The Effects of Sampling and Sample Sizes on Counterfactual Analysis in QCA

Claude Rubinson University of Houston—Downtown rubinsonc@uhd.edu

2nd International QCA Expert Workshop University of Zürich November 5, 2014

# Sample Size in QCA

- QCA is not limited by degrees of freedom; therefore:
- Effects of sample size on QCA are incidental ("correlation, not causation")
  - it's more likely that small-N researchers can return to their cases and collect more data
  - large-N data is more likely to be individual-level data; more inconsistency because people are more inconsistent
  - affects how we conceive of anomalies:
    - small-N: anomalies are unusual observations
    - large-N: anomalies are rarely occurring observations

## Sample Size != Research Strategy

- Small-N research is not necessarily inductive; large-N research, not necessarily deductive
  - Crucial case studies are small-N hypothesis testing
  - Data mining is large-N theory construction
- Small-N is not necessarily case-oriented; nor large-N, variable-oriented
  - Small-N regression
  - Large-N survey data is routinely used to construct contingency tables (taxonomies)

# Sampling in QCA

(usually small-N)

(usually small-N)

- Sampling procedure is what matters
- Three types of samples
  - Complete populations
  - Purposive samples
  - Representative samples (usually large-N)
- Determines generalizability
- Structures interpretation of remainders and constrains analysis of counterfactuals
- Retroductive, iterative analysis is the rule, regardless of sampling

#### Counterfactual Analysis in QCA

- Implemented by treating remainders as if they actually existed, a very strong assumption even for "easy" counterfactuals
- Has primarily been used for simplification, to derive intermediate and parsimonious solutions
- Is arguably over-used because QCA makes it so easy; many researchers are otherwise uncomfortable with counterfactual claims
- Depends not only on theoretical and case knowledge but also the nature of one's data

#### **Complete** Populations

- Common in QCA research
- Usually small-N
- No generalizability concerns
- Strongest basis for counterfactual analysis, if theory and case knowledge is available (but often is not for inductive research)
  - Permits evaluation of the plausibility and coherence of remainders
  - Enables careful, matched selection of counterfactuals

### **Purposive Samples**

- Common in QCA research
- Usually small-N
- Generalizability usually impossible; at best, severely constrained/qualified
- Counterfactual analysis must be applied judiciously, if at all
  - not knowing contours of the population makes counterfactual theorizing difficult
  - projects are often inductive and lack the theory needed for counterfactual analysis

- Not (yet) common in QCA research
- Usually large-N
- Good basis for generalizability; statistical significance tests can quantify confidence
- Projects are often deductive, providing a strong basis for counterfactual theorizing
- Solutions are often relatively complex and have greater need of simplification via counterfactual analysis (particularly for individual-level data)
- But, counterfactual analysis is often problematic

- Counterfactual analysis problematic due to
  - Sampling error
  - Difficulty of distinguishing between limited diversity and rarely-occurring configurations
  - Operationalization of remainders
  - Measurement error

- Counterfactual analysis problematic due to
  - Sampling error
    - not detecting rarely-occurring configurations
  - Difficulty of distinguishing between limited diversity and rarely-occurring configurations
  - Operationalization of remainders
  - Measurement error

- Counterfactual analysis problematic due to
  - Sampling error
  - Difficulty of distinguishing between limited diversity and rarely-occurring configurations
  - Operationalization of remainders
  - Measurement error

- Counterfactual analysis problematic due to
  - Sampling error
  - Difficulty of distinguishing between limited diversity and rarely-occurring configurations
  - Operationalization of remainders
    - it doesn't make sense to define a rarely-occurring configuration as a remainder (via a frequency threshold) and then deploy that configuration as a counterfactual
  - Measurement error

- Counterfactual analysis problematic due to
  - Sampling error
  - Difficulty of distinguishing between limited diversity and rarely-occurring configurations
  - Operationalization of remainders
  - Measurement error
    - is a greater concern for large-N representative samples due to the difficulty of detecting (and correcting) miscodes

### Measurement Error in QCA

- Recent critiques of QCA's sensitivity to measurement error are incorrect
  - Due to misunderstanding how QCA operates or mistakes in the analysis/simulation and/or interpretation of results (or both)
- Effect of measurement error on truth tables:
  - Observation assigned to correct row but degree of membership over/under-estimated; configuration's consistency score will be wrong
  - Observation assigned to wrong row; depending on frequency threshold, may create Type I error (row is actually a remainder) and/or Type II error (row incorrectly classified as a remainder)

### Conclusions: Counterfactual Analysis in QCA

- Complete populations offer the strongest basis for counterfactual analysis, but only if theory and case knowledge is available
- Representative samples may benefit the most from counterfactual simplification but the nature of the data complicates its application

### Conclusions: Counterfactual Analysis in QCA

- All counterfactual claims—even the intermediate solution's "easy" ones—make the very strong assumption that the counterfactual, if it existed, would be associated with the presence of the outcome
- Researchers must be cautious in making such claims and justify them theoretically, empirically, and methodologically
- QCA promises to facilitate researchers' understanding of their cases; counterfactual analysis is an important tool for doing so but only when applied carefully and thoughtfully