Chapter 2

THE LIMITATIONS OF NET-EFFECTS THINKING

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1. INTRODUCTION

Conventional methods of data analysis such as multiple regression form the backbone of most policy-oriented research in the social sciences today. It should not be surprising that they do, for they are considered by many to be the most rigorous, the most disciplined, and the most scientific of the analytic methods available to social researchers. If the results of social research are to have an impact on policy, it stands to reason that such findings should be produced using the most rigorous analytic methods available.

While conventional quantitative methods are clearly rigorous, it is important to understand that these methods are organized around a specific kind of rigor. That is, they have their own rigor and their own discipline, not a universal rigor. While there are several features of conventional quantitative methods that make them rigorous and therefore valuable to policy research, in this contribution I focus on a single, key aspect--namely, the fact that they are centered on the task of estimating the "net effects" of "independent" variables on outcomes. I focus on this central aspect, which I characterize as "net-effects thinking", because this feature of conventional methods can undermine their value to policy.

This contribution presents its critique of net-effects thinking in a practical manner, by contrasting the conventional analysis of a large-N, policy-relevant data set with an alternate analysis, one that repudiates the assumption that the key to social scientific knowledge is the estimation of the net effects of independent variables. This alternate method, known as fuzzy-set/Qualitative Comparative Analysis or fsQCA, combines the use of fuzzy sets with the analysis of cases as configurations, a central feature of case-oriented social research (Ragin 1987). In this approach, each case is examined in terms of its degree of membership in different *combinations* of causally relevant conditions. Using fsQCA, researchers can consider cases' memberships in all of the logically possible combinations of a given set of causal conditions and then use set-theoretic methods to analyze--in a logically disciplined manner--the varied connections between causal combinations and the outcome.

I offer this alternate approach not as a replacement for net-effects analysis, but as a complementary technique. fsQCA is best seen as an exploratory technique, grounded in set theory. While probabilistic criteria can be incorporated into fsQCA, it is not an inferential technique, per se. It is best understood an alternate way of analyzing evidence, starting from very different assumptions about the kinds of "findings" social scientists seek. These alternate assumptions reflect the logic and spirit of qualitative research, where investigators study cases configurationally, with an eye toward how the different parts or aspects of cases fit together.

2. NET-EFFECTS THINKING

In what has become normal social science, researchers view their primary task as one of assessing the relative importance of causal variables drawn from competing theories. In the ideal situation, the relevant theories emphasize different variables and make clear, unambiguous statements about how these variables are connected to relevant empirical outcomes. In practice, however, most theories in the social sciences are vague when it comes to specifying both causal conditions and outcomes, and they tend to be silent when it comes to stating *how* the causal conditions are connected to outcomes (e.g., specifying the conditions that must be met for a given causal variable to have its impact). Typically, researchers are able to develop only general lists of potentially relevant causal conditions based on the broad portraits of social phenomena they find in theories. The key analytic task is typically viewed as one of assessing the relative importance of the listed variables. If the variables associated with a particular theory prove to be the best predictors of the outcome (i.e., the best "explainers" of its variation), then this theory wins the contest. This way of conducting quantitative analysis is the default procedure in the social sciences today – one that researchers fall back on time and time again, often for lack of a clear alternative.

In the net-effects approach, estimates of the effects of independent variables are based on the assumption that each variable, by itself, is capable of producing or influencing the level or probability of the outcome. While it is common to treat "causal" and "independent" as synonymous modifiers of the word "variable", the core meaning of "independent" is this notion of autonomous capacity. Specifically, each independent variable is assumed to be capable of influencing the level or probability of the outcome *regardless of the values or levels of other variables* (i.e., regardless of the varied contexts defined by these variables). Estimates of net effects thus assume *additivity*, that the net impact of a given independent variable on the outcome is the same across all the values of the other independent variables and their different combinations. To estimate the net effect of a given variable, the researcher offsets the impact of competing causal conditions by subtracting from the estimate of the effect of each variable any explained variation in the dependent variable it shares with other causal variables. This is the core meaning of "net effects" – the calculation of the non-overlapping contribution of each variable to explained variation in the outcome. Degree of overlap is a direct function of correlation: generally, the greater the correlation of an independent variable with its competitors, the less its net effect.

There is an important underlying compatibility between vague theory and net-effects thinking. When theories are weak, they offer only general characterizations of social phenomena and do not attend to causal complexity. Clear specifications of relevant contexts and scope conditions are rare, as is consideration of how causal conditions may modify each other's relevance or impact (i.e., how they may display non-additivity). Researchers are lucky to derive coherent lists of potentially relevant causal conditions from most theories in the social sciences, for the typical theory offers very little specific guidance. This guidance void is filled by linear, additive models with their emphasis on estimating generic net effects. Researchers often declare that they estimate linear-additive models because they are the "simplest possible" and make the "fewest assumptions" about the nature of causation. In this view, additivity (and thus simplicity) is the default state; any analysis of non-additivity requires explicit theoretical authorization, which is almost always lacking.

The common emphasis on the calculation of net effects also dovetails with the notion that the foremost goal of social research is to assess the relative explanatory power of variables attached to competing theories. Net-effects analyses provide explicit quantitative assessments of the non-overlapping explained variation that can be credited to each theory's variables. Often, however, theories do not contradict each other and thus do not really compete. After all, the typical social science theory is little more than a vague portrait. The use of the net effects approach thus may create the appearance of theory adjudication in research where such adjudication may not be necessary or even possible.

2.1 Problems with Net-Effects Thinking

There are several problems associated with the net effects approach, especially when it is used as the primary means of generating policy-relevant social scientific knowledge. These include both practical and conceptual problems.

A fundamental practical problem is the simple fact that the assessment of net effects is dependent on model specification. The estimate of an independent variable's net effect is powerfully swayed by its correlations with competing variables. Limit the number of correlated competitors and a chosen variable may have a substantial net effect on the outcome; pile them on, and its net effect may be reduced to nil. The specification dependence of the estimate of net effects is well known, which explains why quantitative researchers are thoroughly schooled in the importance of "correct" specification. However, correct specification is dependent upon strong theory and deep substantive knowledge, both of which are usually lacking in the typical application of net-effects methods.

The importance of model specification is apparent in the many analyses of the data set that is used in this contribution, the National Longitudinal Survey of Youth (NLSY), analyzed by Herrnstein and Murray in *The Bell Curve*. In this work Herrnstein and Murray report a very strong net effect of test scores (the Armed Forces Qualifying Test--AFQT, which they treat as a test of general intelligence) on outcomes such as poverty: the higher the AFQT score, the lower the odds of poverty. By contrast, Fischer *et al.* use the same data and the same estimation technique (logistic regression) but find a weak net effect of AFQT scores on poverty. The key difference between these two analyses is the fact that Herrnstein and Murray allow only a few variables to compete with AFQT, usually only one or two, while Fischer *et al.* allow many. Which estimate of the net effect of AFQT scores is "correct"? The answer depends upon which specification is considered "correct". Thus, debates about net effects often stalemate in disagreements about model specification. While social scientists tend to think that having more variables is better than having few, as in Fischer *et al.*'s analysis, having too many independent variables is also a serious specification error.

A related practical problem is the fact that many of the independent variables that interest social scientists are highly correlated with each other and thus can have only modest non-overlapping effects on a given outcome. Again, *The Bell Curve* controversy is a case in point. Test scores and socio-economic status of family of origin are strongly correlated, as are these two variables with a variety of other potentially relevant causal conditions (years of schooling, neighborhood and school characteristics, and so on). Because social inequalities overlap, cases' scores on "independent" variables tend to bunch together: high AFQT scores tend to go with better family backgrounds, better schools, better neighborhoods, and so on. Of course, these correlations are far from perfect; thus, it is possible to squeeze estimates of the net effects of these "independent" variables out of the data. Still, the overwhelming empirical pattern is one of confounded causes – of clusters of favorable versus unfavorable conditions, not of analytically separable independent variables. One thing social scientists know about social inequalities is that because they overlap, they reinforce. It is their overlapping nature that gives them their strength and durability. Given this characteristic feature of social phenomena, it seems somewhat counterintuitive for quantitative social scientists to rely almost exclusively on techniques that champion the estimation of the separate, unique, net effect of each causal variable.

More generally, while it is useful to examine correlations between variables (e.g., the strength of the correlation between AFQT scores and family background), it is also useful to study cases holistically, as specific configurations of attributes. In this view, cases combine different causally relevant characteristics in different ways, and it is important to assess the consequences of these different combinations. Consider, for example, what it takes to avoid poverty. Does college education make a difference for married White males from families with good incomes? Probably not, or at least not much of a difference, but college education may make a huge difference for unmarried Black females from low-income families. By examining cases as configurations it is possible to conduct context-specific assessments, analyses that are circumstantially delimited. Assessments of this type involve questions about the conditions that enable or disable specific connections between causes and outcomes. Under what conditions do test scores matter, when it comes to avoiding poverty? Under what conditions does marriage matter? Are these connections different for White females and Black males? These kinds of questions are outside the scope of conventional net-effects analyses, for they are centered on the task of estimating context-independent net effects.

Configurational assessments of the type just described are directly relevant to policy. Policy discourse often focuses on categories and kinds of people (or cases), not on variables and their net effects across heterogeneous populations. Consider, for example, phrases like the "truly disadvantaged", the "working poor", and "welfare mothers". Generally, such categories embrace combinations of characteristics. Consider also the fact that policy is fundamentally concerned with social intervention. While it might be good to know that education, in general, decreases the odds of poverty (i.e., that it has a significant, negative net effect on poverty), from a policy perspective it is far more useful to know under what conditions education has a decisive impact, shielding an otherwise vulnerable subpopulation from poverty. Net effects are calculated across samples drawn from entire populations. They are not based on "structured, focused comparisons" (George 1979) using specific kinds and categories of cases. Finally, while the calculation of net-effects offers succinct assessments of the relative explanatory power of variables drawn from different theories, the adjudication between competing theories is not a central concern of policy research. Which theory prevails in the competition to explain variation is primarily an academic question. The issue that is central to policy is determining which causal conditions are decisive in which contexts, regardless of the (typically vague) theory the conditions are drawn from.

To summarize: the net-effects approach, while powerful and rigorous, is limited. It is restrained by its own rigor, for its strength is also its weakness. It is particularly disadvantaged when to comes to studying combinations of case characteristics, especially overlapping inequalities. Given these drawbacks, it is reasonable to explore an alternate approach, one with strengths that differ from those of net-effects methods. Specifically, the net effects approach, with its heavy emphasis on calculating the uncontaminated effect of each independent variables in order to isolate variables from one another, can be counterbalanced and complemented with an approach that explicitly considers combinations and configurations of case aspects.

2.2 Studying Cases as Configurations

Underlying the broad expanse of social scientific methodology is a continuum that extends from small-N, case-oriented, qualitative techniques to large-N, variable-oriented, quantitative techniques. Generally, social scientists deplore the wide gulf that separates the two ends of this continuum, but they typically stick to only one end when they conduct research. With fsQCA, however, it is possible to bring some of the spirit and logic of case-oriented investigation to large-N research. This technique offers researchers tools for studying cases as configurations and for exploring the connections between *combinations* of causally relevant conditions and outcomes. By studying combinations of conditions, it is possible to unravel the conditions or contexts that enable or disable specific connections (e.g., between education and the avoidance of poverty).

The starting point of fsQCA is the principle that cases should be viewed in terms of the combinations of causally relevant conditions they display. To represent combinations of conditions, researchers use an analytic device known as a truth table, which lists the logically possible combinations of causal conditions specified by the researcher and sorts cases according to the combinations they display. Also listed in the truth table is an outcome value (typically coded either true or false) for each combination of causal conditions. The goal of fsQCA is to derive a logical statement describing the different combinations of conditions linked to an outcome, as summarized in the truth table.

A simple, hypothetical truth table with four crisp-set (i.e., dichotomous) causal conditions, one outcome, and 200 cases is presented in table 2.1.

Table 2.1. Hypothetical Truth Table with Four Causal Conditions and One Outcome

	College Educated (C)	High Parental Income (I)	Parent College Educated (P)	High AFQT Score (S)	Poverty Avoidance (A)	Number of Cases
1	0	0	0	0	0	30
2	0	0	0	1	?	3
3	0	0	1	0	?	4
4	0	0	1	1	?	0
5	0	1	0	0	0	25
6	0	1	0	1	0	19
7	0	1	1	0	?	0
8	0	1	1	1	0	20
9	1	0	0	0	?	0
10	1	0	0	1	?	1
11	1	0	1	0	?	0
12	1	0	1	1	?	2
13	1	1	0	0	1	19
14	1	1	0	1	1	22
15	1	1	1	0	1	32
16	1	1	1	1	1	23

The four causal conditions are:

(1) Did the respondent earn a college degree?

(2) Was the respondent raised in a household with at least a middle class income?

(3) Did at least one of the respondent's parents earn a college degree?

(4) Did the respondent achieve a high score on the Armed Forces Qualifying Test (AFQT)?

With four causal conditions, there are 16 logically possible combinations of conditions, the same as the number of rows in the table. More generally, the number of combinations is 2^k, where k is the number of causal conditions. As the number of causal conditions increases, the number of combinations increases dramatically. The outcome variable in this hypothetical truth table is "poverty avoidance" – indicating whether or not the individuals in each row display a very low rate of poverty (1 = very low rate).

In fsQCA outcomes (e.g., "poverty avoidance" in table 2.1) are coded using set-theoretic criteria. The key question for each row is the degree to which the individuals in the row constitute a subset of the individuals who are not in poverty. That is, do the cases in a given row agree in not displaying poverty? Of course, perfect subset relations are rare with individual-level data. There are always surprising cases, for example, the person with every possible advantage, who nevertheless manages to fall into poverty. With fsQCA, researchers establish rules for determining the degree to which the cases in each row are consistent with the subset relation. The researcher first establishes a threshold proportion for set-theoretic consistency, which the observed proportions must exceed. For example, a researcher might argue that the observed proportion of cases in a row that are not in poverty must exceed a benchmark proportion of 0.95. Additionally, the researcher may also apply conventional probabilistic criteria to these assessments. For example, the researcher might state that the observed proportion of individuals not in poverty must be significantly greater than a benchmark proportion of 0.90, using a significance level (alpha) of 0.05 or 0.10. The specific benchmarks and alphas used by researchers depend on the state of existing substantive and theoretical knowledge. The assessment of each row's set-theoretic consistency is straightforward when truth tables are constructed from crisp sets. When fuzzy sets are used, the set-theoretic principles that are invoked are the same, but the calculations are more complex.

As constituted, table 2.1 is ready for set-theoretic analysis using fsQCA. The goal of this analysis would be to identify the different combinations of case characteristics explicitly linked to poverty avoidance. Examination of the last four rows, for example, indicates that the combination of college education and high parental income may be an explicit link – a combination that provides a good recipe for poverty avoidance. Specific details on truth table analysis and the derivation of the causal combinations linked to a given outcome are provided in Ragin (1987, 2000).

2.3 Key Contrasts between Net-Effects and Configurational Thinking

The hypothetical data presented in table 2.1 display a characteristic feature of nonexperimental data; namely, the 200 cases are unevenly distributed across the 16 rows, and some combinations of conditions (i.e., rows) lack cases altogether. (The number of individuals with each combination of causal conditions is reported in the last column). In the net-effects approach, this unevenness is understood as the result of correlated independent variables. Generally, the greater the correlations among the causal variables, the greater the unevenness of the distribution of cases across the different combinations of causal conditions. By contrast, in fsQCA this unevenness is understood as "limited diversity". In this view, the four causal conditions define 16 different kinds of cases, and the four dichotomies become, in effect, a single nominal-scale variable with 16 possible categories. Because there are empirical instances of only a subset of the 16 logically possible kinds of cases, the data set is understood as limited in its diversity.

The key difference between fsQCA and the net-effects approach is that the latter focuses on analytically separable independent variables and their degree of intercorrelation, while the former focuses on kinds of cases defined with respect to the combinations of causally relevant conditions they display. These contrasting views of the same evidence, net-effects versus configurational, have very different implications for how evidence is understood and analyzed. Notice, for example, that in table 2.1 there is a perfect correlation between having a college degree and avoiding poverty. That is, whenever there is a 1 (yes) in the outcome column ("poverty avoidance"), there is also a 1 (yes) in the "college educated" column, and whenever there is a 0 (no) in the "poverty avoidance" column, there is also a 0 (no) in the "college educated" column. From a net-effects perspective, this pattern constitutes very strong evidence that the key to avoiding poverty is college education. Once the effect of college education is taken into account (using the hypothetical data in table 2.1), there is no variation in poverty avoidance remaining for the other variables to explain. This conclusion does not come so easily using fsQCA, however, for there are several combinations of conditions in the truth table where college education is present and the outcome (poverty avoidance) is unknown, due to an insufficiency of cases. For example, the ninth row combines presence of college education with absence of the other three resources. However, there are no cases with this combination of conditions and consequently no way to assess empirically whether this combination of conditions is linked to poverty avoidance.

In order to derive the simple conclusion that college education by itself is the key to poverty avoidance using fsQCA, it is necessary to incorporate what are known as "simplifying assumptions" involving combinations of conditions that have few cases or that lack cases altogether. In fsQCA, these combinations are known as "remainders". They are the rows of table 2.1 with "?" in the outcome column, due to a scarcity of cases. Remainder combinations must be addressed explicitly in the process of constructing generalizations from evidence in situations of limited diversity (Ragin and

Sonnett 2004; Varone, Rihoux and Marx, in this volume). For example, in order to conclude that college education, by itself, is the key to avoiding poverty (i.e., the conclusion that would follow from a net-effects analysis of these data), with fsQCA it would be necessary to *assume* that if empirical instances of the ninth row could be found (presence of college education combined with an absence of the other three resources), these cases would support the conclusion that college education offers protection from poverty. This same pattern of results also should hold for the other rows where college education equals 1 (yes) and the outcome is unknown (i.e., rows 10-12).

Ragin and Sonnett (2004) outline general procedures for treating remainder rows as counterfactual cases and for evaluating their plausibility as simplifying assumptions. Two solutions are derived from the truth table. The first maximizes parsimony by allowing the use of any simplifying assumption that yields a logically simpler solution of the truth table. The second maximizes complexity by barring simplifying assumptions altogether. That is, the second solution assumes that none of the remainder rows is explicitly linked to the outcome in question. These two solutions establish the range of plausible solutions to a given truth table. Because of the set-theoretic nature of truth table analysis, the most complex solution is a subset of the most parsimonious solution. Researchers can use their substantive and theoretical knowledge to derive an optimal solution, which typically lies in between the most parsimonious and the most complex solutions. The optimal solution must be a superset of the most complex solution and a subset of the most parsimonious solution (it is important to note that a set is both a superset and a subset of itself; thus, the solutions at either of the two endpoints of the complexity/parsimony continuum may be considered optimal). This use of substantive and theoretical knowledge constitutes, in effect, an evaluation of the plausibility of counterfactual cases, as represented in the remainder combinations.

The most parsimonious solution to table 2.1 is the conclusion that the key to avoiding poverty is college education. This solution involves the incorporation of a number of simplifying assumptions, specifically, that if enough instances of rows 9-12 could be located, the evidence for each row would be consistent with the parsimonious solution (i.e., each of these rows would be explicitly linked to poverty avoidance). The logical equation for this solution is:

$$C \longrightarrow A$$

[In this and subsequent logical statements, upper-case letters indicate the presence of a condition, lower-case letters indicate its absence, C = college educated, I = at least middle class parental income, P = parent college educated, S = high AFQT score, A = avoidance of poverty, "$\longrightarrow$" indicates "is sufficient for", multiplication ($\cdot$) indicates combined conditions (set intersection), and addition (+) indicates alternate combinations of conditions (set union).] Thus, the results of the first set-theoretic analysis of the truth table are the same as the results of a conventional net-effects analysis. By contrast, the results of the most complex solution, which bars the use of remainders as simplifying assumptions, are:

$C \cdot I \longrightarrow A$

This equation indicates that two conditions, college education and high parental income, must be combined for a respondent to avoid poverty.

As Ragin and Sonnett (2004) argue, in order to strike a balance between parsimony and complexity it is necessary to use theoretical and substantive knowledge to identify, if possible, the subset of remainder combinations that constitute plausible pathways to the outcome. The solution to table 2.1 favoring complex causation shows that two favorable conditions must be combined. In order to derive the parsimonious solution using fsQCA, it must be assumed that *if* cases combining college education and the *absence* of high parental income could be found (thus populating rows 9-12 of table 2.1), they would be consistent with the parsimonious conclusion. This logical reduction proceeds as follows:

observed: $C \cdot I \longrightarrow A$
by assumption: $C \cdot i \longrightarrow A$
logical simplification: $C \cdot I + C \cdot i = C \cdot (I + i) = C \cdot (1) = C \longrightarrow A$

According to the arguments in Ragin and Sonnett (2004) the logical simplification just sketched is *not* warranted in this instance because the *presence* of high parental income is known to be a factor that *contributes* to poverty avoidance. That is, because the assumption $C \cdot i \longrightarrow A$ involves a "difficult" counterfactual, it should not be made, at least not without extensive theoretical or substantive justification. More generally, they argue that theoretical and substantive knowledge should be used to evaluate all such simplifying assumptions in situations of limited diversity. These evaluations can be used to strike a balance between the most parsimonious and the most complex solutions of a truth table, yielding solutions that typically are more complex than the parsimonious solution, but more parsimonious than the complex solution. This use of substantive and theoretical knowledge to derive optimal solutions is the essence of counterfactual analysis.

In conventional net-effects analyses "remainder" combinations are routinely incorporated into solutions; however, their use is invisible to most users. In this approach, remainders are covertly incorporated into solutions via the assumption of additivity – the idea that the net effect of a variable is the same regardless of the values of the other independent variables. Thus, the issue of limited diversity and the need for counterfactual analysis are both veiled in the effort to analytically isolate the effect of independent variables on the outcome.

3. FUZZY SETS AND CONFIGURATIONAL ANALYSIS

Set-theoretic analysis is not limited to conventional, presence/absence sets, the kind used in table 2.1. With fuzzy sets it is possible to assess the degree of membership of cases in sets, using values that range from 0 (non-membership) to 1 (full membership). A fuzzy membership score of 0.90, for example, indicates that a case is mostly but not fully in a set. This score might be used to describe the membership of the U.S. in the set of democratic countries, as demonstrated in the presidential election of 2000. Fuzzy sets are useful because they address a problem that social scientists interested in sets of cases routinely confront – the challenge of working with case aspects that resist transformation to crisp categories. To delineate the set of individuals with high AFQT scores as a conventional crisp set, for example, it would be necessary to select a cut-off score, which might be considered somewhat arbitrary. The use of fuzzy sets remedies this problem, for degree of membership in a set can be calibrated so that it ranges from 0 to 1.

A detailed exposition of fuzzy sets and their uses in social research is presented in Ragin (2000; 2005). For present purposes, it suffices to note that the basic set-theoretic principles described in this contribution, including subset relations, limited diversity, parsimony, complexity, and counterfactual analysis have the same bearing and importance in research using fuzzy sets that they do in research using crisp sets. The only important difference is that with fuzzy sets each case, potentially, can have some degree of (nonzero) membership in every combination of causal conditions. Thus, the empirical basis for set-theoretic assessment using fuzzy sets is much wider than it is using crisp sets because more cases are involved in each assessment. Note, however, that it is mathematically possible for a case to be more "in" than "out" of only one of the logically possible combinations of causal conditions listed in a truth table. That is, each case can have, at most, only one configuration membership score that is greater than 0.50 across the 2^k configurations.

Because of the mathematical continuities underlying crisp and fuzzy sets, table 2.1 could have been constructed from fuzzy-set data (see Ragin 2005).

To do so, it would have been necessary to calibrate the degree of membership of each case in each of the sets defined by the causal conditions (e.g., degree of membership in the set of individuals with high AFQT scores) and then assess the degree of membership of each case in each of the 16 combinations of causal conditions defining the rows of table 2.1. For example, a case with a membership score of .4 in "high AFQT score" and membership scores of .7 in the other three causal conditions would have a membership score of .4 in the combined presence of these four conditions (see Ragin 2000 for a discussion of the use of the minimum when assessing membership in combinations of sets). After calibrating degree of membership in the outcome (i.e., in the set of individuals successfully avoiding poverty), it would be possible to evaluate the degree to which membership in each combination of causal conditions is a fuzzy subset of membership in this outcome. In effect, these analyses assess the degree to which individuals conforming to each row consistently avoid poverty. Such assessments are conducted using fuzzy membership scores, not dichotomized scores, and they utilize a stricter definition of the subset relation than is used in crisp-set analyses (Ragin 2005).

In fuzzy-set analyses, a crisp truth table is used to summarize the results of these fuzzy-set assessments. In this example there would be 16 fuzzy-set assessments because there are four fuzzy-set causal conditions and thus 16 configuration membership scores. More generally, the number of fuzzy-set assessments is 2^k, where k is the number of causal conditions. The rows of the resulting truth table list the different combinations of conditions assessed. For example, row 4 of the truth table (following the pattern in table 2.1) would summarize the results of the fuzzy-set analysis of degree of membership in the set of individuals who combine low membership in "college educated", low membership in "high parental income", high membership in "parents college educated", and high membership in "high AFQT score". The outcome column in the truth table shows the results of the 2^k fuzzy-set assessments – that is, whether or not degree of membership in the configuration of causal conditions specified in a row can be considered a fuzzy subset of degree of membership in the outcome. The examination of the resulting crisp truth table is, in effect, an analysis of *statements* summarizing the 2^k fuzzy-set analyses. The end product of the truth table analysis, in turn, is a logical equation derived from the comparison of these statements. This equation specifies the different combinations of causal conditions linked to the outcome via the fuzzy subset relationship.

Note that with fuzzy sets, the issue of limited diversity is transformed from one of "empty cells" in a k-way cross-tabulation of dichotomized causal conditions (i.e., remainder rows in a truth table), to one of empty sectors in a vector space with k dimensions. The 2^k sectors of this space vary in the degree to which they are populated with cases, with some sectors lacking cases altogether. In other words, with naturally occurring social data it is common for many sectors of the vector space defined by causal conditions to be void of cases, just as it is common for a k-way cross-tabulation of dichotomies to yield an abundance of empty cells. The same tools developed to address limited diversity in crisp-set analyses, described previously in this contribution and in Ragin and Sonnett (2004), can be used to address limited diversity in fuzzy-set analyses. Specifically, the investigator derives two solutions to the truth table, one maximizing complexity and the other maximizing parsimony, and then uses substantive and theoretical knowledge to craft an intermediate solution--a middle path between complexity and parsimony. The intermediate solution incorporates only those counterfactuals that can be justified using existing theoretical and substantive knowledge (i.e., "easy" counterfactuals).

The remainder of this contribution is devoted to a comparison of a net-effects analysis of the NLSY data, using logistic regression, with a configurational analysis of the same data, using the fuzzy-set methods just described. While the two approaches differ in several respects, the key difference is that the net-effects approach focuses on the independent effects of causal variables on the outcome, while the configurational approach attends to combinations of causal conditions and attempts to establish explicit links between specific combinations and the outcome.

3.1 A Net Effects Analysis of *The Bell Curve* Data

In *The Bell Curve*, Herrnstein and Murray (1994) compute rudimentary logistic regression analyses to gauge the importance of AFQT scores on a variety of dichotomous outcomes. They control for the effects of only two competing variables in most of their main analyses, respondent's age (at the time the AFQT was administered) and parental socio-economic status (SES). Their central finding is that AFQT score (which they interpret as a measure of general intelligence) is more important than parental SES when it comes to major life outcomes such as avoiding poverty. They interpret this and related findings as proof that in modern society "intelligence" (which they assert is inborn) has become the most important factor shaping life chances. Their explanation focuses on the fact that the nature of work has changed, and that there is now a much higher labor market premium attached to high cognitive ability.

Table 2.2. Logistic Regression of Poverty Avoidance on AFQT Scores and Parental SES (*Bell Curve* Model)

	B	S.E.	Sig.	Exp(B)
AFQT (z score)	.651	.139	.000	1.917
Parental SES (z score)	.376	.117	.001	1.457
Age	.040	.050	.630	1.040
Constant	1.123	.859	.191	3.074

Chi-Squared = 53.973, df = 3

Their main result with presence/absence of poverty as the outcome of interest is presented in table 2.2 (with absence of poverty = 1). The reported analysis uses standardized data (z scores) for both parental socio-economic status (SES) and AFQT score to facilitate comparison of effects. The analysis is limited to Black males with complete data on all the variables used in this and subsequent analyses, including the fuzzy-set analysis. The strong effect of AFQT scores, despite the control for the impact of parental SES, mirrors the *Bell Curve* results.

A major rebuttal of the *Bell Curve* "thesis", as it became known, was presented by a team of Berkeley sociologists, Claude Fischer, Michael Hout, Martin Sanchez Jankowsk, Samuel Lucas, Ann Swidler, and Kim Voss (1996). In their book, *Inequality By Design*, they present a much more elaborate logistic regression analysis of the NLSY data. Step by step, they include more and more causal conditions (e.g., neighborhood and school characteristics) that they argue should be seen as competitors with AFQT scores. In their view, AFQT score has a substantial effect in the *Bell Curve* analysis only because the logistic regression analyses that Herrnstein and Murray report are radically under-specified. To remedy this problem, Fischer *et al.* include more than 15 control variables in their analysis of the effects of AFQT scores on the odds of avoiding poverty. While this "everything-but-the-kitchen-sink" approach dramatically reduces the impact of AFQT scores on poverty, the authors leave themselves open to the charge that they have misspecified their analyses by being over-inclusive.

Table 2.3. Logistic Regression of Poverty Avoidance on AFQT Scores, Parental Income, Years of Education, Marital Status, and Children

	B	S.E.	Sig.	Exp(B)
AFQT (z score)	.391	.154	.011	1.479
Parental Income (z score)	.357	.154	.020	1.429
Education (z score)	.635	.139	.000	1.887
Married (yes = 1, 0 = no)	1.658	.346	.000	5.251
Children (yes = 1, 0 = no)	-.524	.282	.063	.592
Constant	1.970	.880	.025	7.173

Chi-Squared = 104.729, df = 5

Table 2.3 reports the results of a logistic regression analysis of poverty using only a moderate number of independent variables. Specifically, presence/absence of poverty (with absence = 1) is regressed on five independent variables: AFQT score, years of education, parental income, married versus not married, and one-or-more children versus no children. The three interval-scale variables are standardized (using z scores) to simplify comparison of effects. The table shows the results for Black males only. The rationale for this specification is that the model is more fully specified than the unrealistically spare model presented by Herrnstein and Murray and less elaborate and cumbersome than Fischer *et al.*'s model. In other words, the analysis strikes a balance between the two specification extremes and focuses on the most important causal conditions.

The results presented in table 2.3 are consistent with both Herrnstein and Murray and Fischer *et al.* That is, they show that AFQT score has an independent impact on poverty avoidance, but not nearly as strong as that reported by Herrnstein and Murray. Consistent with Fischer *et al.*, table 2.3 shows very strong effects of competing causal conditions, especially years of education and marital status. These conditions were not included in the *Bell Curve* analysis. More generally, table 2.3 confirms the specification-dependence of net-effects analysis. With an intermediate number of competing independent variables, the effect of AFQT is substantially reduced. It is not nearly as strong as it is in the *Bell Curve* analysis, but not quite as weak as it is in Fischer *et al.*'s analysis.

3.2 A Fuzzy-Set Re-Analysis

The success of any fuzzy-set analysis is dependent on the careful construction and calibration of fuzzy sets. The core of both crisp-set and fuzzy-set analysis is the evaluation of set-theoretic relationships, for example, the assessment of whether membership in a combination of causal conditions can be considered a subset of membership in the outcome. A fuzzy subset relationship exists when the scores in one set (e.g., the fuzzy set of individuals who combine high parental income, college education, high test scores, and so on) are consistently less than or equal to the scores in another set (e.g., the fuzzy set of individuals not in poverty). Thus, it matters a great deal how fuzzy sets are constructed and how membership scores are calibrated. Serious miscalibrations can distort or undermine the identification of set-theoretic relationships. By contrast, for the conventional variable to be useful in a net-effects analysis, it needs only to vary in a meaningful way. Often, the specific metric of a conventional variable is ignored by researchers because it is arbitrary or meaningless.

In order to calibrate fuzzy-set membership scores researchers must use their substantive knowledge. The resulting membership scores must have face validity in relationship to the set in question, especially how it is conceptualized and labeled. A fuzzy score of 0.25, for example, has a very specific meaning – that a case is half way between "full exclusion" from a set (e.g., a membership score of 0.00 in the set of individuals with "high parental income") and the cross-over point (0.50, the point of maximum ambiguity in whether a case is more in or more out of this set). As explained in *Fuzzy-Set Social Science* (Ragin 2000), the most important decisions in the calibration of a fuzzy set involve the definition of the three qualitative anchors that structure a fuzzy set: the point of full inclusion in the set (membership = 1.00), the cross-over point (membership = 0.50), and the point of full exclusion from the set (membership = 0.00). For example, to determine full inclusion in the set of individuals with high parental income, it is necessary to establish a threshold income level. All cases with parental incomes greater than or equal to the threshold value are coded as having full membership (1.00) in the fuzzy set. Likewise, a value must be selected for full exclusion from the set (0.00) and the remaining scores must be arrayed between 0.00 and 1.00, with the score of 0.50 representing the point of greatest ambiguity regarding whether a case is more in or more out of the set.

The main sets in the analysis reported in this study are degree of membership in the outcome, the set of individuals avoiding poverty, and membership in sets reflecting five background characteristics: parental income, AFQT scores, education, marital status, and children. The calibration of these fuzzy sets is explained in the appendix. At this point it is important to note that it is often fruitful to represent a single conventional, interval-scale variable with two fuzzy sets. For example, the variable parental income can be transformed separately into the set of individuals with high parental income and the set of individuals with low parental income. It is necessary to construct *two* fuzzy sets because of the *asymmetry* of these two concepts. Full *non*-membership in the set of individuals with high parental income (a membership score of 0.00 in high parental income) does *not* imply full *membership* in the set with low parental income (a score of 1.00), for it is possible to be fully out of the set of individuals with high parental income without being fully in the set of individuals with low parental income. The same is true for the other two interval-scale variables used as causal conditions in the logistic regression analysis (table 2.3), AFQT scores and years of education. Thus, the fuzzy-set analysis reported here uses eight causal conditions, two crisp sets: married versus not and one-or-more children versus no children, and six fuzzy sets: degree of membership in high parental income, degree of membership in low parental income, degree of membership in high AFQT scores, degree of membership in low AFQT scores, degree of membership in high education (college educated), and degree of membership in low education (less than high school).

After calibrating the fuzzy sets, the next task is to calculate the degree of membership of each case in each of the 2^k logically possible combinations of causal conditions, and then to assess the distribution of cases across these combinations. With eight causal conditions, there are 256 logically possible combinations of conditions. Table 2.4 lists the 55 of these 256 combinations that have at least one case with greater than 0.50 membership.

Recall that a case can have, at most, only one configuration membership score that is greater than 0.50. Thus, the 256 combinations of conditions can be evaluated with respect to case frequency by examining the number of empirical instances of each combination. If a configuration has no cases with greater than 0.50 membership, then there are no cases that are more in than out of the combination. As noted previously, this evaluation of the distribution of cases is the same as determining whether there are any cases in a specific sector of the vector space defined by the causal conditions.

Table 2.4 reveals that the data used in this analysis (and, by implication, in the logistic regression analysis reported in table 2.3) are remarkably limited in their diversity. Only 55 of the 256 sectors contained within the eight-dimensional vector space have empirical instances (i.e., cases with greater then 0.50 membership), and most of the frequencies reported in the table are quite small. The 11 most populated sectors (4.3% of the 256 sectors in the vector space) capture 70% of the listed cases. This number of well-populated sectors (11) is small even relative the number of sectors that exist in a five-dimensional vector space (32). (This is the number of sectors that would have been obtained if the three interval-level variables used in the logistic regression analysis--years of education, parental income, and AFQT scores--had been transformed into one fuzzy set each instead of two.)

Table 2.4: Distribution of Cases across Sectors of the Vector Space

Less than High School	College	Low parental income	High parental income	Low AFQT	High AFQT	Married	Children	Frequency
0	0	1	0	1	0	0	1	118
0	0	0	0	1	0	0	1	51
0	0	1	0	1	0	1	1	51
0	0	1	0	0	0	0	1	35
0	0	1	0	0	0	1	1	34
0	0	1	0	1	0	0	0	34
0	0	0	0	0	0	0	1	32
0	0	0	0	1	0	1	1	30
0	1	0	0	0	0	0	0	29
0	0	0	0	1	0	0	0	24
0	0	0	0	0	0	1	1	20
0	1	1	0	0	0	0	1	17
0	0	0	0	0	0	0	0	15
0	1	0	0	0	0	1	1	14
0	1	0	0	0	0	1	0	12
0	1	1	0	0	0	1	1	12
0	1	0	0	0	0	0	1	10
0	0	1	0	0	0	0	0	9
0	1	0	1	0	0	1	1	9
0	0	1	0	1	0	1	0	8
0	1	1	0	0	0	0	0	8
0	1	0	1	0	0	0	0	7
0	1	1	0	1	0	0	0	6
0	0	0	0	0	0	1	0	5
0	0	0	1	0	0	0	1	4
0	1	0	0	1	0	0	0	4
0	1	0	0	1	0	1	1	4

continued . . .

Less than High School	College	Low parental income	High parental income	Low AFQT	High AFQT	Married	Children	Frequency
0	1	1	0	1	0	0	1	4
0	1	1	0	1	0	1	1	4
1	0	1	0	1	0	0	1	3
0	0	0	0	1	0	1	0	3
0	0	0	1	0	0	1	1	3
0	0	0	1	1	0	0	1	3
0	1	0	0	0	1	0	0	3
0	1	0	0	1	0	0	1	3
0	1	0	1	0	0	0	1	3
0	1	0	1	0	1	1	0	3
0	0	0	1	0	0	1	0	2
0	1	0	0	0	1	0	1	2
0	1	0	0	1	0	1	0	2
0	1	0	1	0	1	0	0	2
1	0	1	0	1	0	0	0	1
1	0	1	0	1	0	1	0	1
1	0	1	0	1	0	1	1	1
0	0	0	1	0	0	0	0	1
0	0	0	1	1	0	0	0	1
0	0	0	1	1	0	1	1	1
0	0	1	0	0	0	1	0	1
0	1	0	0	0	1	1	0	1
0	1	0	0	0	1	1	1	1
0	1	0	1	0	0	1	0	1
0	1	0	1	1	0	0	0	1
0	1	1	0	0	0	1	0	1
0	1	1	0	0	1	0	0	1
0	1	1	0	0	1	0	1	1

In fuzzy-set analyses of this type, it is important to establish a strength-of-evidence threshold for combinations of conditions, using the information on the distribution of cases across sectors just discussed. Specifically, the causal combinations with too few cases should be filtered out and not subject to further empirical analysis. In addition to the fact that it would be unwise to base a conclusion about a combination of individual-level attributes on a small number of cases, the existence of cases in low-frequency sectors may be due to measurement or assignment error. In the fuzzy-set analysis that follows, I use a frequency threshold of 10 cases. Thus, 38 low-frequency rows of table 2.4 are filtered out of the analysis. Because these rows do not meet the strength-of-evidence threshold, they are treated as "remainder" combinations in the fuzzy-set analysis, along with the 201 combinations that lack cases altogether.

The next task is to assess the consistency of the evidence for each of the combinations of conditions (the 17 high-frequency rows of table 2.4) with the subset relation. Specifically, it is necessary to determine whether degree of membership in each combination of conditions is a subset of degree of membership in the outcome. As explained in Ragin (2000; 2005), the subset relation may be used to assess causal sufficiency. If the cases with a specific combination of conditions (e.g., the cases that combine college education, high parental income, high AFQT scores, being married, and having no children) constitute a subset of the cases with the outcome (e.g., cases avoiding poverty), then the evidence supports the argument that this combination of conditions is sufficient for the outcome. With fuzzy sets, the subset relation is demonstrated by showing that degree of membership in a combination of conditions is consistently less than or equal to degree of membership in the outcome.

One simple descriptive measure of the degree to which the evidence on a combination of conditions is consistent with the subset relation is:

$$\sum(\min(X_i,Y_i))/\sum(X_i)$$

where "min" indicates selection of the lower of the two scores; X_i indicates degree of membership in a combination of conditions; and Y_i indicates degree of membership in the outcome. When all Xi values are consistent (i.e., the membership scores in a combination are uniformly less than or equal to their corresponding Y_i values), the calculation yields a score of 1.00. If many of the X_i values exceed their Y_i values by a substantial margin, however, the resulting score is substantially less than 1.00. Generally, scores on this measure that are lower than .75 indicate conspicuous departure from the set-theoretic relation in question ($X_i \leq Y_i$).

Table 2.5: Assessments of Set-Theoretic Consistency (17 Configurations)

Less than High School	College	Low parental income	High parental income	Low AFQT	High AFQT	Married	Children	Fre-quency	Consis-tency	Out-come
0	1	0	0	0	0	1	0	12	0.98	1
0	1	0	0	0	0	1	1	14	0.90	1
0	1	0	0	0	0	0	0	29	0.85	1
0	1	1	0	0	0	1	1	12	0.83	1
0	0	0	0	0	0	1	1	20	0.80	1
0	0	1	0	0	0	1	1	34	0.68	0
0	0	0	0	0	0	0	0	15	0.66	0
0	0	0	0	1	0	1	1	30	0.61	0
0	0	0	0	1	0	0	0	24	0.59	0
0	1	0	0	0	0	0	1	10	0.56	0
0	1	1	0	0	0	0	1	17	0.51	0
0	0	1	0	1	0	1	1	51	0.47	0
0	0	0	0	0	0	0	1	32	0.43	0
0	0	1	0	0	0	0	1	35	0.32	0
0	0	0	0	1	0	0	1	51	0.29	0
0	0	1	0	1	0	0	0	34	0.28	0
0	0	1	0	1	0	0	1	118	0.14	0

Table 2.5 reports the results of the set-theoretic consistency assessments for the 17 combinations in table 2.4 that meet the strength of evidence threshold (a frequency of at least 10 cases that are more in than out of each combination). The consistency scores for the combinations range from 0.14 to 0.98, indicating a substantial spread in the degree to which the subset relation is evident. In the truth table analysis that follows the five combinations with consistency scores of at least 0.80 are treated as subsets of the outcome; the remaining 12 fail to satisfy this criterion. Once this distinction is made, table 2.5 can be analyzed as a crisp truth table (Ragin 1987). The binary outcome, which is based on set-theoretic consistency scores, is listed in the last column of table 2.5.

Using fsQCA (Ragin, Drass, and Davey 2005) it is possible to derive two truth table solutions, one maximizing parsimony and the other maximizing complexity. The most parsimonious solution permits the incorporation of any counterfactual combination that contributes to the derivation of a logically simpler solution. This solution of the truth table yields three relatively simple combinations linked to poverty avoidance:

COLLEGE•children +
COLLEGE•MARRIED +
low_income•low_afqt•MARRIED

In this and subsequent fsQCA results the following notation is used: COLLEGE is the fuzzy set for college education; LESS_THAN_HS is the fuzzy set for less than high school; LOW_INCOME is the fuzzy set for low parental income; LOW_AFQT is the fuzzy set for low AFQT score; CHILDREN is the crisp set for at least one child; and MARRIED is the crisp set for married. A fuzzy set name in upper-case letters indicate original membership scores; lower-case letters indicate *negated* scores (e.g., "low_income" indicates membership in the set of cases with *not*-low parental income because the name is in lower case). Multiplication (•) signals combined conditions (set intersection); addition (+) signals alternate combinations of conditions (set union). The parsimonious solution reveals that there are three combinations of conditions linked to poverty avoidance: college education combined with either marriage or the absence of children, and not-low parental income combined with not-low AFQT scores and marriage.

While parsimonious, this solution involves the incorporation of many counterfactual combinations, and many of these, in turn, are "difficult" (Ragin and Sonnett 2004). For example, the combination of low income parents, low AFQT score, and having at least one child (along with having a college education and being married) is included in the second combination in the solution. There are too few empirical cases of this combination to allow its assessment (N = 4; see table 2.4), but the solution just reported assumes that individuals with this combination are able to avoid poverty. With 256 logically possible combinations of conditions, there are many combinations without cases or with very few cases, as table 2.4 indicates. The parsimonious solution just presented incorporates many such combinations, without regard for their empirical plausibility.

If, instead, the researcher evaluates the plausibility of the counterfactual combinations, a less parsimonious solution is derived. This intermediate solution is obtained by first deriving the most complex solution (not shown here) and then using only "easy" counterfactuals to produce an intermediate solution. The intermediate solution is a subset of the most parsimonious solution and a superset of the most complex solution. The intermediate solution indicates that there are three combinations of conditions linked to poverty avoidance:

COLLEGE·low_income·low_afqt·children +
COLLEGE·low_afqt·MARRIED +
less_than_hs·low_income·low_afqt·MARRIED

The three combinations linked to poverty avoidance are similar in that they all include education (COLLEGE or less_than_hs), *not* having low AFQT scores (low_afqt), and some aspect of household composition (MARRIED or children). Only the second combination lacks parental income as an ingredient, indicating that the second combination holds for cases with both low and high parental income. These results are important because they confirm that the causal conditions linked to poverty avoidance are combinatorial in nature and that it is possible to discern the relevant combinations when cases are viewed as configurations.

The results can be summarized with the aid of a branching diagram, starting with the common causal condition, not having a low AFQT score:

```
                                 MARRIED
                                /
                        COLLEGE
                       /        \
          low_income             children
         /          \
low_afqt             less_than_hs·MARRIED
         \
          LOW_INCOME·COLLEGE·MARRIED
```

The first divide is low parental income versus not-low parental income. In the low income path, it takes both college education and marriage to stay out of poverty. In the not-low parental income path, it is possible to stay out of poverty with a high school education, if this characteristic is combined with marriage. If not-low parental income is combined with college education, however, it is necessary only to avoid being an unmarried parent in order to stay out of poverty.

In addition to revealing the combinatorial complexities of staying out of poverty for Black males, the results also challenge the interpretation of AFQT scores offered by Herrnstein and Murray. Recall that the core of their argument is that the nature of work has changed and that the labor market now places a premium on high cognitive ability. The image they conjure is one of a society that has many positions for the cognitively gifted but few slots for those who are more modest in their cognitive endowments. The results presented here are unequivocal: what really matters when it comes to avoiding poverty is to *not* have low test scores. In other words, the common ingredient across the three causal combinations in the solution is not vaunted cognitive ability, but having at least modest ability. Of course, this interpretation assumes that one accept the questionable claim that AFQT scores indicate cognitive ability. According to many of the critics of the *Bell Curve* thesis, AFQT scores indicate the acquisition of cultural capital. In this light, the findings reported here indicate that an important ingredient in the effort to avoid poverty is the possession of at least modest cultural capital.

The fuzzy-set results also show clearly that household formation and composition matter a great deal--they are part of every recipe for staying out of poverty. When it comes to important life outcomes such as avoiding poverty, these factors should not be ignored. These results reinforce the findings of Fischer *et al.*, and extend their argument by showing that household composition can best be understood as a key ingredient in recipes that include such things as education, test scores, and not having low-income parents. It is also worth noting that even the most advantaged of the pathways shown in the branching diagram (not-low test scores combined with not-low parental income and college education) include household composition as a factor (either marriage or no children--avoid being an unmarried parent).

4. DISCUSSION

The results presented here are preliminary findings drawn from a larger fuzzy-set analysis of the *Bell Curve* data. The primary goal of this illustrative research is to provide a contrast between a net-effects and a configurational analysis of the same data. The contrast between these two approaches is clear.

The findings of the net-effects analysis are expressed in terms of individual variables. They provide the final tally of the competition to explain variation in the outcome, avoiding poverty. Education and marital status win this competition, but AFQT is not eliminated, for it retains a modest net effect, despite the stiff competition (compare table 2.2 and table 2.3). The logistic regression results are silent on the issue of causal combinations. The analysis of causal combinations would require the examination of complex interaction models. The examination of a saturated interaction model, for example, would require the estimation of 32 coefficients in a single equation. Even if such a model could be estimated (extreme collinearity makes this task infeasible), the model would be virtually impossible to interpret, once estimated.

Note also that the assumptions of additivity and linearity in the logistic regression analysis allow the estimation of outcome probabilities for all 32 sectors of the vector space defined by the five independent variables, regardless of whether these sectors are populated with cases. Thus, the net-effects approach addresses the problem of limited diversity in an indirect and covert manner, by assuming that the effect of a given variable is the same regardless of the values of the other variables and that a linear relationship can be extrapolated beyond an observed range of values. To derive the estimated probability of avoiding poverty for any point in the vector space defined by the independent variables, it is necessary simply to insert the coordinates of that point into the equation and calculate the predicted value. The issue of limited diversity is thus sidestepped altogether.

By contrast, this issue must be confronted head-on in a configurational analysis. Naturally occurring data are profoundly limited in their diversity. This fact is apparent whenever researchers examine the distribution of cases across logically possible combinations of conditions, especially when the number of conditions is more than a handful. As the analysis reported here illustrates, the problem of limited diversity is not remedied by having a large number of cases.

When cases are viewed configurationally, it is possible to identify the different combinations of conditions linked to an outcome. The results of the configurational analyses reported in this contribution show that there are several recipes for staying out of poverty. The recipes all include not having low AFQT scores, a favorable household composition--especially marriage for those with liabilities in other spheres (e.g., lacking college education or having low parental income), and educational qualifications. Not having low parental income is also an important ingredient in two of the three recipes. Herrnstein and Murray dramatize the implications of their research by claiming that if one could choose at birth between having a high AFQT score and having a high parental SES (or high parental income), the better choice would be to select having a high AFQT score. The fuzzy-set results underscore the fact that the choice is really about combinations of conditions, about recipes, not about individual variables. In short, choosing to not have a low AFQT score, by itself, does not offer protection from poverty. It must be combined with other resources.

Appendix: Constructing Fuzzy Sets

As previously noted, the calibration of fuzzy sets is central to fuzzy-set analysis. Miscalibrations can seriously distort the results of set-theoretic assessments. The main principle guiding calibration is that the resulting fuzzy set scores must reflect both substantive knowledge and the existing research literature. While some might consider the influence of calibration decisions "undue" and portray this aspect of fuzzy-set analysis as a liability, it is, in fact, a strength. Because calibration is important, researchers must pay careful attention to the definition and construction of their fuzzy sets, and they are forced to concede that substantive knowledge is, in essence, a prerequisite for analysis. The main fuzzy sets in the analysis presented in this contribution are degree of membership in the outcome – the set of individuals avoiding poverty – and degree of membership in sets reflecting various background characteristics and conditions.

Avoiding Poverty. To construct the fuzzy set of individuals avoiding poverty, I use the official poverty threshold adjusted for household size as provided by the NLSY, the same measure used by both Herrnstein and Murray (1994) and Fischer *et al.* (1996). In their analyses, both Herrnstein and Murray and Fischer *et al.* use the poverty status variable as a binary dependent variable in logistic regression analyses. However, this places families whose income is just barely above the poverty level in the same category as those families that are far above the poverty threshold, such as comfortably upper-middle class families. The fuzzy set of cases in poverty avoids this problem. In accordance with the official poverty threshold, households with total family income at or below the poverty level are defined as having full membership in the set of households in poverty. Conversely, households with incomes that are four times the poverty level are defined as fully out of poverty. The fuzzy set of households in poverty is a symmetric set, that is, it is truncated at both ends and the crossover point is set exactly at the halfway mark. Accordingly, the fuzzy set of households *not* in poverty (poverty avoidance) is simply 1 minus membership in the original set.

High School and College Education. To measure educational attainment, the NLSY uses "Highest Grade Completed" (NLSY User's Guide: 138). This variable translates years of education directly into degrees (i.e., completing twelve years of education indicates a high school degree, while completing sixteen years completed indicates a college degree). Respondents with twelve or more years of school are fully excluded from the set with less than a high school education (a score of 0.0). On the other hand, those with only a primary school education (i.e., six years of school or less) are treated as fully in the set of respondents with less that high school (a score of 1.0). The fuzzy set thus embraces the six years of secondary school: 7 years = 0.15; 8 years = 0.30; 9 years = 0.45; 10 years = 0.60; and 11 years = 0.75. The fuzzy set of college-educated respondents was constructed similarly by defining respondents with sixteen or more years of education as having full membership in the set with a college education, while those with twelve years of education or less were coded as fully out of the set: 13 years = 0.20; 14 years = 0.40; and 15 years = 0.60.

Parental Income. The measure of parental income is based on the average of the reported 1978 and 1979 total net family income in 1990 dollars. It is the same measure used by Fischer *et al.* and was generously provided by Richard Arum. These data were used to create two fuzzy sets: respondents with low parental income and respondents with high parental income. The fuzzy set of respondents with low parental income is similar in construction to the fuzzy set of households in poverty. Using NLSY data on the official poverty threshold in 1979, adjusted by household size, respondents are defined as coming from a low parental income household if parental income was at or below the poverty threshold. Conversely, respondents are fully out of the set of those experiencing low parental income if family income was at least four times the poverty level in 1979. The cross-over point in the fuzzy set is pegged at two and a half times the poverty level. Truncation thus occurs for those below the official poverty level and for those with incomes exceeding the official poverty level by a factor of four or greater.

Multiples of the poverty ratio were also used to construct the fuzzy set of respondents with high parental income. At the bottom end, respondents are defined as fully out of the set of high parental income if their household had a poverty ratio of 2.5, thus indicating that their parental income was only two and a half times the official poverty level. This point corresponds to the cross-over point for membership in the set of respondents with low parental income, thus indicating that there is modest overlap between the two sets. (That is, some respondents have low membership in both sets--the set with low parental income and the set with high parental income.) To define full membership in the set of high parental income respondents, I used the median family income in 1990 dollars as a baseline. In 1979, the median family income in the U.S. was about 35,000 dollars. Respondents have full membership in the set of high parental income if their parental income was on average three times the national median income, or $105,000 a year. This translates to about fourteen times the poverty threshold. The crossover point was set at two times the median family income, which translates to about eight times the poverty threshold.

Test Scores. The AFQT scores used by Herrnstein and Murray are based on the *Armed Services Vocational Aptitude Battery* (ASVAB), which was introduced by the Department of Defense in 1976 to determine eligibility for enlistment. In *The Bell Curve*, Herrnstein and Murray pay special attention to those at the two ends of the AFQT score distribution. Specifically, they describe the top five percent as "the cognitive elite", and the bottom five percent as "very dull." While their arguments suggest that these groups are to some extent qualitatively different from the respondents in between, their measure of AFQT and their analysis of its effects largely ignore possible qualitative differences. While using the top and bottom 5 percent of the distribution has some intuitive appeal, it is still a largely arbitrary decision. To construct the fuzzy-set measures of those with high AFQT scores and low AFQT scores, I relied instead on categories used by the Department of Defense to place enlistees. Thus, the calibration of these fuzzy sets is grounded in practical decisions made by the military.

The military divides the AFQT scale into five categories based on percentiles. These five categories have substantive importance in that they determine eligibility as well as assignment into different qualification groups. Persons in categories I and II are considered to be above average in trainability; those in category III are about average; those in category IV below average; and those in category V are markedly below average. To determine eligibility for enlistment, the Department of Defense uses both aptitude and education as criteria. Regarding aptitude, the current legislated minimum standard is the 10^{th} percentile, meaning that those who score in category V (1^{st} to 9^{th} percentile) are not eligible for military service. Furthermore, those scoring in category IV (10^{th} to 30^{th} percentile) are not eligible for enlistment unless they also have at least a high school education. Legislation further requires that no more than 20 percent of the enlistees be drawn from Category IV, which further indicates that respondents in this category are substantially different from those in categories I to III.

To construct the fuzzy set of respondents with low AFQT scores, I define those in category V (who are by law prohibited from enlistment because of their low aptitude) as having full membership in the set of cases with low AFQT scores. At the other end of the distribution, those scoring in category III or higher (and thus are of average or above average trainability) are defined as fully out of the set of low AFQT scores. Respondents in category IV (10^{th} to 30^{th} percentile), who need the additional criterion of a high school degree to be eligible for military service, have varying degrees of partial membership in the set of low AFQT scorers, with the crossover point in the middle of this category at the 20^{th} percentile. Partial membership scores were directly tied to the percentile score, thus providing a continuous measure ranging from zero to one.

For the fuzzy set of respondents with high AFQT scores, I define those in category I (93^{rd} to 99^{th} percentile) as having full membership, while those in category II (65^{th} to 92^{nd} percentile) have partial membership in the set of high AFQT scores, with the crossover point at the 78th percentile. Respondents in categories III, IV, and V are thus fully out of the set of respondents with high AFQT scores. To calculate the fuzzy set scores, I use the percentile scores based on revised procedures established in 1989 and provided by the NLSY (NLSY79 User's Guide: 95).

Household Composition. Household composition has two main components: whether or not the respondent is married and whether or not there are children present in the household. All four combinations of married/not-married and children/no-children are present with substantial frequency in the NLSY data set. I code respondent's marital status as a crisp set, assigning a value of one to those who were married in 1990. In general, married individuals are much less likely to be in poverty. While Fischer *et al.* use the actual number of respondent's children in 1990, I code "having children" as a crisp set. The rationale for this is that being a parent imposes certain status and lifestyle constraints. As any parent will readily attest, the change from having no children to becoming a parent is much more momentous, from a life style and standard of living point of view, than having a second or third child. In general, households with children are more likely to be in poverty than households without children. The most favorable household composition, with respect to staying out of poverty, is the married/no-children combination. The least favorable is the not-married/children combination.

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