"Net benefits of energy-efficiency services: A counterfactual model"

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Agenda/Contents

- **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

Treatment group → Y^1

Control group → Y^0

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

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

Counterfactual model

Intervention (D)

Treatment group	$Y^1 \mid D = 1$	**Naïve estimator**
Control group	$Y^0 \mid D = 0$	
Treatment group	$Y^0 \mid D = 1$	**Unobservable**
Control group	$Y^1 \mid D = 0$	

Average impact = ??

Rubin, 1974+; Fisher 1930s; Neyman, 1920s

Basic counterfactual problem

	Treatment group D=1	Control group D=0
Outcome following intervention (Y^1)	Observable	Unobservable
Outcome following no intervention (Y^0)	Unobservable	Observable

	Treatment group D=1	Control group D=0
Outcome following intervention (ΔY^1)	-40kWh/year	**0kWh/year**
Outcome following no intervention (ΔY^0)	**-10KWh/year**	+5kWh/year

Modified from Morgan & Winship (2007), pp.35, 47

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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?

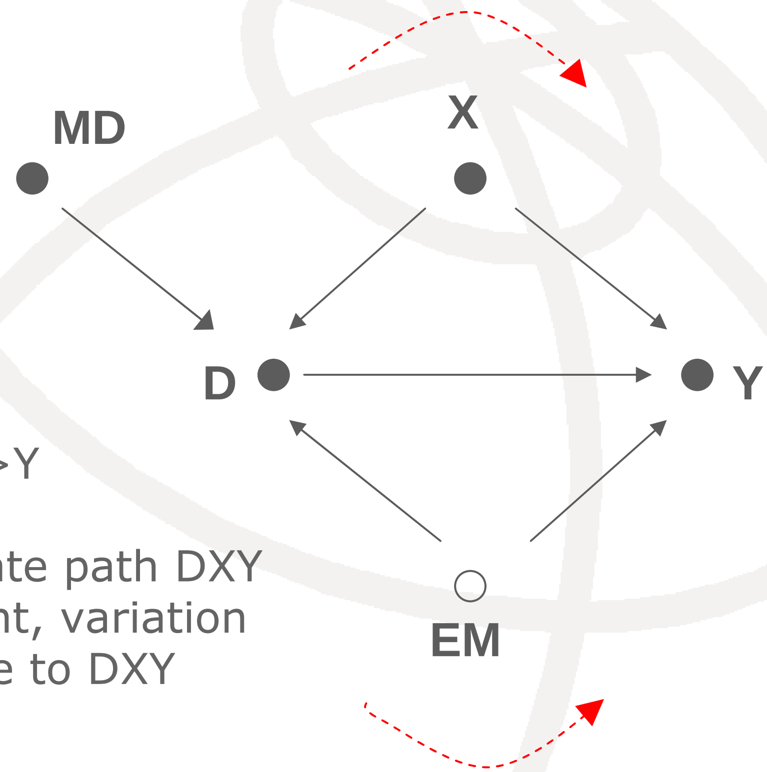
- Multiple pressures for pilot studies to produce clear results
- Strategic influences…
- US utilities report higher impacts of DSM than academic review[1]
  - Hazy on selection bias
- Agreed guidelines would aid transparency and comparability

[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 (eg income)

EM: Env. Motivation

D: free smart meter y/n

MD: Meter Design

Y: energy consumption

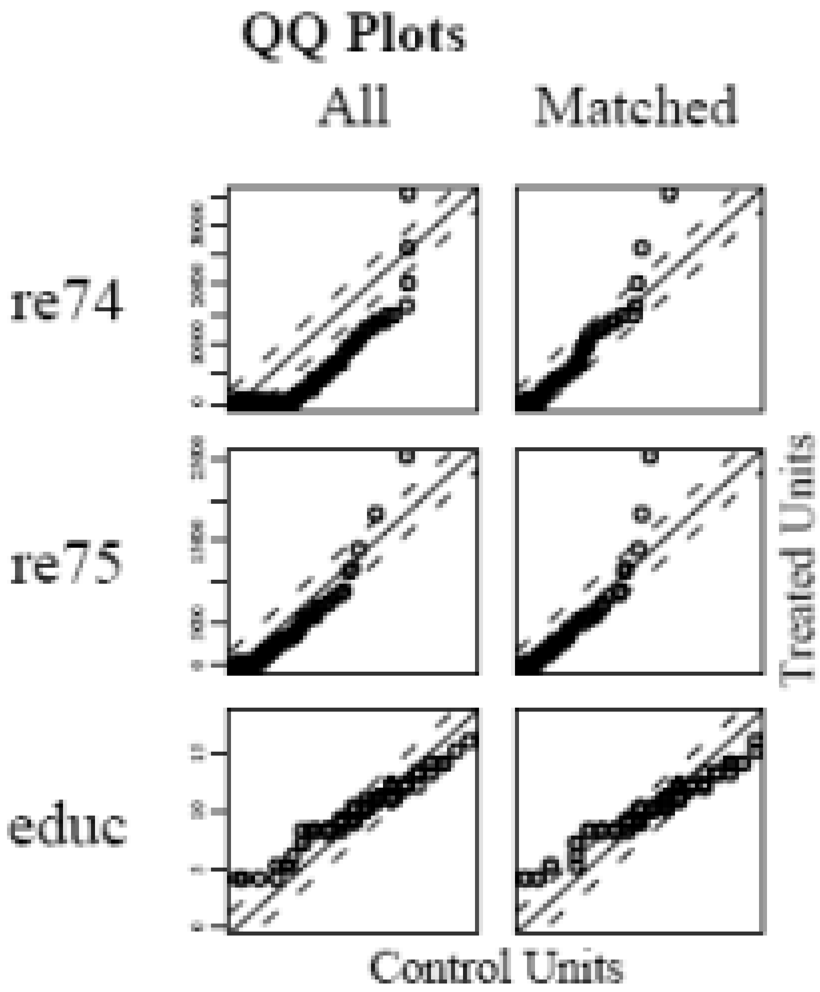
To isolate D->Y
Control on X
Blocks alternate path DXY
If X is constant, variation
of Y is not due to DXY

Pearle, J. (2000). Causality

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



Ho, D. et al (2008) pp.15

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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