Qualitative Comparative Analysis vis-à-vis Regression*

Jason Seawright

Discussions of Charles C. Ragin's Qualitative Comparative Analysis (QCA) have not adequately considered the assumptions about causation on which this method depends. Yet in evaluating any method, it is important to ask the question: How many untestable, or hard-to-test, assumptions must be met for us to believe the findings it produces? Advocates of QCA claim that one of its major strengths is that it requires fewer restrictive assumptions than techniques such as regression analysis. Hence, close assessment of the assumptions that are entailed is particularly salient to evaluating QCA. This article addresses these issues by considering three of the most important kinds of assumptions discussed in the context of regression analysis: assumptions about the correct form of the relationship, missing variables, and inferring causation from association. For each assumption, the role of corresponding assumptions in QCA will be explored and illustrated through an analysis of left-party electoral fortunes in Latin America. Regarding the correct form of causal relationships, QCA in effect builds highly demanding assumptions into measurement procedures. Concerning missing variables, whereas earlier versions of QCA require a strong assumption of no causally relevant missing variables, more recent procedures allow some kinds of missing variables, but build in mutually contradictory statistical assumptions about those variables. Resolving these contradictions essentially converts QCA into an application of regression analysis. Regarding the process of inferring causation from association, QCA makes causal inference on the basis of patterns of association purely by assumption. That is, association is assumed to have a one-to-one relationship with causation. For all three groups of assumptions, QCA is found to require assumptions that are at least as restrictive as those employed in regression analysis.

Introduction

This article proceeds from the belief that discussions of Qualitative Comparative Analysis (QCA) have made a major contribution to methodology in the social

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sciences by raising important issues of research design and analysis. In particular, Charles C. Ragin's (1987, 2000) work on this technique has made a fundamental contribution to the comparative social sciences. For these reasons, as well as because it has influenced a growing number of researchers,[1] QCA deserves close scrutiny.

QCA commands wide attention in part because some of its features fit quite closely with standard qualitative intuitions about causal inference. In particular, this approach more directly captures the idea of placing central analytic emphasis on comparing different types of cases, while de-emphasizing analysis of abstract variables in isolation from the cases that they describe. Writings on QCA have likewise pushed many scholars to pay more attention to the potential importance of interaction terms in causation. Research in the QCA tradition has therefore had a markedly positive effect on social science methodology.

In addition to raising these important themes, Ragin has presented QCA as a powerful tool for causal inference. One of the most frequently discussed and potentially most important bases for this claim is that this approach is said to rely on fewer restrictive assumptions about the causal processes under study. For example, Ragin argues that QCA avoids the "homogenizing assumptions" or "simplifying assumptions" behind regression analysis and other statistical techniques (e.g., Ragin, 1987: x, xii, 32, 61–64, 103, 105, 166; 2000: 23, 120, 332). Likewise, the approach is said to make "no assumptions about the empirical scope or power of the causes examined in social research" (Ragin, 2000: 103). Such assertions are compelling because they promise an alternative, in nonexperimental contexts, to mainstream quantitative analysis that avoids the major weakness of that approach: i.e., untested analytic assumptions (Collier, Brady, and Seawright, 2004). Indeed, if Ragin's claim is correct, it may be a strong argument in favor of replacing regression analysis and related techniques with QCA.

However, as I will argue in this article, the claim that QCA depends on fewer and less-restrictive assumptions than quantitative analysis proves to be, in many respects, false. In attempting to substantiate this counterclaim, I will compare this approach with its major practical competitor as a tool for cross-case analysis in the social sciences: regression analysis. The two traditions will be evaluated through considering the most important restrictive assumptions actually employed in regression analysis—and then exploring the relevance of similar assumptions in QCA. Along the way, I will highlight several points of convergence between QCA and regression analysis. In particular, I will show that resolving contradictions among the assumptions involved in fitting some QCA models can in fact convert QCA into regression analysis.

As is well known, the quality of the inferences that can be drawn from regression analysis depends on the plausibility of several assumptions. Furthermore, the fact that these assumptions are routinely made with no supporting evidence makes them perhaps the major obstacle to credible causal inference in the social sciences (Leamer, 1983). Prominent among these are the assumption that the model has the correct functional form (often this involves an assumption of linearity, even though regression analysis can incorporate some forms of nonlinearity; see Kennedy, 1998: 96–99); the assumption that relevant omitted variables are uncorrelated with included independent variables (also called the assumption of exogeneity; see Kennedy, 1998:

157–82); and the assumption that the estimated parameters reflect causation, rather than merely association (see Humphreys and Freedman, 1996; Freedman, 2000).[2] I will discuss these assumptions and their role in regression analysis, and I will then proceed to explore the extent to which QCA depends on similar assumptions. In each case, I will show that QCA requires assumptions that are at least as restrictive as, and sometimes more restrictive than, those used in regression analysis. At each step, I will illustrate the argument through a running example involving the determinants of left-party electoral success in Latin America during the 1980s and 1990s. Given the central importance of assumptions in evaluating the credibility of causal inference, I conclude that QCA cannot be seen as a genuine methodological advance over regression and other familiar statistical techniques.

In discussing the role of assumptions in regression analysis and in QCA, I will assume that the "best practices" of both traditions are what is at stake. Some common weaknesses of social and political analysis are due to incomplete or incorrect training on the part of analysts; this article will set such issues aside because they are most effectively addressed through improved methodological instruction of researchers, rather than through modifying techniques. For example, regression analysts may on occasion fail to consider the possibility that an interaction term should be added to a regression model. However, regression analysis can certainly accommodate interaction terms, so this kind of difficulty is not a fundamental problem with the technique; rather, it is a difficulty of application.

Setting aside such issues of application and investigator training, the primary remaining determinant of the quality of causal inferences is the plausibility of the assumptions behind those inferences. Hence, the issues discussed below deserve central attention in the evaluation of different methodological traditions.

Introducing QCA

To begin, it is useful to present a brief overview of QCA, which is a set of methodological tools for the social sciences developed primarily by Ragin (1987, 2000). QCA is perhaps better thought of as a family of techniques, rather than as a single tool. In its initial configuration (Ragin, 1987), QCA is an extension of Boolean-algebraic tools from the realm of formal logic to the task of causal inference in social science. Later iterations, sometimes called fuzzy-set QCA, or fs/QCA (see Ragin, 2000), have incorporated mathematical techniques related to fuzzy sets and have focused more on necessary and/or sufficient causation. However, the core concepts of QCA have persisted throughout this evolution. This approach relies centrally on the idea that variables drawn from cases can be dichotomized (or split into more than two categories in versions of QCA using fuzzy sets) and then turned into a truth table, which in turn is collapsed into a minimal formula for predicting the outcome in different kinds of cases. In order to understand QCA, it is necessary to see what happens in each of these three steps.

The original, Boolean-algebraic version of QCA requires all variables to be dichotomized. Boolean algebra uses variables that have two possible values: true or false, which can be represented as 1 or 0. Hence, information about the cases under study in QCA must be turned into such variables. The more recent iteration, fs/QCA, has incorporated fuzzy-set logic. Fuzzy sets allow variables to have some values between true and false. In QCA, these intermediate values are interpreted as partial membership in the set in question. Hence, if a country is given a score of 0.5 on democracy, that score is interpreted as meaning that the country has about half of the characteristics of a democracy.

Once all information about the cases is transformed into either dichotomous or fuzzy-set variables, the second step in QCA is to construct a truth table. A truth table in QCA is a chart that has one row for each possible combination of the independent variables.[3] For each row, the researcher must make a prediction about the value of the outcome variable. This requirement of QCA truth tables has two somewhat awkward consequences. First, if the cases with a specific collection of scores on the independent variables do not all agree on the dependent variable, the researcher is required to resolve those disagreements by an outright decision. Imagine, for example, a researcher who is interested in studying the relationship between democracy and degree of government centralization, on the one hand, and political violence, on the other. If the data set contains three democratic, decentralized countries with high levels of violence and two such countries with low levels of violence, then it is clear that different outcomes are possible in such countries. However, QCA truth tables do not allow for such ambiguity within a single row; in effect, the researcher is required to disregard either the three countries with high levels of political violence or the two with low levels of violence. Making some such decision allows a specific prediction of the value of the dependent variable for each combination of independent variables.

In more recent versions of QCA, this process is made more systematic. A formal statistical test, involving the binomial distribution, is used to determine whether a particular combination of independent variables is associated with a score of 1 on the dependent variable. The researcher begins by choosing a benchmark percentage. Rows in the truth table for which the population percentage of cases experiencing the outcome is below this benchmark are treated as scoring a 0 on the outcome; rows in which the population percentage experiencing the outcome exceeds the benchmark are treated as scoring a 1 on the outcome. If the cases in a given study that correspond to each row in the truth table are hypothesized to be like a random sample from some underlying population, then a straightforward significance test can be used to determine whether there is enough evidence to conclude that the population percentage experiencing the outcome exceeds the benchmark.

A variant of this binomial test is used for fuzzy-set QCA. Here, the quantity of interest is the population proportion of cases in which the score on the dependent variable is at least as high as that of the lowest-scoring independent variable in the combination being tested. That is, if Y_i is the score of case i on the outcome and $X_{1,i}$, $X_{2,i}$, ... , $X_{k,i}$ are the k independent variables being tested for that same case, then the question of interest is whether $Y_i \geq min(X_{1,i}, X_{2,i}, \dots, X_{k,i})$. If a significance test rejects the null hypothesis that this proportion in the population is lower than some specified benchmark percentage, then the combination of causes being tested is assigned a 1 in the truth table. Otherwise, it is assigned a 0.

A second awkward consequence of the requirement that each row in the truth table contain a single prediction about the value of the dependent variable is that researchers are required to make some prediction about the dependent variable even

Table 1
Truth table, based on hypothetical data, for an example involving democracy, decentralization, and political violence.

Democracy	Decentralization	Political Violence
0	0	0
0	1	1
1	0	0
1	1	1

for rows of the truth table that correspond to combinations of independent variables that are not represented in the data (Ragin, 1987: 104–113; 2000: 82–87). Returning to the example from the previous paragraph, suppose that the researcher's data set contains no instances of a decentralized but dictatorial country. In order for the QCA truth table to be complete, the researcher will eventually be forced to make some assumption about the level of political violence that would occur in such countries were they to exist. Researchers employing QCA are encouraged to use available theory to support such assumptions, and to check the analytic consequences of making alternative assumptions. However, in the end, the treatment of such nonexistent categories does require an assumption.

Once a truth table has been assembled, it is transformed into a formula for predicting the outcome. The dependent variable is placed on the left-hand side of an equation. To construct the right-hand side, the researcher examines the truth table, selecting each row in which the dependent variable has a score of 1. The right-hand side of the equation consists of the sum of the combinations of independent variables associated with each selected row. As an example, consider the artificial truth table presented in Table 1, which involves the hypothetical study of democracy, decentralization, and political violence. Two rows show a score of 1 for political violence: the second, which represents decentralized dictatorships; and the fourth, which represents decentralized democracies.

Hence, the initial QCA equation representing this truth table would be as follows (adopting the QCA convention of using upper-case letters to represent variables with a high score and lower-case letters to represent variables with a low score, and substituting "dem" for democracy and "dec" for decentralization):

$$\text{VIOLENCE} = \text{dem} * \text{DEC} + \text{DEM} * \text{DEC} \qquad (1)$$

The final step in QCA is to minimize the equation, in the sense of producing a final equation that is logically equivalent to the original but that has the fewest possible additive terms, each of which consists of the fewest possible multiplicative terms. To achieve this goal, QCA uses the Quine-McCluskey method, as discussed in Ragin (1987).

The Quine-McCluskey method has two components. First, additive terms that differ only by having opposite values of one multiplicative variable are combined—and the variable on which they differ is dropped. For example, in Equation 1, the two additive terms have the same score on decentralization, but they have opposite scores on democracy. This means that, given a score of 1 on decentralization, the democracy score is irrelevant. Hence, the two terms, $dem * DEC$ and $DEM * DEC$ can be combined into one: DEC. In more complicated equations, this process of combining terms that differ only by having opposite values of one multiplicative variable is repeated until no further simplifications are possible. The terms of the resulting equation are called prime implicants. The second component of the Quine-McCluskey method is to eliminate any redundant prime implicants, producing a minimal equation that is logically equivalent to the original. This minimal equation expresses the final inference drawn from a QCA analysis: each term in the equation is interpreted as a separate causal path to the outcome.

Assumptions in QCA

As in most approaches to causal inference in the social sciences, assumptions play a major role in QCA. One specific type of assumption is dealt with directly and explicitly in this approach: assumptions about the outcome for nonexistent combinations of causal variables. As discussed above, QCA techniques require that a value for such combinations be inserted into the truth table before analytic results can be generated. Hence, an assumption must be made about what would have happened had such cases existed.

QCA, to its credit, makes this kind of assumption a central theme, and the available computer software allows researchers to explore the analytic consequences of making different assumptions about such categories of cases. Regression analysis, by contrast, sidesteps this issue by subsuming it in other assumptions: in particular, the assumption of functional form in regression incorporates these issues about the outcome in regions of the design space with only one or a few cases—and even about regions with no cases. To return to the above example, if researchers are studying the relationship between democracy, decentralization, and political violence, they may find no instances of decentralized dictatorships. However, they may be willing to assume that centralization and democracy have an additive, linear relationship with levels of political violence. Making this assumption, a regression model can be fitted to the data and used to extrapolate to cases of decentralized dictatorship. Hence, given that both QCA and regression resolve these issues by making assumptions of one kind or another about the nonexistent cases, it would be difficult to conclude that either technique is superior on this account.

While the frank discussion of these assumptions is a standard feature of QCA, a substantial set of usually unacknowledged assumptions is also required for descriptive and causal inference using QCA. This article will now consider three categories of assumptions: those concerning the correct form of the relationship, omitted variables, and the treatment of associational evidence as justifying causal inference.

Correct Form of the Relationship

Estimates derived from most statistical techniques require the analyst to assume that the model specifies the correct form of the relationships under study. Generally, if this assumption is not met, inferences will be biased. In the typical social science regression analysis, the assumption of correct functional form consists of the claim that the effects of the independent variables are additive and linear, and that randomness arises only through an additive error term. Divergences from this assumption can be easily accommodated within a regression framework, but the analyst must explicitly model such divergences.[4]

QCA also requires assumptions about the form of the relationship—assumptions which may be less obvious than for linear regression. Indeed, it is likely that the way QCA has been designed and discussed has tended to obscure the nature and importance of these assumptions. Nevertheless, assumptions about the form of the relationship cannot be avoided in this approach.

To take a first cut at understanding assumptions about the form of the relationship in QCA, we might ask what kinds of relationships are—and, more importantly, are not—automatically found through this approach. QCA can certainly find additive linear relationships, as well as what might be described as multiplicative linear relationships, i.e., causal relationships that consist of sums of multiplicative interaction terms.[5] Such forms of relationships can easily be represented by the logical equations that are the end product of causal inference in this approach.[6]

However, other kinds of relationships are never found automatically by QCA. For instance, this type of analysis never unexpectedly finds a relationship in which a moderate level of an independent variable is associated with the occurrence of an outcome, whereas either higher or lower levels of the independent variable are associated with negative cases. More generally, the technique will never produce results that are not either an additive linear or a multiplicative linear combination of the included variables. It therefore follows that QCA assumes the true relationship to be either additive linear or multiplicative linear.[7]

QCA could be applied in novel ways to accommodate some forms of relationships that are not permissible in standard analyses, i.e., by changing the nature of the included variables. For example, a researcher could test the relationship discussed in the previous paragraph—where moderate levels of the independent variable produce the outcome but high and low levels do not—by creating a variable that is equal to one when the independent variable is at a moderate level, and equal to zero when the independent variable is either high or low. Using this variable in QCA, the researcher could check whether it has the predicted relationship with the outcome. This approach would, in effect, adopt the statistical practice of recoding variables to accommodate nonstandard functional forms. Ragin's (2000: 316–32) discussion of interpretive aspects of the use of fuzzy sets in effect discusses this approach to considering alternative forms of a relationship.

Yet this proposed means of expanding the range of relationships that can be considered through QCA analyses actually raises new issues involving the form of the relationship, issues that are more often treated as claims about measurement and set membership. As can be seen in the preceding paragraph, specific hypothesized forms of relationships must be reflected in newly constructed independent variables. Hence, the thresholds employed in mapping underlying concepts and graded measures into the dichotomies or fuzzy sets employed in QCA in effect involve assumptions about forms of relationships. This idea is complex and may even be counterintuitive, so it is worthwhile to consider it at greater length.

Probably most often, the (dichotomous or fuzzy) measures of set membership employed in QCA represent judgments or mappings off of some collection of underlying interval- or ratio-level data or evidence (for examples using fuzzy sets, see Ragin 2000: 158–59, 164–65, 170–71, 271, 292–94).[8] For present purposes, I will refer to this evidence as the variable, which may be either latent or observed, underlying a given set. The basic model in the QCA approach is of a threshold, in which the effect of each underlying independent variable kicks in after it passes a critical value. Choosing a particular set of dichotomization thresholds for the independent and dependent variables therefore implies an assumption about the form of the relationship.

The meaning of this assumption may be made clearer by reference to the representation of a dichotomous QCA relationship shown in Figure 1. The vertical axis in this figure represents the variable underlying the outcome in an analysis. The horizontal axis represents the variable behind a dichotomous hypothesized cause.[9] In the figure, the horizontal boundary between the shaded and white regions represents the point on the variables underlying the causes at which set membership crosses over from zero to one; the vertical boundary represents the same transition for the outcome. The shaded areas represent the combinations of values on the independent and dependent variables that can exist without contradicting the hypothesis; the white region represents the combinations of values that would contradict the hypothesis.[10] The sudden jump, for a certain value of the independent variable, in the minimum predicted value of the dependent variable is a characteristic feature of QCA. Because of this feature, it is reasonable to describe QCA as modeling a threshold relationship. Dichotomizing measures for use in QCA in effect involves setting the boundary between the grey region and the white region. Changing the measurement of the independent variables moves this boundary left or right; changing the dependent variable moves it up or down. Because a change in measurement of this kind produces a change in the causal claims that are made, it follows that a particular measurement specification entails assumptions about the form of the relationship.

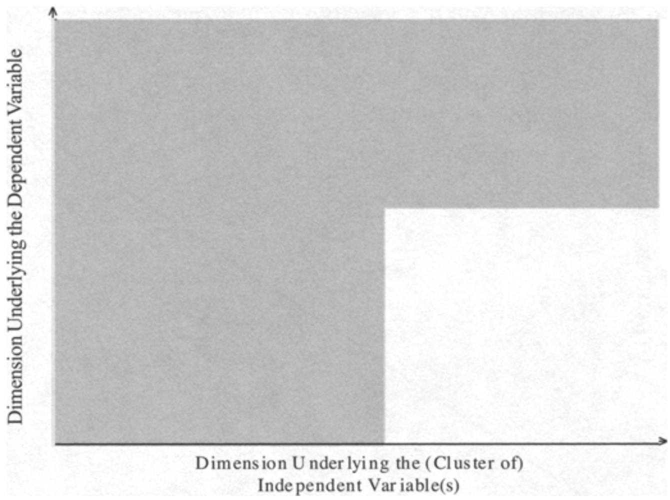
A brief mathematical analysis will help show that this is true. Suppose we have a pair of underlying ratio-level variables, X and Y, which are to be dichotomized at the thresholds T_X and T_Y (respectively) to produce the dichotomized, Boolean variables X_t and Y_t. What, then, is the precise mathematical meaning of a QCA equation in which Y_t is the dependent variable and X_t appears additively as an independent variable?

All values of X greater than or equal to T_X are grouped and treated identically because they must produce the outcome; all values lower than T_X are similarly grouped because they do not produce the outcome—although such values do not block other causes from operating. Hence, two logical statements must be employed in interpreting the claim that X_t should appear additively in a QCA equation for Y_t, as follows:

$$(X < T_X) \rightarrow (0 \leq Y \leq 1) \qquad (2)$$

$$(X \geq T_X) \rightarrow (1 \geq Y \geq T_Y) \qquad (3)$$

Figure 1
A simplified image of the basic threshold model underlying Boolean-algebraic QCA.

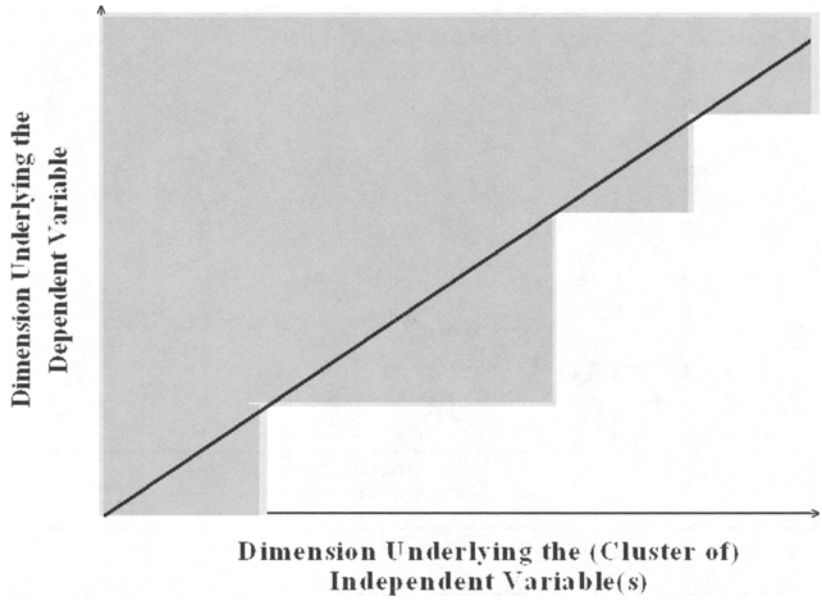


A threshold model can be seen in the fact that the basic causal claim in QCA involves two disjoint subsets of the range of X that map onto two subsets of the range of Y. This model becomes a maintained assumption in QCA analyses; no tools or extensions of QCA that I am aware of allow the researcher to modify this fundamental conception. Hence, the threshold model in QCA plays the same foundational role as does the linear model in regression.

Furthermore, in dichotomizing variables, scholars are forced to choose values for T_X and T_Y. In QCA, these values must be chosen on the basis of theory or background knowledge (Ragin, 2000: 121, 153–55). In other words, such thresholds are not estimated or directly tested using the empirical data in a QCA analysis; hence, they represent assumptions. Scholars may try to fine-tune such assumptions through an informal process of adjusting measures in light of unexpected results, a process Ragin calls a "dialogue between ideas and evidence." Such informal adjustment processes are also common (and, to some extent, controversial) in regression analysis, and in either context, the relevant point is that, while such processes might help researchers manage the necessary assumptions, they do not eliminate them. More recent versions of QCA incorporate fuzzy sets, which allow researchers to consider variables with more than two values (Ragin 2000: 154–59). Specifically, fuzzy sets in QCA allow intermediate categories between full membership in a set and full nonmembership—the set-theoretic interpretation of pure dichotomies. Does this extension of QCA change the character of the assumptions about the form of the relationship?

No, it does not; identical assumptions must be made. The only change is that a greater number of assumptions are involved for each variable. This conclusion fol-

Figure 2
A simplified image of the basic threshold model underlying fuzzy-set QCA.



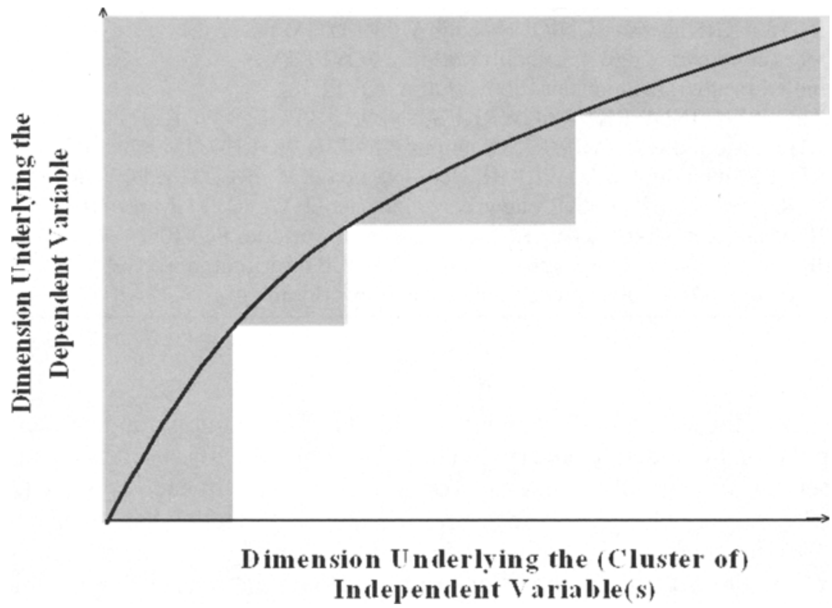
lows directly from the simple observation that partial membership in the set Q is the same as full membership in the set of cases that have at least partial membership in the set Q. In other words, a fuzzy set with three categories has a direct correspondence with two dichotomous sets, one with a lower threshold than the other. Since fuzzy sets are a direct logical derivation of dichotomous sets, it must necessarily be true that fuzzy sets depend on the same assumptions as dichotomous sets.

In fact, a fuzzy set with n categories is logically equivalent to an ordered collection of $n - 1$ dichotomous sets. As such, the fuzzy set requires assumptions about $n - 1$ different causal thresholds, making the assumptions about the form of the relationship involved in a fuzzy set several orders of magnitude more complex than those necessary for a single dichotomous set.

A graphical depiction of a QCA causal claim involving fuzzy sets is presented in Figure 2. This figure can be interpreted in the same way as Figure 1, with the multiple thresholds on both axes representing fuzzy-set gradations. Figure 3 shows how different measurement decisions with respect to the same underlying variables can produce an altered relationship.

In summary, descriptive representations of independent and dependent variables as dichotomies—or as fuzzy, graded membership in sets—involve implicit, but very real, causal claims that the researcher has identified the correct threshold values. This assumption about the form of the relationship clearly affects the resulting causal inference. Hence, it should be taken quite seriously as a central element of that inference.

Figure 3
An alternative form of the relationship, using different thresholds to split up the same underlying variables.



Example Concerning the Form of the Relationship

To illustrate the importance of assumptions about the form of the relationship in QCA, I will now present an example of how simple changes in this assumption can alter the conclusions that are drawn from an analysis. This example, which is inspired by work on the strength of left parties in Europe by Przeworski and Sprague (1986), Kitschelt (1994), and Bartolini (2000), will focus on the analysis of the electoral success of left parties in Latin America since 1980. Two different forms of relationships, involving different dichotomization thresholds for the dependent variable, will be considered.

The dependent variable, left vote share, is drawn from Coppedge's (1998) data set on Latin American party systems, measured at each election between 1980 and 1996. Independent variables are drawn primarily from the World Development Indicators (World Bank, 2003). These variables include each country's aggregate economic wealth at the time of the election (*HighGDP*), whether the country was going through an economic downturn during the election (*Recession*), whether the country had an unusually high proportion of agricultural workers (*Agworkers*) or industrial workers (*Indworkers*), and whether the country's government followed an economic policy package consistent with the neoliberal expectations of low government spending combined with low taxes on trade (*Neoliberalism*). Two additional independent variables are drawn from the *Statistical Abstract of Latin America* (1968): proportion of workers that belonged to a union in the 1960s, which is treated

Table 2
Results of a Boolean-algebraic analysis, using the original coding and the full set of independent variables.

highgdp INDWRKRS agwrkrs unions neolib WORLDTIM POVERTY +
highgdp INDWRKRS agwrkrs UNIONS neolib WORLDTIM poverty +
highgdp recessio indwrkrs agwrkrs neolib worldtim POVERTY +
highgdp indwrkrs agwrkrs unions neolib worldtim POVERTY +
highgdp RECESSIO INDWRKRS AGWRKRS UNIONS NEOLIB WORLDTIM poverty +
HIGHGDP recessio indwrkrs AGWRKRS unions NEOLIB WORLDTIM POVERTY +
highgdp RECESSIO indwrkrs AGWRKRS UNIONS neolib WORLDTIM POVERTY +
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HIGHGDP recessio INDWRKRS agwrkrs unions NEOLIB worldtim poverty +
highgdp recessio INDWRKRS agwrkrs unions neolib worldtim poverty

as a measure of the strength of a country's union heritage (*Union*), and percentage of the population in moderate poverty by the mid-1990s, which is used as an admittedly imperfect measure of the intensity of chronic poverty in each country (*Poverty*). Finally, the variable *Postcom* measures whether each election happened before or after 1989, in an attempt to capture the potential discrediting effects on the global left of the Leninist extinction in Eastern Europe and the former Soviet Union.

For an initial Boolean-algebraic analysis, each of these variables, including the dependent variable, was dichotomized at approximately its median value. Such a dichotomization scheme is by no means natural or automatic; it is merely convenient for a research procedure in which some dichotomization scheme must be chosen. The results of this analysis are shown in Table 2. In the table, as in all QCA results in this article, variables with a score of 1 are written in upper case and variables with a score of 0 are written in lower case. Further, each additive term is estimated to be sufficient to produce the outcome.

As discussed earlier, the key assumptions about the form of the relationship in this analysis are expressed in the way the variables are dichotomized. Thus, altering the dichotomization threshold changes the assumption about the form of the relationship. In order to demonstrate the effects of such changes in the simplest way possible, I recoded the dependent variable in this analysis, changing the dichotomization threshold from the median value to a lower value.[11] The results of the analysis with the revised dependent variable are shown in Table 3, which can be read in the same manner as Table 2.

Given the complexity of both results, it is helpful to focus on a specific combination of values on the independent variables in one country in order to compare the two sets of results. For example, scholars have been particularly fascinated by the political situation in Argentina in the 1990s, where a political party with strong ties to a powerful labor union movement instituted radical marketizing reforms (Levitsky and Way, 1998; Murillo, 2001; Stokes, 2001; Levitsky, 2003). In the original analysis (Table 2), the combination of high GDP and a strong union heritage—a category that includes Argentina—is immune to strong leftist electoral performance, regard-

Table 3
Results of a Boolean-algebraic analysis, using the modified coding of the dependent variable and the full set of independent variables.

highgdp INDWRKRS agwrkrs unions neolib WORLDTIM POVERTY +
highgdp INDWRKRS agwrkrs UNIONS neolib WORLDTIM poverty +
HIGHGDP recessio INDWRKRS agwrkrs NEOLIB worldtim poverty +
highgdp RECESSIO agwrkrs unions neolib worldtim POVERTY +
highgdp recessio indwrkrs agwrkrs neolib worldtim POVERTY +
highgdp recessio INDWRKRS agwrkrs neolib worldtim poverty +
highgdp RECESSIO INDWRKRS AGWRKRS UNIONS NEOLIB WORLDTIM poverty +
HIGHGDP recessio indwrkrs AGWRKRS unions NEOLIB WORLDTIM POVERTY +
highgdp RECESSIO indwrkrs AGWRKRS UNIONS neolib WORLDTIM POVERTY +
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highgdp recessio indwrkrs AGWRKRS UNIONS NEOLIB WORLDTIM poverty +
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HIGHGDP recessio indwrkrs AGWRKRS unions neolib worldtim POVERTY +
highgdp RECESSIO indwrkrs AGWRKRS unions neolib WORLDTIM poverty

less of its policy decisions. By contrast, under the revised assumptions about the form of the relationship used in the analysis shown in Table 3, a strong union heritage no longer has the effect of definitively precluding left political challenges in high-income countries, especially when the government pursues neoliberal reforms. Thus, these two models would lead to different substantive conclusions, and to quite divergent interpretations of the causal patterns behind Argentine politics during the 1990s.

A fuzzy-set analysis of the same basic data reveals an even more extreme dependence on assumptions about the form of the relationship. This analysis uses the same variables as the Boolean-algebraic analysis just discussed. This time, however, rather than being dichotomized, the variables are split into equally spaced categories centered on the median for each variable. This set-up would reflect a kind of linear relation among the variables in which a given change in one cluster of independent variables is associated with a constant magnitude of change in the dependent variable. The results are shown in Table 4. In this analysis, the results are by far the simplest we have yet seen. In particular, a combination of recession, weak union heritage, few agricultural workers, and neoliberalism emerges as causally crucial for leftist electoral success.

Suppose, however, that the assumption of an essentially linear underlying relation is incorrect. Will these key results remain constant? To explore this possibility,

Table 4
Results of a fuzzy-set analysis, using the original coding and the full set of independent variables.

RECESSION union poverty agworkers NEOLIBERALISM +
RECESSION union agworkers INDWORKERS NEOLIBERALISM

Table 5
Results of a fuzzy-set analysis, using the revised coding of the dependent variable and the full set of independent variables.

POVERTY INDWORKERS +
highgdp postcom INDWORKERS +
postcom union INDWORKERS +
RECESSION union INDWORKERS +
postcom AGWORKERS INDWORKERS +
POVERTY indworkers neoliberalism +
HIGHGDP postcom union neoliberalism +
HIGHGDP postcom POVERTY neoliberalism +
RECESSION union agworkers NEOLIBERALISM +
postcom POVERTY AGWORKERS neoliberalism +
HIGHGDP postcom indworkers neoliberalism

the dependent variable was recoded to fit one particular model by making fine-grained distinctions at the lower end of the variable and much coarser distinctions toward the upper end of the variable's range, producing a relationship in which the lower boundary of the region containing permissible cases is roughly quadratic. As can be seen in Table 5, the results are radically more complex. In particular, none of the four decisive variables from the prior specification plays a particularly important role in these results. Instead, this specification would probably lead researchers to highly idiosyncratic interpretations of different case trajectories.

These brief examples have illustrated why assumptions about the form of the relationship in QCA are not of merely methodological interest. Contrasting choices about this assumption, involving different dichotomization thresholds, can dramatically alter the substantive and theoretical results from a given analysis. Hence, just as in regression analysis, the value of QCA inferences depends directly on whether the underlying assumptions about the form of the relationship are correct.

Assumptions About Missing Variables

One of the more troubling assumptions behind causal inference in regression analysis is the claim that the included independent variables are statistically unrelated to any causally relevant omitted variables. Violations of this assumption, which is sometimes called the assumption of no confounding or the specification assumption, can produce major distortions in causal inference. The primary concerns with this assumption are that it is not directly testable, and that it is rarely plausible in observational studies.

These important weaknesses of regression analysis would seem to be a major argument in favor of using QCA. But in fact, causal inference with QCA requires fundamentally similar—and often stronger—assumptions. This section reviews these issues in the context of QCA and then places them in perspective by reconsidering the importance of assumptions about missing variables in regression analysis.

The original Boolean-algebraic formulation of QCA requires researchers to assume that no causally relevant variables are missing from the analysis. The intuitive reason this assumption is needed is the following: because QCA requires researchers to resolve all contradictions in the process of creating the truth table, the technique in effect treats all cases with the same combination of values on the independent variables as causally identical. If cases that are identical on the included variables turn out to differ on causally relevant omitted variables, then QCA's assumption that these cases are identical is false.

The type of "no missing variables" assumption required for Boolean-algebraic QCA can be illustrated with an abstract example. Suppose we know, due to unimpeachable prior knowledge, that a particular outcome Y is caused by some subset of a specific combination of several independent variables: variables X_I through X_n, for which we have measures, and variables Z_I through Z_m, which remain unmeasured. Hence, by prior knowledge, we know the following Boolean statement to be correct:

$$X_I * \cdots * X_n * Z_I * \cdots * Z_m = Y \tag{4}$$

This statement, while known to be true, is empirically useless because it involves some number of unmeasured variables. For empirical analysis, these variables must somehow be removed. In standard QCA analysis, unmeasured variables are removed by making the simplifying assumption that:

$$X_I * \cdots * X_n = Y \tag{5}$$

Dropping a specific variable from a logical statement of this kind means that the variable in question is believed to be causally irrelevant—whether the variable is dropped through logical manipulations, as in Quine-McCluskey Boolean minimization, or through a priori assumption, as when the unmeasured Z_i's are dropped from the analysis. Therefore, by moving from Equation 4 to Equation 5, Boolean QCA builds in the assumption that no causally relevant variables have been omitted from the analysis.

This assumption is severely restrictive, and it deserves to be a major point of concern in evaluating QCA. In order for a Boolean-algebraic analysis to produce useful causal inferences, no variables of any kind that have any causal influence whatsoever on the outcome can be omitted. Researchers must include measures of all theoretically interesting independent variables, including the variables involved in theories that have not yet been invented—but they cannot stop there. They must also include measures of all idiosyncratic conditions or events that might have causal influence on the outcome. Credible applications of Boolean QCA might therefore be required to include measures of weather conditions, traffic patterns, sickness trends, and many other idiosyncratic and (typically) theoretically uninteresting conditions that occasionally have some causal influence on social and political outcomes. Moreover, any inference based on a Boolean QCA analysis that omits this broad range of factors is unreliable; after all, it violates the central assumption of no causally relevant omitted variables.

It might be argued that general knowledge of cases helps researchers using QCA to identify and include all relevant independent variables. In response to this claim, let us consider two points. First, knowledge of cases is neither unique to nor inherent in QCA; therefore, the proposed solution is neither distinctively relevant to QCA nor automatic. Indeed, the analytic procedures involved in QCA involve data sets that look almost identical to those used in regression analysis: rows of scores on different variables. If the kinds of data involved in regression and QCA are fundamentally similar, it seems reasonable to suppose that scholars may equally well apply knowledge of cases to identify missing variables in regression analysis as to avoid missing variables in QCA. Second, as pointed out above, identifying all missing variables requires more than detailed knowledge of cases. It also requires a perfect knowledge of the underlying causal processes. If a particular cause is mistakenly believed to be irrelevant, or if it is as yet unmeasured or even undiscovered, researchers will omit the relevant variable regardless of the extent of their case-based knowledge. In other words, there is no easy way out of the problem of missing variables.

With fs/QCA, decisions about which of the measured variables to include and exclude depend primarily on simple significance tests based on the binomial distribution, as discussed above. Do these tests require any particular assumptions about excluded variables? Ragin's discussion of the tests (2000: 109-16) is, unfortunately, silent on this point. However, it can be seen that an assumption about missing variables is indeed required for these tests. The binomial distribution is used in QCA to test whether the probability of randomly selecting a case that experienced the outcome, conditional on the presence of the cluster of independent variables, is higher than some pre-specified value. Probability distributions for the dependent variable, conditional on the independent variables, are of course one of the major products of regression analysis. Consider the following linear probability model, using Y_i to represent the dependent variable for the ith case and X_i to represent a single cluster of independent variables for that case:

$$P(Y_i = 1) = \beta_0 + \beta_1 X_i \tag{6}$$

In this equation, the probability of the outcome, conditional on the presence of the cluster of independent variables, is equal to $\beta_0 + \beta_1$. Hence, Ragin's binomial tests serve the same purpose as statistically fitting the model in Equation 6 and then conducting an appropriately designed significance test on the linear combination, $\beta_0 + \beta_1$.

The success of such a significance test depends primarily on the success or failure of the statistical fit for the model described in Equation 6. In particular, a standard statistical result is that, if relevant omitted variables are correlated with the included variable, X, the estimate of β_1 will be inconsistent—and any significance tests based on that estimate will be unreliable. This implies that fs/QCA relies on the same missing-variables assumption as regression: all missing variables must be uncorrelated with all included variables.

However, things are, in fact, somewhat worse for fs/QCA than for standard regression. The reason is that the fs/QCA test for sufficiency is fundamentally "bivariate," in the specific sense that only one of the many configurations of independent variables involved in a given model is tested in each iteration. Yet the basic assumptions of the test must be met for each iteration. Hence, every time that fs/QCA researchers conduct a test for the sufficiency of a given causal combination, they are assuming either that no other causal combinations are relevant or that all other causal combinations are uncorrelated with the combination being tested. In a context where analyzing 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, the missing variables assumption discussed above is especially problematic.[12] 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. In effect, other than in this highly unusual situation, the assumptions about missing variables employed in each of the multiple iterations of the test are logically incompatible with each other.

This problem of logically incompatible assumptions also frequently arises in regression contexts when researchers sequentially fit several different models to the same data. In this situation, the assumptions made when fitting diverse models are frequently mutually incompatible. This kind of logical contradiction across models creates a situation in which it can be difficult to know how to interpret the analytic results. However, for present purposes, it may be worth emphasizing that, while conflicting assumptions can arise across models in regression analysis, in QCA analyses, this problem actually arises within the process of fitting what is typically seen as a single model.

We can thus conclude that QCA, in both its Boolean-algebraic form and its more recent fuzzy-set version, requires extremely restrictive assumptions about missing variables. Boolean-algebraic QCA is only appropriate in contexts where the researcher is certain that no variables are missing—which, in practice, will typically require elaborate specifications of numerous, largely uninteresting independent variables. The tests of sufficiency behind fuzzy-set QCA are applicable when researchers are confident in advance that only one causal conjunction is relevant—and that all other variation can be treated as completely unsystematic. If such contexts are rare in the social sciences, then QCA techniques may be of somewhat limited practical value.

In fact, regression analysis was originally developed as a way of making inferences in the presence of specific kinds of omitted variables that are uncorrelated with the included variables.[13] In particular, the error term in a standard regression analysis is designed to capture the effects of relevant independent variables that were omitted from the analysis. For regression to succeed, these omitted variables must meet quite specific conditions. Most importantly, they must be uncorrelated with the included independent variables. Thus, ordinary regression fails whenever omitted variables are correlated with the included variables, but it can succeed if omitted variables are uncorrelated with included variables. By contrast, Boolean-algebraic QCA always fails when there are omitted variables of any sort, and fuzzy-set QCA can only handle missing variables when the systematic portion of the model only includes one causal combination. In this sense, QCA represents a step backwards from regression analysis: it fails to address the very problem that regression was invented to resolve.

Can We Extend fs/QCA to Fix the Missing Variables Problem?

A first step in coming to grips with the problem of missing variables in QCA is to ask, can existing QCA techniques be extended to make these assumptions less restrictive? In particular, can the statistical tests used in fs/QCA be modified so that multiple causal combinations can be considered without invoking mutually contradictory assumptions? This section will provide a sketch of such a modification. In the process, it will demonstrate that many of the perceived advantages of QCA over regression analysis are lost when this major weakness is corrected—because QCA in fact becomes a kind of regression analysis.

The existing test for sufficiency in fs/QCA relies, as discussed above, on a binomial statistical model.[14] The binomial model requires two assumptions. First, cases must be independent of each other. Second, all cases within one category on the independent variables must have the same probability of success, meaning that all cases must have the same probability of experiencing the outcome in question. In mathematical terms, if the probability of success for case i is denoted as π_i and the number of cases that have the specific multiplicative combination of independent variables of interest is n, it must be true that:

$$\pi_1 = \pi_2 = \cdots = \pi_n \qquad (7)$$

What kind of causal model could justify making this assumption? The clearest answer would be that the social and political processes in question are assumed to follow this equation:

$$\pi_i = f(x_{1,i}) \qquad (8)$$

where $f()$ is some unspecified mathematical function and $x_{1,i}$ is the ith case's score on the multiplicative combination of variables of current interest. If Equation 8 holds, then all cases with the same score on x_1 will have the same π. Hence, the researcher can apply the binomial distribution by simply selecting cases with a constant score on the specific combination of independent variables. This result would seem to justify the fs/QCA application of the binomial distribution whenever Equation 8 holds.

When more than one multiplicative combination of independent variables is relevant, however, Equation 8 does not hold. Instead, for some combination of independent variables $x_{1,i}, x_{2,i}, \cdots, x_{k,i}$ and for some unknown function $g()$,

$$\pi_i = g(x_{1,i}, x_{2,i}, \cdots, x_{k,i}) \qquad (9)$$

Without making additional assumptions, it is impossible for us to proceed past Equation 9. However, progress can be made if we are willing to adopt the standard assumption in QCA that the form of the relationship is additive-multiplicative.[15] Under this assumption, each of the multiplicative combinations of independent variables will enter the model additively. For the sake of flexibility, let us allow each combination of independent variables to be weighted by a multiplicative parameter which will be estimated from the data. We now have the following more specific model:

$$\pi_i = x_{1,i}\beta_1 + x_{2,i}\beta_2 + \cdots + x_{k,i}\beta_k \quad (10)$$

This model cannot yet be estimated, because it contains π_i, for which there is no direct measure. Therefore, let us make one final substitution, standard in statistical analysis of dichotomous data such as logit models or linear probability models (Aldrich and Nelson, 1984). Let us use the observed values of the dependent variable y_i as a rough measure of each case's probability π_i. A striking conclusion emerges here. What we are left with is, in fact, a standard linear probability model. Such models are typically estimated using linear regression, with Goldberger corrections to adjust for the unusual features of the distribution of the residual in this model.

Hence, adapting fs/QCA to correct the incompatible assumptions made about missing variables when testing more than one causal combination can convert QCA into a form of linear regression with interaction terms. Obviously, the standard limitations of linear regression immediately apply. In particular, the scholar is forced to select a specific set of interaction terms to test, and those interaction terms cannot be too multicollinear or serious estimation problems will result.

Yet problems such as multicollinearity among interaction terms are likely to be unavoidable if we are to address the problematic missing variable assumptions in fs/QCA's tests for sufficiency. In effect, the apparent methodological strengths of fs/QCA in comparison with regression turn out to derive directly from the very strong missing variable assumptions that justify the use of bivariate tests. This is so because relaxing these assumptions somewhat transforms fs/QCA into regression analysis.

Example Concerning Missing Variables

To illustrate the relevance of assumptions about missing variables to a specific substantive application of QCA, let us return to the discussion of differences in the electoral strength of the left in Latin America after 1980. Let us suppose that a researcher has adopted a more restricted specification than the one we considered above. In particular, this analyst has chosen to omit the labor-market variables from the prior specification: *Union*, *Indworkers*, and *Agworkers*. Will this decision alter the conclusions to be drawn about included variables?

Table 6 shows the results of omitting these three variables from the Boolean-algebraic analysis. As is quickly apparent, these results are not identical to the full-specification results from Table 2. Consider, for example, wealthier countries that

Table 6
Results of a Boolean-algebraic analysis, using the original coding and the revised set of independent variables.

highgdp neolib POVERTY +
highgdp RECESSIO WORLDTIM poverty +
recessio neolib worldtim POVERTY +
HIGHGDP recessio NEOLIB WORLDTIM POVERTY

Table 7
Results of a fuzzy-set analysis, using the original coding and the revised set of independent variables.

HIGHGDP postcom POVERTY +
postcom recession POVERTY NEOLIBERALISM

are suffering from recessions. In the new specification, such countries should only see electorally weak leftist parties; by contrast, in the full specification, there is a causal combination in which wealthy countries in recession do experience strong leftist challenges.

A similar contradiction occurs with respect to countries with low levels of poverty that are not in recession. For the new specification, such countries are categorically excluded from the set of countries with electorally effective leftist parties. By contrast, in the full specification, several combinations exist in which countries with low levels of poverty and no recession are expected to experience electorally strong leftist parties. Several other such substantively and theoretically crucial changes in results can be found in comparing Table 2 and Table 6.

In practice, missing variables are therefore a serious issue for Boolean-algebraic QCA. Are they equally critical for fuzzy-set QCA? Compare the fuzzy-set results for the new specification shown in Table 7 with the conclusions from the full specification in Table 4. Once again, we find substantively and theoretically vital differences between the two with respect to the effects of the included variables. In the new specification, only countries with high levels of poverty are expected to have strong leftist parties—and strong leftist parties are only expected for elections before 1989. In the full specification, by contrast, the timing of the election (i.e., before or after 1989) is deemed causally irrelevant, and countries with higher levels of poverty are probably somewhat less likely to experience leftist electoral strength.

Likewise, in the full specification, neoliberalism and recession play a central role in producing leftist electoral strength; in the new specification, neither variable is crucial. Neoliberalism does appear in one of the two causal combinations, but not in both, as in the full specification. Further, recession appears in one combination—but with its causal polarity now reversed.

In summary, the assumption that all causally relevant variables have been included in the model has important substantive ramifications. Scholars who omit important variables are likely to draw different conclusions about the included variables than they would had they included all relevant variables. The practical implications of this problem are far-reaching, since scholars can never be confident that they have included all relevant independent variables. For example, the model discussed above as the "full specification" is only full by assumption; there could easily be one, five, fifty, or more relevant variables missing from the analysis. This uncertainty, combined with the major analytic consequences of missing variables discussed above, implies that scholars should approach the results of most QCA applications with a great deal of caution and healthy skepticism—just as they would the results of a regression analysis or some other statistical procedure.

Assumptions that Allow Association to Imply Causation

The third major assumption behind causal inference with regression analysis in the context of observational studies is perhaps the most restrictive and controversial of all. This is the assumption that the patterns of association found in the data reflect causation. Such assumptions are so problematic that one debate compares them, with regard to their plausibility, to the idea of a whale leaping up Niagara Falls (Humphreys and Freedman, 1996).

Regression analysis in nonexperimental contexts obviously relies on assumptions that association is equivalent to causation. After all, the data used in statistical analysis generally do not provide any evidence that distinguishes spurious correlations from causal relationships. Nor does the evidence provide a way of telling independent from dependent variables. The researcher typically provides such differentiation by assumption as part of the process of specifying the model.[16] In fact, when regression analysis of observational data provides all of the empirical evidence behind a causal inference, the major assumption that a particular association reflects causation goes untested.

As with applied regression analysis in the social sciences, the results of QCA analyses are also usually given causal interpretations. Hence, if QCA provided tools that differentiated genuine causal relationships from spurious correlations or other noncausal relationships, the technique would have a major, and perhaps insurmountable, advantage in comparison to regression analysis. Unfortunately, QCA converts patterns of association into causal inference on the basis of the identical set of assumptions as regression analysis.

A brief consideration of the basic properties of Boolean algebra can show that the older version of QCA relies on the assumption that association is causation. One way of describing Boolean algebra is as a set of "truth-preserving" logical operations (Hailperin, 1986: 70). This means that the results of Boolean algebra have the same characteristics as the original data. If the data are associational (i.e., from an observational study), then the result is also associational. Thus, treating the result as a causal inference requires assuming that the association reflects causation.

Fuzzy-set versions of QCA require the same assumption, that association reflects causation, which drives statistical techniques such as regression—for the simple reason that the key test of causation in fs/QCA is a statistical test. Because the data are not experimental, this test must necessarily produce causal inferences by assumption. In other words, QCA does not represent any progress past the baseline of regression analysis in terms of this key assumption that association is equivalent to causation.

Example Concerning Association and Causation

The above analyses of leftist electoral strength in Latin America are clearly vulnerable to the critique that they can make causal inference only by assuming that association is causation. The reason is that the data employed are purely observational: they are simply measures of the unfolding of social and political processes, with no outside manipulation or random assignment. Therefore, it is hard to be certain about the causal processes through which different countries come to fall into different categories on the independent variables—and it is therefore possible that leftist strength causes some of the independent variables, or that some omitted variable or unknown process causes both leftist strength and the independent variables.

In other words, even setting aside the issues of the form of the relationship and missing variables discussed above, there is a fundamental difficulty: we cannot conclude that leftist electoral strength is caused by some combination of these independent variables without first assuming that leftist strength is caused by these independent variables. In other words, causal inferences from observational studies cannot be made using these tools alone. Some other source of inferential leverage will always be needed to successfully apply these techniques. This weakness, which QCA shares with regression analysis, should be a source of major concern for social science researchers.

Conclusion

This article has compared QCA to regression analysis in terms of three of the major assumptions required to make causal inferences. For two of the assumptions, concerning the correct form of the relationship and the presumption that association is causation, QCA has proved to be essentially as problematic as regression analysis. For the other category of assumptions, about missing variables, QCA turned out to be even weaker than regression analysis—requiring either more restrictive or mutually inconsistent assumptions. These disappointing results suggest that, given the centrality of untested assumptions as a current challenge to social science methodology, QCA is not an improvement over regression analysis.

In closing, however, it is worth reiterating that research on the development of QCA has usefully called additional attention to some broad methodological themes. In particular, discussions of QCA have highlighted the potential importance of high-order interaction terms, a theme that both qualitative and quantitative researchers have begun to take more seriously since the publication of Ragin's 1987 book. Likewise, the development of fs/QCA has usefully emphasized the idea that researchers should consider non-linear measurement models. This reminder is obviously of substantial value.

Nonetheless, the weaknesses of QCA in terms of the assumptions discussed above should not be ignored. By rejecting ideas and research tools developed in probability theory and statistics, QCA takes a major step backwards. It may therefore be most effective to import the valuable ideas raised by work on QCA into other methodological frameworks—including quantitative analysis and the comparative case-study tradition (George, 1979)—that have already put substantial effort into addressing these fundamental assumptions underlying causal inference.

Notes

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1. To date, over 250 studies have been published applying QCA methodology (Rihoux and Ragin, 2004).
2. All of these assumptions involve aspects of what is sometimes discussed as the specification assumption (Collier et al., 2004), but for present purposes it is more useful to divide this large topic into more manageable pieces. The specific assumptions below will be discussed in increasing order of what I view as their substantive importance.
3. In Boolean-algebraic QCA, each variable has only two possible values: true or false. Hence, if the number of independent variables in the study is k, the number of rows in the truth table is 2^k. In fuzzy-set QCA, this stage of the analysis is handled somewhat differently, as discussed below.
4. According to Franzese, about 25% of published regression analyses now include a multiplicative interaction term (Franzese, 2003)—and such interaction terms should probably be considered in even more analyses. Likewise, statistical techniques can accommodate a wide variety of nonlinear functional forms.
5. Both addition and multiplication, in discussions of QCA, refer to logical, rather than standard arithmetic, operations. The differences are as follows: logical multiplication returns the minimum of the two multiplicands, while logical addition returns the maximum. In effect, the choice between logical arithmetic and standard arithmetic involves somewhat divergent assumptions about the form of the relationship. Can high scores on one cause or combination of causes compensate for low scores on another? If not, then logical arithmetic may be appropriate. In practice, however, the major characteristics of logical arithmetic can easily be incorporated in standard arithmetic models. If a researcher is interested in two causal combinations, A and B, then including a third term, A*B, allows for the possibility that the two combinations do not compensate for each other—incorporating the features of logical addition. Likewise, if desired, the terms A and B can be scored according to the rules of logical multiplication by choosing the lowest score in each combination rather than by multiplying the variables in the combination using arithmetic rules.
6. Obviously, such relationships can also be represented by linear regression models, potentially with interaction terms.
7. This assumption is obviously much less of a problem for truly dichotomous variables, which were the original focus of QCA. However, as discussed below, assumptions about the form of the relationship sometimes arise for dichotomous variables via the measurement process.
8. In some cases, concepts may be conceptualized as fundamentally dichotomous (Collier and Adcock, 1999). Much of the time, however, even judgments about fundamentally dichotomous conceptual categories will rely on underlying graded evidence. For example, while many scholars treat revolution as a dichotomous outcome, decisions about whether a particular event should count as a revolution typically revolve around explicit interval—or ratio-level evidence about numbers of participants and levels of violence, as well as implicitly graded evidence about the degree of transformation that the event produces in politics and society. Thus, very often, the measurement of conceptually dichotomous categories relies on a mapping from underlying interval—or ratio-level evidence.
9. Often in QCA, researchers consider interaction terms involving many independent variables. In such cases, there should be one dimension per independent variable in the cluster. However, constraints related to human perception make this problematic. Therefore, the figure presents a simplified image in which only one independent variable is considered.
10. Obviously, the hypothesis that the independent variable causes the dependent variable is supported by cases in which both are absent or both are present. In QCA, the hypothesis also allows for cases in which the outcome is present but a specific cause is absent—because a different cause is at work. However, cases in which the cause is present but the outcome is absent do contradict the hypothesis. These cases fall inside the white rectangle toward the lower right in Figure 1.
11. Specifically, the dichotomization threshold fell from the median of about a 15% vote share for the left to a 5% vote share.
12. During each run of the fs/QCA software, tests are sequentially carried out for all possible combinations of the independent variables.
13. The specific category of omitted variables of initial concern had to do with measurement error in the dependent variable. See Stigler (1986).
14. For the sake of simplicity, this exposition will focus on the dichotomous tests. A similar argument applies to the fuzzy-set versions of the same tests.

15. In most discussions of QCA, logical addition is employed, which involves taking the maximum of the terms to be summed. By contrast, in the discussion below, I use arithmetic addition. This change in the relationship is made for the sake of mathematical simplicity. As discussed above, the properties of logical addition could be duplicated in an arithmetic model by including additional interaction terms.
16. Such modeling assumptions typically draw on theory and knowledge of cases. However, such knowledge is always both imperfect and incomplete, and therefore the assumptions in question are never fully justifiable in non-experimental contexts.

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