“Net benefits of energy-efficiency services: A counterfactual model”

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Proposition

- Counterfactual perspective can improve accuracy of pilot evaluations
- Innovation directed to services with most impact (cost-benefit)
- Reduce unhelpful impact of optimism bias
- Credibility with customers and policy makers

FG ICT&CC suggestion

- Guidance to members; standard checklist for pilot studies?
  - Comparability and usefulness of results
Counterfactual model

- Growing use with development projects
- Quantitative impact assessment in non-experimental conditions
- Acknowledge quasi-experimental limitations
- Two broad features:
  - Explicit causal assumptions
    - Diagrams (case study)
  - Econometric techniques
    - Matched pairs of control and treatment cases
    - Mimic random selection of experiment
- More accurate quantitative impact assessment
Energy-saving services

- Internally and for customers:
  - Conferencing
  - Home-shoring
  - Green IT
  - Smart grid/renewable energy
  - Network/data centre efficiency
  - Building management
  - Fleet logistics
  - etc

- From lab => internal study => operational conditions => working practices and individual behaviour
Perfect experiment

Intervention: $D = 1$
Smart meter/ enhanced billing

Criteria: short causal pathways, large-N, random allocation

Average impact
$= Y^1 - Y^0$
Counterfactual model

Intervention (D)

Treatment group  \( Y^1 | D = 1 \)

Control group  \( Y^0 | D = 0 \)

Treatment group  \( Y^0 | D = 1 \)

Control group  \( Y^1 | D = 0 \)

Average impact = ??

Rubin, 1974+; Fisher 1930s; Neyman, 1920s
Basic counterfactual problem

<table>
<thead>
<tr>
<th></th>
<th>Treatment group D=1</th>
<th>Control group D=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome following intervention (Y^1)</td>
<td>Observable</td>
<td>Unobservable</td>
</tr>
<tr>
<td>Outcome following no intervention (Y^0)</td>
<td>Unobservable</td>
<td>Observable</td>
</tr>
</tbody>
</table>

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<tr>
<th></th>
<th>Treatment group D=1</th>
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</thead>
<tbody>
<tr>
<td>Outcome following intervention (ΔY^1)</td>
<td>-40 kWh/ year</td>
<td>0 kWh/ year</td>
</tr>
<tr>
<td>Outcome following no intervention (ΔY^0)</td>
<td>-10 kWh/ year</td>
<td>+5 kWh/ year</td>
</tr>
</tbody>
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Modified from Morgan & Winship (2007), pp.35, 47
Energy feedback pilot

- >400 participant HHs
- Portable visual display
  - C$, kWh, CO2; inc projections
- Diverse sample:
  - Weather, geography, HH configurations & demographics
- Stratified by average consumption
- Panel data 1.5yr before, monthly 1yr after
Feedback pilot results

- Conclusion: 7%-10% average reduction feasible with additional information
- BUT treatment ≠ control group (selection bias)
  - Self-install
  - 3 x qualitative surveys
What if…?

- Treatment group has higher proportion of environmentally motivated households?
- If treatment group *not* given a meter, would they improve their efficiency anyway?
  - What are the *net* benefits?
- Would the control group improve efficiency to the same degree?
  - Should resources be targeted at less motivated households, or not?
Credibility gap?

- Multiple pressures for pilot studies to produce clear results
- Strategic influences...
- US utilities report higher impacts of DSM than academic review\(^1\)
  - Hazy on selection bias
- Agreed guidelines would aid transparency and comparability

\(^1\)Loughran & Kulick (2004)
Counterfactual alternative

- Attempt to quantify selection bias effect
- Specify causality
  - Diagrams
  - Awareness of assumptions
- Matching of control and treatment cases
Plot assumed relationships

X: HH vars (e.g., income)
EM: Env. Motivation
D: free smart meter y/n
MD: Meter Design
Y: energy consumption

To isolate D->Y
Control on X
Blocks alternate path DXY
If X is constant, variation of Y is not due to DXY


Directed Acyclic Graph
Matching techniques

- Techniques to make treatment & control groups look similar
- Engineer a set of matched pairs
  - On known exogenous variables
  - On propensity to participate
  - Other
  - Drop unmatchable cases
- Much debate about matching criteria....
- Then regression etc
- Compare with naïve estimator
Research design checklist

- Refer to case study to uncover and verify causal relationships
- Plot assumed causal relationships (DAG)
- What are the ‘what ifs...’?
- Internal trials to approximate experiments
- Randomise!
  - Eg restrict access to trial, lottery
- Large samples
  - Allow for loss of cases
- Look for similar control samples
  - Eg clustered characteristics of customer base
Design considerations

- Contamination!
  - Before/after
  - Anticipation problem
  - Network effects (vs case independence)
Interpretation checklist

- Omitted variables?
  - ‘Known unknowns’
- Selection bias?
  - If so, declare it
- Recognised econometric techniques to match imperfect treatment and control groups
- => Credible, comparable and replicable results
Thank you!

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References

- Pearle, J (2000), Causality, Cambridge University Press
- MatchIt, plug-in for R http://rss.acs.unt.edu/Rdoc/library/MatchIt/html/00Index.html