QUALITATIVE COMPARATIVE ANALYSIS AND FUZZY SETS

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Background Material

The case-oriented/variable-oriented dimension

Single Case Study	Method of Agreement	Comparative Study of Configurations	QN Study of Covariation

Case-Oriented	Variable-Oriented
Small-N	Large-N
Qualitative	Quantitative
Intensive	Extensive
With-in Case Analysis	Cross-Case Analysis
Problem of Representation	Problem of Inference

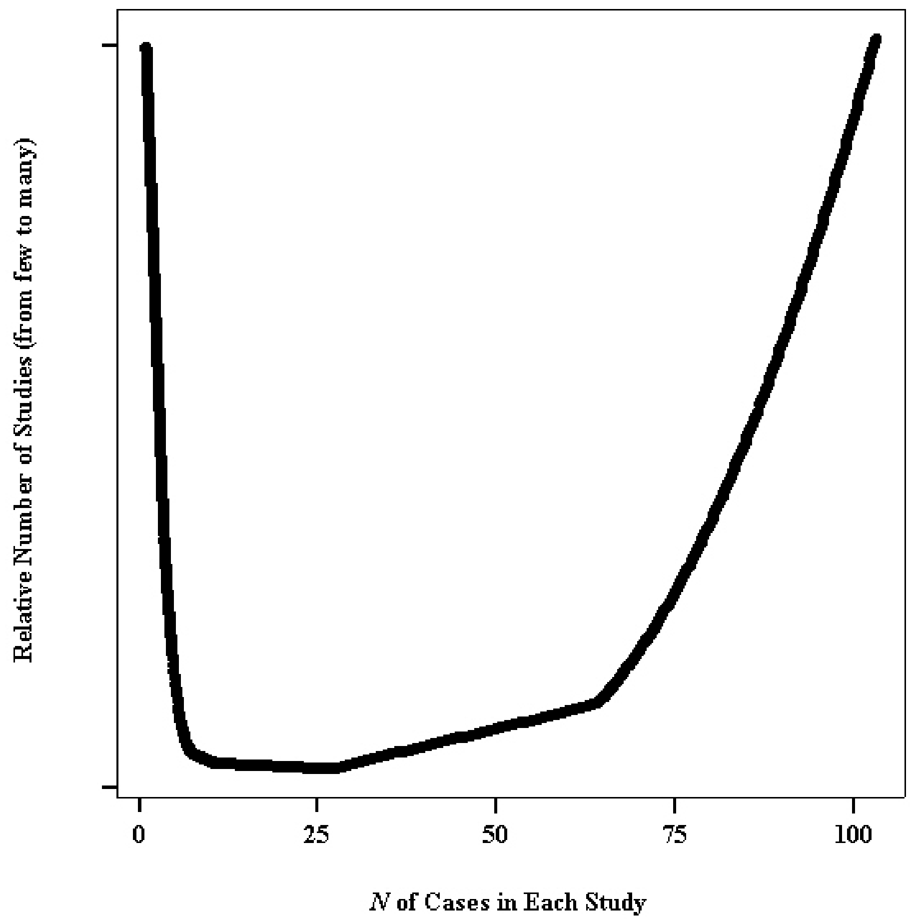


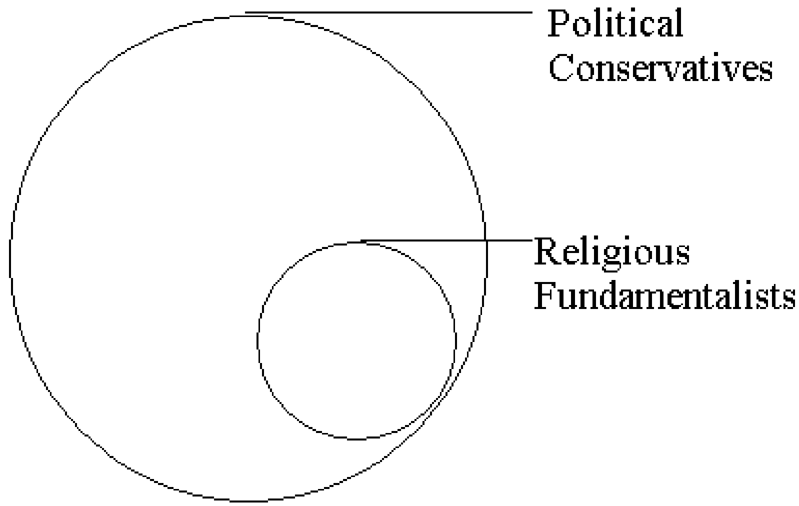
Figure 1.1 Plot of Relative Number of Studies against N of Cases in Each Study

SETS ARE CENTRAL TO SOCIAL SCIENTIFIC DISCOURSE

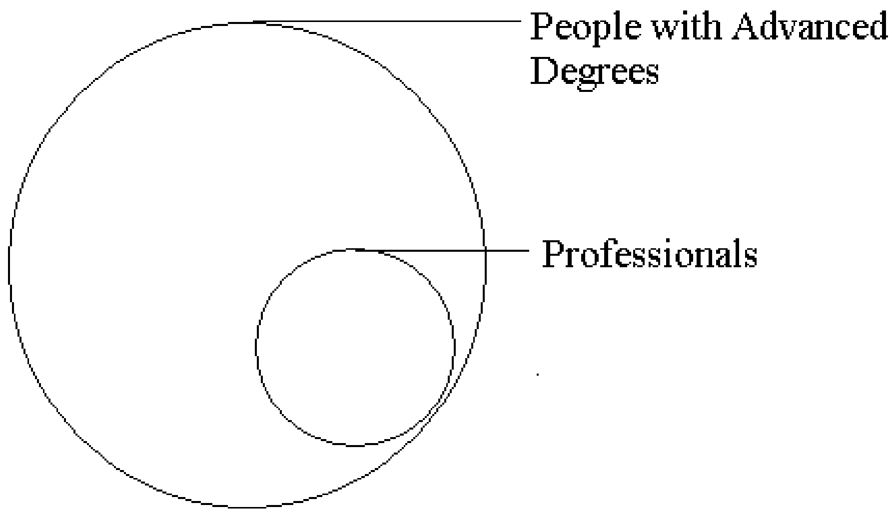
Many, if not most, social scientific statements, especially empirical generalizations about cross-case patterns, involve set-theoretic relationships:

A. Religious fundamentalists are politically conservative. (Religious fundamentalists are a subset of politically conservative individuals.)
B. Professionals have advanced degrees. (Professionals are a subset of those with advanced degrees.)
C. Democracy requires a state with at least medium capacity. (Democratic states are a subset of states with at least medium capacity.)
D. "Elite brokerage" is central to successful democratization. (Instances of successful democratization are a subset of instances of elite brokerage.)
E. "Coercive" nation-building was not an option for "late-forming" states. (States practicing coercive nation-building are a subset of states that formed "early.")

Usually, but not always (e.g., D), the subset is mentioned first. Sometimes, it takes a little deciphering to figure out the set-theoretic relationship, as in E.



The cause is a subset of the outcome.



The outcome is a subset of the cause.

CONVENTIONAL VIEW OF SETS

- Sets are binary, nominal-scale variables, the lowest and most primitive form of social measurement.

- The cross-tabulation of two sets is the simplest and most primitive form of variable-oriented analysis.

- This form of analysis is of limited value because: (1) the strength of the association between two binary variables is powerfully influenced by how they are created (e.g., the choice of cut-off values), and (2) with binary variables researchers can calculate only relatively simple measures of association. These coefficients may be useful descriptively, but they tell us little about the contours of relationships.

- In short, examining relations between binary variables might be considered adequate as a descriptive starting point, but this approach is too crude to be considered *real* social science.

Correlational Connections

- Correlation is central to conventional quantitative social science. The core principle is the idea of assessing the degree to which two series of values parallel each other across cases.

- The simplest form is the 2x2 table cross-tabulating the presence/absence of a cause against presence/absence of an outcome:

	Cause absent	Cause present
Outcome present	cases in this cell (#1) contribute to error	many cases should be in this cell (#2)
Outcome absent	many cases should be in this cell (#3)	cases in this cell (#4) contribute to error

- Correlation is strong (and in the expected direction) when there are as many cases as possible in cells #2 and #3 (both count in favor of the causal argument, equally) and as few cases as possible in cells #1 and #4 (both count against the causal argument, equally).

- Correlation is completely symmetrical.

Correlational Versus Explicit Connections

- A correlational connection is a description of tendencies in the evidence:

	Presidential form	Parliamentary form
3rd wave democracy survived	8	11
3rd wave democracy collapsed	16	5

- An explicit connection is a subset relation or near-subset relation:

	Presidential form	Parliamentary form
3rd wave democracy survived	18	16
3rd wave democracy collapsed	6	0

In the second table all democracies with parliamentary systems survived, that is, they are a subset of those that survived. The first table is stronger and more interesting from a correlational viewpoint; the second is stronger and more interesting from the perspective of **explicit** connections.

NECESSITY AND SUFFICIENCY AS SUBSET RELATIONS

Anyone interested in demonstrating necessity and/or sufficiency must address set-theoretic relations. Necessity and sufficiency cannot be assessed using conventional quantitative methods.

CAUSE IS NECESSARY BUT NOT SUFFICIENT		
	Cause absent	Cause present
Outcome present	1. no cases here	2. cases here
Outcome absent	3. not relevant	4. not relevant

CAUSE IS SUFFICIENT BUT NOT NECESSARY		
	Cause absent	Cause present
Outcome present	1. not relevant	2. cases here
Outcome absent	3. not relevant	4. no cases here

CAUSAL COMPLEXITY

Another important benefit of set theoretic analysis is that it is much more compatible with the analysis of causal complexity than conventional techniques.
Example: a researcher studies production sites in a strike-prone industry and considers four possible causes of strikes:

technology = the introduction of new technology
wages = stagnant wages in times of high inflation
overtime = reduction in overtime hours
sourcing = outsourcing portions of production

Possible findings include:

(1) technology → strikes
(2) technology·wages → strikes
(3) technology + wages → strikes
(4) technology·wages + overtime·sourcing → strikes

In (1) technology is necessary and sufficient; in (2) technology is necessary but not sufficient; in (3) technology is sufficient but not necessary; in (4) technology is neither necessary nor sufficient. The fourth is the characteristic form of causal complexity: no cause is either necessary or sufficient.

INUS CAUSATION

In situations of *causal complexity*, no single cause may be either necessary or sufficient, as in the equation:

TECHNOLOGY*WAGES + OVERTIME*SOURCING → STRIKES

In *The Comparative Method*, this situation is called “multiple conjunctural causation.”

In *The Cement of the Universe*, Mackie labels these causal conditions INUS causes because each one is:

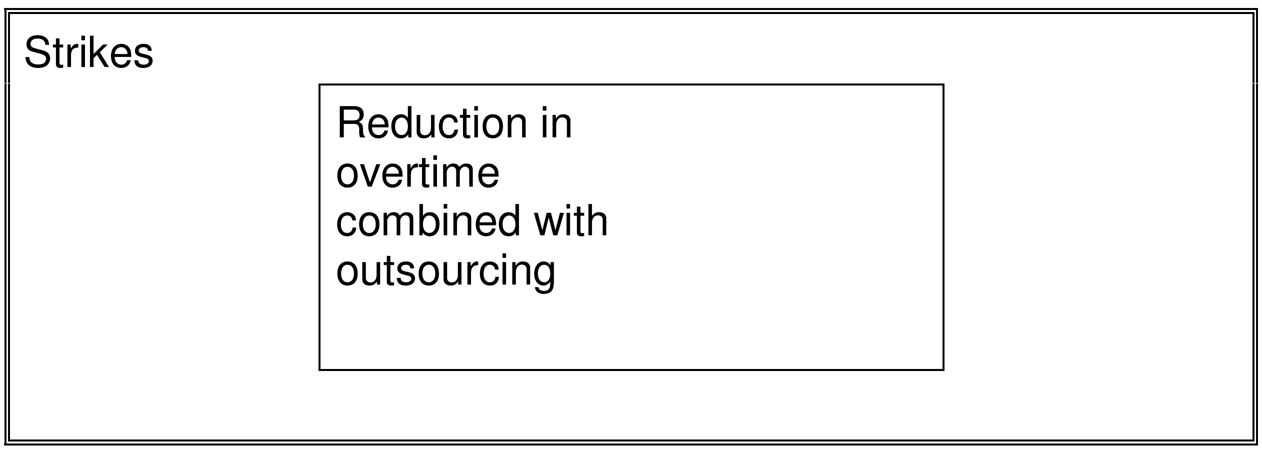
Insufficient (not sufficient by itself) but
Necessary components of causal combinations that are
Unnecessary (because of multiple paths) but
Sufficient for the outcome

ASSESSING CAUSAL COMPLEXITY

I. Logical equation: technology·wages + overtime·sourcing → strikes
II. Formulated as a partial crosstabulation:

	Causal combination absent	Causal combination present
Strike present (1)	Cell 1: 20 cases	Cell 2: 23 cases
Strike absent (0)	Cell 3: 18 cases	Cell 4: 0 cases

III. Expressed as a Venn diagram:



The key to assessing the sufficiency of a combination of conditions, even if it is one among many combinations, is to select on instances of the combination and assess whether these instances agree on the outcome.

Analysis of Causal Complexity Using QCA

THE FOUR PHASES OF RESEARCH USING QCA

1. Learn as much as you can about the cases. If possible, construct a narrative for each case. Use case comparisons to refine and systematize your understandings.

2. Construct a truth table, which both represents what you've learned and disciplines your representations of the cases.

3. The Analytic Moment: Analyze the evidence using QCA. Actually, preliminary results usually send you back to phase 1.

4. Take the results back to the cases. The real "test" of the results is how useful they are. Do they help you understand the cases better? Do the different paths (causal combinations) make sense at the case level? Do the results place the cases in a new light, perhaps revealing something that would not have been evident before the analysis (phase 2).

SIMPLE EXAMPLE OF QCA USING HYPOTHETICAL DATA

A. Truth Table:

C	*L*	*H*	*G*	*U*	*N of Cases*
0	0	0	0	0	4
0	0	0	1	0	3
0	0	1	0	0	6
0	0	1	1	1	2
0	1	0	0	1	3
0	1	0	1	1	4
0	1	1	0	0	3
0	1	1	1	1	5
1	0	0	0	0	7
1	0	0	1	0	8
1	0	1	0	0	1
1	0	1	1	1	7
1	1	0	0	1	3
1	1	0	1	1	2
1	1	1	0	0	7
1	1	1	1	1	6

C = Corporatist wage negotiations
L = At least five years of rule by Left or Center-Left parties
H = Ethnic-cultural homogeneity
G = At least ten years of sustained economic growth
U = Adoption of universal pension system

B. Table simplified through row-wise comparisons (positive outcomes only)

-10- (or L·h: Left rule combined with ethnic diversity)[a]

-1-1 (or L·G: Left rule combined with economic growth)

--11 (or H·G: ethnic homogeneity combined with economic growth)

Dashes indicate that a condition has been eliminated (found to be irrelevant)

C. Finding Redundant Terms:

		Terms to be Covered (Rows with Outcome = 1)							
		0100	1100	0101	1101	0011	1011	0111	1111
Simplified Terms (from B)	-10-	x	x	x	x				
	-1-1			x	x			x	x
	--11					x	x	x	x

D. Final Results (logically minimal):

$$U = L \cdot h + H \cdot G$$

Lower-case letters indicate condition must be absent.
Upper-case letters indicate that condition must be present.
Multiplication indicates combined conditions (logical *and*).
Addition indicates alternate combinations (logical *or*).

Territorially Based Linguistic Minorities in Western Europe

Austria:	Slovenes Magyars Croats
Belgium:	Flemings Walloons Germans
Great Britain:	Gaels (Scotland) Gaels (Isle of Man) Gaels (N. Ireland) Welsh Channel Islanders
Denmark:	Germans Faroe Islanders Greenlanders
Finland:	Swedes (mainland) Swedes (Aaland) Lapps
France:	Occitans Corsicans Alsatians Flemings Bretons
West Germany:	Danes North Frisians
Ireland:	Gaels
Italy:	Friulians Ladins Valdotians South Tyroleans Slovenes Sards Greeks Albanians Occitans
Netherlands:	West Frisians
Norway:	Lapps
Spain:	Catalans Basques Galicians
Sweden:	Lapps Finns
Switzerland:	Jurassians

SUMMARY PRESENTATION OF PREDICTIONS OF THREE THEORIES OF ETHNIC POLITICAL MOBILIZATION

	Guiding Perspective		
Characteristic	*Developmental*	*Reactive*	*Competitive*
Size of Subnation (S)	(1)[a]	(1)[a]	1
Linguistic Base (L)	1	0	(1)[a]
Relative Wealth (W)	(0)[a]	0	1
Economic Status (G)	0	?[b]	?[b]

[a] Predictions in parentheses are only weakly indicated by the theories.
[b] Question marks indicate that no clear prediction is made.

DATA ON TERRITORIALLY BASED LINGUISTIC MINORITIES

Minority	S	L	W	G	E
Lapps, Finland	0	0	0	0	0
Finns, Sweden (Torne Valley)	0	0	0	0	0
Lapps, Sweden	0	0	0	0	0
Lapps, Norway	0	0	0	0	0
Albanians, Italy	0	0	0	0	0
Greeks, Italy	0	0	0	0	0
North Frisians, Germany	0	0	0	1	1
Danes, Germany	0	0	0	1	1
Basques, France	0	0	0	1	1
Ladins, Italy	0	0	1	0	0
Magyars, Austria	0	1	0	0	0
Croats, Austria	0	1	0	0	0
Slovenes, Austria	0	1	0	0	1
Greenlanders, Denmark	0	1	0	0	1
Aalanders, Finland	0	1	1	0	2
Slovenes, Italy	0	1	1	1	1
Valdotians, Italy	0	1	1	1	2
Sards, Italy	1	0	0	0	1
Galicians, Spain	1	0	0	0	1
West Frisians, Netherlands	1	0	0	1	1
Catalans, France	1	0	0	1	1
Occitans, France	1	0	0	1	1
Welsh, Great Britain	1	0	0	1	2
Bretons, France	1	0	0	1	2
Corsicans, France	1	0	0	1	2
Friulians, Italy	1	0	1	1	1
Occitans, Italy	1	0	1	1	1
Basques, Spain	1	0	1	1	2
Catalans, Spain	1	0	1	1	2
Flemings, France	1	1	0	0	1
Walloons, Belgium	1	1	0	1	2
Swedes, Finland	1	1	1	0	2
South Tyroleans, Italy	1	1	1	0	2
Alsatians, France	1	1	1	1	1
Germans, Belgium	1	1	1	1	2
Flemings, Belgium	1	1	1	1	2

S = Size of subnation
L = Linguistic ability
W = Relative wealth of subnation
G = Growth vs. decline of subnational region
E = Degree of ethnic political mobilization

TRUTH TABLE REPRESENTATION OF DATA ON CAUSES OF ETHNIC POLITICAL MOBILIZATION

S	L	W	G	E	N
0	0	0	0	0	6
0	0	0	1	0	3
0	0	1	0	0	1
0	0	1	1	?	0
0	1	0	0	0	4
0	1	0	1	?	0
0	1	1	0	1	1
0	1	1	1	1	2
1	0	0	0	0	2
1	0	0	1	1	6
1	0	1	0	?	0
1	0	1	1	1	4
1	1	0	0	0	1
1	1	0	1	1	1
1	1	1	0	1	2
1	1	1	1	1	3

S = Size of subnation
L = Linguistic ability
W = Relative wealth of subnation
G = Growth vs. decline of subnational region
E = Degree of ethnic political mobilization

EQUATION: E = SG + LW

Solution for Presence of Ethnic Political Mobilization

	raw coverage	unique coverage	consistency
L·W+	0.421053	0.263158	1.000000
S·G	0.736842	0.578947	1.000000

solution coverage: 1.000000
solution consistency: 1.000000

Solution for Absence of Ethnic Political Mobilization

	raw coverage	unique coverage	consistency
w·g+	0.764706	0.411765	1.000000
s·l	0.588235	0.235294	1.000000

solution coverage: 1.000000
solution consistency: 1.000000

The solution for “absence” includes remainders as “don’t cares.”

FREQUENCIES AND CODES FOR VARIABLES USED IN BOOLEAN ANALYSIS OF CHALLENGING GROUPS

	Value	Freq.	Percent
Bureaucracy			
	0	29	54.7
	1	24	45.3
Lower Strata Constituency			
	0	28	52.8
	1	25	47.2
Displacement as Primary Goal			
	0	37	69.8
	1	16	30.2
Help From Outsiders			
	0	35	66.0
	1	18	34.0
Acceptance Achieved			
	0	28	52.8
	1	25	47.2
New Advantages Won			
	0	27	50.9
	1	26	49.1

Values show coding in qualitative comparative analysis: 1 indicates presence; 0 indicates absence.

Truth Table For Causes of New Advantages*

BUR	LOW	DIS	HLP	ACP	Number of Cases	New Adv.	No New Adv.
0	0	0	0	0	4	2	2
0	0	0	0	1	2	2	0
0	0	0	1	0	2	2	0
0	0	0	1	1	2	2	0
0	0	1	0	0	4	0	4
0	0	1	0	1	1	1	0
0	0	1	1	0	2	0	2
0	0	1	1	1	1	0	1
0	1	0	0	0	2	0	2
0	1	0	0	1	0	remainder	
0	1	0	1	0	0	remainder	
0	1	0	1	1	2	2	0
0	1	1	0	0	5	0	5
0	1	1	0	1	0	remainder	
0	1	1	1	0	2	0	2
0	1	1	1	1	0	remainder	
1	0	0	0	0	3	0	3
1	0	0	0	1	4	1	3
1	0	0	1	0	1	1	0
1	0	0	1	1	1	1	0
1	0	1	0	0	1	0	1

1	0	1	0	1	0	remainder	
1	0	1	1	0	0	remainder	
1	0	1	1	1	0	remainder	
1	1	0	0	0	2	1	1
1	1	0	0	1	7	6	1
1	1	0	1	0	0	remainder	
1	1	0	1	1	5	5	0
1	1	1	0	0	0	remainder	
1	1	1	0	1	0	remainder	
1	1	1	1	0	0	remainder	
1	1	1	1	1	0	remainder	

* Column headings: BUR = bureaucratic organization; LOW = lower strata constituency; DIS = displacement as primary goal; HLP = help from outsiders; ACP = acceptance of the organization. 1 indicates presence; 0 indicates absence. The output is coded as follows: U = uniform new advantages; L = new advantages likely; P = new advantages possible. The don't care output coding is indicated with a dash.

Sorted Truth Table Spreadsheet for Gamson's Data (by frequency)

BUR	LOW	DIS	HLP	ACP	freq	cumul freq	consistency
1	1	0	0	1	7	7	0.857143
0	1	1	0	0	5	12	0
1	1	0	1	1	5	17	1
0	0	0	0	0	4	21	0.5
0	0	1	0	0	4	25	0
1	0	0	0	1	4	29	0.25
1	0	0	0	0	3	32	0
0	0	0	0	1	2	34	1
0	0	0	1	0	2	36	1
0	0	0	1	1	2	38	1
0	0	1	1	0	2	40	0
0	1	0	0	0	2	42	0
0	1	0	1	1	2	44	1
0	1	1	1	0	2	46	0
1	1	0	0	0	2	48	0.5
0	0	1	0	1	1	49	1
0	0	1	1	1	1	50	0
1	0	0	1	0	1	51	1
1	0	0	1	1	1	52	1
1	0	1	0	0	1	53	0

QCA RESULTS: GAMSON DATA

```
File:  G:/578/05/Gamson/GAMSON.DAT
Model: ADV = BUR + LOW + DIS + HLP + ACP

Algorithm: Quine-McCluskey
 1 Matrix: 1
 - Matrix: R

*** CRISP-SET SOLUTION ***
                  raw       unique
                coverage    coverage   consistency
               ----------  ----------  -----------
dis*HLP+       0.500000    0.153846    1.000000
bur*ACP+       0.269231    0.115385    0.875000
LOW*ACP        0.500000    0.230769    0.928571
solution coverage: 0.846154
solution consistency: 0.916667

*************************************************************************
File:  G:/578/05/Gamson/GAMSON.DAT
Model: ADV = BUR + LOW + DIS + HLP + ACP

Algorithm: Quine-McCluskey
 1 Matrix: 1

*** CRISP-SET SOLUTION ***
                          raw       unique
                        coverage    coverage   consistency
                       ----------  ----------  -----------
bur*low*dis*HLP+       0.153846    0.076923    1.000000
bur*low*dis*ACP+       0.153846    0.076923    1.000000
BUR*LOW*dis*ACP+       0.423077    0.230769    0.916667
LOW*dis*HLP*ACP        0.269231    0.076923    1.000000
solution coverage: 0.730769
solution consistency: 0.950000
```

Fuzzy Sets

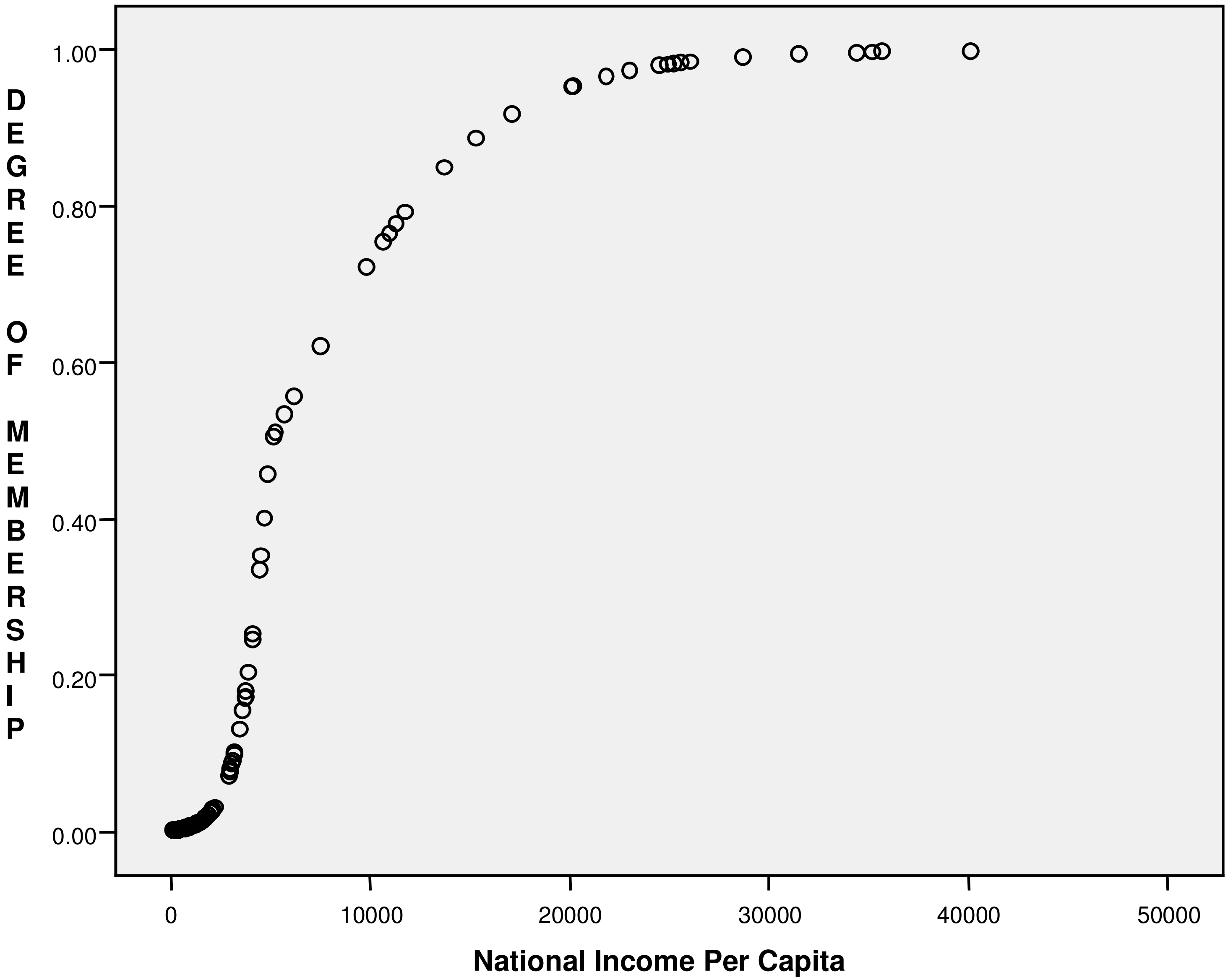
CRISP VERSUS FUZZY SETS

Crisp set	**Three-value fuzzy set**	**Four-value fuzzy set**	**Six-value fuzzy set**	**"Continuous" fuzzy set**
1 = fully in 0 = fully out	1 = fully in .5 = neither fully in nor fully out 0 = fully out	1 = fully in .75 = more in than out .25 = more out than in 0 = fully out	1 = fully in .8 = mostly but not fully in .6 = more or less in .4 = more or less out .2 = mostly but not fully out 0 = fully out	1 = fully in Degree of membership is more "in" than "out": $.5 < x_i < 1$ .5 = cross-over: neither in nor out Degree of membership is more "out" than "in": $0 < x_i < .5$ 0 = fully out

FUZZY MEMBERSHIP IN THE SET OF "DEVELOPED" COUNTRIES

GNP/capita:	Membership (M):	Verbal Labels:
lowest $\rightarrow$ 2,499	$M \approx 0$	clearly not-rich
2,500 $\rightarrow$ 4,999	$0 < M < .5$	more or less not-rich
5,000	$M = .5$	cross-over point
5,001 $\rightarrow$ 19,999	$.5 < M < 1.0$	more or less rich
20,000 $\rightarrow$ highest	$M \approx 1.0$	clearly rich

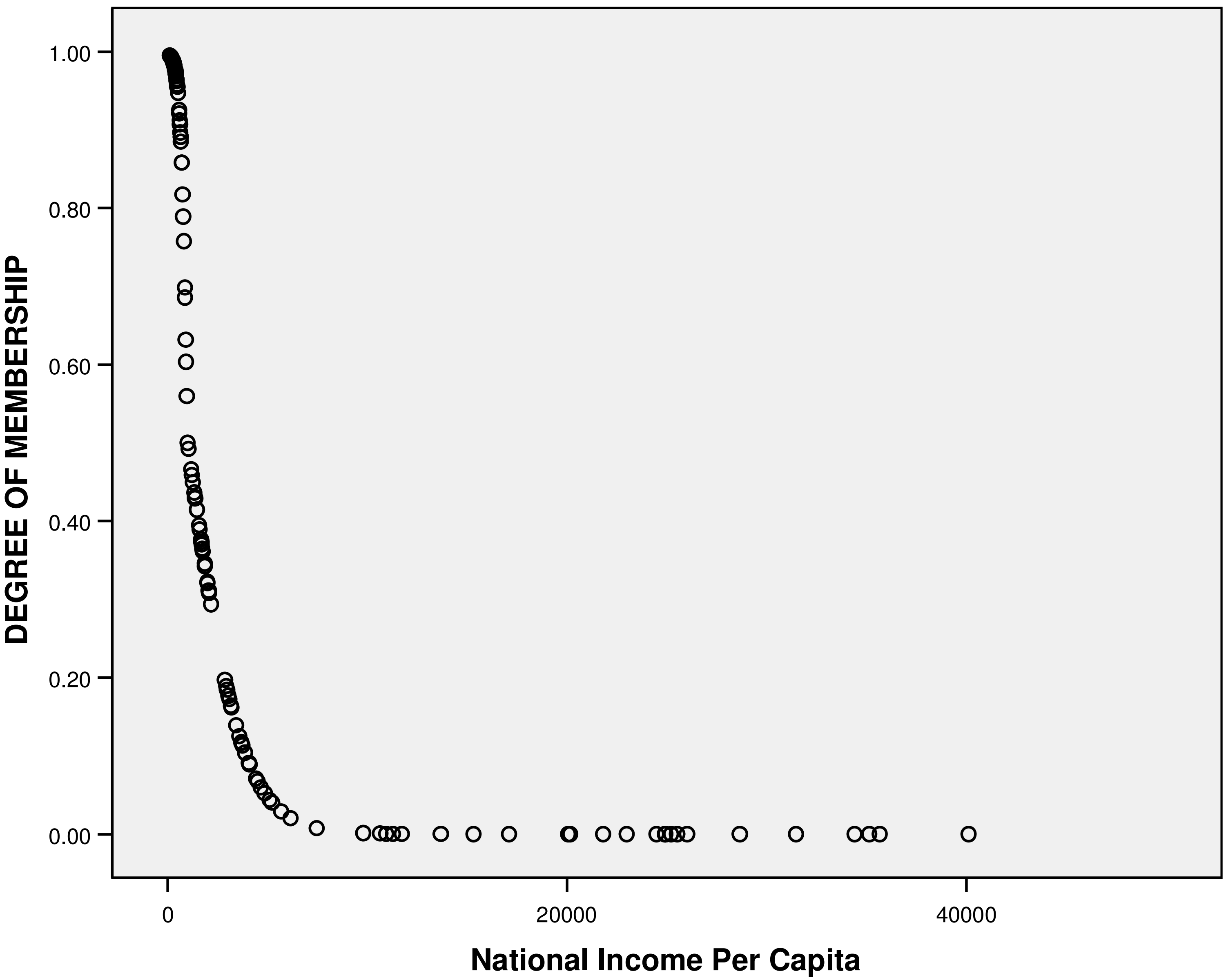
Plot of Degree of Membership in the Set of Developed Countries Against National Income Per Capita



FUZZY MEMBERSHIP IN THE SET OF "LESS-DEVELOPED" COUNTRIES

GNP/capita (US$):	Membership (M):	Verbal Labels:
100 $\rightarrow$ 499	$M \approx 1.0$	clearly poor
500 $\rightarrow$ 999	$.5 < M < 1$	more or less poor
1,000	$M = .5$	cross-over point
1,001 $\rightarrow$ 4,999	$0 < M < .5$	more or less not-poor
5,000 $\rightarrow$ 30,000	$M \approx 0$	clearly not-poor

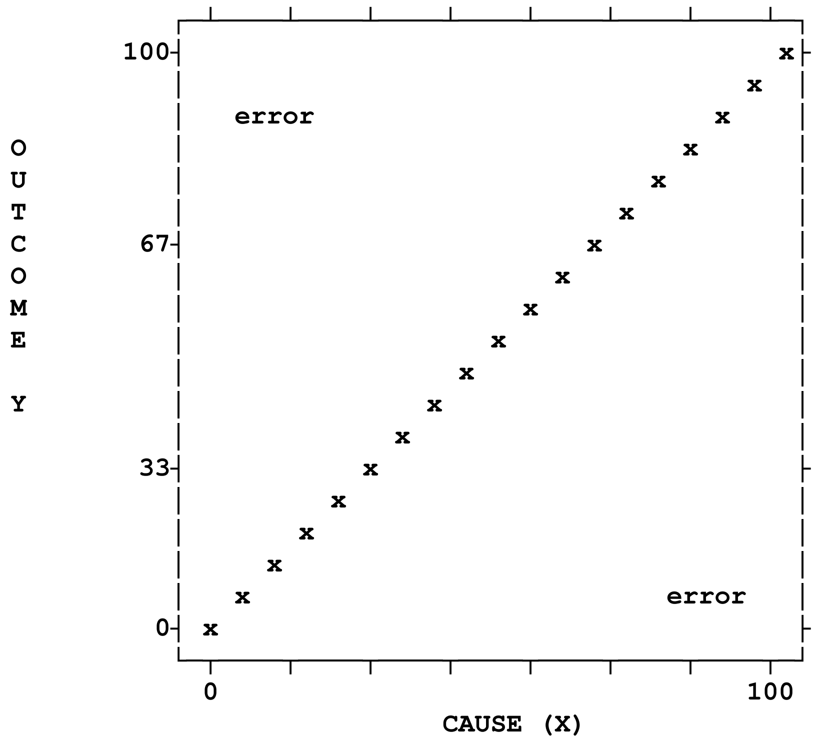
Plot of Degree of Membership in the Set of Less-Developed Countries Against National Income Per Capita



OPERATIONS ON FUZZY SETS

1. Set union: $A + B = \max(A, B)$
2. Set intersection: $A*B = \min(A, B)$
3. Set negation: $\sim A = 1 - A$
4. Concentration: "very" $A = A^2$
5. Dilation: "somewhat" $A = A^{½}$ (square root of A)
   (or "sort of" A)
6. Combining Operations:
   "not very" $A = 1-A^2$
   "sort of not" $A = (1-A)^{½}$
7. Subset relation: $X_i \leq Y_i$
   (fuzzy set X is a subset of fuzzy set Y)

DECONSTRUCTING THE CONVENTIONAL SCATTERPLOT



In conventional quantitative analysis, points in the lower-right corner and the upper-left corner of this plot are "errors," just as cases in cells 1 and 4 of the 2X2 crisp-set table are errors.

With fuzzy sets, cases in these regions of the plot have different interpretations: Cases in the lower-right corner violate the argument that the cause is a subset of the outcome; cases in the upper-left corner violate the argument that the cause is a superset of the outcome (i.e., that the outcome is a subset of the cause).

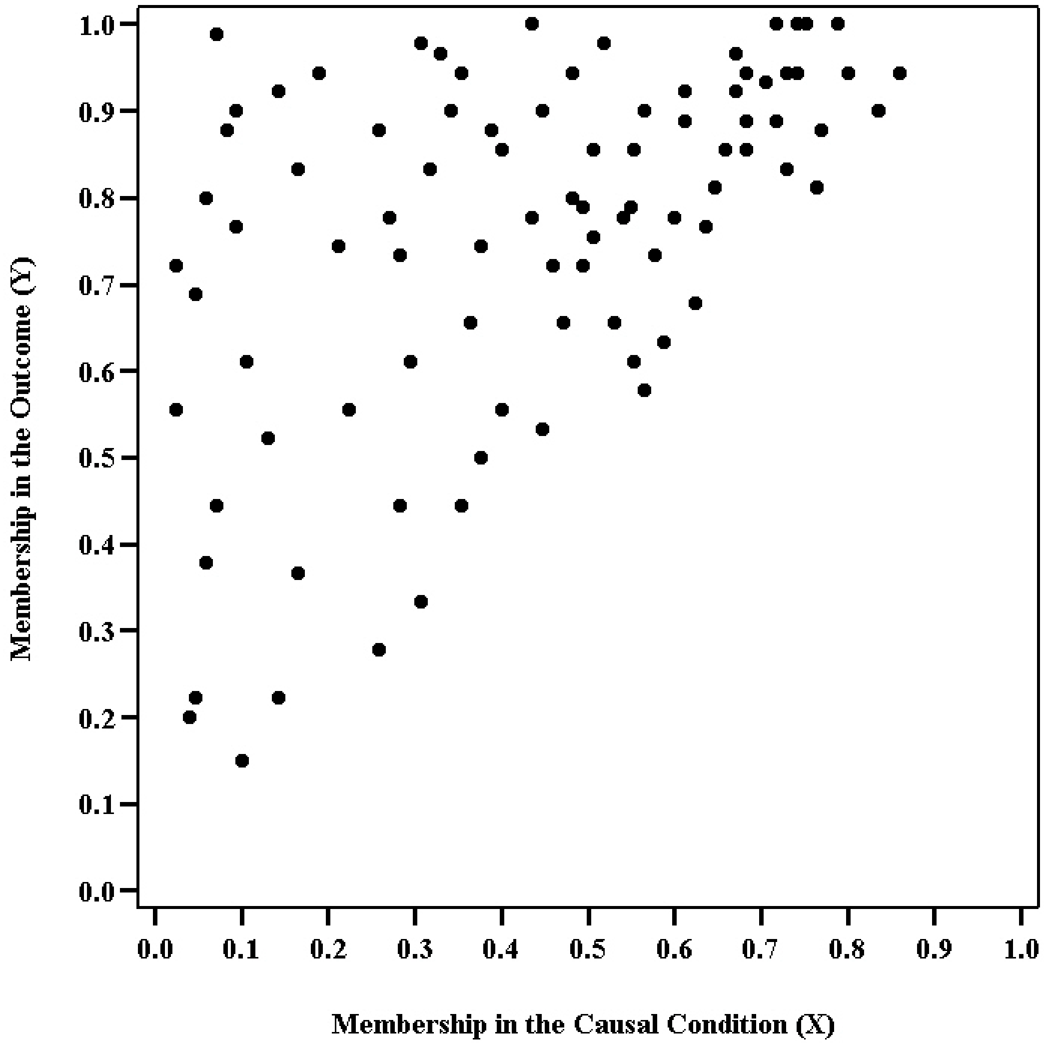


Figure 1: Fuzzy Subset Relation Consistent with Sufficiency

This plot illustrates the characteristic upper-triangular plot indicating the fuzzy subset relation: $X \leq Y$ (cause is a subset of the outcome). This also can be viewed as a plot supporting the contention that X is sufficient for Y.

Cases in the upper-left region are not errors, as they would be in a conventional quantitative analysis. Rather, these are cases with high membership in the outcome due to the operation of other causes. After all, the argument here is that X is a subset of Y (i.e., X is one of perhaps several ways to generate or achieve Y). Therefore, cases of Y without X (i.e., high membership in Y coupled with low membership in X) are to be expected.

In this plot, cases in the lower-right region would be serious errors because these would be instances of high membership in the cause coupled with low membership in the outcome. Such cases would undermine the argument that there is an explicit connection between X and Y such that X is a subset of Y.

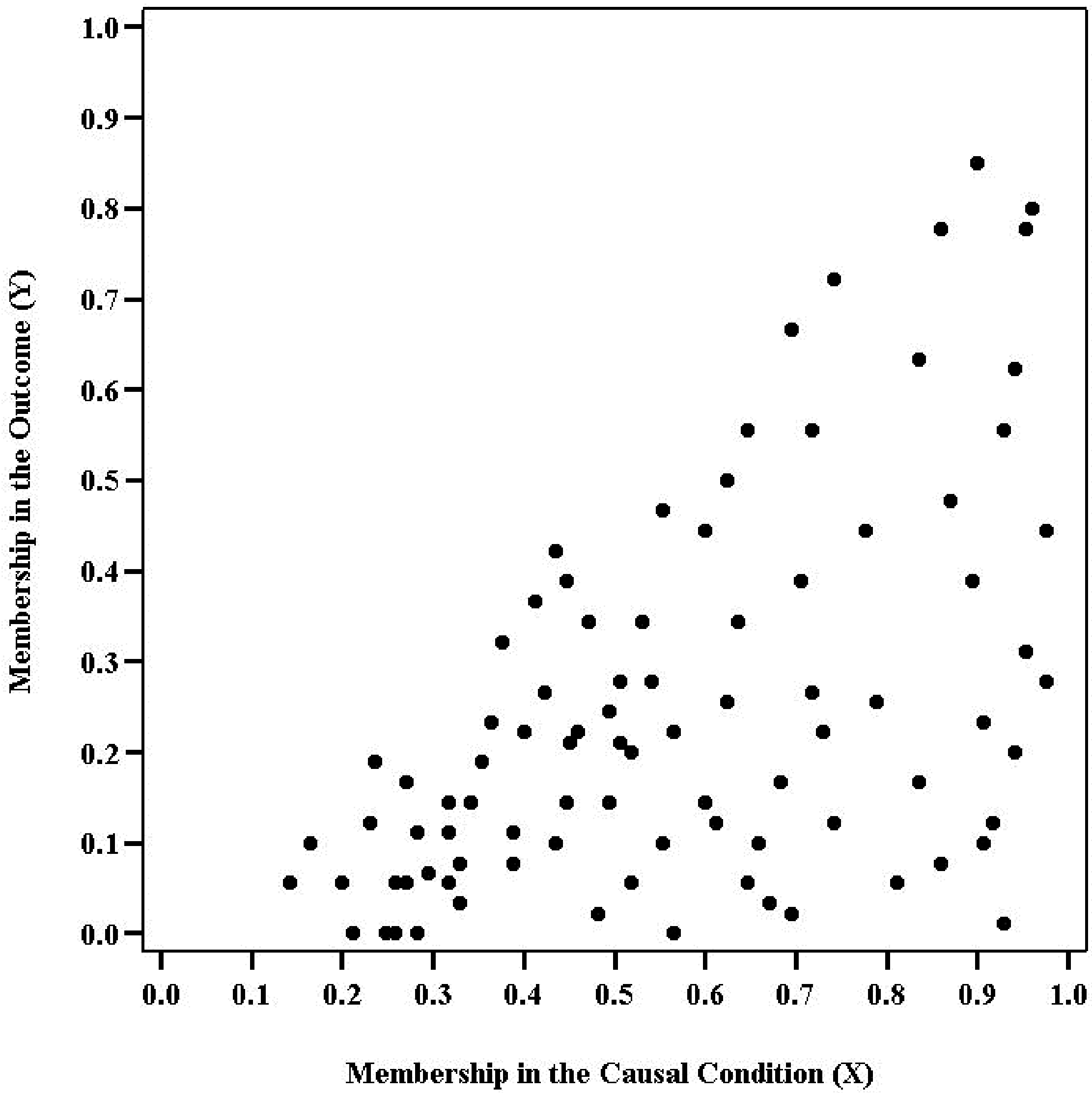


Figure 2: Fuzzy Subset Relation Consistent with Necessity

This plot illustrates the characteristic lower-triangular plot indicating the fuzzy superset relation: X ≥ Y (cause is a superset of the outcome). This also can be viewed as a plot supporting the contention that X is necessary for Y.

Cases in the lower-right region are not errors, as they would be in a conventional quantitative analysis. Rather, these are cases with low membership in the outcome, despite having high membership in the cause. This pattern indicates that Y is a subset of X: condition X must be present for Y to occur, but X may not be capable of generating Y by itself. Other conditions may be required as well. Therefore, cases of X without Y (i.e., high membership in X coupled with low membership in Y) are to be expected.

Cases in the upper-left region would be serious errors because these would be instances of low membership in the cause coupled with high membership in the outcome. In this plot, such cases would undermine the argument that there is an explicit connection between X and Y such that X is a superset of Y (or Y is a subset of X).

Fuzzy-set data on class voting in the advanced industrial societies

Country	Weak Class voting (**W**)	Affluent (**A**)	Income Inequality (**I**)	Manufacturing (**M**)	Strong Unions (**U**)
Australia	0.6	0.8	0.6	0.4	0.6
Belgium	0.6	0.6	0.2	0.2	0.8
Denmark	0.2	0.6	0.4	0.2	0.8
France	0.8	0.6	0.8	0.2	0.2
Germany	0.6	0.6	0.8	0.4	0.4
Ireland	0.8	0.2	0.6	0.8	0.8
Italy	0.6	0.4	0.8	0.2	0.6
Netherlands	0.8	0.6	0.4	0.2	0.4
Norway	0.2	0.6	0.4	0.6	0.8
Sweden	0.0	0.8	0.4	0.8	1.0
United Kingdom	0.4	0.6	0.6	0.8	0.6
United States	1.0	1.0	0.8	0.4	0.2

Assessing the distribution of cases across combinations of causal conditions

	a.i.m.u	a.i.m.U	a.i.M.u	a.i.M.U	a.I.m.u	a.I.m.U	a.I.M.u	a.I.M.U	A.i.m.u	A.i.m.U	A.i.M.u	A.i.M.U	A.I.m.u	A.I.m.U	A.I.M.u	A.I.M.U
1.Australia	.200	.200	.200	.200	.200	.200	.200	.200	.400	.400	.400	.400	.400	.600	.400	.400
2.Belgium	.200	.400	.200	.200	.200	.200	.200	.200	.200	.600	.200	.200	.200	.200	.200	.200
3.Denmark	.200	.400	.200	.200	.200	.400	.200	.200	.200	.600	.200	.200	.200	.400	.200	.200
4.France	.200	.200	.200	.200	.400	.200	.200	.200	.200	.200	.200	.200	.600	.200	.200	.200
5.Germany	.200	.200	.200	.200	.400	.400	.400	.400	.200	.200	.200	.200	.600	.400	.400	.400
6.Ireland	.200	.200	.400	.400	.200	.200	.400	.600	.200	.200	.200	.200	.200	.200	.200	.200
7.Italy	.200	.200	.200	.200	.400	.600	.200	.200	.200	.200	.200	.200	.400	.400	.200	.200
8.Netherlands	.400	.400	.200	.200	.400	.400	.200	.200	.600	.400	.200	.200	.400	.400	.200	.200
9.Norway	.200	.400	.200	.400	.200	.400	.200	.400	.200	.400	.200	.600	.200	.400	.200	.400
10.Sweden	.000	.200	.000	.200	.000	.200	.000	.200	.000	.200	.000	.600	.000	.200	.000	.400
11.UK	.200	.200	.400	.400	.200	.200	.400	.400	.200	.200	.400	.400	.200	.200	.400	.600
12.US	.000	.000	.000	.000	.000	.000	.000	.000	.200	.200	.200	.200	.600	.200	.400	.200
13.# > 0.5	0	0	0	0	0	1	0	1	1	2	0	2	3	1	0	1

Assessing the consistency of causal combinations with the fuzzy subset relation

Affluence	Inequality	Manufacturing	Unions	Consistency	Outcome
1	0	0	0	1.00	1
1	1	0	0	1.00	1
0	1	1	1	0.87	0
1	1	0	1	0.84	0
0	1	0	1	0.82	0
1	0	0	1	0.79	0
1	1	1	1	0.78	0
1	0	1	1	0.72	0

Consistency and Coverage—fuzzy sets

CONSISTENCY AND COVERAGE

I, X as a subset of Y (sufficiency)

Consistency $(\mathbf{X_i} \leq \mathbf{Y_i}) = \Sigma(\min(\mathbf{X_i},\mathbf{Y_i}))/\Sigma(\mathbf{X_i})$

Coverage $(\mathbf{X_i} \leq \mathbf{Y_i}) = \Sigma(\min(\mathbf{X_i},\mathbf{Y_i}))/\Sigma(\mathbf{Y_i})$

II. Y as a subset of X (necessity)

Consistency $(\mathbf{Y_i} \leq \mathbf{X_i}) = \Sigma(\min(\mathbf{X_i},\mathbf{Y_i}))/\Sigma(\mathbf{Y_i})$

Coverage $(\mathbf{Y_i} \leq \mathbf{X_i}) = \Sigma(\min(\mathbf{X_i},\mathbf{Y_i}))/\Sigma(\mathbf{X_i})$ (aka “relevance” of X)

Notice that the formulas overlap, that is, the consistency of X as a subset of Y is the same as the coverage of Y as a subset of X, while the coverage of X as a subset of Y is the same as the consistency of Y as a subset of X.

Calculation of Consistency Comes First!

The first task is to determine whether there is a set-theoretic relation between the cause or causal combination (X) and the outcome (Y). If X is a subset of Y, then X may be sufficient for Y. If Y is a subset of X, then X may be necessary for Y. Note that if the X scores indicate membership in a *combination* of conditions, then it is unlikely for Y to be a subset of X. Recall that when conditions are combined, membership in the combination is determined by the minimum value of the component memberships.

The set-theoretic consistency calculations are:

(a) The degree to which X is a subset of Y: $\Sigma(\min(X_i,Y_i))/\Sigma(X_i)$

(b) The degree to which Y is a subset of X: $\Sigma(\min(X_i,Y_i))/\Sigma(Y_i)$

These two calculations differ only in the denominator. If X scores are consistently less than Y scores, then the value of (a) will be 1.0 and the value of (b) will be substantially less than 1.0, perhaps 0.5 or even lower. If X scores are consistently greater than Y scores, then the value of (a) will be substantially less than 1.0, perhaps 0.5 or lower, and the value of (b) will be 1.0.

The closer the value of (a) or (b) is to 1.0, the stronger the case that a set-theoretic relation exists. If they are both close to 1.0, then X and Y scores are approximately equal across cases. In general, (a) is the key calculation when working with combinations of conditions, because it is very rare for scores in a combination of conditions to be consistently greater than scores in the outcome.

Calculation of Coverage

Once it has been established that a set-theoretic relation exists, it is reasonable to assess its coverage (sufficiency) or relevance (necessity). If X is a subset of Y, this assessment is the same asking how important is the combination of conditions represented by X in accounting for Y: How much of Y does X cover? If Y is a subset of X, then the calculation of coverage shows the relevance of X as a necessary condition. If Y is dwarfed by X, then X is not really providing a ceiling on the expression of Y. It just happens to be something that is strongly present whenever there is any membership in Y. On the other hand, if Y is a substantial subset of X, then X is more relevant as a necessary condition--X's limiting power on Y is more apparent.

Assume we have shown that X is a rough subset of Y, that is, calculation (a), shown previously, is 1.0 or close to 1.0. The calculation of coverage is simply:

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

Notice that this is the same as calculation (b) above. It makes sense as a calculation of the coverage of Y by X ONLY IF it has been established that X is a subset of Y.

Assume we have shown that Y is a rough subset of X, that is, calculation (b), shown previously, is 1.0 or close to 1.0. The calculation of coverage (relevance of a necessary conditions) is:

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

Notice that this is the same as calculation (a) above. It makes sense as a calculation of the coverage of X by Y (relevance of X as a necessary condition for Y) ONLY IF it has been established that Y is a subset of X.

Crosstabulation of Poverty Status and Educational Achievement: Preliminary Frequencies

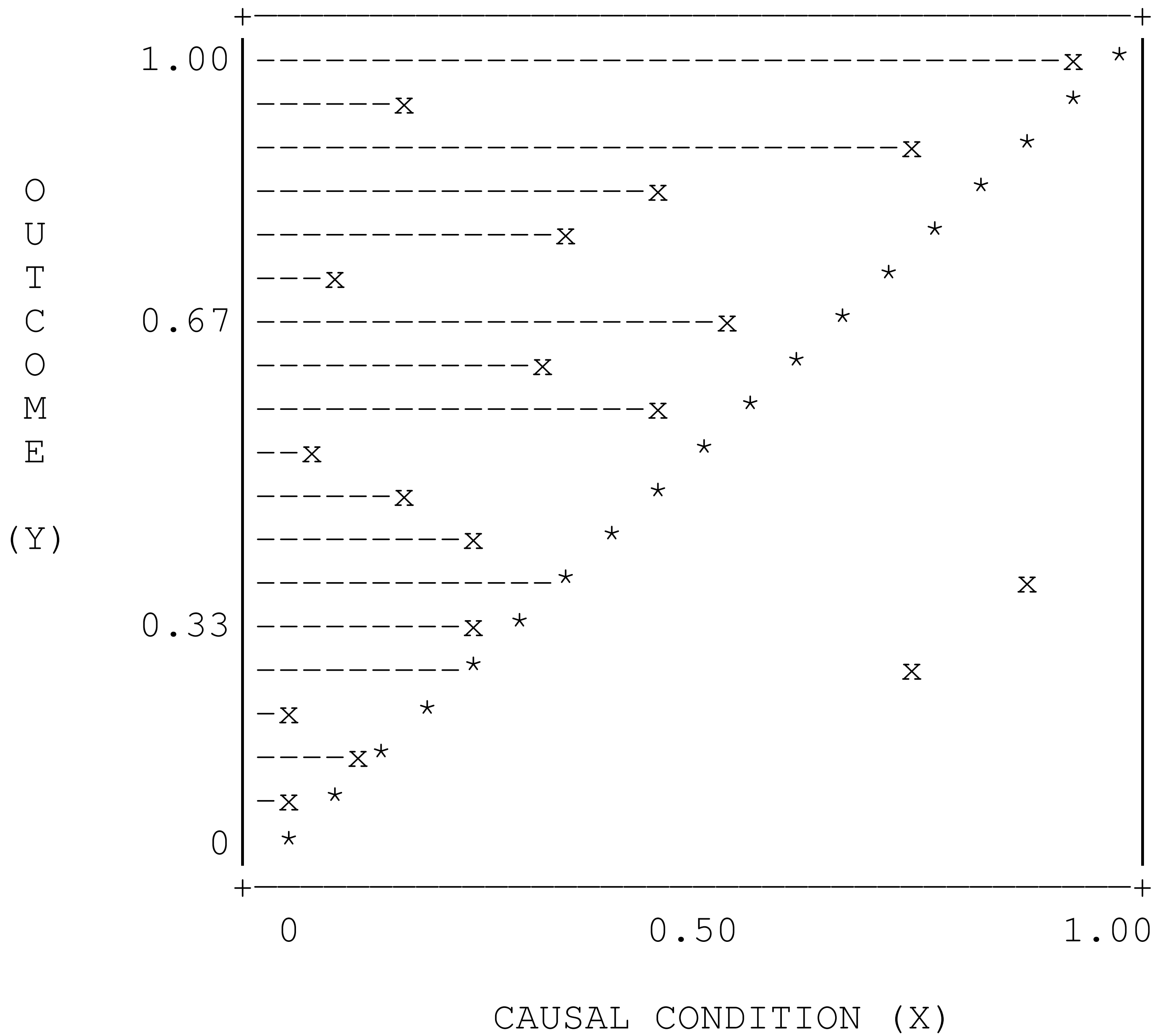
	Low/Average Educational Achievement	High Educational Achievement
Not In Poverty	a. 3046	b. 1474
In Poverty	c. 625	d. 55

Crosstabulation of Poverty Status and Educational Achievement: Altered Frequencies

	Low/Average Educational Achievement	High Educational Achievement
Not In Poverty	a. 4373	b. 147
In Poverty	c. 675	d. 5

Consistency remains about the same, but coverage declines dramatically once cases are shifted to the first column.

Fuzzy Plot Illustrating the Concept of Coverage Using Fuzzy Sets



Partitioning Coverage

As with crisp sets, it is possible to partition coverage to assess the degree of overlap of the causal combinations. With crisp sets, a case is either covered by a combination or its not covered. With fuzzy sets, by contrast, different combinations can cover a given case's outcome to different degrees. For example, membership in the outcome might equal .8; membership in causal combination A·B might be .6 and membership in causal combination C·D might be .4. Both combinations offer some coverage, though A·B's coverage is superior (i.e., closer to .8 without exceeding it).

Consider the analysis of the impact of high test scores (T), high parental income (I), and college education (C) on avoiding poverty (~P) for white males. The results show:

$$T \cdot I + I \cdot C \rightarrow {\sim}P$$

Here are some coverage calculations associated with these data:

Causal Conditions	**Sum of Consistent Scores: $\Sigma(\min(X_i, Y_i))$**	**Sum of Outcome Scores: $\Sigma(Y_i)$**	**Coverage**
T·I	181.830	949.847	.191
I·C	226.792	949.847	.239
T·I + I·C	253.622	949.847	.267
T·I·C	155.000	949.847	.163

First, notes that membership in T·I + I·C is the maximum of (T·I, I·C). That is, when calculating membership in a fuzzy logic statement that includes logical *or* (+) it is necessary to take the maximum score. Thus, if your membership is 0.6 in T·I and 0.9 in I·C, then your membership in the union of these two is 0.9.

Second, notice that on the bottom row I have included calculations for membership in the intersection of the two terms. This is included because the two paths overlap substantially. Most of the folks who are T·I also have C and most of the folks who have I·C also have T. (We live in a world of overlapping inequalities.)

Unique coverage of T·I is given by cov(T·I + I·C) - cov(I·C), which is 2.8%; unique coverage of I·C is given by cov(T·I + I·C) - cov(T·I), which is 7.6%. (These calculations are produced automatically by fsQCA.) Notice also that the coverage of T·I·C (16.3%) plus the two unique calculation (2.8% + 7.6%) is equal to the whole equation coverage (26.7%).

Counterfactual Analysis

The Distinctiveness of Case-Oriented Research

In a recent article in *Studies in Comparative International Development*, Christopher Achen, a well-known quantitative researcher, notes:

> Few social scientists dispute the need to combine qualitative and quantitative methods and evidence in the profession. The question is how. As . . . [many] scholars have said, first-rate social science theorizing seems to integrate the two in ways we do not fully understand. For example, contemporary case-study methods are difficult to explicate in conventional statistical theory, and yet they are frequently quite powerful and successful in ways that no statistical methods could match. *An important clue is that they often carry out an implicit comparison against known background relationships*, most obviously so in single-case studies (Ragin 2000:206). But what is the precise inferential logic of this step and why is it so successful? *No one knows*. (*Italics added*)

Olav Stokke's Truth Table for Causes of Successful Shaming in International Regimes

Advice (A)	Commitment (C)	Shadow (S)	Inconvenience (I)	Reverberation (R)	Success (Y)
1	0	1	1	1	1
1	0	0	1	0	0
1	0	0	1	1	0
0	0	0	1	0	0
1	1	1	1	1	1
1	1	1	1	0	0
1	1	1	0	0	1
1	0	0	0	0	1

1. Advice (A): Whether the shamers can substantiate their criticism with reference to explicit recommendations of the regime's scientific advisory body.
2. Commitment (C): Whether the target behavior explicitly violates a conservation measure adopted by the regime's decision-making body.
3. Shadow of the future (S): Perceived need of the target of shaming to strike new deals under the regime--such beneficial deals are likely to be jeopardized if criticism is ignored.
4. Inconvenience (I): The inconvenience (to the target of shaming) of the behavioral change that the shamers are trying to prompt.
5. Reverberation (R): The domestic political costs to the target of shaming for not complying (i.e., for being scandalized as a culprit).

HOW STOKKE'S EVIDENCE IS TYPICAL

- The number of cases (10) is more than a handful, but still small enough to permit familiarity with each case. (Two of the 8 listed combinations have a frequency of 2.)
- From the viewpoint of conventional quantitative social science, however, the number of cases is very small relative to the number of causal conditions (5). This ratio essentially eliminates the possibility of any form of multivariate statistical analysis.
- If the cases are viewed configurationally, then the prospects seem even more dismal, for there are 2^5 logically possible combinations of five causal conditions. We have empirical evidence on only eight of the 32 combinations.
- This pattern of **limited diversity** is characteristic of comparative research and, more generally, of research on naturally occurring social and political phenomena.
- However, causal combinations without cases are potential counterfactual cases. Counterfactual analysis provides an opening.

Simple Example of Limited Diversity

Strong Unions (U)	Strong Left Parties (L)	Generous Welfare State (G)	N of Cases
Yes	Yes	Yes	6
Yes	No	No	8
No	No	No	5
No	Yes	????	0 (they don't exist)

Is it strong left parties (L) that cause generous welfare states (G) or is it the combination of strong unions and strong left parties (L*U) that causes generous welfare states (G)?

From a correlational viewpoint, having a strong left party (L) is perfectly correlated with having a generous welfare state (G). A **parsimonious** explanation has been achieved: L → G

From a case-oriented perspective, however, all instances of generous welfare state share two causally relevant conditions (strong left parties and strong unions) and none of the negative cases display this combination. This pattern suggests a more **complex** explanation: L*U → G. ("*" indicates set intersection.)

LIMITED DIVERSITY AND FUZZY SETS

How diversity is limited (hypothetically) in this example:

Strong left parties are a subset of strong unions, meaning that strong left parties develop only where there are strong unions, but having strong unions is no guarantee that strong left parties will develop.

For this to be true, degree of membership in the set of cases with strong left parties must be ≤ degree of membership in strong unions.

To make the analysis parallel to the crisp set analysis, degree of membership in the set of countries with generous welfare states is a subset of degree of membership in the set of cases with strong left parties. Thus, the two causal conditions are both necessary for the outcome:

generous welfare states	≤	strong left parties	≤	strong unions

Hypothetical set membership scores consistent with the set relations just described are:

Unions	Left	Generous	Country
.0	.0	.0	USA
.2	.1	.1	CAN
.4	.3	.1	SPAIN
.4	.2	.2	PORTUGAL
.3	.3	.3	FRANCE
.6	.2	.2	ITALY
.6	.6	.5	GERMANY
.8	.6	.5	BELGIUM
.2	.2	.1	SWITZERLAND
.8	.5	.4	AUSTRIA
.7	.5	.5	FINLAND
1	.9	.8	SWEDEN
.8	.8	.8	NORWAY
.9	.7	.7	DENMARK
.6	.6	.4	UK
.4	.2	.2	AUSTRALIA
.4	.3	.2	NEW ZEALAND
.7	.5	.5	IRELAND

RESULTS OF A CONVENTIONAL REGRESSION ANALYSIS

Dependent Variable: GENEROUS

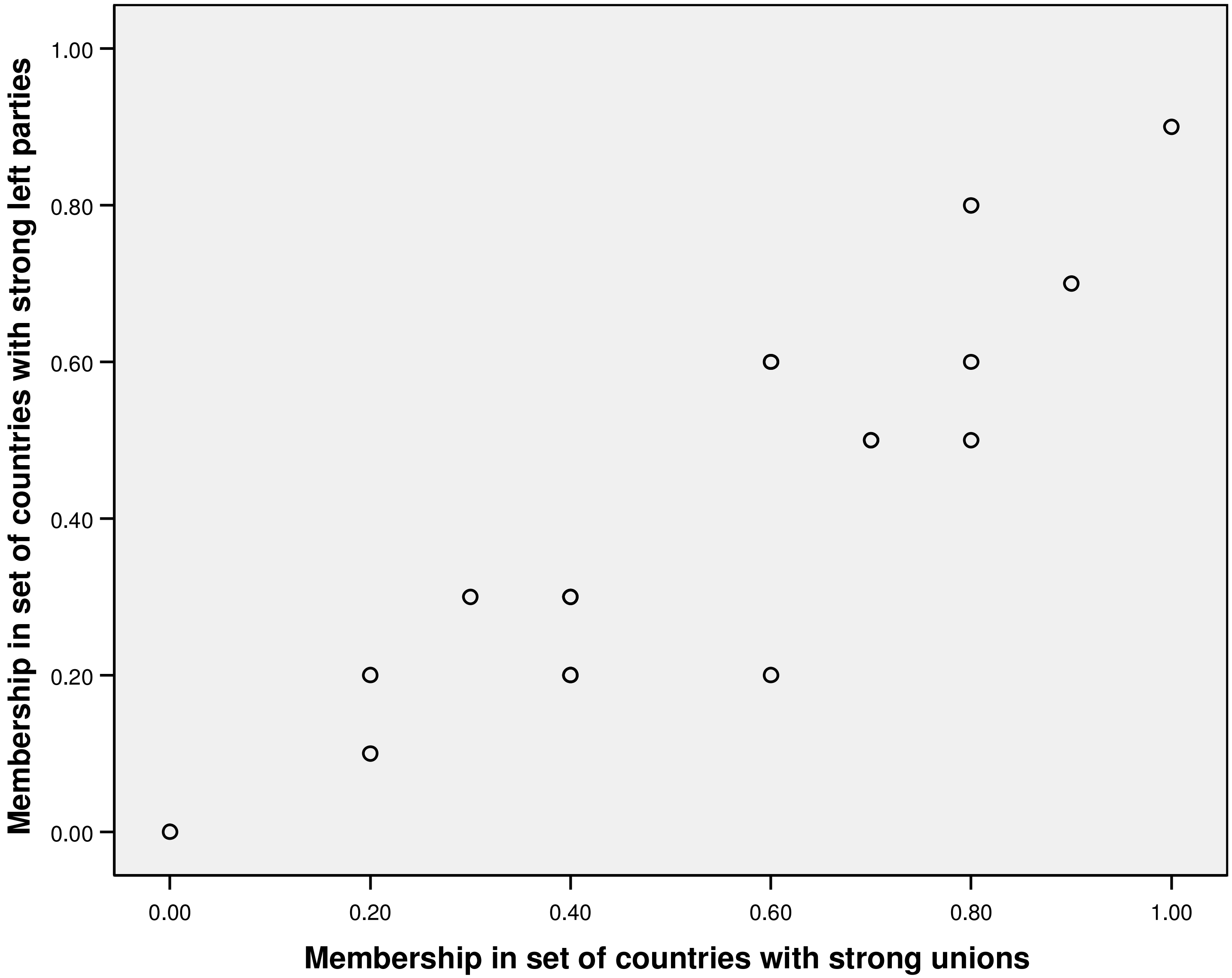
	Unstandardized Coefficients		*Standardized Coefficients*	*t*	*Sig.*
	B	Std. Error	Beta		
(Constant)	-4.852E-02	.038		-1.267	.225
UNIONS	.152	.145	.169	1.052	.309
LEFT	.784	.156	.808	5.016	.000

a

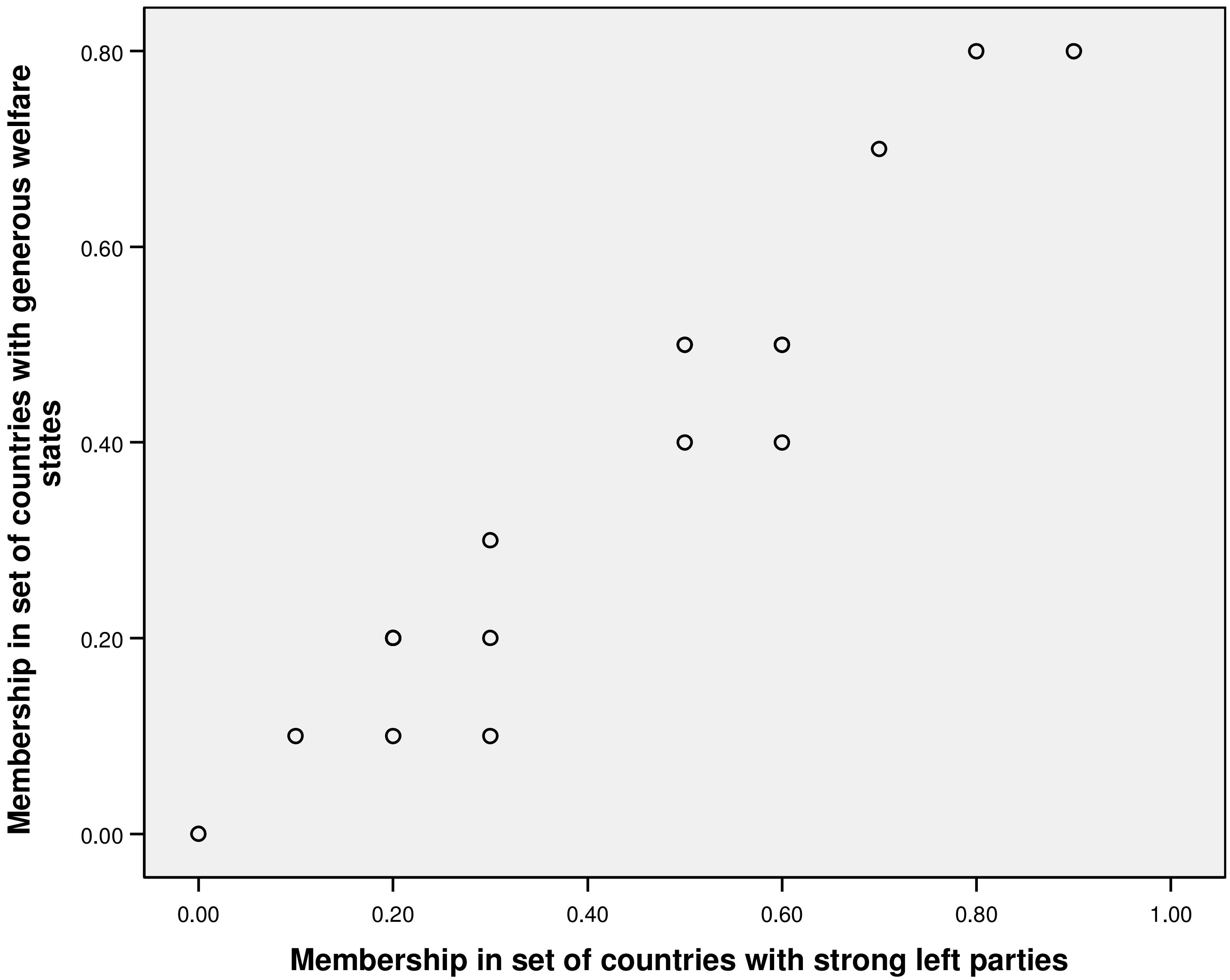
In short, the results indicate that all that matters is having a strong left party, even though the set-theoretic analysis reveals that having strong unions is a necessary condition.

The scatterplots for these data are not unusual from the viewpoint of conventional quantitative analysis, other than the fact that they indicate very strong relationships. In other words, there is nothing special about the scatterplots that would make you think you should do anything other than a conventional “net effects” analysis, which is “won” by strong left parties.

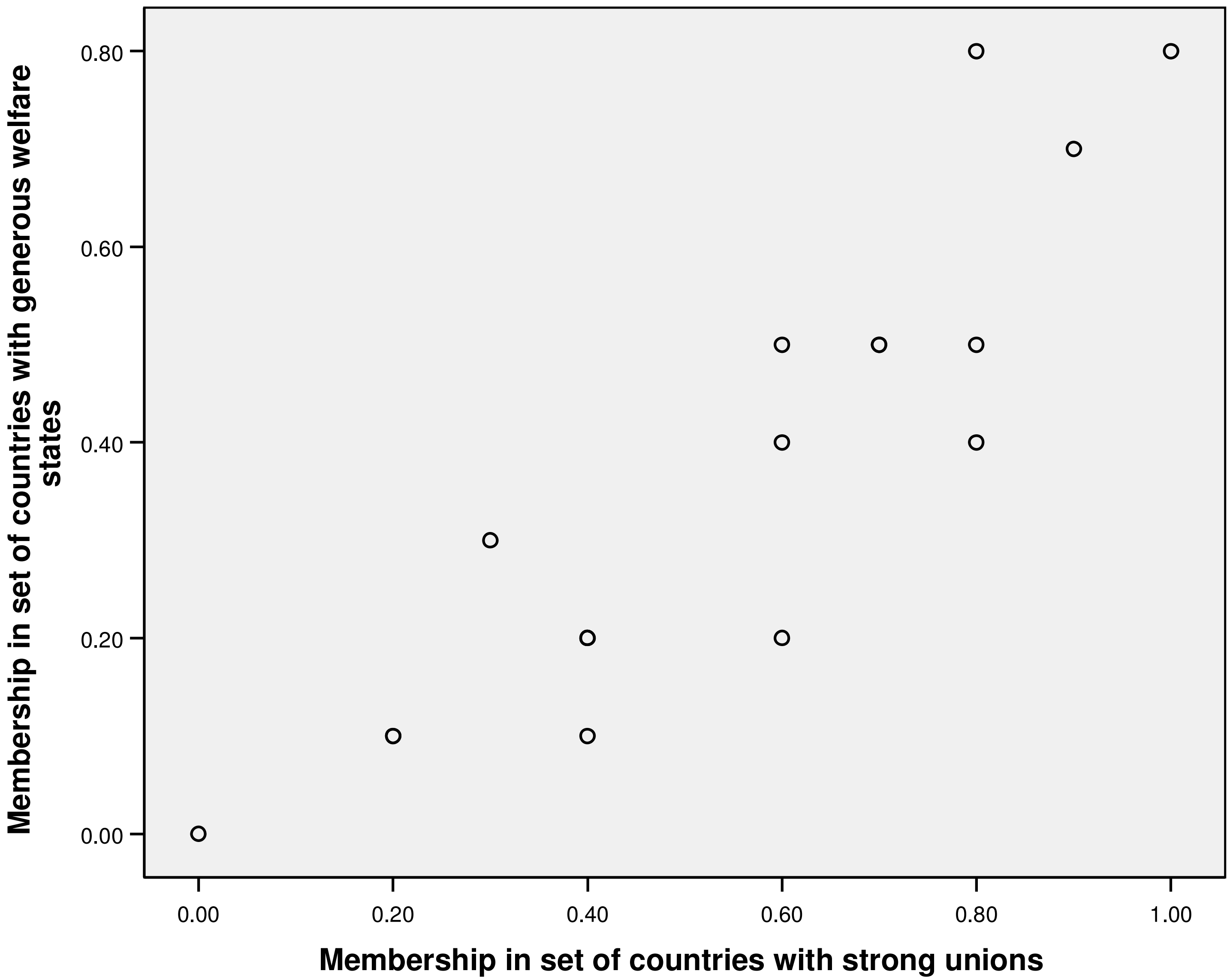
Scatterplot of Degree of Membership in Strong Left Parties Against Degree of Membership in Strong Unions



Scatterplot of Degree of Membership in Generous Welfare States Against Degree of Membership in Strong Left Parties



Scatterplot of Degree of Membership in Generous Welfare States Against Degree of Membership in Strong Left Unions



Limited Diversity in a Truth Table with Four Causal Conditions

A	**B**	**C**	**D**	**Y**
no	no	no	no	no
no	no	no	yes	?
no	no	yes	no	?
no	no	yes	yes	?
no	yes	no	no	no
no	yes	no	yes	no
no	yes	yes	no	?
no	yes	yes	yes	no
yes	no	no	no	?
yes	no	no	yes	?
yes	no	yes	no	?
yes	no	yes	yes	?
yes	yes	no	no	yes
yes	yes	no	yes	yes
yes	yes	yes	no	?
yes	yes	yes	yes	?

PARSIMONY VERSUS COMPLEXITY
(HYPOTHETICAL DATA)

A*B*c ——————————————— A

complex solution ——— parsimonious solution

A*B

A*B*c ——— A*c ——— A

possible intermediate
solutions

At the left end of the continuum is the complex solution; the right end shows the parsimonious solution. The complex solution is a subset of the parsimonious solution.

Assume theoretical and substantive knowledge indicates that it is the presence of these four conditions (A, B, C, D) and not their absence (a, b, c, d) that should be linked to the outcome (Y). This knowledge defines A*B*C as an **easy** counterfactual, yielding solution A*B; it defines A*b*c as a **difficult** counterfactual. (This second counterfactual is what is required to produce A*c as a solution.)

Olav Stokke's Truth Table for Causes of Successful Shaming in International Regimes

Advice (A)	Commitment (C)	Shadow (S)	Inconvenience (I)	Reverberation (R)	Success (Y)
1	0	1	1	1	1
1	0	0	1	0	0
1	0	0	1	1	0
0	0	0	1	0	0
1	1	1	1	1	1
1	1	1	1	0	0
1	1	1	0	0	1
1	0	0	0	0	1

1. Advice (A): Whether the shamers can substantiate their criticism with reference to explicit recommendations of the regime's scientific advisory body.
2. Commitment (C): Whether the target behavior explicitly violates a conservation measure adopted by the regime's decision-making body.
3. Shadow of the future (S): Perceived need of the target of shaming to strike new deals under the regime--such beneficial deals are likely to be jeopardized if criticism is ignored.
4. Inconvenience (I): The inconvenience (to the target of shaming) of the behavioral change that the shamers are trying to prompt.
5. Reverberation (R): The domestic political costs to the target of shaming for not complying (i.e., for being scandalized as a culprit).

PARSIMONY VERSUS COMPLEXITY IN STOKKE'S EVIDENCE

A·c·s·i·r +	
A·C·S·i·r +	i +
A·S·I·R	S·R
complex	parsimonious

A·c·s·i·r +		
A·C·S·i·r +	A·i +	i +
A·S·I·R	A·S·R	S·R
	intermediate	

In the complex solution, none of the combinations without cases is used as a counterfactual case. In the parsimonious solution, any combination without cases that yields a logically simpler solution is incorporated into the solution (i.e., both easy and difficult counterfactuals have been incorporated). The assumptions are: A, C, S, i, R. These assumptions yield the intermediate solution.

Combination A·S·I·R:

1. Causal conditions S and R cannot be removed because they appear in the corresponding parsimonious term at the other end of the continuum.
2. The support of the regime's the scientific advisory body (A) is certainly linked to the success of shaming. This causal condition should be retained.
3. The fact that it is inconvenient for the targets of shaming to change their behavior (I) does *not* promote successful shaming. Thus, inconvenience (I) can be dropped from the combination A·S·I·R because inconvenience of behavioral change to the target of shaming is not central to the success of A·S·R in generating conformity.

The intermediate combination is **A·S·R**.

Combination A·C·S·i·r:

1. Condition i (the behavioral change is not inconvenient) cannot be dropped because it appears in the corresponding parsimonious term.
2. Condition A (support from the regime's scientific advisory board) should remain because this condition is clearly linked to the success of shaming.
3. Condition C (the offending behavior clearly violates a prior commitment) also should not be dropped, for this too is something that should only contribute to the success of shaming.
4. Condition S (the violator will need to strike future deals with the regime) is also a factor that should only promote successful shaming.
5. Condition r (absence of domestic reverberations for being shamed) can be removed. Clearly, the presence of domestic reverberation (R) would promote successful shaming.

The intermediate combination is **A·C·S·i**.

Combination A·c·s·i·r:

1. Condition i must be retained because it appears in the corresponding parsimonious term.
2. Condition A is retained as well, for the reasons stated previously.
3. Condition r (absence of domestic reverberations) can be removed, as it was from the previous combination, for the same reason provided.
4. Condition c (absence of violation of a commitment) can be removed, for surely these instances of successful shaming would still have been successful if there had been an explicit violation of a commitment (C).
5. Condition s (absence of a need to strike future deals with the regime) can be safely removed because only its presence (S) should contribute to the success of shaming.

The intermediate term is **A·i**.

These three intermediate terms can be joined into a single equation:

$$\mathbf{A \cdot S \cdot R + A \cdot C \cdot S \cdot i + A \cdot i \longrightarrow Y}$$

which can then be simplified to:

$$\mathbf{A \cdot S \cdot R + A \cdot i \longrightarrow Y}$$

because the term A·C·S·i is a subset of the term A·i and is thus logically redundant. (All cases of A·C·S·i are also cases of A·i.) These results indicate that there are two paths to successful shaming: (1) support from the regime's scientific advisory body (A) combined with the need to strike future deals (S) and domestic reverberations for being shamed (R), and (2) support from the regime's scientific advisory body (A) combined with the fact that the behavioral change is not inconvenient (i).

QCA PROCEDURE (“Standard Analysis”)

	Should contribute to Y when cause is:		
	Present	Absent	Present or Absent
Causal Condition:			
A	0	0	0
C	0	0	0
S	0	0	0
I	0	0	0
R	0	0	0

This dialogue box, in effect, makes it possible for you to input your theoretical and substantive knowledge, with respect to the links between causal conditions and the outcome. The impact is to permit the use of “easy” counterfactual cases, which in turn make it possible to remove counterintuitive elements from the complex solutions (provided that these removals do not violate the parsimonious solution).

QCA RESULTS: STOKKE DATA

Complex Solution:

	raw coverage	unique coverage	consistency
A*S*I*R+	0.500000	0.500000	1.000000
A*c*s*i*r+	0.250000	0.250000	1.000000
A*C*S*i*r	0.250000	0.250000	1.000000

solution coverage: 1.000000
solution consistency: 1.000000

Parsimonious Solution:

	raw coverage	unique coverage	consistency
i+	0.500000	0.500000	1.000000
S*R	0.500000	0.500000	1.000000

solution coverage: 1.000000
solution consistency: 1.000000

Intermediate Solution:

	raw coverage	unique coverage	consistency
A*i+	0.500000	0.500000	1.000000
A*S*R	0.500000	0.500000	1.000000

solution coverage: 1.000000
solution consistency: 1.000000

Limited Diversity in Commonly Used Data Sets

College	Parental Income	AFQT Score	Married	Children	Freq.	Cum Freq	Cum %
0	0	0	0	0	327	327	0.431398
0	0	0	1	1	154	481	0.634565
0	0	0	0	1	65	546	0.720317
1	0	0	0	0	57	603	0.795515
0	0	0	1	0	41	644	0.849604
1	0	0	1	1	24	668	0.881266
0	1	0	0	0	14	682	0.899736
1	0	0	1	0	13	695	0.916887
0	1	0	1	1	10	705	0.930079
1	1	0	0	0	10	715	0.943272
1	0	0	0	1	7	722	0.952507
1	0	1	1	1	6	728	0.960422
0	1	0	1	0	5	733	0.967018
1	1	0	1	0	4	737	0.972296
1	1	1	0	0	4	741	0.977573
1	0	1	0	0	3	744	0.98153
1	1	0	1	1	3	747	0.985488
1	1	1	1	0	3	750	0.989446
0	0	1	1	1	2	752	0.992084
1	1	1	1	1	2	754	0.994723
0	0	1	0	0	1	755	0.996042
0	0	1	0	1	1	756	0.997361
0	1	0	0	1	1	757	0.998681
1	0	1	1	0	1	758	1
0	0	1	1	0	0	758	1
0	1	1	0	0	0	758	1
0	1	1	0	1	0	758	1
0	1	1	1	0	0	758	1
0	1	1	1	1	0	758	1
1	0	1	0	1	0	758	1
1	1	0	0	1	0	758	1
1	1	1	0	1	0	758	1

Logistic Regression of Poverty Avoidance on AFQT scores, Parental Income, Years of Education, Martial Status and Children: Black males only

	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

Parsimonious Solution:

	raw coverage	unique coverage	consistency
FZHPINC*fzlafqt+	0.251873	0.095484	0.855435
MAR*kid+	0.149603	0.077881	0.828581
fzlafqt*FZCLED	0.284320	0.123384	0.838994

solution coverage: 0.474250
solution consistency: 0.799374

These results suggest that there are three routes--the parental income route, the education route, and the family formation route.

Intermediate Solution:

	raw coverage	unique coverage	consistency
FZHPINC*fzlafqt*kid*FZHSED+	0.168798	0.055832	0.872747
FZHPINC*fzlafqt*MAR*FZHSED+	0.120040	0.028533	0.899077
MAR*kid*FZHSED+	0.147777	0.076056	0.840419
fzlafqt*kid*FZCLED+	0.186080	0.068566	0.855591
fzlpinc*fzlafqt*MAR*FZCLED	0.124963	0.036630	0.894302

solution coverage: 0.440591
solution consistency: 0.813448

These results, by contrast, shows that the routes are not quite so distinct. For example, there are family formation aspects on each route.

COUNTERFACTUAL ANALYSIS:
SUMMARY

1. Limited diversity is a characteristic feature of naturally occurring social phenomena.

2. The resolution of the problem of limited diversity involves the use of counterfactual analysis in some way.

3. In case-oriented comparative research, the resolution of the problem of limited diversity is knowledge and theory dependent. "How" this happens in case-oriented research (Achen's query) is through the incorporation of "easy" counterfactuals.

4. In order to define "easy" counterfactuals, researchers must apply their substantive and theoretical knowledge to the "remainder" combinations. In practice, this allows them to craft an intermediate solution, situated between the "most complex" and "most parsimonious" QCA solutions. It is necessary to maintain the subset relationship among possible solutions along the complexity/parsimony continuum..

5. In quantitative research, the problem of limited diversity is also addressed through assumptions. However, these assumptions (e.g., linearity and additivity) are usually invisible to most users.

6. The incorporation of background knowledge through "easy" counterfactuals is central to case-oriented comparative research. This process is made explicit in QCA.

Calibrating Fuzzy Sets

Calibration

In physics, chemistry, biology, astronomy and other “hard” sciences, researchers *calibrate* their measuring devices and the readings these instruments produce by adjusting them so that they match or conform to dependably known external standards.

More familiar to social scientists are calibration breakdowns, as when a thermostat reports that an office is a comfortable 70 degrees while the cup of coffee on this desk turns to ice.

Most measures in social science are uncalibrated. They indicate cases’ positions in distributions relative to each other, but not relative to a known standard. For example, measures in the social sciences can reveal that one case has a higher temperature than another, but not whether it is hot or cold.

Calibration is Rare But Not Unknown in the Social Sciences

Some examples:

1. The measurement of poverty

2. GNP/cap adjusted for purchasing power (quasi)

3. Human Development Index

4. Not an example: calibration of models in econometrics
   (where specific coefficients are purposefully fixed).

Conventional Measurement: Quantitative Research

1. Find the best possible indicator of the underlying construct, preferably an interval or ratio scale indicator. Examples: church attendance/year as an indicator of religiosity; years of education as an indicator of learning (accumulated school-based knowledge); and so on.

2. Psychometric approach: identify multiple, correlated indicators of the same underlying theoretical concept; construct an index by first putting the various indicators in the same metric and then averaging the scores. Example: an index of development based on GNP/cap, literacy, life expectancy, energy consumption, labor force composition, and so on.

3. Structural Equation Models (SEM): same as #2, except the measurement construction is tweaked in the context of a causal model with other constructs included. It's all on automatic pilot: correlations with other variables and constructs in the model do the tweaking.

What These Three Have In Common

1. Indicators meet only a minimum measurement requirement: cases must vary in a way that (at least roughly) reflects the underlying construct (i.e., the indicator's variation must correlate with how the construct is thought to vary).

2. There is a deep reliance on observed variation, which is sample specific in definition and construction (the mean and standard deviation are inductively generated). (Calibration is mechanistic and automatic, not explicit.)

3. Cases' scores are defined and ranked relative to each other.

4. All variation is typically treated as meaningful and taken at face value.

5. External criteria are only occasionally used to evaluate observed scores.

Conventional Measurement: Qualitative Research

1. Inductively oriented: understanding of measures changes and develops as researchers learn more about cases.

2. Iterative: there is a back-and-forth between understanding of cases and concept development.

3. Indicators may be used, but scores must be interpreted (metrics not taken at face value). Example: “early” state formation.

4. Case-oriented: Focus is on defining “kinds of cases” rather than dimensions of variation, e.g., the “the democracies” versus “degree of democracy.”

Bottom line: researcher’s knowledge plays an important role in calibrating measures, but the process is often implicit and not formalized.

Let’s Have the Best of Both Worlds

Namely, measures that are precise and explicitly measured, but which also reflect the researcher’s understanding. They should be calibrated according to the **external criteria** that the researcher brings to the investigation.

These **external criteria** may reflect standards based on social knowledge (e.g., 12 years of education as constituting an important educational threshold), collective social scientific knowledge (e.g., about variation in economic development--what it takes to be considered “developed”) or the researcher’s own knowledge (e.g., derived from in-depth study of cases).

The key is that these external standards must be stated explicitly and they must be applied systematically and transparently.

Remember, the key to measurement calibration is the application of known and explicit external standards.

Fuzzy Sets and Calibration

Fuzzy sets provide a good platform for the development of calibrated measures:

1. Membership scores in sets (e.g., the set of regular church-goers) can be scaled from 0 to 1, with 0 indicating full exclusion and 1 indicating full inclusion. A score of .5 is the cross-over point. They allow precision.

2. Fuzzy sets are simultaneously qualitative and quantitative. Full membership and full non-membership are qualitative states. In between these two qualitative states are degrees of membership.

3. Fuzzy sets distinguish between relevant and irrelevant variation.

4. Because they are all about set membership (e.g., the set of “democracies”), they are “case-oriented” in nature.

5. They can be used to evaluate both set-theoretic and correlational arguments. Almost all social science theory is set-theoretic!

Table 1: Mathematical Translations of Verbal Labels: The Three Metrics

1. Verbal label	*2. Degree of membership*	*3. Associated odds*	*4. Log odds of full membership*
Full membership	0.993	148.41	5.0
Threshold of full membership	0.953	20.09	3.0
Probably in	0.881	7.39	2.0
More in than out	0.622	1.65	0.5
Cross-over point	0.500	1.00	0.0
More out than in	0.378	0.61	-0.5
Probably out	0.119	0.14	-2.0
Threshold of full nonmembership	0.047	0.05	-3.0
Full nonmembership	0.007	0.01	-5.0

Table 2: Calibrating Degree of Membership in the Set of Developed Countries: Direct Method

Country	*1. National income*	*2. Deviations from cross-over*	*3. Scalars*	*4. Product of 2 x 3*	*5. Degree of membership*
Switzerland	40110	35110.00	.0002	7.02	1.00
United States	34400	29400.00	.0002	5.88	1.00
Netherlands	25200	20200.00	.0002	4.04	.98
Finland	24920	19920.00	.0002	3.98	.98
Australia	20060	15060.00	.0002	3.01	.95
Israel	17090	12090.00	.0002	2.42	.92
Spain	15320	10320.00	.0002	2.06	.89
New Zealand	13680	8680.00	.0002	1.74	.85
Cyprus	11720	6720.00	.0002	1.34	.79
Greece	11290	6290.00	.0002	1.26	.78
Portugal	10940	5940.00	.0002	1.19	.77
Korea, Rep	9800	4800.00	.0002	.96	.72
Argentina	7470	2470.00	.0002	.49	.62
Hungary	4670	-330.00	.0012	-.40	.40
Venezuela	4100	-900.00	.0012	-1.08	.25
Estonia	4070	-930.00	.0012	-1.12	.25
Panama	3740	-1260.00	.0012	-1.51	.18
Mauritius	3690	-1310.00	.0012	-1.57	.17
Brazil	3590	-1410.00	.0012	-1.69	.16
Turkey	2980	-2020.00	.0012	-2.42	.08
Bolivia	1000	-4000.00	.0012	-4.80	.01
Cote d'Ivoire	650	-4350.00	.0012	-5.22	.01
Senegal	450	-4550.00	.0012	-5.46	.00
Burundi	110	-4890.00	.0012	-5.87	.00

Figure 1: Plot of Degree of Membership in the Set of Developed Countries Against National Income Per Capita: Direct Method

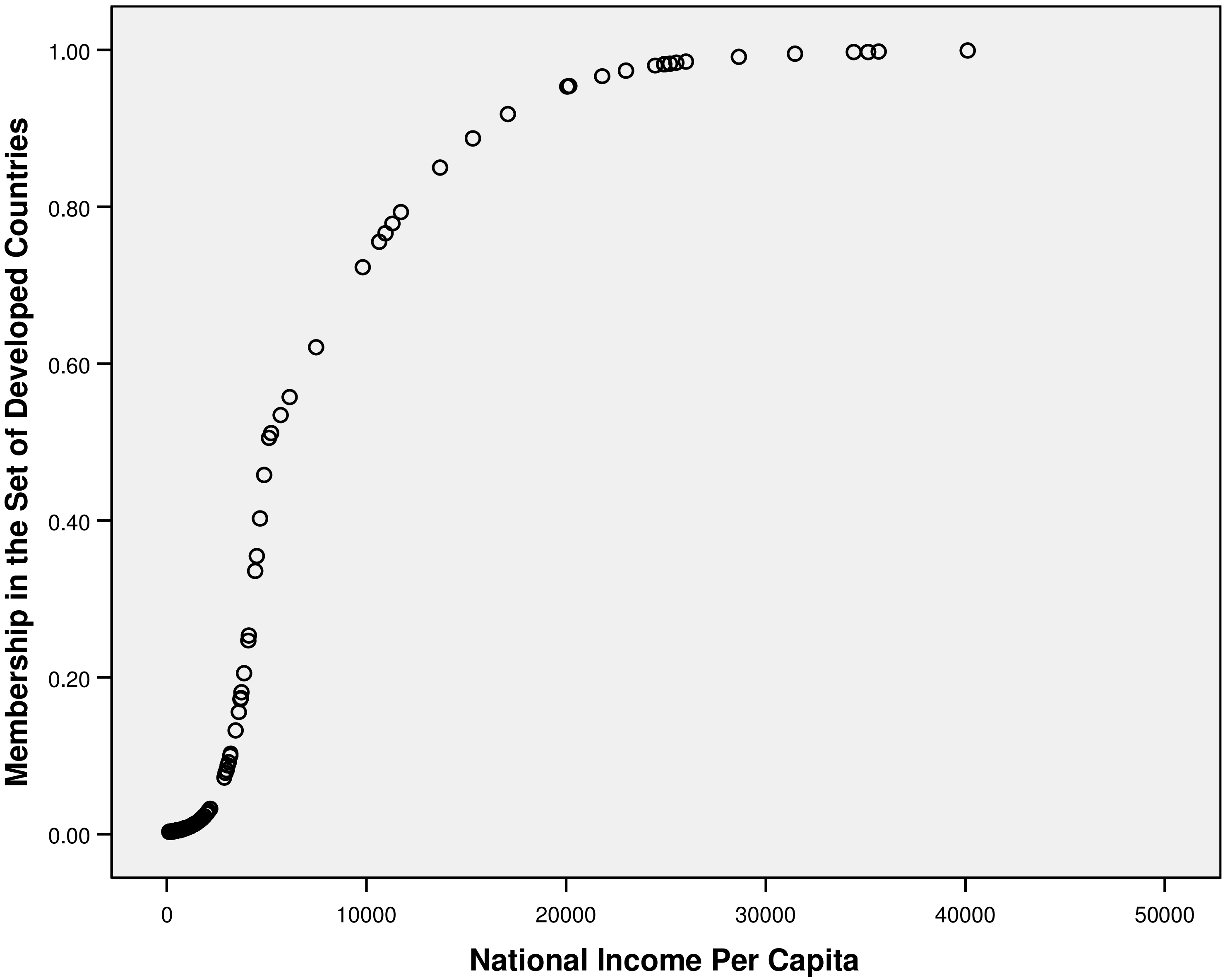
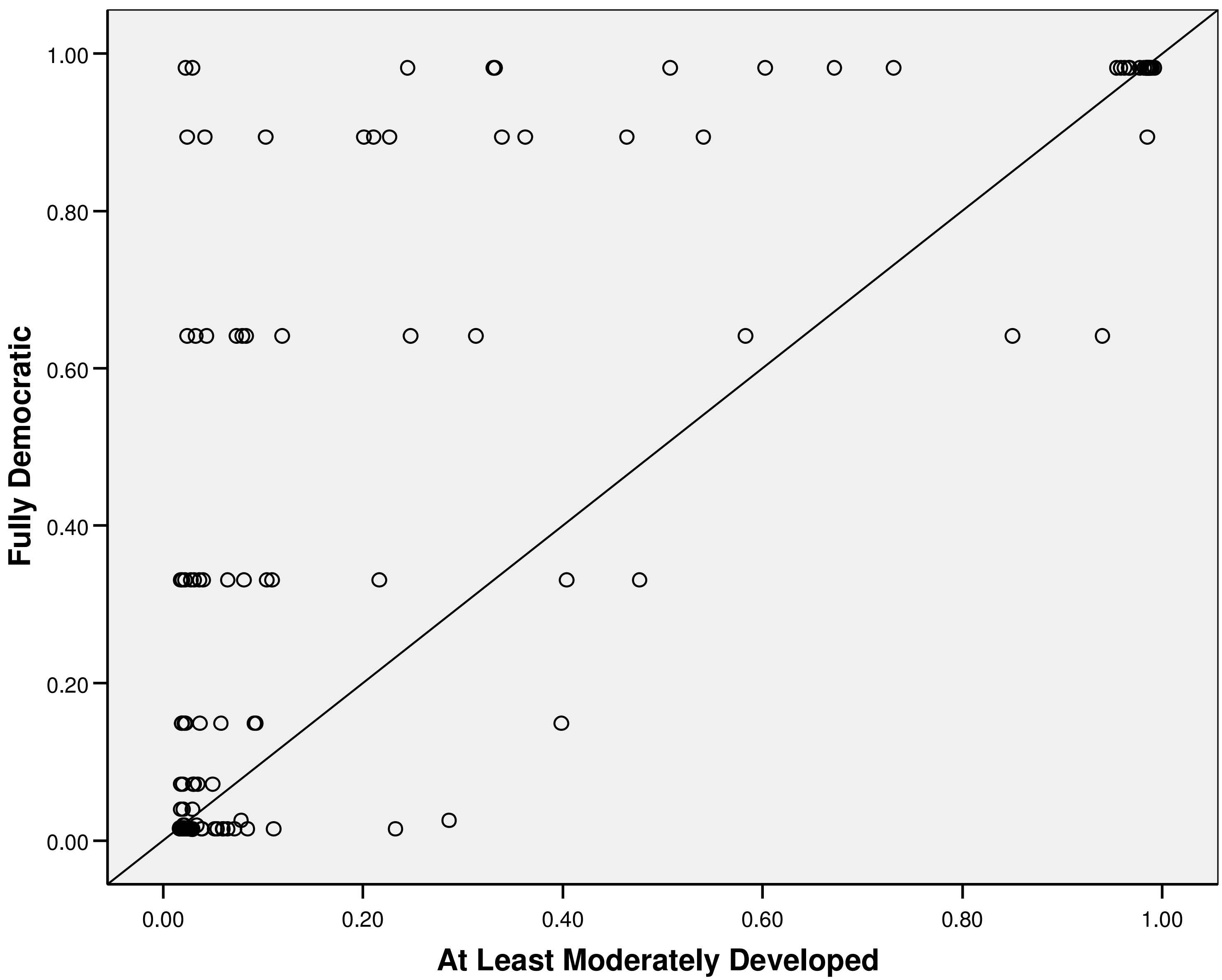


Table 3: Calibrating Degree of Membership in the Set of "Moderately" Developed Countries: Direct Method

Country	*1. National income*	*2. Deviations from cross-over*	*3. Scalars*	*4. Product of 2 x 3*	*5.Degree of membership*
Switzerland	40110	37610	.0006	22.57	1.00
United States	34400	31900	.0006	19.14	1.00
Netherlands	25200	22700	.0006	13.62	1.00
Finland	24920	22420	.0006	13.45	1.00
Australia	20060	17560	.0006	10.54	1.00
Israel	17090	14590	.0006	8.75	1.00
Spain	15320	12820	.0006	7.69	1.00
New Zealand	13680	11180	.0006	6.71	1.00
Cyprus	11720	9220	.0006	5.53	1.00
Greece	11290	8790	.0006	5.27	.99
Portugal	10940	8440	.0006	5.06	.99
Korea, Rep	9800	7300	.0006	4.38	.99
Argentina	7470	4970	.0006	2.98	.95
Hungary	4670	2170	.0006	1.30	.79
Venezuela	4100	1600	.0006	.96	.72
Estonia	4070	1570	.0006	.94	.72
Panama	3740	1240	.0006	.74	.68
Mauritius	3690	1190	.0006	.71	.67
Brazil	3590	1090	.0006	.65	.66
Turkey	2980	480	.0006	.29	.57
Bolivia	1000	-1500	.0020	-3.00	.05
Cote d'Ivoire	650	-1850	.0020	-3.70	.02
Senegal	450	-2050	.0020	-4.10	.02
Burundi	110	-2390	.0020	-4.78	.01

Table 4: Calibrating Degree of Membership in the Set of Democratic Countries: Direct Method

Country	*1. Polity score*	*2. Deviations from cross-over*	*3. Scalars*	*4. Product of 2 x 3*	*5. Degree of Membership*
Norway	10	8.00	0.43	3.43	0.97
United States	10	8.00	0.43	3.43	0.97
France	9	7.00	0.43	3.00	0.95
Korea, Rep	8	6.00	0.43	2.57	0.93
Colombia	7	5.00	0.43	2.14	0.89
Croatia	7	5.00	0.43	2.14	0.89
Bangladesh	6	4.00	0.43	1.71	0.85
Ecuador	6	4.00	0.43	1.71	0.85
Albania	5	3.00	0.43	1.29	0.78
Armenia	5	3.00	0.43	1.29	0.78
Nigeria	4	2.00	0.43	0.86	0.70
Malaysia	3	1.00	0.43	0.43	0.61
Cambodia	2	0.00	0.60	0.00	0.50
Tanzania	2	0.00	0.60	0.00	0.50
Zambia	1	-1.00	0.60	-0.60	0.35
Liberia	0	-2.00	0.60	-1.20	0.23
Tajikistan	-1	-3.00	0.60	-1.80	0.14
Jordan	-2	-4.00	0.60	-2.40	0.08
Algeria	-3	-5.00	0.60	-3.00	0.05
Rwanda	-4	-6.00	0.60	-3.60	0.03
Gambia	-5	-7.00	0.60	-4.20	0.01
Egypt	-6	-8.00	0.60	-4.80	0.01
Azerbaijan	-7	-9.00	0.60	-5.40	0.00
Bhutan	-8	-10.00	0.60	-6.00	0.00



Fully Democratic
1.00
0.80
0.60
0.40
0.20
0.00
0.00
0.20
0.40
0.60
0.80
1.00
At Least Moderately Developed