of the maximum likelihood estimator. Thus, in some research (including some fairly large-N situations) there is a potential risk that the method may not yield any meaningful results.

Another important distinction, although its importance should not be overstated in this particular situation, is that configurational approaches more explicitly focus on knowledge and understanding of each particular case under investigation. This is obviously much easier when dealing with a fairly small number of cases, since it is possible then to have detailed knowledge of every single case, but it becomes increasingly difficult when considering medium- or large-sized datasets. Even though configurational approaches were originally intended to provide tools to ‘help researchers represent and synthesize what they have learned about their cases’, which in turn requires the researcher to gain ‘a deep, ‘thick’ understanding of each case’ (Ragin, 2005:33-34), this is difficult to accomplish if moderately large datasets are being examined, since knowledge of the individual cases generally becomes fairly limited as the number of cases increases. Thus, for instance, published applications of QCA in studies of hundreds or thousands of cases are evidently far from the case-study tradition (see for example Amoroso & Ragin, 1999; Ragin & Fiss, 2008; Ishida, Yonetani, & Kosaka, 2005; Miethe & Drass, 1999).
Table 1. QCA, Fuzzy sets, Interactive linear regression, Boolean logit/probit: A comparison

| QCA | Fuzzy sets | Interactive(nonlinear)/ linear regression | Boolean logit/probit |
|-----|------------|-------------------------------------------|---------------------|
| **Starting assumption** | Maximum complexity (Sometimes theoretical models – e.g. with large datasets) | Maximum complexity (Sometimes theoretical models – e.g. with large datasets) | Theoretical model | Theoretical model |
| **Procedure** | Bottom-up; reduce complexity | Bottom-up; reduce complexity | Top-down and model testing | Top-down and model testing |
| **Goal** | To discover (sets of) causal conditions | To discover (sets of) causal conditions | To determine significant effects; hypothesis testing | To determine significant effects; hypothesis testing |
| **Causal logic** | Contextual by combinations and substitutability | Contextual by combinations and substitutability | Additive and/or multiplicative | Additive and/or multiplicative |
| **Causal types** | Necessary and sufficient; multiple causality/equifinality | Necessary and sufficient; multiple causality/equifinality | Necessary and sufficient (usually not pursued); One-way causality (but occasionally two-directional causality/feedback loops; etc.) | Necessary and sufficient; multiple causality/equifinality |
| **Causal epistemology** | Determinism (declining); positivist empiricism (deductive-nomological/ inductive method) | Determinism (declining); positivist empiricism (deductive-nomological/ inductive method) | Probability; positivist empiricism (deductive-statistical/ hypothetico-deductive method) | Probability; positivist empiricism (deductive-statistical/hypothetico-deductive method) |
| **Dependent variable/outcome** | Event/membership (dichotomous/crisp) | Event/membership (fuzzy) | Any (dichotomous or continuous) | Event/membership (dichotomous) |
| **Independent variables/ conditions** | Any, but preferably dichotomies | Fuzzy; dichotomies | Any | Any |
| **Requirements on number of cases** | No limitations (in practice a minimum required by number of conditions); small-N to large-N | No limitations (in practice a minimum required by number of conditions); small-N to large-N | A minimum required by degrees of freedom; medium-N to large-N | A minimum required by degrees of freedom; preferably large N |
| **Complete model** | An exhaustive truth table | An exhaustive truth table | Correctly specified according to theory; all constitutive interaction terms included | Correctly specified according to theory |
| **Weakness of complete model** | Exponential growth of combinations leads to limited diversity; measurement error; omitted conditions | Exponential growth of combinations leads to limited diversity; measurement error; omitted conditions | May be too few observations to achieve sufficient statistical power; measurement error; omitted variables | May be too few observations to achieve sufficient statistical power; measurement error; omitted variables |
| **Solution for complete model** | Limit number of conditions | Limit number of conditions | Usually include all constitutive interaction terms | Achieve convergence |

*Note: This table is an extended and modified form of a table presented by Grendstad (2007:123).*
Application

I will now illustrate the abovementioned methods through an analysis of party-based Euroscepticism in 14 Western European countries (i.e. the 15 EU member states as of 1995, excluding Luxembourg) in 1999. The goal of this analysis is to demonstrate how the two methods can be combined in a mixed-method approach, in which QCA analysis is followed by a corresponding statistical analysis (which provides probabilistic tests of sufficiency of the results from the QCA).

In the last two decades research on political parties’ attitudes towards European integration and party-based Euroscepticism has attracted substantial scholarly attention. Since Taggart’s (1998) seminal paper on the emergence of Eurosceptic parties in Western Europe, theoretical debate has focused on two related issues: how to define and measure Euroscepticism among national political parties, and the factors that cause parties to adopt Eurosceptic positions (cf. Szczepanik & Taggart, 2008). I briefly address both of these issues below. Concerning the first of these issues, several authors have formulated specific definitions of Euroscepticism (e.g. Kopecky & Mudde, 2002; Ray, 2007; Taggart, 1998; Taggart & Szczepanik, 2002). For instance, Taggart (1998:366) originally stated that Euroscepticism ‘expresses the idea of contingent or qualified opposition, as well as incorporating outright and unqualified opposition to the process of European integration’ among political parties. In contrast, a more recent definition distinguishes between principled or ‘Hard opposition’ to European integration and contingent or ‘Soft opposition’, in which attitudes towards a country’s membership of the EU determine whether a party’s stance is categorised as ‘Hard’ or ‘Soft’ opposition to European integration. More precisely:

“Hard Euroscepticism is where there is a principled opposition to the EU and European integration and therefore can be seen in parties who think that their countries should withdraw from membership, or whose policies towards the EU are tantamount to being opposed to the whole project of European integration as it is currently conceived.

Soft Euroscepticism is where there is NOT a principled objection to European integration or EU membership but where concerns on one (or a number) of policy areas lead to the expression of qualified opposition to the EU, or where there is a sense that ‘national interest’ is currently at odds with the EU’s trajectory’ (Taggart & Szczepanik, 2002:7).”

Although this pair of definitions, which clearly define and distinguish between two types of Eurosceptic attitudes, has been established in the literature, it has been criticised by various scholars. For instance, it has been criticised for: being too vague, particularly regarding the kinds of opposition that should be designated ‘soft’ Euroscepticism (e.g. Katz, 2008; Kopecky & Mudde, 2002); for not providing exhaustive, mutually exclusive concepts but partially overlapping categories (Berglund, Ekman, Vogt, & Aarebrot, 2006:148); and for not covering the whole range of possible positions towards Europe (Conti, 2003; Ray, 2007:155-156). An alternative to the hard-soft concept of Euroscepticism is presented by Kopecky and Mudde (2002), who distinguish between scepticism towards the EU as an existing set of institutions on the one hand (EU optimism/pessimism) and scepticism towards European integration as an ideal on the other (Europhilia/Europhobia). These distinctions can be used to define four ideal types: ‘Euro-rejects’ who reject both the EU and the ideal of European integration; ‘Eurosceptics’ who support the general ideas of European integration, but not its current or future reflection of these ideas; ‘Euro-pragmatists’ who do not support (or necessarily oppose) integration, but consider the EU to be beneficial; and ‘Euro-enthusiasts’ who support both the EU and the general ideas of European integration. Although these popular ideal-type classifications of Euroscepticism can sometimes be useful, they can lead to somewhat strange bedfellows, since categorical classification does not necessarily create mutually exclusive categories (as some parties could be equally validly assigned to more than one group). This is because (truncated) classifications are merely loosely connected to actual positions reflecting varying degrees of support or opposition for the EU, i.e. within each category, parties vary in their positions on European integration.

For the purposes of this paper, I will operationalise Euroscepticism using information from both Chapel Hill expert survey data (Steenbergen & Marks, 2007) and party manifesto data (Klingemann, et al., 2007). The Chapel Hill expert surveys are a series of surveys in which local experts were asked to quantify the level of support for European integration using a seven-point scale, where 1 indicates strong opposition to integration and 7 indicates strong support for integration. In addition, I use information regarding references to Europe in election manifestos of national political parties to determine their degrees of Euroscepticism. The frequencies
of positive and negative statements regarding European integration in the manifestos of each party in each election year were recorded. The difference between the two frequencies also provides a proxy of the parties’ overall position on European integration. By using these measurements, I view party positions on Europe as a one-dimensional concept, without distinguishing between opposition to the EU and opposition to the European project in general (cf. Ray, 2007). Consequently, I provide alternative classifications of party-based Euroscepticism that correspond closely to those previously presented in the literature on party-based Euroscepticism (i.e. Ray, 2007; Taggart, 1998; Taggart & Szczerbiak, 2002). Categorising parties according to their degrees of Euroscepticism also has an analytical (or illustrational) purpose, since this proxy better corresponds to the original scaled measurement that is used in the statistical analysis (and it is not uncommon in QCA applications to derive crisp or fuzzy measurements from scale measurements). The measurements used in this application of QCA and the corresponding statistical analysis are discussed in the next section.

Turning to the second issue, several factors that may prompt parties to adopt negative stances to European integration have been raised in the literature. Essentially, these factors can be divided into two broadly defined sets of reasons (ideological-programmatic and strategic-tactical) for parties to adopt Eurosceptical positions (cf. Szczerbiak & Taggart, 2008). In the literature that focuses solely on party-based Euroscepticism, Taggart (1998), for instance, observes that Euroscepticism is mainly limited to parties on the periphery of their respective countries’ party systems, whereas those at the core of the political system (i.e. established mainstream parties) are merely likely to express Euroscepticism through party factions. Similarly, Sitter (2001, 2002) views party-based Euroscepticism mainly in terms of strategic positioning or as a ‘politics of opposition’ from smaller, peripheral parties mainly from the left and right, but also from populist anti-establishment parties (and to a lesser extent special-interest and identity-based parties). As a result, Eurosceptic parties should be expected to modify or avoid Euro-scepticism when they seek to, or actually do, participate in governing coalitions. Consequently, a government-opposition dynamics hypothesis has been raised, postulating that parties’ position within a party system will affect whether or not they adopt a Eurosceptic stance, although their opinions will rarely be detached from their core values. For instance, as Kopecky and Mudde (2002:319-320) argue, ‘ideology determines a party’s support for the ideas underlying the process of European integration, whereas strategy can play an important role in explaining a party’s support for the EU’ (for a similar argument, see also Szczerbiak & Taggart, 2008:255-256). Thus, even though the strategic-tactical considerations of parties are emphasised, they are rarely considered in isolation from parties’ ideologies or values. Studies that consider party positions on Europe more broadly, rather than merely focusing on party-based Euroscepticism, have viewed party positions in ideological-programmatic terms (Marks & Wilson, 2000), but also usually in combination with strategic-tactical terms, taking into account the government-opposition dynamics in party-based Euroscepticism (e.g. Hellström, 2008; Marks et al. 2002). Similar observations are made in these studies, i.e. that party positions cross-cut the left/right dimension, so that mainstream centre parties tend to be (moderately) pro-integrationist, with Euro-scepticism for the most part restricted to marginal, oppositional radical left and right parties. Somewhat conversely, it has also been suggested that radical right and right-populist parties should adopt Eurosceptical positions irrespective of their relative electoral weight and country of origin (Hooghe, et al., 2002), while it is argued that this is not the case for radical left parties (Brinegar & Jolly, 2005; Ray, 2004). More precisely it is argued that whether parties at the left will oppose European integration is dependent on whether they expect integration to increase or decrease welfare redistribution, relative to their national status quo. Consequently, in social democratic welfare states the left may perceive the EU as a threat to a more encompassing welfare state as a consequence of the relaxation of regulatory regimes, increased competition and harmonisation. From this summarised theoretical discussion three possible asymmetric or conditional hypotheses can be derived, namely that the following type of parties should be likely to be Eurosceptic: 1a) radical right/right-populist parties; or alternatively 1b) oppositional and radical right/right-populist parties; 2a) peripheral (small), oppositional radical left parties; or alternatively 2b) peripheral (small), oppositional radical left parties in social democratic welfare regimes.

Measurement

In this empirical application I use both crisp set and fuzzy set QCA (csQCA and fsQCA, respectively), i.e. I measure conditions and outcomes according to their presence or non-presence using dichotomous measures of 1 and 0, as well as five fuzzy membership scores. Thus, to facilitate a comparison between configurational and statistical methods, four different measures of response variables are used here: two crisp/binary measurements, one fuzzy measurement and one scalar (statistical) measurement, all of which are proxies for...
party-based Euroscepticism. The first and second measures are used in the comparisons of csQCA vis-à-vis logit/probit with interaction effects and Boolean logit/probit. The third measurement is used in the comparison of Fuzzy sets (fsQCA) analysis and regression analysis with interaction effects (in which statistical measurements are used in their original form).

Euroscepticism

For the crisp/binary measurement I do not distinguish between ‘hard’ and ‘moderate’ Euroscepticism, but rather include them in the same category. More precisely, two outcome variables of Euroscepticism were created: Eurosceptic1, in which parties that scored 2 or less in the Chapel Hill expert survey data were classified as Eurosceptic parties, and Eurosceptic2, including parties as Eurosceptic that had fuzzy membership-scores exceeding 0.5 (i.e. more in the set than out). The following procedure was used to create the fuzzy measurement and assign degrees of membership to the parties. I chose to use a fuzzy variable with five categories, where 1 denotes full membership of the set of Eurosceptic parties (strong Eurosceptics), 0.75 part membership (moderate Eurosceptics), 0.5 (neither in nor out of the set), 0.25 mostly positive and 0 strongly positive (and hence out of the set). All parties that scored less than 2 according to the Chapel Hill expert survey data were considered to be strong Eurosceptics, as well as those that scored 2-2.5 and had mostly Eurosceptic references in their electoral manifestos. Moderately Eurosceptic parties were identified in a similar manner; parties that obtained Chapel Hill expert survey scores between 2 and 3, or between 3-3.5 if they fulfilled the abovementioned criteria. Parties that scored 3.5 to 4.5 were assigned to the middle category, while parties that scored 4.5 to 5 were assigned the membership value of 0.25. The remaining parties were considered to be supportive towards the EU and the European project in general and were considered to be not part of the set (i.e. had values of 0). A few parties were recoded since these could not be considered to be strongly Eurosceptical by any of the established definitions (e.g. the British conservative party, although the party has long advocated a moderately Eurosceptical party line).

The fuzzy-set scores and the statistical values for the dependent variable are compared in figure 1, in which the thick line represents the fuzzy-set scores for membership of the set of Eurosceptic parties, and the thin line represents party positions on European integration. From the classification of Euroscepticism displayed in the figure, it is evident that most parties in the dataset are not Eurosceptic. More precisely, 22 parties are indentified as moderately Eurosceptic and 23 as strongly Eurosceptic out of 142 parties in total.¹⁵

Figure 1. Fuzzy-set versus statistical measurements of parties’ Euroscepticism

Turning to the conditions (or independent variables), these consist of seven indicators measuring: the parties’ ideological locations (two binary, far-left or far right; and two fuzzy, radical-right or radical-left); strategic placement within the party system (government or opposition); size and geographical location, i.e. whether the
party’s country has a social democratic welfare state system or not. Again I make use of both crisp/binary, fuzzy and statistical measurements, and I briefly discuss how the crisp/binary and fuzzy measurements have been created below.

**Ideological extremity**

To identify ideological extreme parties at the left and right, I use two separate distinctions. Party ideology can be conceptually defined simply as the policy alternatives presented and pursued by individual parties, i.e. their general orientation in the left/right ideological continuum; or more broadly in terms of party identities and party labels, as summarised in the notion of party families (Mair & Mudde, 1998). Following the first definition, parties located at the ends of the ideological spectrum were coded as either far-left or far-right parties (creating two crisp and two fuzzy measurements). Following the second definition, I also chose to define radical parties as belonging to a certain party family, creating two separate dichotomous measurements: radical right and radical left (used in both the QCA and fs/QCA analysis).

**Oppositional status**

The oppositional status of a party was operationalised as those parties that were not currently in government or had never had any formal governmental experience, thus creating a dichotomous variable that takes the value 0 if the party was currently in government (or had been in the past) and 1 otherwise (called neveringov in the analysis).

**Peripheral position in the party system**

To evaluate whether marginal or peripheral parties take more radical positions than mainstream parties, it seems reasonable to account for their relative sizes (i.e. if they are ‘small’ or not) in the analysis. However, distinguishing small parties dichotomously is not easy, since one has to identify an appropriate cut-off point that captures the notion of ‘small parties’. Such a classification could rest on Sartori’s (1976:108-109,123-124) idea that small parties are relevant, regardless of their size, as long as they prove to have influence over time through demonstrating either ‘coalition’ or ‘blackmail’ potential, i.e. the ability to influence electoral competition either by their inclusion in a governing coalition or the ability to threaten other parties if they do not follow the smaller party’s issue positions. Since parties’ ‘blackmail potential’ is not easy to empirically verify and the goal of this empirical analysis is to examine factors that characterise party-based Euroscepticism, rather than the influence of small parties per se, another typology should be used. One such criterion is whether the party has parliamentary representation (i.e. any parliamentary seats), despite winning a small share of the electoral votes. Unfortunately, such a classification would exclude smaller parties that have previously had, but lost, representation or gained representation in subsequent elections. Since the use of legal thresholds and informal effective thresholds for parliamentary representation differs in the countries examined (see, for instance, Taagepera, 2002), I tested various classification criteria for ‘small’ parties, using several electoral vote share thresholds that could potentially be used to define them accurately, ranging from < 5 percent to < 10 percent. Some of these cut-off points excluded many right-wing populist parties. Consequently, among the countries studied, far-right Eurosceptic parties differ from those at the left in their electoral success, since the far-right parties include both small and larger parties, while the latter include only parties that attracted less than 10 percent of the votes (except for the Swedish Vänsterpartiet, which gained about 12 percent of the votes in the general election in 1999 and the Spanish Izquierda Unida which received about 10.5 percent of the vote in the 1996 election). Since these two left parties can still be considered marginal, I chose to code them as ‘small’. The fuzzy measurement of small parties uses a five value coding, in which parties with vote shares of less than 5 percent are assigned full membership (i.e. coded 1); 5-10 percent are considered to be partly in the set (i.e. coded 0.75); 10-15 percent are considered to be neither in nor out of the set (i.e. coded 0.5); 15-20 percent are regarded as more out than in the set (i.e. coded as 0.25); and parties with more than 20 percent of the vote share are coded 0 (completely out of the set).

**Welfare state regime**

Since one of the hypotheses tested in this paper predicts that left-parties in social democratic welfare regimes should be more Eurosceptic than other left-parties, the final measurement, social, consists of a dichotomous variable that takes the value of 1 if the party is located in a country with a social democratic (i.e. Nordic) welfare regime and 0 otherwise.
Analysis and results

With five causal conditions, there are thirty-two logically possible combinations of conditions, all of which are included in the truth table (although some of these are not simultaneously possible, e.g. being a far-left and far-right party at the same time). The goal of QCA analysis is to summarise or reduce truth tables to less complex sets of conditions, and thereby attempt to discover the ways in which causal conditions, singly or in combination, give rise to observed outcomes (Ragin, 1987, 2000). The analysis conducted here focuses on three different membership (or outcome) measurements to be explained: two crisp or binary and one fuzzy.¹⁹

Below I report the primary results obtained using csQCA, fsQCA and the three comparable statistical techniques in the following tables. The statistical techniques combined with the csQCA analysis considered here are logit/probit regression (LR/PR) with interactions and Boolean logit/probit regression (BLR/BPR).²⁰ Similarly, fsQCA is supplemented with linear regression with interactions (IR).

In the tables below (table 2a, 3a and 4a), the configurations are presented as equations applying the logical operator and (*) to indicate a compound set of two or more combined conditions (i.e. set intersection), and the logical operator or (+) to represent alternative combinations of conditions (i.e. the union of sets)²¹. Upper-case and lower-case letters indicate the presence and absence of a condition, respectively. The parties covered by the respective expressions are listed in parentheses.

In QCA analysis, it is possible to derive three truth table solutions - one that maximises parsimony, one that maximises complexity and an intermediate solution. The difference between these solutions is whether or not the researcher assigns a particular value on the outcome for ‘logical remainders’, i.e. theoretical possible configurations not empirically observed among the cases. The parsimonious solution allows the combination of any counterfactual cases that contributes to the derivation of a logically simpler solution, the complex solution avoids incorporating any counterfactual cases, whereas so-called ‘intermediate solution’ uses the aid of only those logical remainders that are consistent with the researcher's theoretical and substantive knowledge (Ragin 2008).

In the analyses presented in tables 2a, 3a and 4a below, I use parsimonious solutions in tables 2a and 3a, and intermediate solutions (where the latter, in this particular case, is identical to the complex solution) in table 4a.²²

In the QCA analysis the fit of the reduced solutions is described by two terms: consistency and coverage. Raw coverage refers to the proportions of memberships of the outcome explained by each term of the solution, while unique coverage refers to the share of the outcome by one of the solution terms that is not covered by any other solution terms. A high (raw or unique) coverage is an indication that a certain path is relevant, i.e. has empirical weight. The consistency score expresses the degree to which a given condition in each solution term is a subset of the outcome. Thus, a high consistency score (close to 1) indicates that a solution term is near to being sufficient for an outcome. Solution coverage indicates shares of memberships of the outcome that are explained by the complete solution, and solution consistency indicates the degree to which the whole set of solution terms is a subset of the outcome (for a more comprehensive discussion, see Ragin, 2008).

In this empirical application I test the suggested propositions discussed above. I am not trying to explore what explains party-based Euroscepticism more generally, thus the solution coverage is not of major concern in this investigation. As shown in table 2a, the consistency for the individual set of conditions, and the solution consistency, is very high, but the coverage is quite low. These findings indicate that the suggested conditions are sufficient for the outcome, but do not cover a large proportion of the Eurosceptic parties (i.e. scepticism can also be explained by other factors).

Turning to the individual results, the first csQCA analysis using Eurosceptic1 as an outcome variable produces only one consistent solution (or ‘causal’ path), LEFT*right*NEVERINGOV*SOCIAL, which indicates support for the hypothesis (2b) that small, oppositional radical left parties in social democratic welfare regimes is sufficient for Euroscepticism. For statistical tests of quasi-sufficiency (presented in table 2b and 2c), I use logit/probit regression with interaction effects (LR/PR) and Boolean logit/probit regression (BLR/BPR). None of the two statistical models can be said to directly support the QCA results of this hypothesis. However, in logit/probit models, the equivalent interaction term perfectly predicts a subset of the outcome (thus making it impossible to estimate). This kind of estimation problem can frequently occur when
estimating interacting variables with logit/probit. In addition, assessing the effects and significance of the interaction terms is far from straightforward in logit and probit models (see for example Ai & Norton, 2003). In contrast, Boolean logit/probit is easily combined with csQCA and rests on Boolean logic. To fit the Boolean logit/probit model one first has to posit some preliminary conditions, in this case that LEFT*right*NEVERINGOV*SOCIAL should be associated with the outcome (or the latent dependent variable). Although the results in table 2c appear to support the hypothesis, the results were extremely sensitive to minor model modifications, which is not surprising as Boolean logit/probit estimation, as other statistical techniques used to evaluate interacting causes, depends heavily on existing covariation between the interacting variables and the outcome variable.

The second csQCA results using Eurosceptic2 as an outcome variable also indicate that the same combination of conditions is quasi-sufficient for party-based Euroscepticism. However, the coverage is lower since more parties are coded as Eurosceptic using this alternative proxy.

Turing to the fuzzy-set analysis, the results presented in table 2a indicate that two combinations may predict Euroscepticism:

\[
\text{LEFT* NEVERINGOV* SOCIAL + RIGHT*social*NEVERINGOV}
\]

The first combination is identical to the one identified in the csQCA analysis, i.e. far-left parties in social democratic welfare regimes in opposition are inclined to adopt Eurosceptical positions. The second combination indicates that far-right parties, in opposition and outside social democratic welfare regimes, are also prone to take Eurosceptical positions. The statistical tests of quasi-sufficiency are reported in table 2d. Model 1 and 2 in table 2d estimates the interacting variables, i.e. NEVERINGOV*RIGHT*social and LEFT*NEVERINGOG*SOCIAL, individually, while model 3 estimates the full model (i.e. including both interacting variables). In addition, I include two additional control variables, left-right position and its square, since parties’ positions on European integration are related to the left/right ideological space in a non-linear, single-peaked, bell-shaped curve – the well-known inverted U-pattern (cf. Hellström, 2008). Therefore, it should be important to take this into account in the statistical analysis (however, omitting these variables does not substantially alter the results).
Table 2a. Configurational analysis and summary of the statistical analysis (party ideology): results

|                   | csQCA/fsQCA | LR/PR | BLR/BPR | IR |
|-------------------|-------------|-------|---------|----|
|                   | Solution    | Raw coverage | Unique coverage | Consistency | Solution coverage | Solution consistency |
| Eurosceptic1      | LEFT*right*NEVERINGOV*SOCIAL | 0.294 | 0.294 | 1.000 | 0.294 | 1.000 | (Sign.) (Sign.) |
|                   | (EL; MP; V; JuniB; FolkB)    |       |        |       |       |       |          |
| Eurosceptic2      | LEFT*right*NEVERINGOV*SOCIAL | 0.111 | 0.111 | 1.000 | 0.111 | 1.000 | (Sign.) (Sign.) |
|                   | (EL; MP; V; JuniB; FolkB)    |       |        |       |       |       |          |
| Eurosceptic3      | RIGHT*NEVERINGOV*social      | 0.0734 | 0.0734 | 0.1000 |       |       | Sign. |
|                   | (DVU; FN)                 |       |        |        |       |       |          |
|                   | LEFT* NEVERINGOV *SOCIAL   | 0.102 | 0.102 | 1.000 |       |       | Sign. |
|                   | (MP; V; FolkB; EL; JuniB)   |       |        |        |       |       |          |

Note: For a list of party abbreviations, see [http://www.unc.edu/~hooghe/assets/data/pp/1999_ChapelHillSurvey_codebook.pdf](http://www.unc.edu/~hooghe/assets/data/pp/1999_ChapelHillSurvey_codebook.pdf)
Table 2 b. Results from statistical analysis LR/PR

| Variable                        | Eurosceptic1 | Eurosceptic2 |
|--------------------------------|--------------|--------------|
| LEFT*right*NEVERINGOV*SOCIAL    | n.a.         | n.a.         |
| LEFT                           | -11.3***     | -1.66**      |
|                                | (1.27)       | (0.76)       |
| NEVERINGOV                     | 1.93         | 1.65*        |
|                                | (1.09)       | (0.92)       |
| SOCIAL                         | 1.93*        | 1.14**       |
|                                | (1.09)       | (0.53)       |
| LEFT*NEVERINGOV                | 12.8***      | -0.42        |
|                                | (2.26)       | (1.46)       |
| LEFT*SOCIAL                    | n.a.         | n.a.         |
| NEVERINGOV*SOCIAL              | -2.22        | -0.67        |
|                                | (1.65)       | (1.18)       |
| RIGHT                          | 1.89**       | 1.05*        |
|                                | (0.79)       | (0.59)       |
| VOTE SHARE                     | -0.10*       | -0.02        |
|                                | (0.05)       | (0.02)       |
| Constant                       | -2.29***     | -2.08***     |
|                                | (0.87)       | (0.60)       |
| LR chi2                        | 22.69**      | -71.12***    |
| (Pseudo) R-square              | 0.170        | 0.137        |

Note: Un-standardised coefficients with robust standard errors in parenthesis; where *** p<0.01, ** p<0.05, * p<0.1. n.a.=not available.
Table 2c. Results from statistical analysis BLR/BLP

|                      | Dependent variable: Eurosceptic1 | Dependent variable: Eurosceptic2 |
|----------------------|----------------------------------|----------------------------------|
| LEFT*SOCIAL*NEVERINGOV|                                  |                                  |
| LEFT                 | 0.596***                         | 0.525***                         |
|                      | (0.342)                          | (0.382)                          |
| Constant             | -0.221                           | 0.290                            |
|                      | 0.318                            | 0.367                            |
| SOCIAL               | 6.135***                         | 4.951***                         |
|                      | (0.326)                          | (0.406)                          |
| Constant             | -0.584                           | 0.411                            |
|                      | 0.290                            | 0.392                            |
| NEVERINGOV           | 6.297***                         | 5.709***                         |
|                      | (0.426)                          | (0.287)                          |
| Constant             | -0.910                           | -0.443*                          |
|                      | 0.402                            | 0.268                            |

*Note: Un-standardised coefficients with robust standard errors in parenthesis; where *** p<0.01, ** p<0.05, * p<0.1.*
### Table 2d. Results from statistical analysis IR

| Dependent variable: Eurosceptic3 (scale) | (1)       | (2)       | (3)       |
|----------------------------------------|-----------|-----------|-----------|
| NEVERINGOV*RIGHT*social                | -1.62*    | -1.69**   |           |
|                                        | (0.74)    | (0.739)   |           |
| LEFT*NEVERINGOV*SOCIAL                 | -2.88***  | -2.58***  |           |
|                                        | (1.09)    | (0.739)   |           |
| Left-right position                    | 12.03***  | 1.90***   | 2.10***   |
|                                        | (0.23)    | (0.23)    | (0.23)    |
| Left-right position squared            | -0.20***  | -0.19***  | -0.21***  |
|                                        | (0.022)   | (0.020)   | (0.02)    |
| NEVERINGOV                            | -1.06***  | -0.78***  | -0.93***  |
|                                        | (0.26)    | (0.29)    | (0.30)    |
| SOCIAL                                 |           |           |           |
|                                        | -0.58     | -0.56     |           |
|                                        | (0.39)    | (0.40)    |           |
| LEFT                                   |           |           |           |
|                                        | -0.23     | -0.30     |           |
|                                        | (0.38)    | (0.31)    |           |
| NEVERINGOV*SOCIAL                      |           |           |           |
|                                        | -0.25     | -0.61     |           |
|                                        | (0.28)    | (0.82)    |           |
| NEVERINGOV*LEFT                        | -0.67     | 0.92**    |           |
|                                        | (0.41)    | (0.43)    |           |
| LEFT*SOCIAL                            | -1.30***  | 1.30***   |           |
|                                        | (0.46)    | (0.46)    |           |
| VOTE SHARE                             | -0.011    | -0.012    | n.a.      |
|                                        | (0.010)   | (0.009)   |           |
| RIGHT                                  | 0.073     | -0.03     |           |
|                                        | (0.56)    | (0.54)    |           |
| Constant                               | 6.64***   | 6.67***   | 1.08*     |
|                                        | (0.66)    | (0.70)    | (0.65)    |
| R-squared                              | 0.59      | 0.583     | 0.609     |

*Note:* Un-standardised coefficients with robust standard errors in parenthesis; where *** p<0.01, ** p<0.05, * p<0.1, n.a.=not available (due to collinearity).

Tables 3a and 4a summarise the QCA results of examining party-based Euroscepticism using party families rather than party ideology. In this analysis I choose only to use fuzzy-set QCA and regression with interacting effects. On purely combinatorial grounds, there are 4096 (i.e. 2^12) logically possible combinations of conditions that could be included in the truth table. However, most of these are not simultaneously possible, e.g. being part of different party families, thus in practice the possible number of combinations is much lower.
The parsimonious solution presented in table 3a indicates that three combinations of conditions are quasi-sufficient for party-based Euroscepticism:

social*RADICAL_RIGHT+
NEVERINGOV*RADICAL_LEFT+
SOCIAL*NEVERINGOV*radical_right

The consistency for the individual sets of conditions, as well as the solution consistency, are rather high. In addition, the coverage is moderately high at 0.588. The statistical tests of quasi-sufficiency are presented in table 3b. Not surprisingly, as the solution is not overly complex, all these solutions are statistically (and substantially) significant. Again (as in table 2 above), models 1 and 2 estimate these interacting variables individually, while model 3 estimates the full model.

The intermediate solution in table 4a indicates that five combinations of conditions are quasi-sufficient for party-based Euroscepticism:

NEVERINGOV*SMALL *RADICAL_LEFT+
social*NEVERINGOV*RADICAL_RIGHT*SMALL+
SOCIAL*NEVERINGOV*GREEN*SMALL+
SOCIAL*NEVERINGOV*SPECIAL_ISSUE*SMALL+
social*neveringov*small*RADICAL_RIGHT

In table 4b I limit the presentation to the significant results, i.e. for the following combinations of conditions NEVERINGOV*SMALL *RADICAL_LEFT and SOCIAL*NEVERINGOV*SPECIAL_ISSUE* SMALL. The second combination of conditions, i.e. social*NEVERINGOV* RADICAL_RIGHT*SMALL, is not significant partly because there are several radical right parties that have gained a fairly large share of the electoral vote (as mentioned above). Nonetheless, investigation of lower-order interaction effects (not shown here), between radical right parties and the share of the electoral vote, and between radical right parties and oppositional status, clearly indicated that smaller radical right parties are more sceptical than larger parties, and radical right parties in opposition are more sceptical than those with governmental experience. The third combination of conditions involving green parties is also not significant. To investigate fourth-order interactions effects with the given sample size and the few cases covered by the solution would not be appropriate in most cases. Again, examining lower-order interaction effects, I found support for the hypothesis that small, Nordic green parties are more overtly Eurosceptical than other small green parties. Finally, I find support (albeit based on a detected interaction effect involving four mutually conditional variables) for the hypothesis that small Nordic special issue parties in opposition are more sceptical toward Europe than other special issue parties. However, similarly social*neveringov*small*RADICAL_RIGHT also yielded a statistically significant result, but both these results should be treated with caution, as nearly all constitutive terms (lower order interaction terms) were dropped from the estimation due to colinearity.
### Table 3a. Fuzzy-set analysis and summary of the statistical analysis (party families): results - parsimonious solution

| fsQCA                        | IR          |
|------------------------------|-------------|
| **Solution**                 | Raw coverage | Unique coverage | Consistency | Solution coverage | Solution consistency |
| social*RADICAL_RIGHT         | 0.254       | 0.254           | 0.938       |                   | Sign.                 |
| VB; FN; REP; DVU; FN; RPF; MN; AN; MS; CD; UKIP; FPO |             |                 |             |                   |                      |
| NEVERINGOV*RADICAL_LEFT      | 0.220       | 0.175           | 0.813       |                   |                      |
| EL; KKE; DIKKI; IU; LO-LCR; SP; RC; PDUP; SP; CDU - Portugal; BE; V |             |                 |             |                   |                      |
| SOCIAL*NEVERINGOV*radical_right | 0158       | 0113            | 0785        |                   |                      |
| EL; JUNIB; FOLKB; SEP/EKA; REM; KIPU; V; MP |             |                 |             |                   | 0588 0867           |

*Note: For a list of party abbreviations, see [http://www.unc.edu/~hooghe/assets/data/pp/1999_ChopelHillSurvey_codebook.pdf](http://www.unc.edu/~hooghe/assets/data/pp/1999_ChopelHillSurvey_codebook.pdf)*
Table 4a. Fuzzy-set analysis and summary of the statistical analysis (party families): results - intermediate solution

| fsQCA                                      | Raw coverage | Unique coverage | Consistency | Solution coverage | Solution consistency | IR     |
|--------------------------------------------|--------------|-----------------|-------------|-------------------|----------------------|--------|
| NEVERINGOV*SMALL *RADICAL_LEFT             | 0.209        | 0.209           | 0.860       |                   |                      | Sign.  |
| LO-LCR; EL; SP; PDUP; SP; BE; DIKKI; RC;   |              |                 |             |                   |                      |        |
| CDU - Portugal; V; IU; KKE                |              |                 |             |                   |                      |        |
| social*NEVERINGOV*RADICAL_RIGHT*SMLLL      | 0.192        | 0.192           | 0.971       |                   |                      | Not sign. |
| CD; MS; UKIP; FN; RPF; DVU; REP; VB        |              |                 |             |                   |                      |        |
| SOCIAL*NEVERINGOV*GREEN*SMALL              | 0.040        | 0.040           | 0.875       |                   |                      | Not sign. |
| KIPU; MP                                  |              |                 |             |                   |                      |        |
| SOCIAL*NEVERINGOV*SPECIAL_ISSUE*SMALL      | 0.073        | 0.073           | 0.813       |                   |                      | Sign.  |
| FOLKB; EKA; JUNIB; REM                     |              |                 |             |                   |                      |        |
| social*neveringov*small*RADICAL_RIGHT      | 0.040        | 0.040           | 0.875       |                   |                      | (Sign.) |
| FPO                                        |              |                 |             |                   |                      |        |
|                                           | 0.554        | 0.891           |             |                   |                      |        |

Note: For a list of party abbreviations, see http://www.unc.edu/~hooghe/assets/data/pp/1999_ChapelHillSurvey_codebook.pdf
Table 3b. Results from statistical analysis IR (parsimonious solution)

| Dependent var.: Eurosceptic3 (scale) | (1)       | (2)       | (3)       | (4)       |
|-------------------------------------|-----------|-----------|-----------|-----------|
| social*RADICAL_RIGHT                | -2.13***  | -4.08***  |           |           |
|                                     | (0.44)    | (0.33)    |           |           |
| NEVERINGOV*RADICAL_LEFT             | -1.42**   | -1.25*    |           |           |
|                                     | (0.67)    | (0.73)    |           |           |
| SOCIAL*NEVERINGOV*radical_right     |           | -1.50**   | -3.59**   |           |
|                                     |           | (0.58)    | (1.43)    |           |
| Constant                            | 5.59***   | 6.41***   | 4.18***   | 6.26***   |
|                                     | (0.39)    | (0.46)    | (0.53)    | (0.290)   |
| R-squared                           | 0.602     | 0.579     | 0.467     | 0.654     |

Note: Un-standardised coefficients with robust standard errors in parenthesis; where *** p<0.01, ** p<0.05, * p<0.1. Lower-order interaction effects, additional covariates and other party dummies are excluded from the table to save space but are available on request from the author.

Table 4b. Results from statistical analysis IR (intermediate solution)

| Dependent variable: Eurosceptic3 (scale) | 2.31** | |
|------------------------------------------|-------|---|
| NEVERINGOV*SMALL*RADICAL_RIGHT           | (1.05)| |
| SOCIAL*NEVERINGOV*SPECIAL_ISSUE*SMALL    | 2.44***| |
| Constant                                 | 5.56***| 5.25***|
|                                          | (0.36) | (0.40) |
| R-squared                                | 0.587  | 0.636 |

Note: Un-standardised coefficients with robust standard errors in parenthesis; where *** p<0.01, ** p<0.05, * p<0.1. Lower-order interaction effects and other party dummies are excluded from the table to save space but are available on request from the author.

Discussion

To summarise the empirical results, it is evident that most of the (Eurosceptic) cases covered by the solutions are either small, Nordic, radical left parties in opposition or marginal radical right parties in opposition. Thus, the results from these analyses show that Euroscepticism is partly associated with small, non-governmental niche parties, e.g. far left, (Nordic) green and far right parties. These results are thus in line with findings of previous strictly variable-oriented research (e.g. Hellström, 2008; Hooghe et al. 2002; Marks et al. 2002).

Turning to the main methodological points, this empirical example demonstrates that configurational methods can be successfully combined with statistical methods and supplement the QCA-framework by providing statistical tests of ‘quasi’-sufficiency. However, for assessing ‘almost sufficient’ claims in crisp-sets QCA, logit or probit models with interaction terms are not very suitable if there are not very large numbers of cases and if they are overly complex, as direct estimation of the interaction effects is not always possible (because of the so-called ‘separation’ problem). Thus, in many cases Boolean logit/probit is a better alternative for supplementing crisp-set QCA analysis, since it is designed to account for causal complexity, e.g. multiple conjunctural causation, substitutability, multiple causal paths to a given outcome (equifinality) etc.
For fuzzy-set QCA, linear interactive regression models should provide adequate and straightforward tools for probabilistic evaluations of sufficiency (and necessity) for any given set of combination of causal conditions identified in fsQCA analysis. Even when the sample sizes are not extremely large (i.e. there are fewer than several hundred or thousands of observations) and the fsQCA results involve multiple and conjunctional causal claims, it should still be possible to evaluate them in a probabilistic manner in many practical research situations. Nonetheless, all the above-mentioned statistical techniques have their limitations, mainly because of their requirements of having sufficient variation (or diversity) to identify meaningful relationships. If there are too few cases together with limited variation, estimating interaction effects involving conjunctional or interacting variables will not be fruitful. Applying Boolean logit/probit procedures in situations with limited variation (e.g. too little information) and a small number of cases will also result in estimates that are essentially meaningless. Another limitation of regression (but not Boolean logit/probit) is that interactive regressions are very difficult to interpret when involving more than three interacting factors, particularly when the variables involved are not (mostly) dichotomies. These limitations do not apply to QCA analysis, but if one wants to supplement QCA with the above-mentioned statistical equivalents it will not always be possible because of the limitations mentioned above. In such cases, a researcher can only argue that a subset relation really exists (based on sufficiently high consistency and coverage scores), without using any probabilistic criteria.

Configurational methods do bridge, to some extent, the gap between qualitative case study methods and statistical methods (cf. Ragin, 1987, 2000; Rihoux, 2006), since QCA provides a useful tool for comparative analyses when there are small-to-medium numbers of cases. However, when addressing a larger number of cases statistical techniques for studying causal complexity (Braumoeller, 2003), conditional or asymmetrical causal claims, or sufficient and/or necessary causal claims (Clark, et al., 2006) are also available.

Thus, I argue that, given a fairly large number of cases, statistical methods can supplement QCA analysis in a mixed-method approach. QCA analysis provides greater leverage than statistical analysis through its ability to explore causal substitutability (i.e. multiple paths to a given outcome) and the ways in which many multiple causes interact with one another to produce effects. Nevertheless, before using statistical methods designed to handle ‘causal complexity’, as an addition to QCA, researchers should ideally consider whether there are sufficient observations to acquire accurate and reliable estimations. If there are too few observations together with limited diversity (i.e. insufficient information) to draw reliable statistical inferences using the statistical methods discussed here, configurational techniques can be used in combination with more robust small sample techniques, descriptive statistics, and cross-tabular statistical tests (as often suggested in the QCA literature). Alternatively, if there are very few cases one should follow standard advice and rely on empirical knowledge of the cases and theoretical judgments. Almost certainly, trying to incorporate the methods proposed in this paper in moderately small-N analyses (with say 5-40 cases) would produce only nonsensical results.

The empirical example presented in this paper, i.e. the investigation of party-based Euroscepticism in Western Europe, illustrates that configurational methods can be successfully combined with statistical methods to strengthen conclusions drawn from analyses of a moderately large dataset. However, when moderately large numbers of cases are available for investigation (i.e. between approximately 40 to a few hundred) this is not entirely unproblematic. Using logit or probit models with interaction terms to evaluate results originating from csQCA analyses can be challenging in terms of both interpretation of the conditional effects (cf. Ai & Norton, 2003) and estimation (because of the ‘separation’ problem). However, as shown by Grendstad (2007), such an approach can be valuable when there are fairly large numbers of cases for comparing results obtained from QCA and logistic regression analyses (with interaction effects). On the other hand, Boolean logit and probit have clear merits, since they directly incorporate Boolean logic and expressions, in particular when there is sufficient complex covariation.

As outlined above, interactive regression models should provide straightforward tools that are capable of incorporating probabilistic evaluations of sufficiency and necessity in fsQCA analysis, but regression analysis has limitations for estimating interaction effects involving a large number of conjunctional conditions or interacting variables. Is then the answer to restrict a mixed-method approach to genuine large-N research situations? Although Ragin originally intended to develop a method for systematic cross-case comparisons in
First, we note some methodological techniques to gain a more complete explanation of an outcome. On the other hand, additive relationships have been criticized, as they provide “solutions” at the expense of some statistical techniques that can take into account some types of omitted causally relevant variables, e.g. “instrumental variable” regression, and “fixed effects” or “difference in difference” models. However, all these techniques provide “solutions” at the expense of introducing additional (model) assumptions, some of which are not always tenable. So, again, it is up to the researcher to demonstrate that the research design and the assumptions made are suitable for the particular research situation.

For a more elaborate discussion of mixed-method approaches and triangulation see Tashakkori & Teddlie (1998). As showed by Smithson and Verkuilen (2006) fuzzy measurement theory could also, in an unchallenging way, be used for providing fuzzy measurements to conventional statistical techniques.

Notes

1 These terms all refer to situations in which outcomes are determined by interacting causes (i.e. interactive relationships), in contrast to causes that have effects that are independent of other causes (i.e. additive relationships).
2 Defining what is meant by small, medium and large datasets is not easy since the number of sufficient cases or observations depends on the number and richness of outcome variables and conditions in fs/QCA/MVQCA-analysis.
3 Nonetheless, extending the QCA technique to (massive) large-N studies can in many cases still provide additional understanding - particularly as QCA has a greater ambition than statistical methods to gain a more complete explanation of an outcome. On the other hand, large-N applications of QCA are still fairly rare, so its possible benefits in comparison to, or in conjunction with, statistical methods have not yet been fully explored.

For a nice discussion of the non-linearity of political phenomena see Brown (1995).
4 However, more recent applications, drawing on the rationale of statistical equivalencies, have extended configurational methods to cross-sectional time-series (Caren & Panofsky, 2005; Ragin & Strand, 2008) and multilevel/hierarchical analysis (Denk, 2009).
5 Thus, the effect of an independent variable on the dependent variable is neither constant, nor independent, as in a purely linear additive regression model.
6 Inferential statistics is in theory based on taking a random sample from a larger population so as to draw conclusions about the larger population from the data. However, when the data represents a complete amount of data that can be measured from the real world, we have a so called “apparent population”. Thus, the data is not a result of a random sampling from a larger population. This does not make inferential statistics unusable, as it would be unrealistic to believe that there is no measurements errors, no omitted variables, or that we have completely deterministic relationships. Nonetheless, Bollen (1995) suggest using resampling methods, i.e. bootstrapping (using random sampling with replacement from the original dataset) to get random samples when having an apparent population.

Using bootstrapping estimation for the models estimated in this paper does not alter the results.
7 Surprisingly, Seawright’s (2005) serious criticism regarding the assumption of no omitted conditions was not mentioned in the responses of De Meur et al (2009) to critiques of QCA.
8 Nonetheless, when data, theory and the research problem permit there are some statistical techniques that can take into account some types of omitted causally relevant variables, e.g. “instrumental variable” regression, and “fixed effects” or “difference in difference” models. However all these techniques provide “solutions” at the expense of introducing additional (model) assumptions, some of which are not always tenable. So, again, it is up to the researcher to demonstrate that the research design and the assumptions made are suitable for the particular research situation.
The argument that configurational techniques can be combined with statistical counterparts may be accepted by some and rejected by others (for a detailed discussion of epistemological problems associated with nested/mixed methods research see e.g. Rohlffing 2008.) I am not arguing that a quantitative template should always be applied when using qualitative approaches, but rather draw attention to the fact that QCA analysts could utilise related statistical procedures when appropriate.

More specifically, the possibility to draw any reliable inference from the data is dependent on several aspects relating to standard probability theory. In a hypothetical situation with a correctly specified model, four aspects are important for making correct inferences: the given significance (alpha) level, the desired power, the strength of the relationships between variables (or more accurately the expected effect sizes) and sample size, together with the number of estimated parameters.

Since these two datasets do not have the same coverage, mainly because the Chapel Hill party data set also includes information on small parties with little or no parliamentary representation, I mainly rely on the Chapel Hill party data set.

More precisely, these studies mainly focus on public opinion, but as Szczerbiak and Taggart (2008) argued, underlying party positions on the issue of European integration are determined not only by party ideology, but also by the perceived interests of the party’s supporters (i.e. if the process of European integration will benefit or adversely affect its supporters). Therefore, it is reasonable to extend this argument to include political parties.

The reason for the comparatively large number of moderately or strongly Eurosceptic parties (relative to corresponding numbers identified by Taggart 1998; Taggart & Szczerbiak, 2002) is that the Chapel Hill expert survey dataset includes data on many small parties that have no parliamentary representation.

More precisely, the ideological position as indicated by a left-right measurement was used to identify relevant parties. Parties at the ends of the ideological continuum were coded either as fully or partly in the set of far-left or far-right parties, respectively. See the appendix for further details.

The following right-wing populist parties were consequently not coded as small parties (election results in closest previous election in parenthesis): Front National (14.9%), Freiheitliche Partei Österreichs (26.9%), Lega Nord (10.1%) and Alleanza Nazionale (15.7%).

In addition, for both the crisp/binary coding and fuzzy set coding I tested different cut-off points to examine if the results were sensitive to the chosen levels of electoral vote share. The substantive results remained the same.

The QCA analyses were implemented in ‘fsQCA 2.5’ (Ragin, Kriss, & Davey, 2006) and all statistical analyses were conducted using Stata 11.2. The Boolean logit and probit functions were estimated using the user-written Stata program ‘mlBoolean’ (Braumoeller, 2004).

In fact, although logit and probit models differ in their underlying assumptions, they usually yield the same results in practical research situations. This is also the case here.

This should not be mistaken for the mathematical operator (+) in regression equations, since this represents an additive relationship between covariates (in regression analysis), whereas in QCA it represents alternative ‘causal paths’ between combinations (i.e. sets) and the outcome.

In the analysis I used a frequency cut-off of 1 and consistency cut-off of 0.8. I tried different consistency scores cut-off thresholds, which resulted in somewhat differing results (not shown here), but for simplicity I use a consistency cut-off of 0.8. A comparison of the parsimonious and complex solutions showed that these yielded different results, but when excluding combinations that did not have any unique coverage or merely covered one case, the results were identical. For the intermediate solution in table 4a I assume that the presence of both radical left and radical right parties should favour the outcome being achieved, as these are the only conditions that have firm theoretical support (and also appear in the parsimonious solution terms).

This problem is called ‘complete separation’ or ‘quasicomplete separation’, which basically means that the presence of one or more covariates perfectly predicts a subset or all of the observations in the data. To overcome this problem one has to rely on post-hoc data correction or examine this relationship using an appropriate method, see for instance Zorn (2005).

In short, the ‘probability calculus’ for a Boolean interaction is simple: if the combination of A and B and C causes Y, then \( p_Y = p_A \times p_B \times p_C \). If either A or B or C causes Y, as in suggested here, then \( p_Y = 1 - \{(1 - p_A) \times (1 - p_B) \times (1 - p_C) \} \). The Boolean logit/probit procedure then models the probabilities of the latent dependent variables as ordinary logit and probit curves and constructs a likelihood function based on the hypothesised logic of their interaction and the observed dependent variable to obtain coefficient estimates (Braumoeller 2003). Thus, in Boolean logit/probit no specific interaction term is estimated, but the parameters estimated can still be evaluated in a interactive sense. If an parameter shows no significant influence on the dependent variable, this means that in interacting with other variables this predictor loses its predictive power.
Using the intermediate solution (assuming that both parties at the far left and far right of the ideological continuum are a subset of the outcome) yields somewhat different results. The same parties are covered (except for the Swedish radical-left party, Vänsterpartiet), but SMALL remains after the minimisation process.

Changing the threshold for what constitutes a small party does not affect the results, and nor does using a single fuzzy measurement containing information about both parties’ oppositional status (i.e. lack of government experience) and size (defined in various ways).

A closer examination of the data (see the truth tables in the appendix) can explain the fairly low coverage and consistency scores. For instance, to mention two examples, there exist some radical parties that have participated in government (to varying degrees), but are nonetheless more or less sceptical towards European integration, e.g. the French radical left party Parti Communiste Français. Conversely, among the group of radical right parties the Italian Alleanza Nazionale and the Swedish Ny Demokrati had a rather positive stance towards European integration.

In order to simplify the interpretation of higher-order interaction effects I used dichotomous variables, rather than continuous variables, when constructing these interacting variables. It was not possible to estimate the interacting variables in one single model.

Two of these parties (covered in the expression) are Danish single issue Eurosceptical parties, Folkbevægelsen mod EU (FolkB) and JuniBevægelsen (JuniB), and two are small Finnish special issue parties; Eläkeläiset Kansan Asialla, a senior citizens’ party (EKA) and Nuorsuomalainen Puolue/Nuorsuomalaiset a (neo)liberal few-issue party (REM). The last mentioned party cannot be classified as Eurosceptical.

For a detailed discussion on ways to evaluate necessary and sufficient causal claims using standard multiplicative interaction models see Clark, Gilligan & Golder (2006); Kam & Franzese (2007).

Although it is not possible to give any general rules about sample sizes required, when having a dataset of 20-30 observations (multiplicative) interaction models are hardly an alternative, but a large medium-size dataset with at least 40 observations and no more than two conditions/factors should work in many cases. If we have three conjunctural conditions/factors a rough estimate of about 70 or more observations is usually advisable. If the relationships under investigation are rather strong (i.e. show a high degree of regularity) fewer observations are needed to gain adequate statistical power.

Grendstad (2007) included about 500-700 cases in his comparison between QCA and logistic regression (with interaction effects), showing that the two methods provide converging indications of causes at work, and how these causes combine to produce an outcome.

In large-N analyses, of several hundred or thousands of observations, statistical methods have major strengths over QCA analysis since one can retain all the variance in the measurements and account (at least to some extent) for potentially problematic features of the model and dataset e.g. omitted variables, measurement errors, spatial and temporal dependence between cases, recursive relationships, hierarchal relationships, etc.

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Biography

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Appendix

All data used in the analysis are described, and their data sources listed in table A1 and the truth tables are shown in table A2-A4. How the variables used in the analysis were constructed is described in the paper, with the exception of the two crisp/binary measurements far-left and far-right and fuzzy measurements radical-left and radical-right (i.e. membership in either the group of far-left parties or far-right parties). These measurements were constructed using information about parties’ general orientation on the left/right ideological continuum, i.e. their left-right positions, where parties located at the ends of the ideological spectrum were coded as either fully or partly in the sets of far-left or far-right or radical-left and radical-right parties. To construct the two crisp/binary measurements I code those parties being two units or less away from the ends of the proxy for parties left-right positions as either far-left or far-right. To construct the two fuzzy measurements the following criteria were used: those parties less than one unit away from the ends of the Chapel Hill measurement (i.e. between 0-1 and 9-10) of parties ideological positions were coded 1; as well as parties being one standard deviation below or above the mean position and at the same time being less than 2 units away from the ends of the ideological measurement. Those parties between 1 to 2.5 units away from the ends of the measurement were coded 0.5. Parties between 2.5 to 3 units away from the ends of the measurement were coded 0.25. All remaining parties were coded 0 (i.e. out of the set). Examining which were parties coded as either fully or partly in the set, it is evident that this procedure does capture those parties that are generally classified as either radical left, left-green parties, or at the other end of the ideological continuum, right-wing populist or nationalist parties. This coding procedure is classifying about 5 percent of the parties as fully in the set (i.e. given the value of 1) of either far-left and far-right parties, respectively; about 7 percent of the parties as more in than out the set (i.e. 0.75); about 8 percent as neither in or out the set; and about 9 percent more out than in the set (i.e. 0.25).

Table A1. List of variables

| Variables          | Mean   | Std    | Min | Max |
|--------------------|--------|--------|-----|-----|
| Eurosceptic1       | 0.119  | 0.325  | 0   | 1   |
| Eurosceptic2       | 0.315  | 0.466  | 0   | 1   |
| Eurosceptic3 (fuzzy) | 0.315 | 0.407  | 0   | 1   |
| Eurosceptic3 (scale) | 4.722 | 1.889  | 1   | 7   |
| Left               | 0.127  | 0.334  | 0   | 1   |
| Right              | 0.141  | 0.349  | 0   | 1   |
| Radical_left       | 0.204  | 0.287  | 0   | 1   |
| Radical_right      | 0.0880 | 0.255  | 0   | 1   |
| Neveringov         | 0.472  | 0.501  | 0   | 1   |
| Small              | 0.190  | 0.394  | 0   | 1   |
| Small (fuzzy)      | 0.695  | 0.397  | 0   | 1   |
| Social             | 0.218  | 0.415  | 0   | 1   |
| Left-right position| 5.106  | 2.290  | 0.6 | 9.889|
| Vote share         | 9.512  | 11.629 | 0   | 44.1|

Note: All variables originate from the Chapel Hill expert party dataset (Steenbergen & Marks 2007), which two exceptions: ‘Neveringov’ which was created from Mackie and Rose (1998); Woldendorf, et al (2000);
Koole and Katz (2000), and ‘Eurosceptic2’ and ‘Eurosceptic3’ which also uses information from party manifesto data (Klingemann, et al. 2007).

**Truth tables**

**Table A2. Truth table (table 2 in the paper; outcome Eurosceptic1)**

| Far left | Far Right | Small | Social | Neveringov | Outcome | Consistency | No. of cases |
|----------|-----------|-------|--------|------------|---------|-------------|--------------|
| 1        | 0         | 0     | 1      | 1          | 1       | 1.000       | 1            |
| 1        | 0         | 1     | 1      | 1          | 1       | 1.000       | 4            |
| 0        | 1         | 1     | 1      | 1          | 0       | 0.500       | 2            |
| 1        | 0         | 1     | 0      | 1          | 0       | 0.333       | 3            |
| 0        | 1         | 1     | 0      | 1          | 0       | 0.333       | 6            |
| 0        | 0         | 0     | 0      | 1          | 0       | 0.250       | 4            |
| 0        | 0         | 1     | 1      | 0          | 0       | 0.167       | 6            |
| 0        | 1         | 0     | 0      | 0          | 0       | 0.125       | 8            |
| 0        | 0         | 1     | 0      | 1          | 0       | 0.098       | 41           |
| 0        | 0         | 0     | 1      | 0          | 0       | 0.083       | 12           |
| 0        | 0         | 1     | 1      | 1          | 0       | 0.000       | 3            |
| 1        | 0         | 0     | 0      | 0          | 1       | 0.000       | 3            |
| 0        | 0         | 1     | 0      | 0          | 0       | 0.000       | 6            |
| 0        | 1         | 0     | 1      | 0          | 0       | 0.000       | 2            |
| 0        | 0         | 0     | 0      | 0          | 0       | 0.000       | 2            |
| 1        | 0         | 0     | 1      | 0          | 0       | 0.000       | 32           |
| 1        | 0         | 0     | 0      | 0          | 0       | 0.000       | 1            |
| 1        | 0         | 0     | 0      | 0          | 0       | 0.000       | 6            |

**Table A3. Truth table (table 2 in the paper; outcome Eurosceptic2; fuzzy)**

| Far left | Far Right | Small | Social | Neveringov | Outcome | Consistency | No. of cases |
|----------|-----------|-------|--------|------------|---------|-------------|--------------|
| 1        | 0         | 1     | 1      | 1          | 1       | 1.000       | 5            |
| 0        | 1         | 1     | 0      | 1          | 1       | 0.813       | 3            |
| 0        | 0         | 1     | 1      | 1          | 0       | 0.786       | 3            |
| 1        | 0         | 1     | 0      | 1          | 0       | 0.591       | 6            |
| 0        | 1         | 0     | 0      | 0          | 0       | 0.545       | 2            |
| 0        | 1         | 1     | 1      | 1          | 0       | 0.500       | 2            |
| 0        | 1         | 1     | 0      | 0          | 0       | 0.500       | 1            |
| 0        | 0         | 1     | 0      | 1          | 0       | 0.436       | 44           |
| 0        | 0         | 1     | 1      | 0          | 0       | 0.390       | 11           |
| 1        | 0         | 1     | 0      | 0          | 0       | 0.240       | 5            |
| 0        | 0         | 0     | 1      | 0          | 0       | 0.208       | 5            |
| 1        | 0         | 1     | 1      | 0          | 0       | 0.200       | 2            |
| 0        | 0         | 0     | 0      | 0          | 0       | 0.123       | 17           |
| 0        | 1         | 0     | 1      | 0          | 0       | 0.111       | 2            |
Table A4. Truth table (table 3 in the paper; outcome Eurosceptic2; fuzzy)

| Sm | So | NG | RR  | Con | Lib | CD | S | RL | G | R/E | O | Outcome | Consistency | No. of cases |
|----|----|----|-----|-----|-----|----|---|----|---|-----|---|----------|--------------|-------------|
| 0  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 1        | 1.000        | 2           |
| 1  | 0  | 1  | 1   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 1        | 0.971        | 9           |
| 1  | 1  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 1 | 0   | 0 | 1        | 0.875        | 2           |
| 0  | 0  | 0  | 1   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 1        | 0.875        | 1           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 1  | 0 | 0   | 0 | 1        | 0.833        | 10          |
| 1  | 1  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 1 | 1        | 0.813        | 4           |
| 1  | 1  | 1  | 1   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.636        | 3           |
| 1  | 1  | 0  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 1 | 0        | 0.500        | 2           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 1 | 0        | 0.500        | 2           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0  | 0 | 1  | 0 | 0   | 0 | 0        | 0.462        | 4           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 1 | 0        | 0.438        | 8           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 1   | 0 | 0        | 0.421        | 5           |
| 1  | 1  | 0  | 0   | 0   | 1   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.368        | 5           |
| 1  | 1  | 0  | 0   | 0   | 0   | 1  | 0 | 0  | 0 | 0   | 0 | 0        | 0.364        | 3           |
| 0  | 1  | 0  | 0   | 0   | 0   | 1  | 0 | 0  | 0 | 0   | 0 | 0        | 0.333        | 2           |
| 1  | 0  | 0  | 0   | 1   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.222        | 2           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 1   | 0 | 0        | 0.176        | 17          |
| 0  | 0  | 0  | 0   | 0   | 1   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.174        | 5           |
| 1  | 0  | 0  | 0   | 0   | 0   | 1  | 0 | 0  | 0 | 0   | 0 | 0        | 0.071        | 3           |
| 0  | 0  | 0  | 0   | 0   | 0   | 0  | 1 | 0  | 0 | 0   | 0 | 0        | 0.055        | 3           |
| 0  | 1  | 0  | 0   | 1   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.000        | 2           |
| 0  | 0  | 0  | 0   | 0   | 1   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.000        | 2           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 1 | 0  | 0 | 0   | 0 | 0        | 0.000        | 2           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0  | 0 | 1  | 0 | 0   | 0 | 0        | 0.000        | 4           |
| 1  | 0  | 0  | 0   | 0   | 0   | 1  | 0 | 0  | 0 | 0   | 0 | 0        | 0.000        | 5           |
| 0  | 1  | 0  | 0   | 0   | 0   | 0  | 0 | 1  | 0 | 0   | 0 | 0        | 0.000        | 3           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0  | 0 | 0  | 1 | 0   | 0 | 0        | 0.000        | 6           |
| 0  | 0  | 0  | 0   | 0   | 0   | 0  | 1 | 0  | 0 | 0   | 0 | 0        | 0.000        | 9           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0   | 0 | 0  | 0 | 1   | 0 | 0        | 0.000        | 1           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 1  | 0 | 0   | 0 | 0        | 0.000        | 1           |
| 1  | 0  | 1  | 0   | 0   | 1   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.000        | 1           |
| 1  | 0  | 0  | 0   | 0   | 0   | 0  | 0 | 0  | 1 | 0   | 0 | 0        | 0.000        | 1           |
| 1  | 0  | 1  | 0   | 0   | 0   | 0  | 0 | 0  | 0 | 0   | 0 | 0        | 0.000        | 3           |

Party family abbreviations: RR= Radical right; Con = Conservative; Lib= Liberal; CD= Christian democratic; S= Socialist (Social democratic); RL= Radical Left; G=Green; R/E=Region/Ethnic; O=Other (no family)