Redesigning Social Inquiry

Charles C. Ragin
Department of Sociology and
Department of Political Science
University of Arizona
Tucson, AZ 85721 USA

www.fsqca.com
www.compasss.org
www.u.arizona.edu/~cragin
cragin@u.arizona.edu

The context

Designing Social Inquiry (DSI) was published by three Harvard political scientists in 1994 (at least they were all at Harvard when it was written). They argue that the best way to do qualitative research is to make it as much like quantitative research as possible.

King, Gary, Robert O. Keohane and Sidney Verba. 1994. *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton: Princeton University Press.

Rethinking Social Inquiry (RSI) was published by two Berkeley political scientists in 2004. It criticizes DSI from the perspective of qualitative research and from the perspective of statistical theory, in effect attacking DSI from both the left and the right at the same time.

Brady, Henry and David Collier, editors. 2004. *Rethinking Social Inquiry: Diverse Tools, Shared Standards*. Lanham, MD: Rowman and Littlefield.

Redesigning Social Inquiry (RDSI) is the title of my forthcoming book, which attempts to transcend the debate between DSI and RSI by offering new analytic tools that bridge qualitative and quantitative research methods.

Ragin, Charles C. 2008. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago: University of Chicago Press.

The conventional template for conducting social inquiry

1. Identify the phenomenon to be explained, conceived as something that varies across cases and/or over time (the **dependent variable**).

2. Read relevant theory and study existing **research literatures** regarding causally relevant phenomena linked to #1.

3. Based on #2, develop a list of the most important causes, conceived as "**independent variables**." Associate the different causal variables with different theories or perspectives, if possible.

4. Develop **measures** of the dependent variable and the independent variables. Cases should vary meaningfully on every variable.

5. Locate a **given population** or data set in which there is variation in both the dependent variable and the independent variables. If the population is large, develop a sampling strategy.

The conventional template, continued

6. Identify additional **control variables** which may be required, depending on the selected population or data set. Include these variables among the study's "independent variables."

7. Specify **hypotheses** and one or more **models**, if possible.

8. Conduct a **multivariate analysis** using relevant variables. Estimate the **"net effect**" of each "independent variable," based on the intercorrelation of the independent variables and their correlations with the dependent variable.

9. Identify the most important independent variables; perhaps drop those that seem least influential (weak effects on the outcome) or that seem marginal in some way (e.g., weakly justified by theory). Continue to **re-specify the analysis** until a satisfactory set of results is obtained.

10. **Partition explained variation** according to the variables associated with each theory or perspective; the theory that explains the most variation in the dependent variable wins the contest.

Alternatives to key elements of the conventional template

Conventional	Redesigned
1. variables	sets
2. measurement	calibration
3. dependent variables	qualitative outcomes
4. given populations	constructed populations
5. correlations	set theoretic relations
6. correlation matrix	truth table (kinds of cases)
7. net effects	causal recipes (INUS conditions)
8. counterfactual estimation	counterfactual analysis

1. Use sets (both crisp and fuzzy) instead of variables

A **variable** captures a dimension of variation, an aspect that varies by level or degree across observations. Variables sort, rank, or array cases relative to each other. For example, some countries are “more democratic” and some are “less democratic.” Some individuals have “more income” and some have “less income.”

A **set** is a grouping and thus is more **case-oriented** than a variable because it entails membership criteria and has classificatory consequences. While a variable can be labeled “degree of democracy,” a set cannot, because the label does not refer to instances. However, it is possible to construct “the set of democracies” and then to list the relevant cases as members of this set.

This is not to say that a set is simply a nominal-scale variable. Cases can vary in the degree to which they satisfy membership criteria, which is the inspiration behind **fuzzy sets**. With fuzzy sets membership can vary from 0.0 (nonmembership) to 1.0 (full membership). Fuzzy sets are simultaneously quantitative and qualitative. Full membership and full nonmembership are qualitative states; between these two are varying degrees of membership in the set; 0.5 is the cross-over point between “more in” versus “more out.” The assignment of set membership scores follows directly from the definition and labeling of the set.

Crisp versus fuzzy sets

Crisp set	**Three-value fuzzy set**	**Four-value fuzzy set**	**Six-value fuzzy set**	**"Continuous" fuzzy set**
1 = fully in	1 = fully in	1 = fully in	1 = fully in	1 = fully in
			0.8 = mostly but not fully in	Degree of membership is more "in" than "out": $0.5 < x_i < 1$
		0.75 = more in than out	0.6 = more or less in	
	0.5 = neither fully in nor fully out			.5 = cross-over: neither in nor out
			0.4 = more or less out	
		0.25 = more out than in	0.2 = mostly but not fully out	Degree of membership is more "out" than "in": $0 < x_i < .5$
0 = fully out	0 = fully out	0 = fully out	0 = fully out	0 = fully out

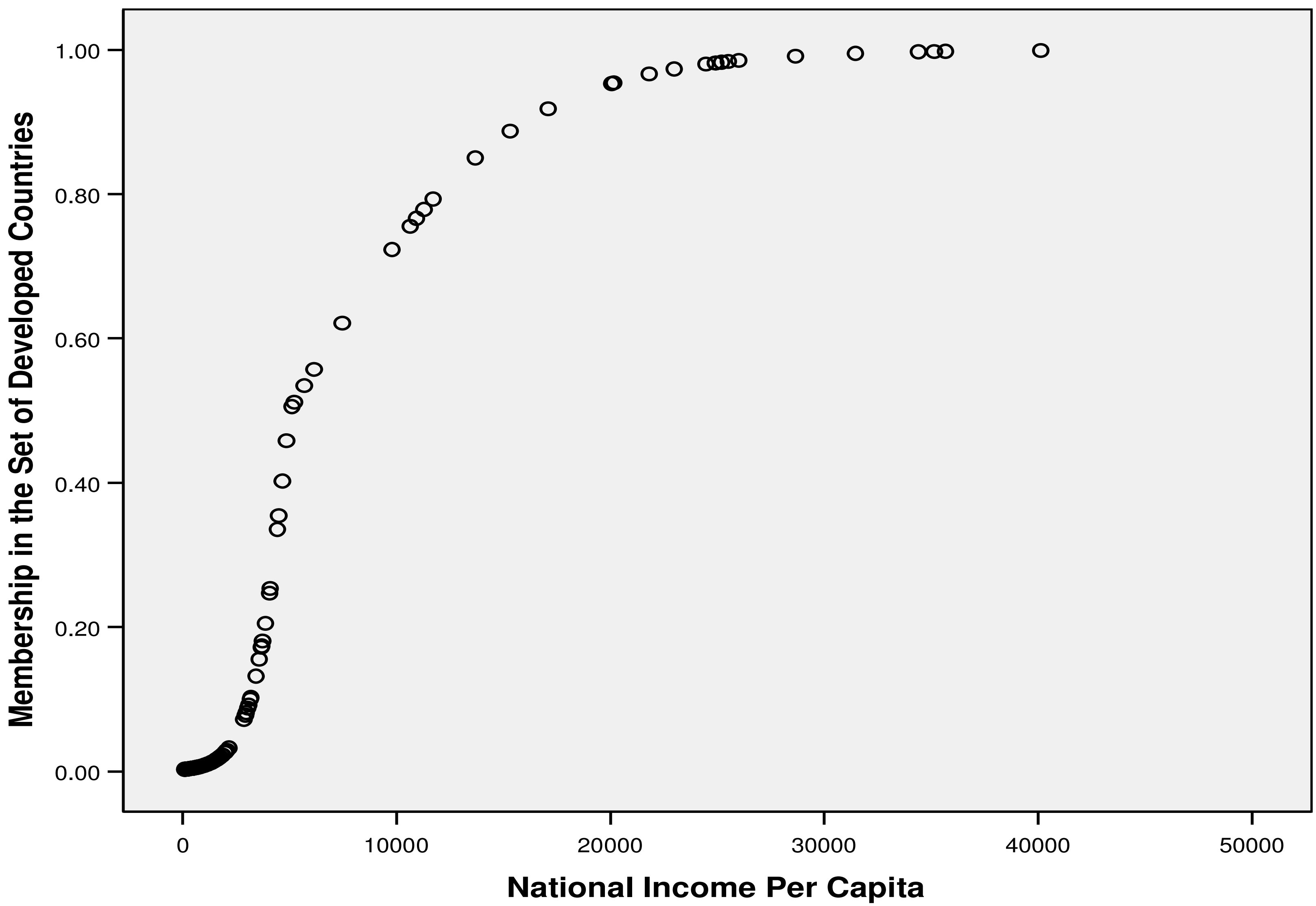
2. Don’t just measure, calibrate

Measurement in conventional social science is usually based on the use of indicators. Indicators must meet a minimum requirement, namely, they must array cases in a way that (at least roughly) reflects the underlying theoretical construct. Cases’ scores are evaluated relative to each other, based on inductively derived, sample-specific statistics such as the mean and standard deviation. For example, a high score is well above the mean score. All variation in an indicator is usually treated as meaningful and taken at face value.

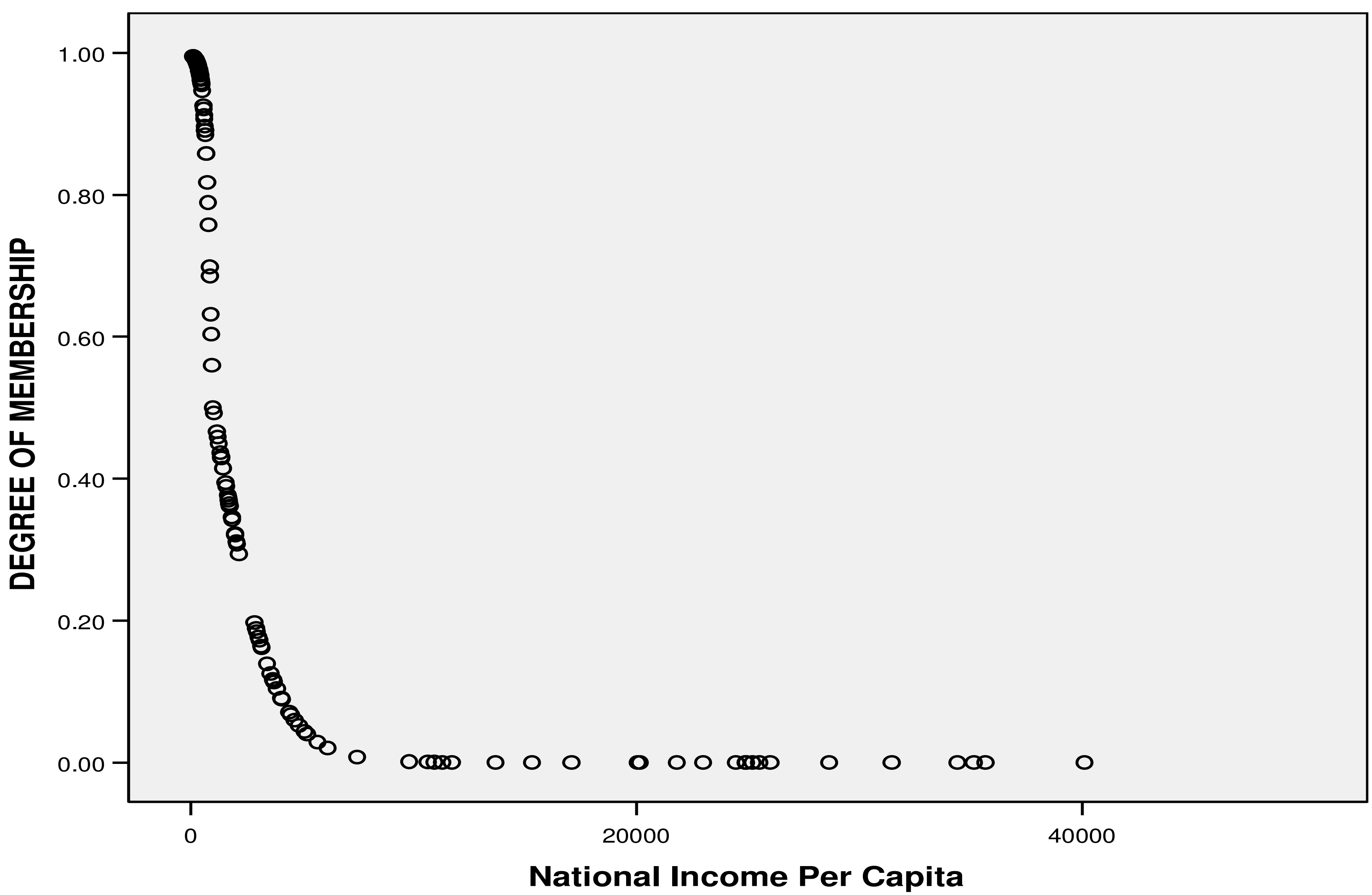
However, the conventional variable is **uncalibrated**. Scores are meaningful only relative to each other. For example, it is possible to say that one country is more democratic than another or even more democratic than average, but still not know if it is more a democracy or an autocracy. Calibrated measures, by contrast, are interpreted relative to external standards. We know, for example, that at 100 ˚C water boils and at 0 ˚C water freezes. External standards make it possible to calibrate measures.

To be useful, fuzzy sets must be **calibrated**. For example, to calibrate degree of membership the set of “developed countries” (the target set) using an uncalibrated variable such as GNP/capita, it is necessary to specify the score that would qualify a country for full membership in the set of developed countries and also the score that would completely exclude it from this set.

Plot of degree of membership in the set of developed countries against national income per capita



Plot of degree of membership in the set of poor countries against national income per capita



The correspondence between fuzzy sets and theoretical constructs

Notice that the set of poor countries is not the reverse of the set of developed countries, for it is possible to be well “out” of the set of developed countries, but still not be “in” the set of poor countries. With fuzzy sets**, fidelity to verbal formulations** is accomplished by calibrating degree of membership so that it directly corresponds to theoretical constructs.

With the conventional variable, by contrast, there is only “variation” in the “underlying dimension” (development, with GNP/capita as its indicator), which is (typically) accepted at face value and left uncalibrated. If a theoretical statement pertains to poor countries, then the expectation is that GNP/capita will have a negative effect (or connection); if a theoretical statement pertains to developed countries, then the expectation is that GNP/capita will have a positive effect (or connection).

Fuzzy sets and the elaboration of causal mechanisms

Just as it is possible to calibrate fuzzy sets in ways that differentiate between different “kinds” of cases (e.g., “developed” versus “poor” countries), it is also possible to calibrate fuzzy sets **that differentiate between different kinds of causal connections**. For example, is it having parents who are “well off” that is linked to avoiding poverty or is it NOT having parents who are poor? These two are not mirror images, for there are plenty of people who are not well off but still not in poverty. Is it having high test scores in school that is linked to later success in life or is it NOT having low test scores that matters? Again, these two are not mirror images, and with fuzzy sets it is a simple matter to calibrate these dual sets in a way that allows adjudication between competing arguments.

For example, *The Bell Curve* argues that having higher test scores is linked to avoiding poverty because today’s job market places a premium on high cognitive ability. But if the results show that the key to success is to NOT have low test scores, then the mechanism linking test scores to life chances is not likely to be the one cited in *The Bell Curve*. With fuzzy sets, these issues can be addressed by applying different calibration schemes to the same indicator (e.g., test scores).

3. Think in terms of outcomes, not dependent variables

The **dependent variable** is the focal point of the conventional template. Its variation matters in some way (e.g., variation in income, crime, democracy, civic culture, and so on). Conversations between researchers often begin with, "What's your dependent variable?" Researchers conventionally assume that the goal of research is to explain cross-case and/or over time variation in the dependent variable. A study of "welfare state retrenchment," for example, might examine variation in welfare spending across the advanced industrial societies over the last three or four decades. Different theories and perspectives offer different explanations of this variation.

The problem with explaining "variation in the dependent variable" is that the variation that is studied is usually undifferentiated and uncalibrated. Researchers calculate total pools of variation, and their observations all contribute to these pools, but they still may not know which cases actually exhibit the **outcome** that inspired the research in the first place.

The focus on explaining variation instead of studying outcomes derives in part from an infatuation with interval-scale dependent variables, such as income and education, and the ease with which these can be subjected to conventional multivariate techniques.

Instead, researchers should conceptualize the phenomenon to be explained as a **qualitative outcome**—an observable change or discontinuity. For example, instead of trying to explain variation in levels of welfare spending across countries and over decades, researchers should conceptualize "welfare state retrenchment" as an outcome that has occurred in specific times and places. How do we know "welfare retrenchment" when we see it? After identifying several good instances and studying them in some depth, it is possible to develop criteria for assessing the degree to which different cases (across time and space) have membership in this outcome. In short, these criteria make it possible to calibrate degree of membership in the outcome.

A few examples:
Periods of democratization, instead of levels of democracy
Outbreaks of mass protest, instead of levels of discontent
Marital breakups, instead levels of marital (dis)satisfaction
Schools with substantial improvement, instead of levels of school performance

An important key to assessing **outcomes**, as opposed to dependent variables, is that they should involve explicit criteria and also should be calibrated. That is, researchers should use external, substantive criteria to define the phenomenon of interest and to evaluate its degree of expression. In general, defining qualitative outcomes requires much more researcher input than simply selecting a dependent variable.

4. Use constructed, not given, populations

Most applications of conventional methods use either **given (i.e., taken for granted) populations** or samples derived from such populations. The ideal typic population is the national random sample. Researchers are also fond of given populations that are of interest to corporate actors or to specific audiences (e.g., the population of elementary schools in Tucson, Arizona is of interest to Tucson residents and to the State of Arizona). Such populations typically have face validity, and researchers rely on this to justify their procedures.

If researchers are interested in “qualitative outcomes,” however, it may be hazardous to use “given” populations. Research on qualitative outcomes typically begins by identifying good instances of the qualitative outcome in question. In-depth research on these cases helps to define and clarify the outcome and establish membership criteria. Once positive instances have been identified, it is possible to construct the **population of candidates** for the outcome, embracing both positive and *relevant* negative cases (e.g., cases where food riots might have occurred, but did not). With **constructed populations**, the definition of negative cases is not given, but follows from an argument of “candidacy.”

Of course, if the goal of research is to make inferences about populations, then given populations should be use. If the focus is on qualitative change and how it happens, then using a given population is less important.

The hazard of using given populations

Often given populations are appropriate. Sometimes, however, populations should be constructed, especially when studying qualitative outcomes. For example, in a study of food riots what is the appropriate “given” population?

All countries
Less developed countries (LDCs)
LDCs dependent on agricultural imports
LDCs dependent on agricultural imports, lacking government price subsidies
. . .

It is hazardous to use a given population that includes **irrelevant cases**. Correlations are strengthened when there are many cases **lacking both the hypothesized cause and the effect.** Thus, the conventional strategy of using large given populations (which may contain an abundance of irrelevant cases—cases that are not true candidates for the outcome) and relying on correlational methods simply increases the likelihood of spurious findings.

The case-oriented strategy dictates **careful selection of relevant negative cases**, matched as closely as possible with positive cases on important causal conditions, especially conditions that might be considered necessary for the outcome.

5. Analyze set relations, not correlations

Conventional quantitative social science is based almost entirely on **correlational analysis**. From multiple regression to factor analysis to structural equation models, all that is required is a matrix of bivariate correlations, along with the means and standard deviations of the variables.

Correlation is completely **symmetric** in its calculation. Thus, when correlation is used to test for a connection between a cause and an effect, it tests equally for a connection between the absence of the cause and the absence of the effect.

Consequently, correlation is blind to **set theoretic relationships**. The most common set theoretic relation is the subset relation. For example, the observation that the developed countries are democratic is set relational: the developed countries constitute a subset of the democratic countries. Unlike correlational relationships, **set theoretic relationships are asymmetric**. The assertion that “the developed countries are democratic” does not require that the not-developed countries be not-democratic. There can be many not-developed countries that are democratic, but such cases do not challenge the proposition that the developed are democratic and should not count against the asymmetric claim, as stated.

Correlational versus set-theoretic connections

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

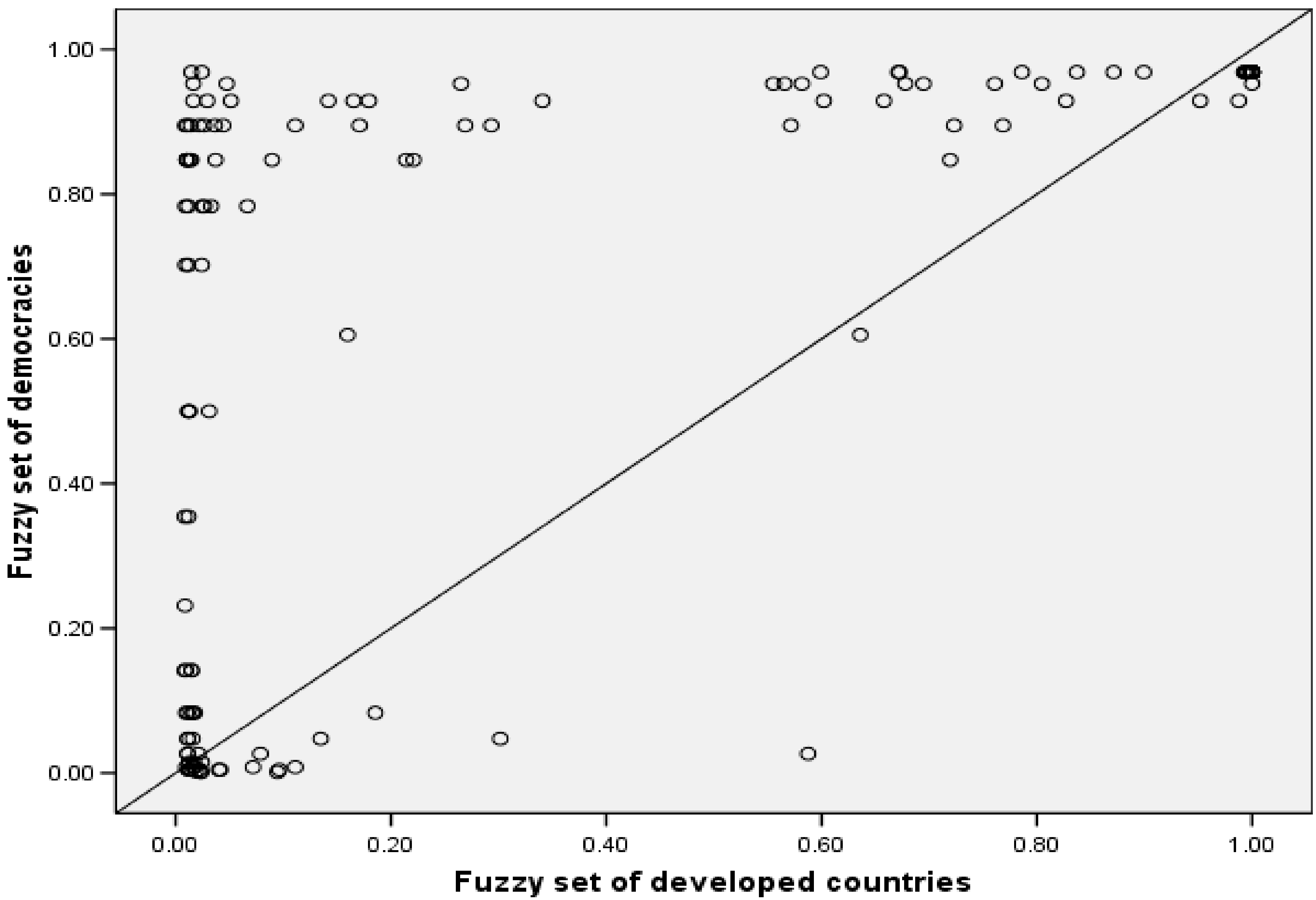
	Not developed	Developed
Democratic	8	11
Not democratic	16	5

By contrast, a set-theoretic relationship is evidence of an explicit connection:

	Not Developed	Developed
Democratic	17	16
Not democratic	7	0

In the second table all developed countries are democratic, that is, the developed countries form a subset of the democratic countries. The first table is stronger and more interesting from a correlational viewpoint; the second is stronger and more interesting from a set-theoretic viewpoint.

Consider the same set-theoretic relationship using fuzzy sets. This plot shows degree of membership in “democratic” plotted against degree of membership in “developed” (using published data, converted to fuzzy sets):



Why set relations?

1. Theory is largely **verbal** in nature and verbal statements are largely set theoretic in nature. Set-theoretic analysis thus offers an analytic system that is **faithful to verbal theory**. Correlation is not. Correlation forces symmetry on asymmetric theoretical claims. Asymmetrically formulated theoretical arguments should be evaluated with appropriate (set-theoretic) tools, not with correlation.

2. **Qualitative analysis** is centered on set relations. For example, the observation that “all the anorectic girls I interviewed have highly critical mothers” is a set theoretic analysis, pointing to the fact that set of “anorectic girls” is a consistent subset of the set of “girls with highly critical mothers.” The search for **commonalities and uniformities** is the lifeblood of qualitative analysis.

3. **Constitutive** connections are set theoretic in nature. The argument that a “strong civil society” is essential to “democracy” asserts, in effect, that instances of the latter constitute a subset of instances of the former.

4. Important causal connections, especially sufficiency and necessity, involve asymmetric connections and thus require appropriately asymmetric analytic techniques. With **sufficiency**, instances of the causal condition constitute a subset of instances of the outcome; with **necessity**, instances of the outcome constitute a subset of instances of the causal condition.

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

6. Analyze truth tables, not correlation matrices

Most conventional quantitative methods simply parse **matrices of bivariate correlations**. These correlations, in turn, assess how well two series of values parallel each other across cases. Using correlations, there is no direct examination of how case aspects fit together **within** cases. It is also important to remember that while the calculation of the "net effect" of an "independent variable" may seem to take "competing variables" into account, such calculations are all based on formulas using bivariate correlations, again, without any consideration of how case aspects fit together within cases.

A **truth table** is a direct examination of the kinds of cases that exist in a given set of data. It lists all the different combinations of causally relevant conditions and treats each combination as a different "kind" of case. Cases with the same profile on the causal conditions are grouped together, making it possible to assess whether they agree on the outcome. Each profile (combination) can be examined on its own terms, as a specific set of circumstances. If the cases disagree on the outcome, this can be taken as a signal that other causal conditions should be added to the truth table (or that the truth table needs to be respecified in some way), based on the comparison of cases positive and negative cases in each "contradictory" row.

Truth table for eruption of protest against IMF austerity

Row#	Prior mobiliz.?	Severe austerity?	Gov't corrupt?	Rapid price rise?	Cases w/ protest?	Cases w/o protest	Consis- tency
1	0 (no)	0 (no)	0 (no)	0 (no)	0	0	??
2	0 (no)	0 (no)	0 (no)	1 (yes)	0	0	??
3	0 (no)	0 (no)	1 (yes)	0 (no)	0	4	0.0
4	0 (no)	0 (no)	1 (yes)	1 (yes)	1	5	0.167
5	0 (no)	1 (yes)	0 (no)	0 (no)	0	0	??
6	0 (no)	1 (yes)	0 (no)	1 (yes)	4	0	1.0
7	0 (no)	1 (yes)	1 (yes)	0 (no)	0	0	??
8	0 (no)	1 (yes)	1 (yes)	1 (yes)	5	0	1.0
9	1 (yes)	0 (no)	0 (no)	0 (no)	0	3	0.0
10	1 (yes)	0 (no)	0 (no)	1 (yes)	1	7	0.125
11	1 (yes)	0 (no)	1 (yes)	0 (no)	0	10	0.0
12	1 (yes)	0 (no)	1 (yes)	1 (yes)	0	0	??
13	1 (yes)	1 (yes)	0 (no)	0 (no)	1	5	0.167
14	1 (yes)	1 (yes)	0 (no)	1 (yes)	6	0	1.0
15	1 (yes)	1 (yes)	1 (yes)	0 (no)	6	2	0.75
16	1 (yes)	1 (yes)	1 (yes)	1 (yes)	8	0	1.0

Table Notes:

a. This table has five rows without cases (1, 2, 5, 7, 12). In QCA, these rows are known as “remainders.” Having remainders is known as “limited diversity.”

b. There are seven noncontradictory rows, three that are uniform in not displaying the outcome (consistency = 0.0; rows 3, 9, 11) and four that are uniform in displaying the outcome (consistency = 1.0; rows 6, 8, 14, 16).

c. The remaining four rows are contradictory. Three are close to 0.0 (rows 4, 10, 13), and one is close to 1.0 (row 15).

d. Suppose that the three (unexpected) positive cases (in rows 4, 10, 13) are all cases of contagion—a neighboring country with severe IMF protest spawned sympathy protest in these countries. These contradictory cases can be explained using case knowledge. Thus, these three cases can be safely set aside.

e. Suppose the comparison of the positive and negative cases in row 15, reveals that the (unexpected) negative cases all had severely repressive regimes. This pattern suggests that having a not-severely-repressive regime is part of the recipe and that the recipe has five key conditions, not four.

f. Truth tables like this also can be constructed from fuzzy sets, without dichotomizing the fuzzy membership scores.

7. Think in terms of causal recipes, not net effects

The conventional template for conducting social research emphasizes the competition between theories to explain variation in the dependent variable. Thus, the calculation of the **net effect** of each variable and the partitioning of explained variation are central tasks in this approach. The net effect of each causal variable is based on its unique (nonoverlapping) contribution to explained variation in the dependent variable. The greater an independent variable's correlation with the dependent variable and the lower its correlation with its competitors, the greater its net effect.

Net effect thinking isolates causal variables from each other and attempts to purify the estimate of each variable's effect. In case-oriented research, by contrast, researchers often focus on **how causes combine** to generate outcomes. The idea that causal conditions have "independent" effects that can be "estimated" runs counter to this fundamentally "chemical" understanding of how conditions generate outcomes. In this view, an outcome may be generated by one or more **causal recipes**. All the ingredients in a given recipe have to be present for the outcome to occur. This view pays attention to how conditions combine in each case and thus is much more case-oriented than the "net effects" understanding of causation, which is completely variable oriented.

INUS conditions are central to the notion of recipes

An INUS condition is an insufficient but necessary part of a combination of conditions that is itself unnecessary but sufficient for the outcome. In the "recipe" view of causation, most causal conditions are INUS.

Consider, for example, one possible solution to the truth table shown previously

(1) PRIOR_MOBILIZATION•SEVERE_AUSTERITY•GOV'T_CORUPTION +
(2) SEVERE_AUSTERITY•RAPID_PRICE_RISE

(Multiplication indicates set intersection—combined conditions; addition indicates set union—alternate combinations.)

There are two recipes. The first combines three ingredients; the second combines two. Prior mobilization is neither necessary nor sufficient because (1) it is not capable of generating IMF protest by itself, and (2) it does not appear in every case of IMF protest. It is an INUS condition, appearing in a single combination of conditions. In fact, all the conditions except for severe austerity (which appears in both recipes) are INUS conditions.

The study of INUS conditions is beyond the reach of conventional quantitative methods.

8. Replace counterfactual estimation with counterfactual analysis

One long-standing issue in **causal inference** is the fact that observational data do not meet the standards of experimental design. That is, researchers would like to estimate the causal effects of variables that they cannot manipulate (for example, deciding who gets to go to college, so that a proper estimate of its impact on life chances could be calculated). As a substitute, researchers **estimate counterfactuals**; that is, for cases without the treatment (e.g., without a college education) they try to estimate what their outcomes would have been with the treatment, and for cases with the treatment, they try to estimate what their outcomes would have been without the treatment.

Counterfactual analysis is understood differently in the case-oriented tradition. It is linked explicitly to the notion of limited diversity, the fact that not all combinations of causal conditions are empirically observable. Limited diversity is a fact of life when working with nonexperimental data.

Consider the following truth table:

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 having strong left parties (L) that causes generous welfare states (G) or is it the combination of strong unions and strong left parties (L•U) that causes generous welfare states (G)? ("•" indicates set intersection—combined causes.)

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: $L \rightarrow G$

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 displays this combination. This pattern suggests a more **complex** explanation: $L \bullet U \rightarrow G$.

Which is correct? It depends on the fourth row, which requires a thought experiment. This experiment would be based on existing theoretical, substantive, and case knowledge. Thought experiments are central to successful applications of fsQCA.

Concluding remarks

Am I saying the Emperor has no clothes?

No. I'm saying that the Emperor wears the same outfit far too often, and he should dress appropriately for different occasions. The "net effects" outfit is very attractive and it projects power, but its strength is also its weakness.

What is the key to redesigning social inquiry?

For each major point, my argument has been that we need to push analysis in a more case-oriented or at least more case-friendly direction. Some useful goals:

1. To balance within-case analysis and cross-case analysis
2. To balance discourse on cases and discourse on "variables"
3. To build general knowledge from knowledge of specifics
4. To connect to cases at every opportunity in the research process

It is important to remember that causation is most accessible to researchers at the case level. Consider:

Conventional methods: which ingredients are more important
INUS methods: causal recipes (which ingredients must be combined and what are the different combinations)
Case methods: how to combine the ingredients (causal processes)

THANK YOU!