Methods for Handling Mode Effects

Survey Futures Webinar, April 2026

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Presenters


Liam Wright


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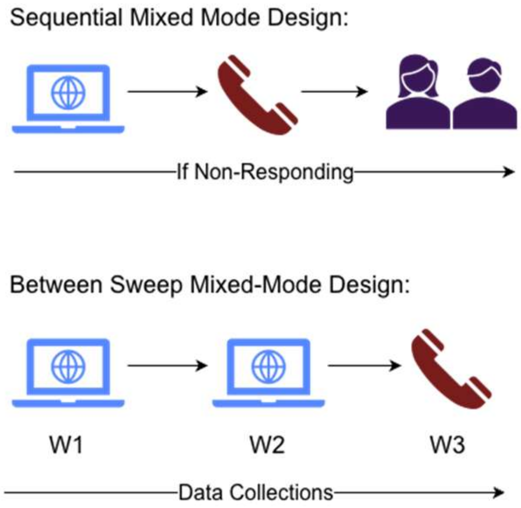
Background

Mixed Mode Survey Designs

- Surveys are carried out in a **mode** – e.g., face-to-face (F2F), telephone, or video interview or paper or web questionnaire.
- Modes may be mixed between participants ***within*** a data collection
- In longitudinal surveys, modes may be mixed ***between*** survey sweeps.



Mode Effects

- Each mode has its idiosyncratic features.
- Modes vary on:
  - Presence of interviewer (social desirability, motivation and instruction)
  - Presentation (response grids, visual or aural)
  - Context of response (e.g., while distracted, in public, etc.)
- This can affect how people respond to survey items: *mode effects*.

	Often	Some-times	Not Often	Never
My age prevents me from doing the things I would like to do				
I feel what happens to me is out of my control				
I feel left out of things				
I feel full of energy these days				
I feel that life is full of opportunities				
I feel that the future looks good to me				

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Empirical Evidence

- Mode effects can manifest as differences in: survey response, item response, item means, and response behaviour (e.g., straightlining)
- Tomova et al. (2026) review effects on item means.
  - Effect sizes rarely exceed 0.3 SD
  - Anonymous vs. non-anonymous a key difference for sensitive questions (e.g., mental health)
  - Physical presence sufficient even in self-complete.

	Often	Some-times	Not Often	Never
My age prevents me from doing the things I would like to do		x		
I feel what happens to me is out of my control		x		
I feel left out of things		x		
I feel full of energy these days		x		
I feel that life is full of opportunities		x		
I feel that the future looks good to me		x		

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Empirical Evidence

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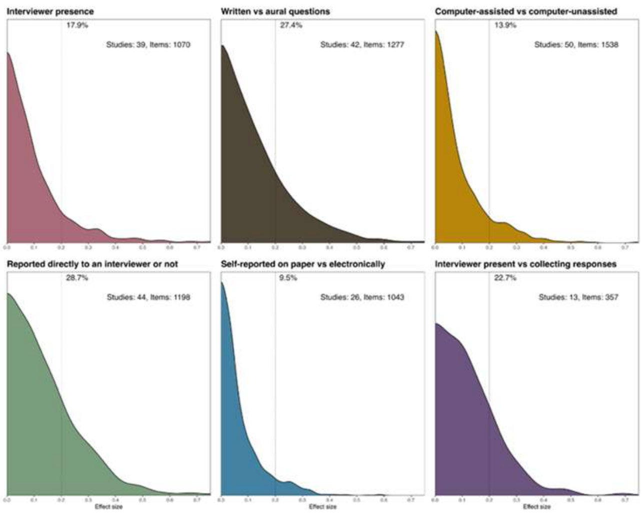

Tomova, G., et al., 'Mode Effects on Survey Item Measurement', Survey Futures Working Paper 12, 2016.
https://surveyfutures.net/wp-content/uploads/2026/01/working-paper-12-mode-effects-on-survey-item-measurement.pdf

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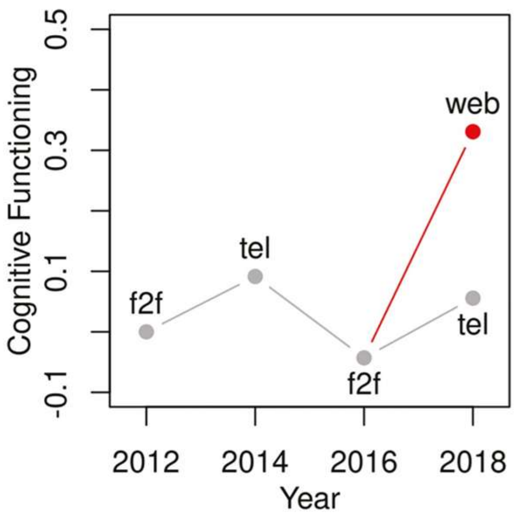
Bias from Mode Effects: Univariate Descriptives



Domingue, B W., et al. 'The Mode Effect of Web-Based Surveying on the 2018 U.S. Health and Retirement Study Measure of Cognitive Functioning'. The Journals of Gerontology, 2023. https://doi.org/10.1093/geronb/gbad068.

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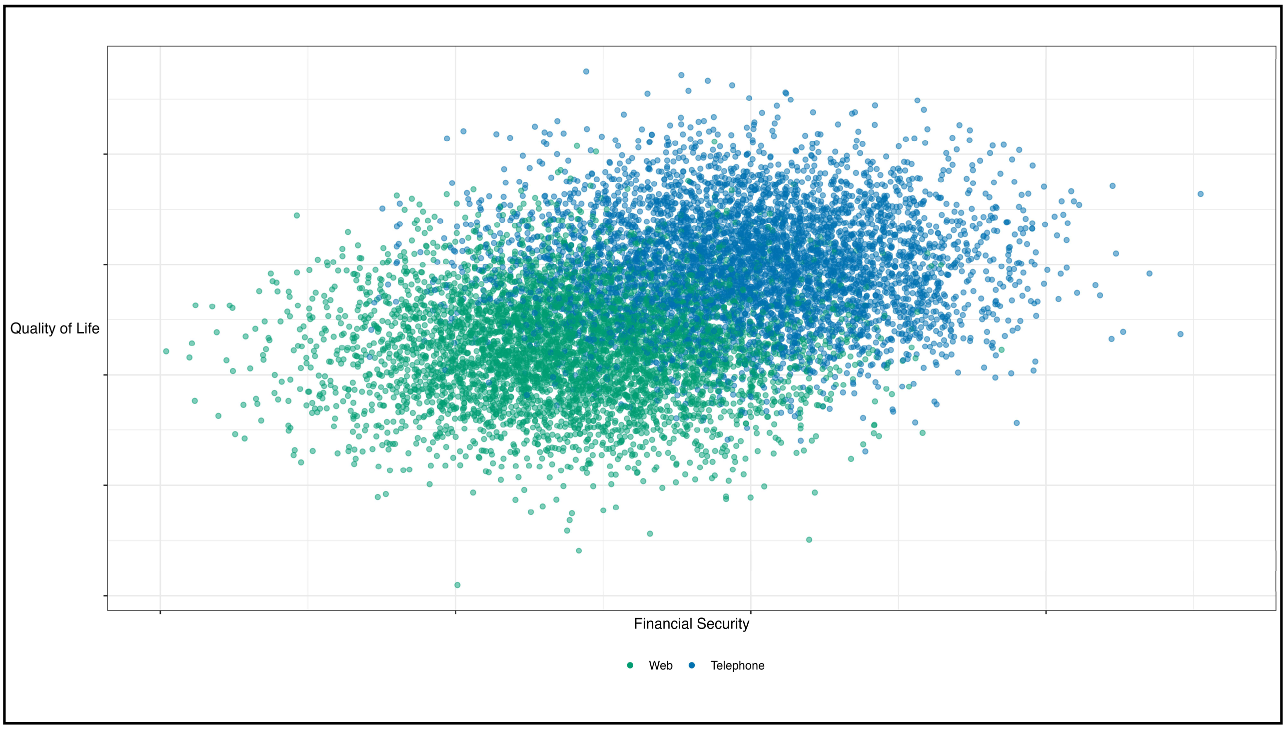
Quality of Life
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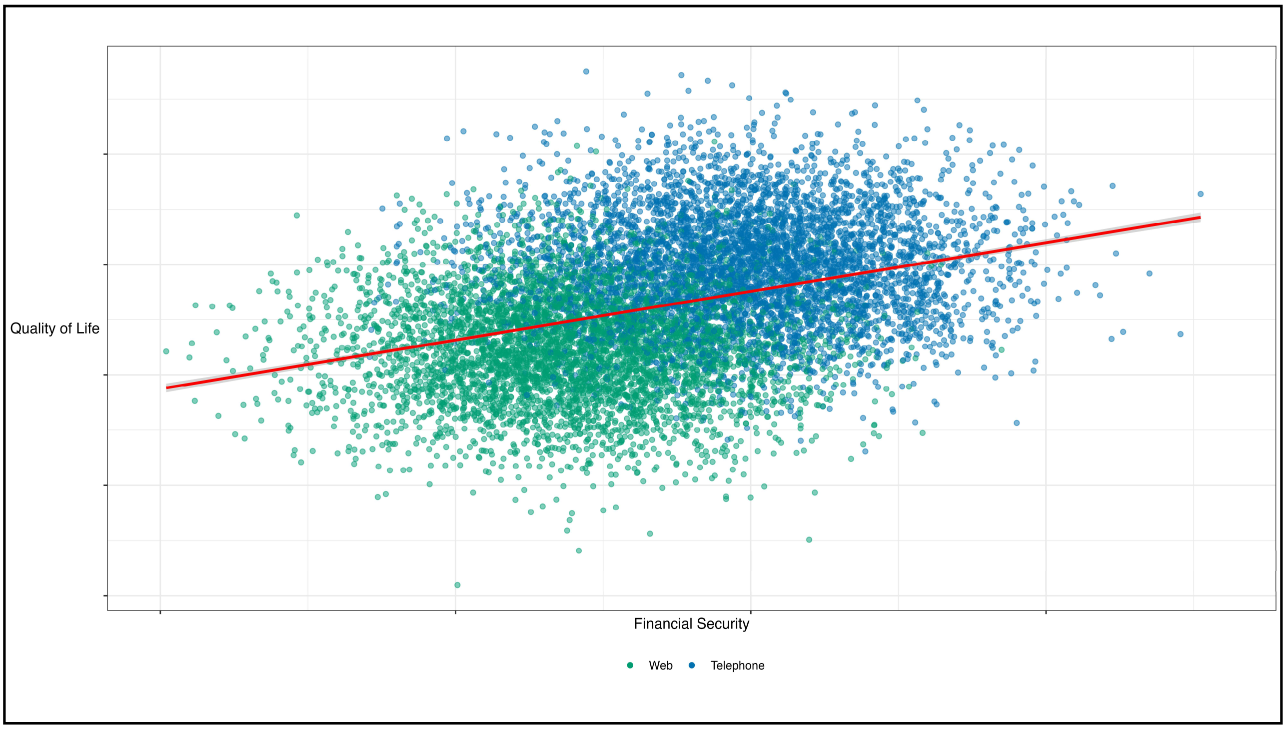
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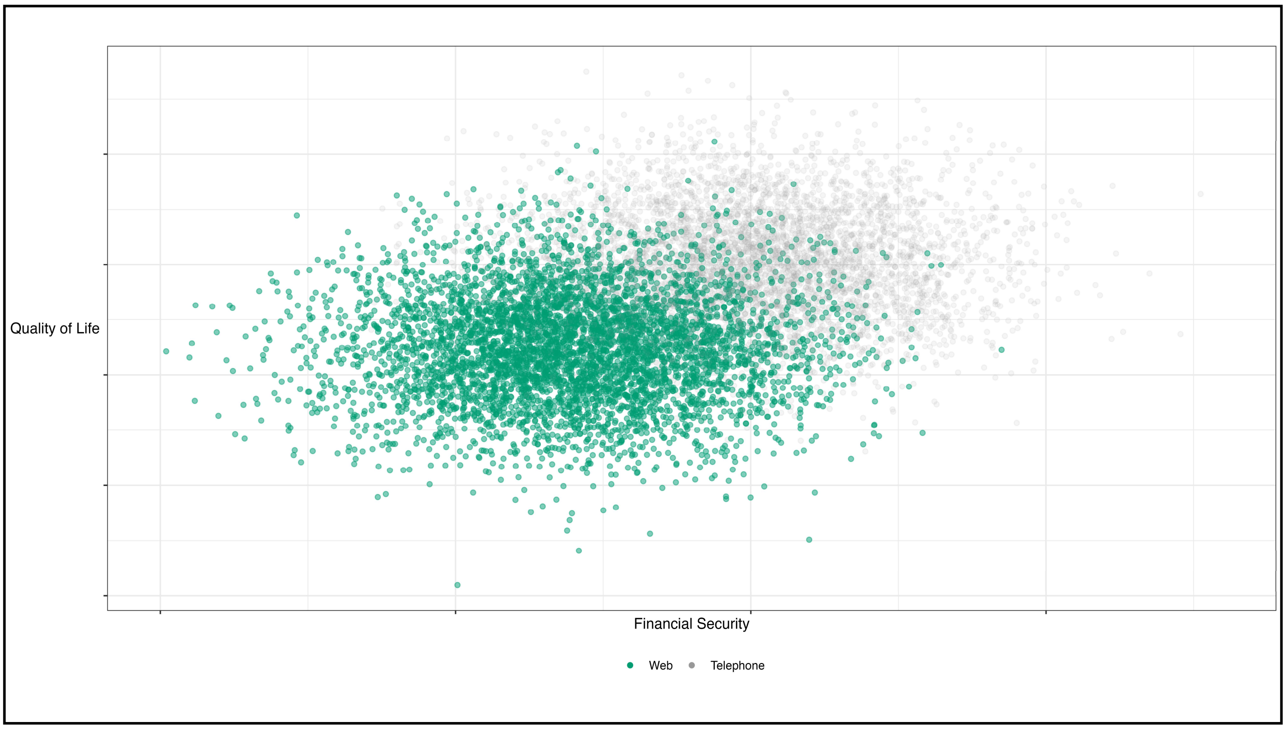
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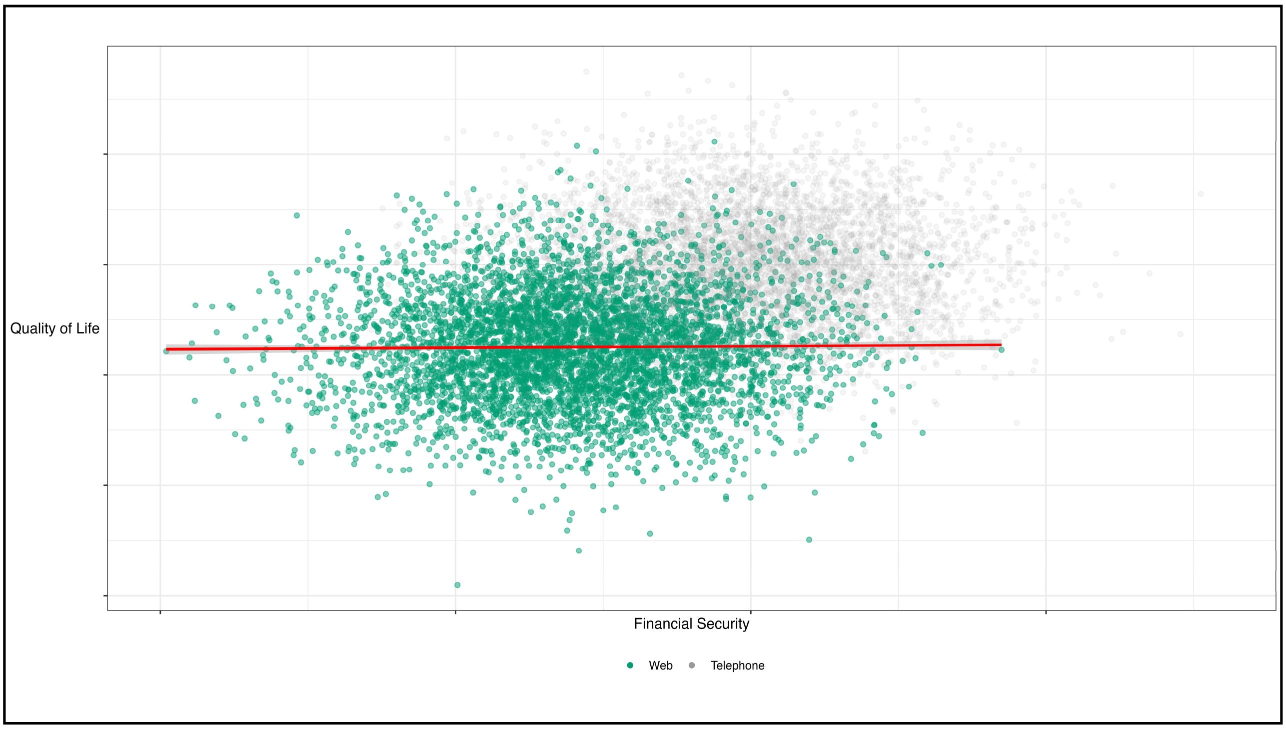
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Telephone

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Mode Selection

- Mode Selection = Differences in responses between modes due to ***who*** is responding.
- Causes:
  - Coverage (e.g., not in sampling frame for one mode)
  - Preference (e.g., older people may use paper)
  - Late response in sequential mixed-mode design.
- The combination of mode effects and mode selection can also induce bias.

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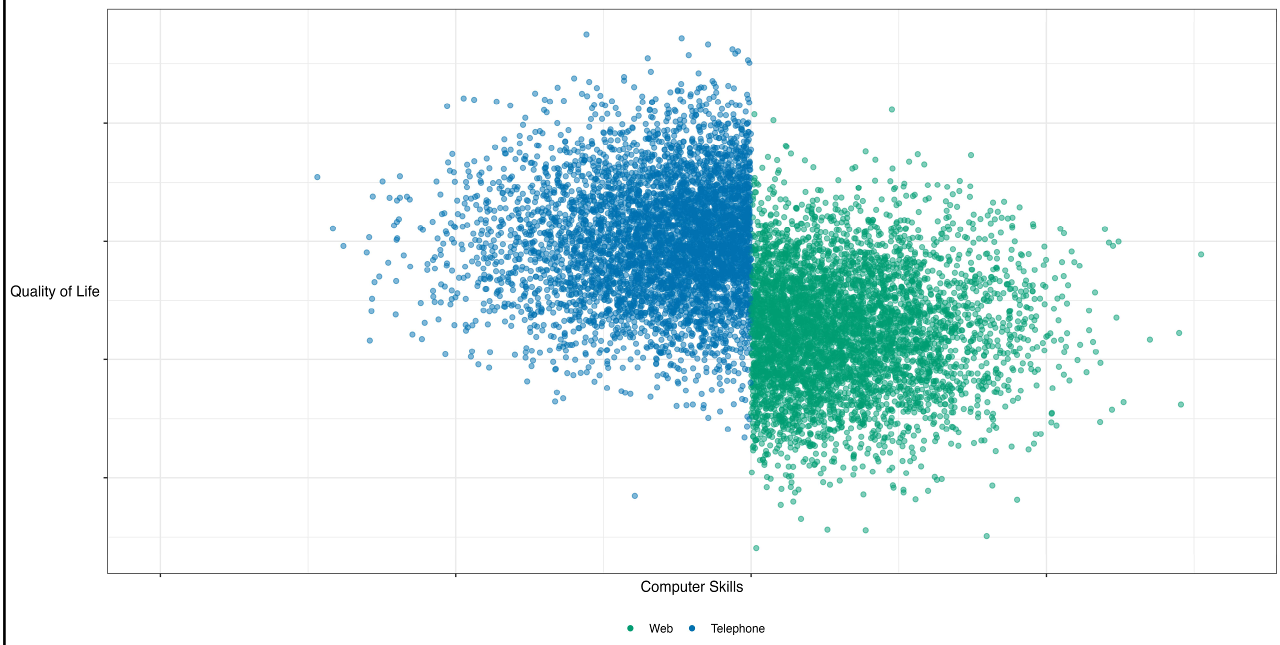

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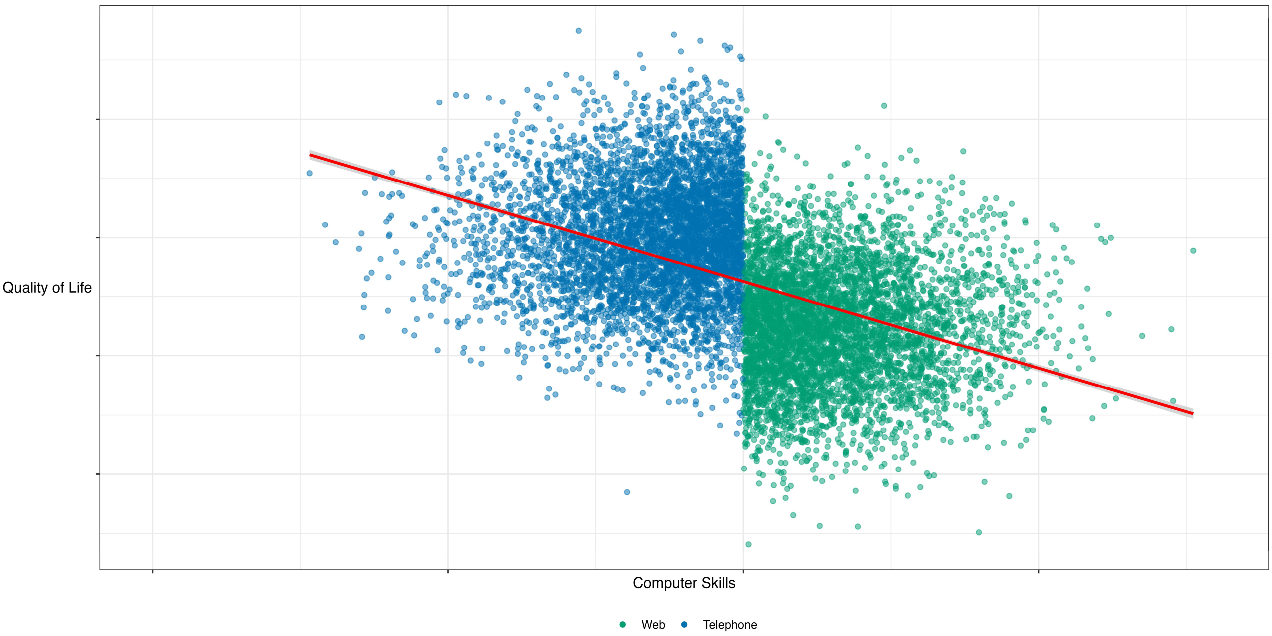
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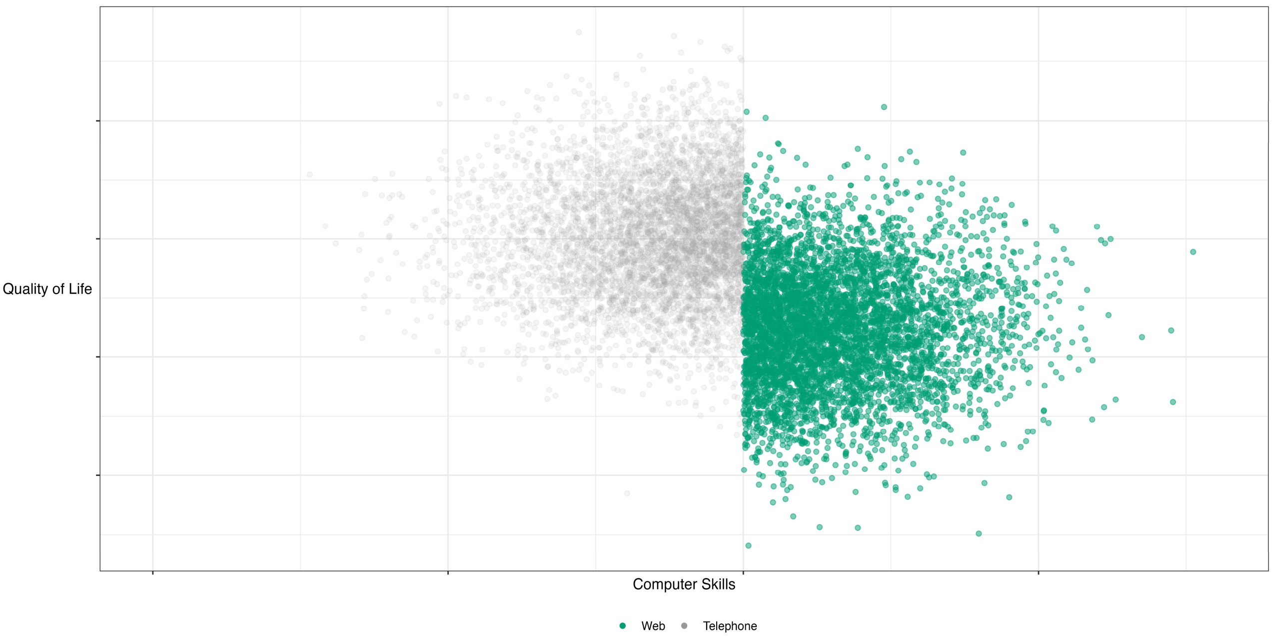
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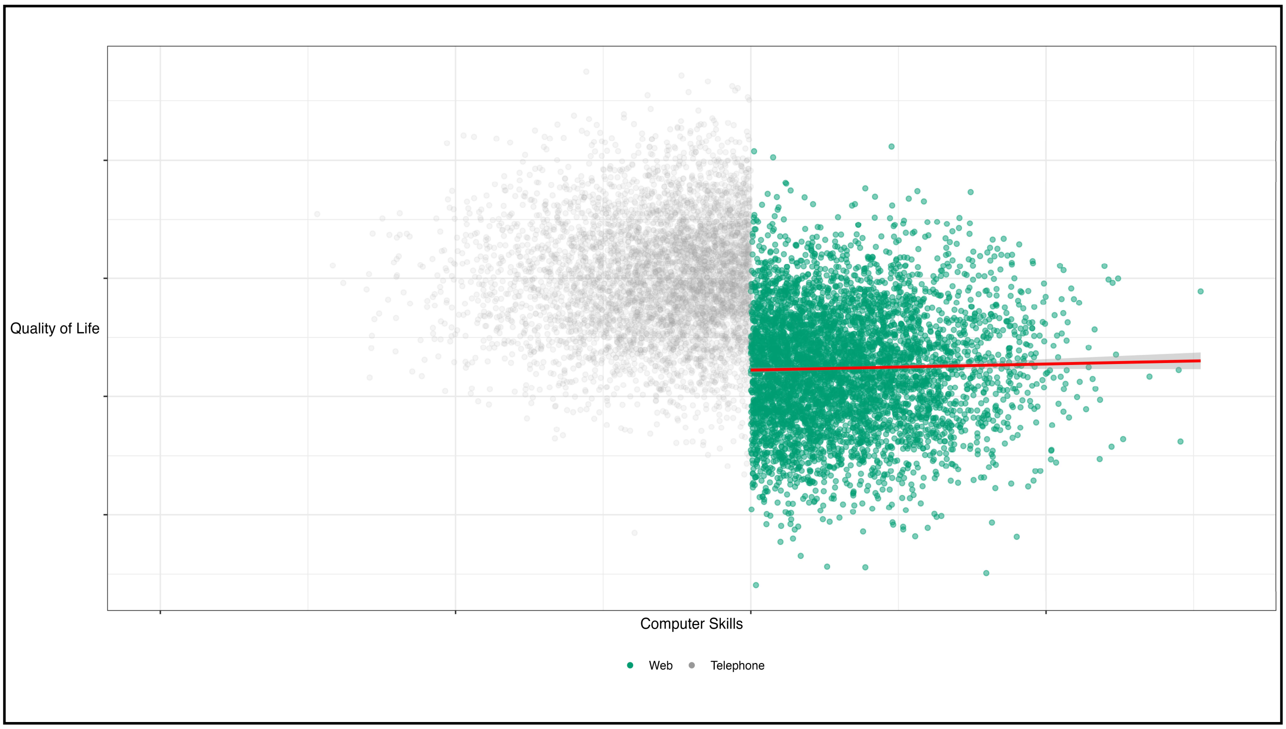
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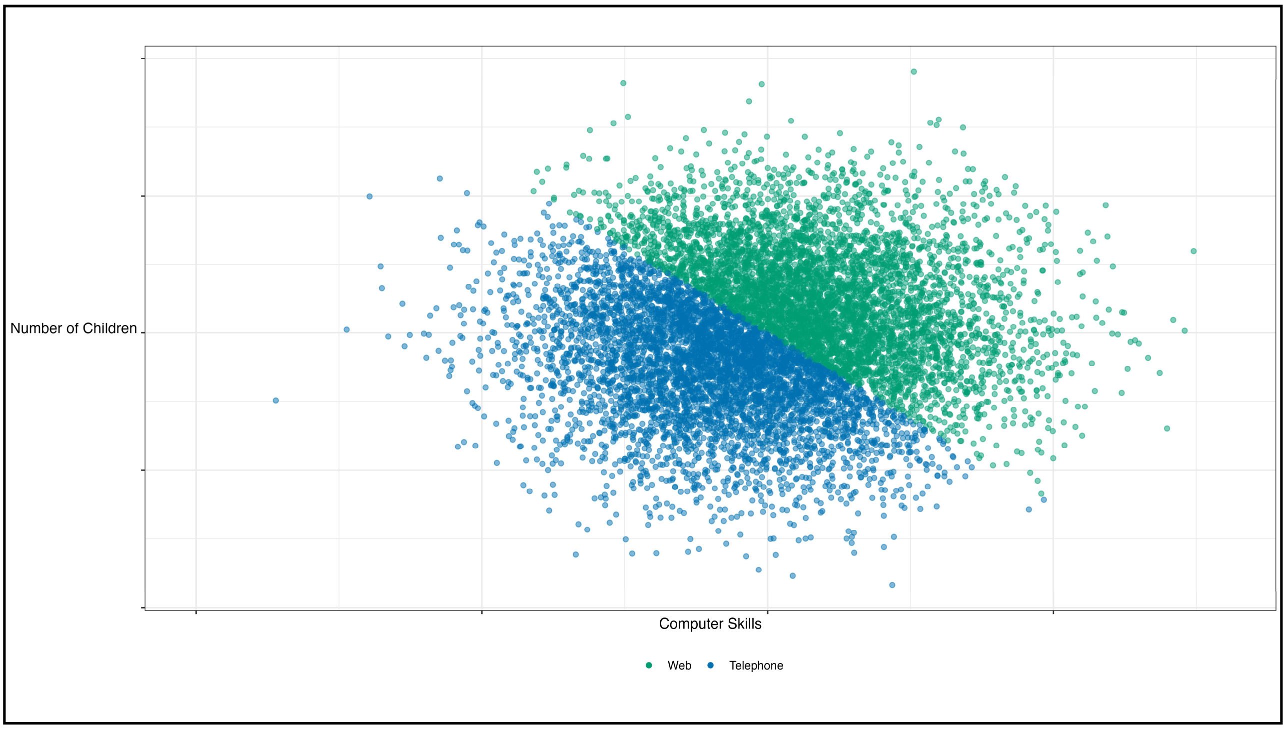
Number of Children
Computer Skills
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Number of Children
Computer Skills
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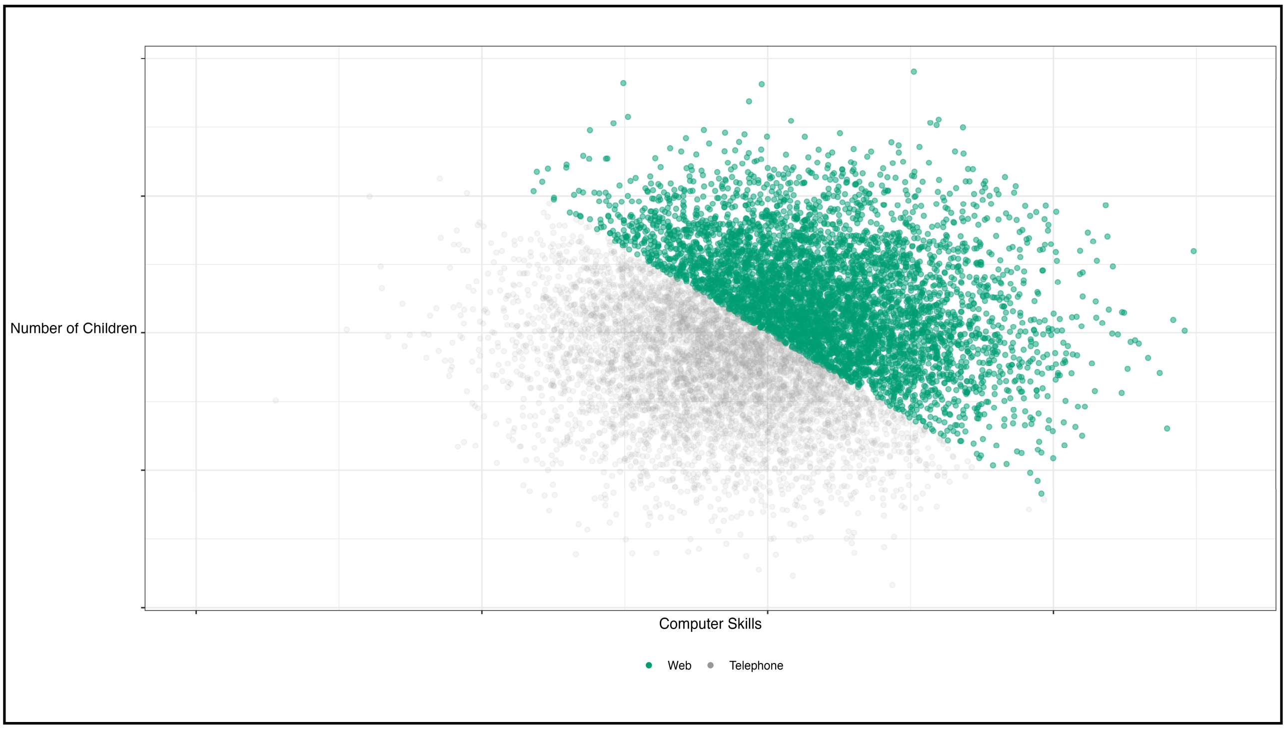
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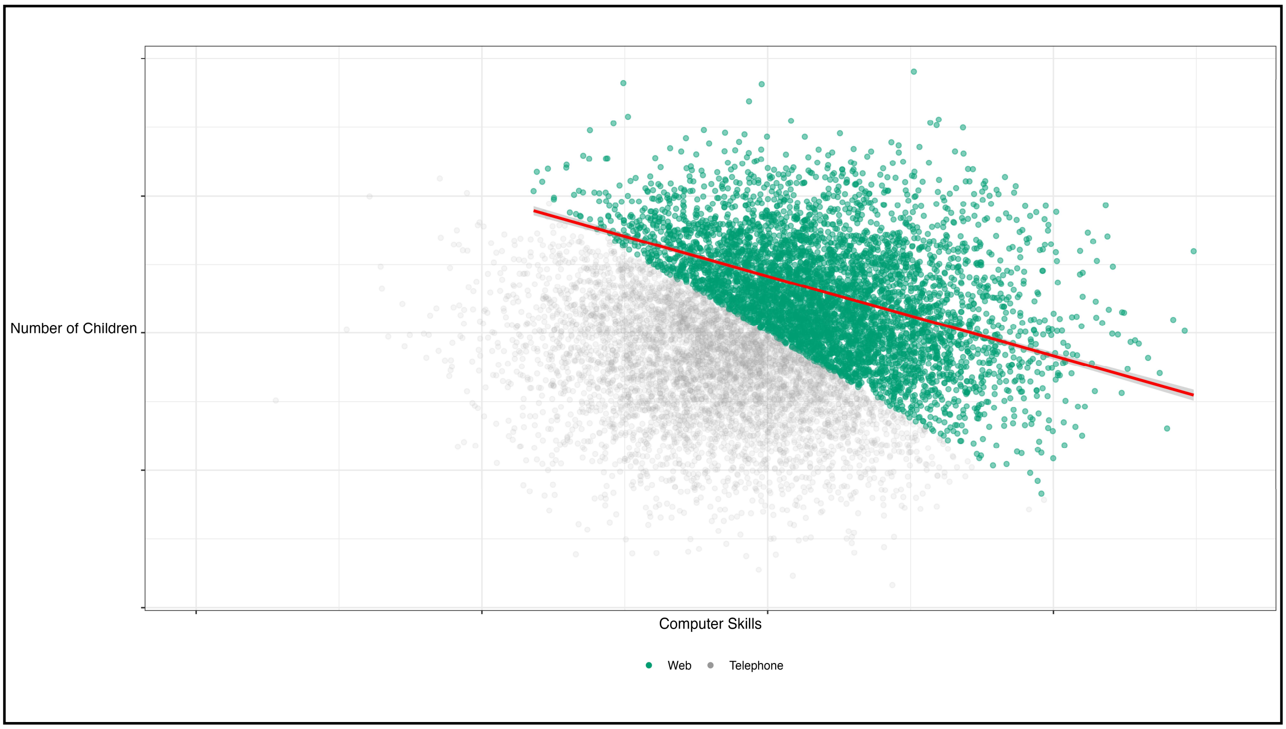

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Outline of Workshop

- 12.15 – 12.50: Conceptualising Mode Effects with DAGs (GDT)
- 12.50 – 12.55: Q&A on DAGs
- 12.55 – 13.15: Standard Methods for Handling Mode Effects (RJS)
- 13.15 – 13.35: Quantitative Bias Analysis for Mode Effects (LW)
- 13.35 – 14.00: Q&A

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Conceptualising Mode Effects using DAGs

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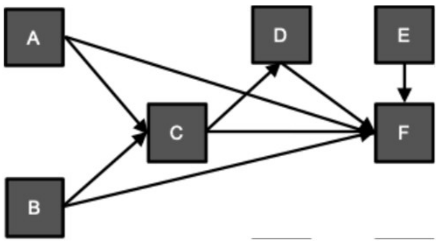
Directed acyclic graphs (DAGs)

- DAGs are a type of causal diagram
- They are representations of (hypothesised) causal relationships between variables
- Useful for both applied and methodological research



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DAGs in applied research

- In experimental data, randomisation ensures groups have the same probability of the outcome at baseline
- In observational data, we try to achieve this via statistical control (e.g. adjustment for confounders)
- DAGs can help us select the most appropriate adjustment set

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DAGs in methodological research

- DAGs have also helped explain many methodological issues

ORIGINAL ARTICLE

A Structural Approach to Selection Bias

Hernán, Miguel A.[*]; Hernández-Díaz, Sonia[†]; Robins, James M.[*]

Author Information

Epidemiology 15(5):p 615-625, September 2004. | *DOI:* 10.1097/01.ede.0000135174.63482.43

The Table 2 Fallacy: Presenting and Interpreting Confounder and Modifier Coefficients

Daniel Westreich[*] and Sander Greenland

[*] Correspondence to Dr. Daniel Westreich, Department of Obstetrics and Gynecology, Duke Global Health Institute, Duke University, DUMC 3967, Durham, NC 27710 (e-mail: daniel.westreich@duke.edu).

Initially submitted January 13, 2012; accepted for publication October 11, 2012.

The Birth Weight "Paradox" Uncovered?

Sonia Hernández-Díaz[1,2], Enrique F. Schisterman[3], and Miguel A. Hernán[1]

[1] Department of Epidemiology, Harvard School of Public Health, Boston, MA.
[2] Slone Epidemiology Center, Boston University, Boston, MA.
[3] Epidemiology Branch, National Institute of Child Health and Human Development, Bethesda, MD.

Received for publication February 7, 2005; accepted for publication January 23, 2006.

Article | Open access | Published: 12 November 2020

Collider bias undermines our understanding of COVID-19 disease risk and severity

Gareth J. Griffith, Tim T. Morris, Matthew J. Tudball, Annie Herbert, Giulia Mancano, Lindsey Pike, Gemma C. Sharp, Jonathan Sterne, Tom M. Palmer, George Davey Smith, Kate Tilling, Luisa Zuccolo, Neil M. Davies & Gibran Hemani

Nature Communications 11, Article number: 5749 (2020) | Cite this article

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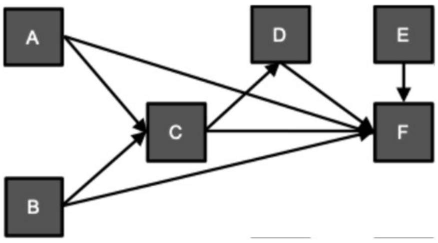
DAGs

Graphical representations of (hypothesised) causal relationships between variables, where:

- Variables represented as 'nodes' (e.g. A - F)
- Causal effects represented as directed 'arcs' (arrows)



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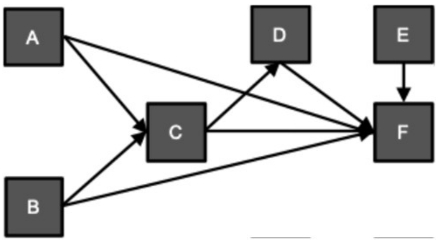
DAGs

- 'Directed', i.e. explicitly depicting direction over time
- 'Acyclic', i.e. no circular paths
- Non-parametric, i.e. do not consider the strength, sign direction, or shape
- Probabilistic, e.g. A changes the probability of C
  (but A is not necessary or sufficient for C)



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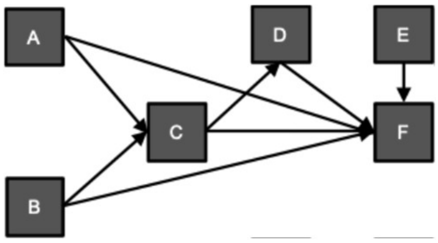
Paths

A path exists between two variables if they are connected by one or more arcs (regardless of direction)
e.g. A → C → F
e.g. D → F ← E

- Open paths transmit associations (dependencies)
- Closed paths do not



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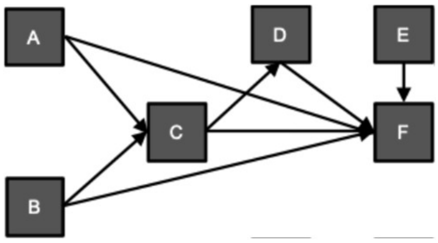
Causal paths

A causal (or directed) path exists where all arcs run in the same direction
e.g. A → C → D → F

The path can be closed by conditioning (controlling, adjusting) for a variable on the path
e.g. conditioning on C will close the path



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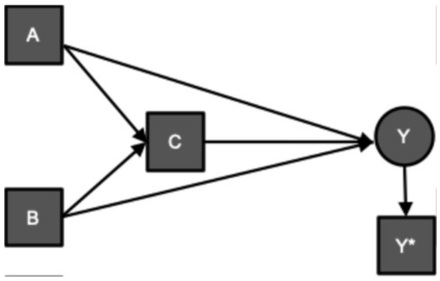
DAGs for measurement

With additional notation, DAGs can also be modified to depict measurement error:

- Latent variables represented by ellipses (or circles)
- Observed variables by squares

e.g. Y* is a measure of the latent Y



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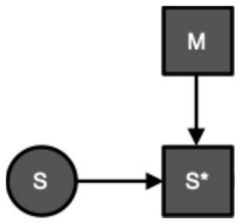
Mode effects

Mode effects can be understood as a form of systematic measurement error

e.g. a measure of smoking (S*) will have variation introduced by the survey mode (M)



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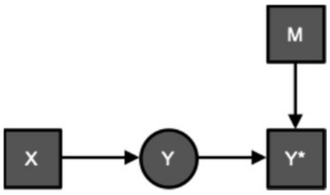
Mode effect on outcome

Such measurement error may have consequences for analyses

Example: occupation (X) and smoking (Y)

This may introduce error in the observed association



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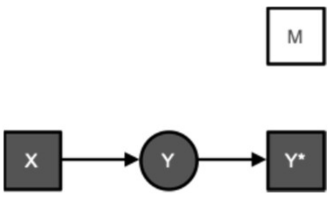
Mode effect on outcome

Such measurement error may have consequences for analyses

Example: occupation (X) and smoking (Y)

This may introduce error in the observed association

Controlling for mode (M) will resolve this



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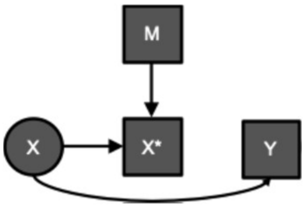
Mode effect on exposure

Such measurement error may have consequences for analyses

Example: smoking (X) and stroke (Y)

This may introduce bias (typically dilution) in the observed association



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Mode effect on exposure

Such measurement error may have consequences for analyses

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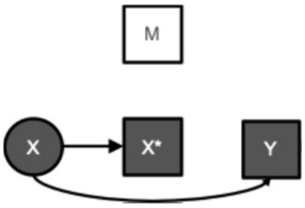

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Mode effect on both exposure and outcome

Often, mode effects may affect both the exposure and outcome,
e.g. anxiety and smoking

This introduce (mode-)dependent measurement error

We can conceptualise mode as a source of confounding

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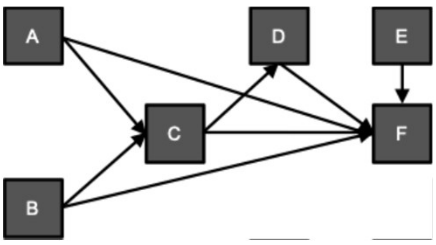
Confounding paths

A confounding (or 'backdoor') path is a type of non-causal path

e.g. in the path C ← B → F

B is a common cause of C and F and will create a non-causal association between C and F



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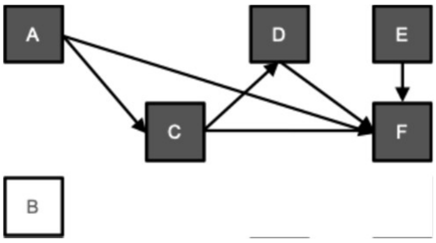
B is a common cause of C and F and will create a non-causal association between C and F

Confounding paths can be closed by conditioning



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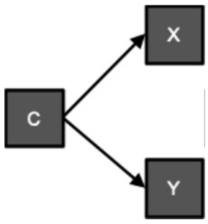
Confounding

In observational data, ice cream (X) consumption is associated with incidence of shark attacks (Y)

This is because weather (C) is a common cause, introducing confounding



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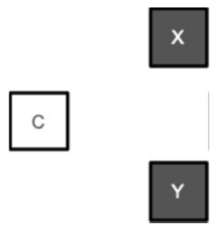
Confounding

In observational data, ice cream consumption (X) is associated with incidence of shark attacks (Y)

This is because weather (C) is a common cause, introducing confounding

Controlling for C will close the confounding path



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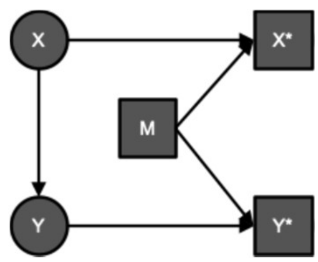
Mode as a confounder

Example: anxiety (X) and smoking (Y)

Both may be subject to mode effects, i.e. their observed association may be confounded by mode (M)



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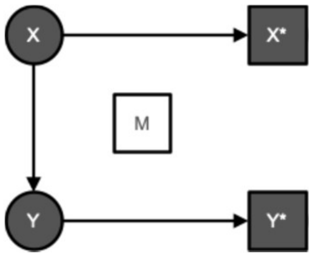
Mode as a confounder

Example: anxiety (X) and smoking (Y)

Both may be subject to mode effects, i.e. their observed association may be confounded by mode (M)

Controlling for mode will close this confounding path



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Mode selection

Reminder:
mode effects (***how*** people respond) are distinct from mode selection (***who*** responds)

Mode selection can be affected by a variety of factors, including the latent exposure and outcome themselves

Mode selection must be considered carefully before deciding to control for mode

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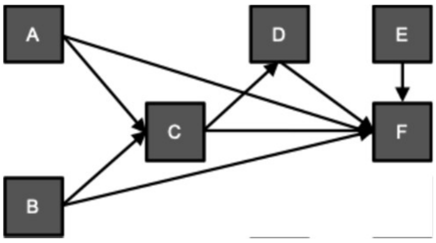
Collider paths

A collider path is another type of non-causal path

e.g. in the path D → F ← E

F is a collider of D and E

Collider paths are closed and therefore do not automatically introduce any bias



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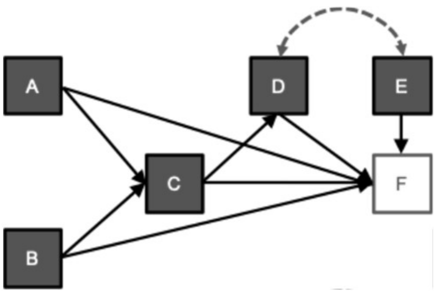
Collider paths

But they can be opened by conditioning (controlling) for the collider

e.g. conditioning on F will open the path D → F ← E and introduce a spurious association between D and E

This is known as 'collider bias'



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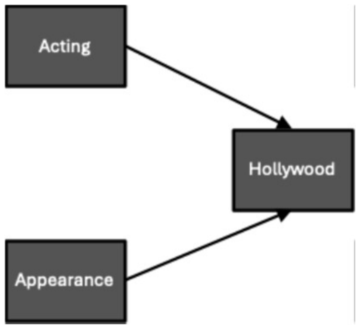
Collider bias

Two reasons why someone may become a Hollywood star:
acting ability and physical appearance



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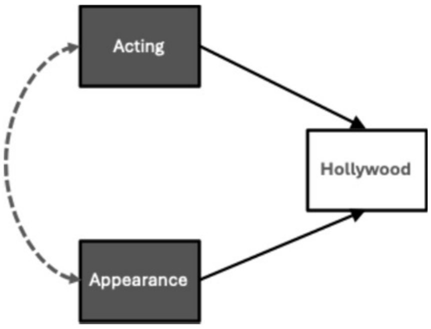
Collider bias

Two reasons why someone may become a Hollywood star:
acting ability and physical appearance

Conditional on being a Hollywood actor, there will appear to be a negative association between the two



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Collider bias

The 'obesity paradox' is a counter-intuitive finding that obesity results in lower mortality among people with chronic conditions

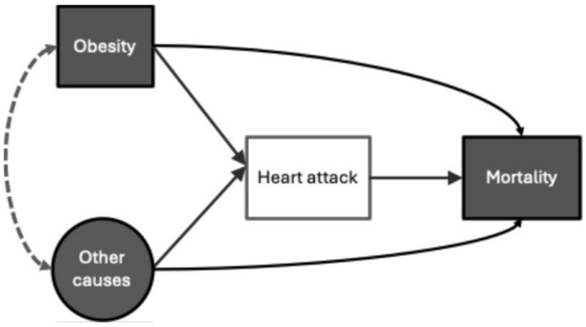
Although a combination of several biases, collider bias is one of them

Collider bias

In a sample of people who have experienced a heart attack
(i.e. conditional on heart attack)

There will be a spurious association between obesity and all other cause of heart attack

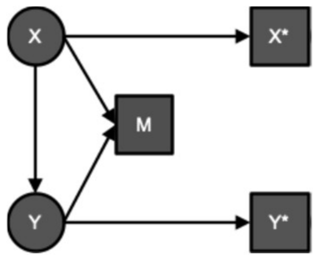
This may make obesity appear protective



Collider bias: survey mode

Example: years of education (X) and frequency of internet use (Y)

Both will likely be related to participation via a certain mode



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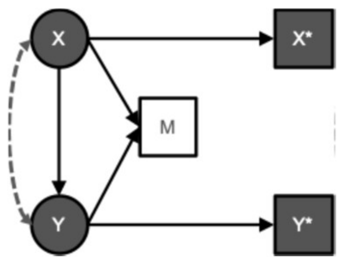
Collider bias: survey mode

Example: years of education (X) and frequency of internet use (Y)

Both will likely be related to participation via a certain mode

Naïve conditioning on mode might introduce collider bias



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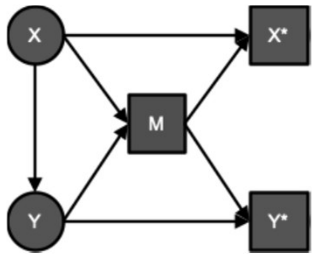
Mode effects and mode selection

Example: depression (X) and alcohol intake (Y)

Both are likely subject to mode effects and a source of mode selection



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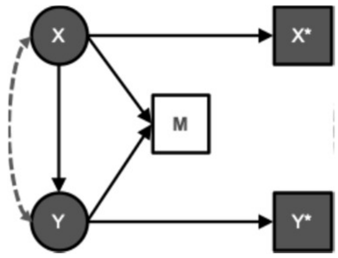
Mode effects and mode selection

Example: depression (X) and alcohol intake (Y)

Both are likely subject to mode effects and a source of mode selection

Controlling for mode (M) may resolve one problem but introduce another



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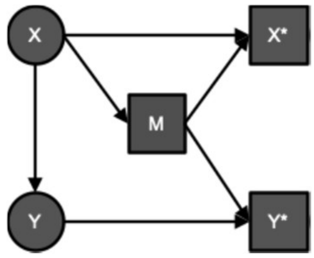
Mode effects and mode selection

Example: depression (X) and fruit & veg intake (Y)

Fruit & veg unlikely to cause mode selection



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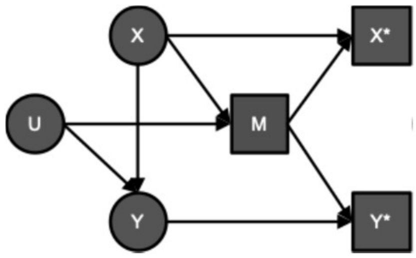
Mode effects and mode selection

Example: depression (X) and fruit & veg intake (Y)

Fruit & veg unlikely to cause mode selection

But other variables (U) may be causes of both mode (M) and fruit & veg intake (Y)



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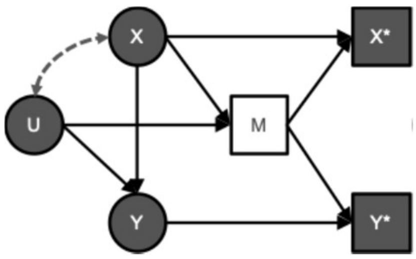
Mode effects and mode selection

Example: depression (X) and fruit & veg intake (Y)

Fruit & veg unlikely to cause mode selection

But other variables (U) may be causes of both mode (M) and fruit & veg intake (Y)

Collider bias is still possible



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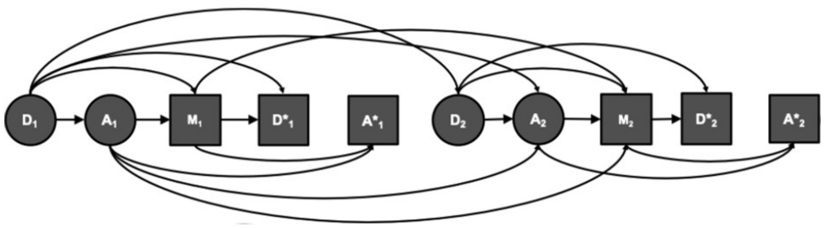
Longitudinal analyses



Example: depression (D_T) and Alcohol intake (A_T) over time

- Mode may change over time
- What is the research question? – this will determine the most appropriate action
- In most cases, conditioning on mode might lead to collider bias, while not conditioning might lead to confounding bias

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Summary

The presence of mode effects and/or mode selection will be context-specific

Where mode effects occur without mode selection, any consequences can be reduced by controlling for mode

In the presence of mode selection, controlling for mode risks introducing bias, which may necessitate alternative approaches to handling mode effects

DAGs are very helpful tools for reasoning about this

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Standard Methods for Handling Mode Effects

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Standard methods for handling mode effects

1. Statistical control
2. Multiple imputation

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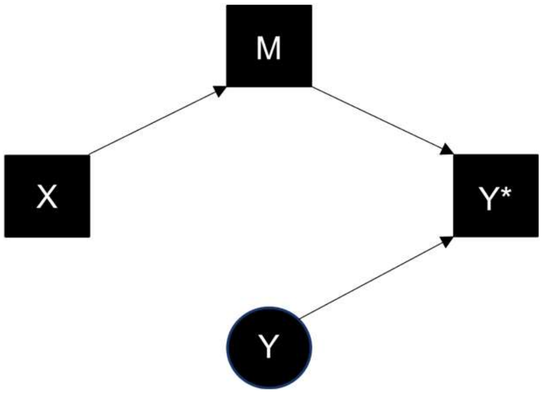
Statistical control

- Where the aim is to obtain an estimate of the effect of an exposure on an outcome, it may be possible to account for mode effects using control variables.
- Where there is no relevant mode selection, this could simply involve adding an indicator variable for mode to the substantive model (or, alternatively, stratifying by mode).

62

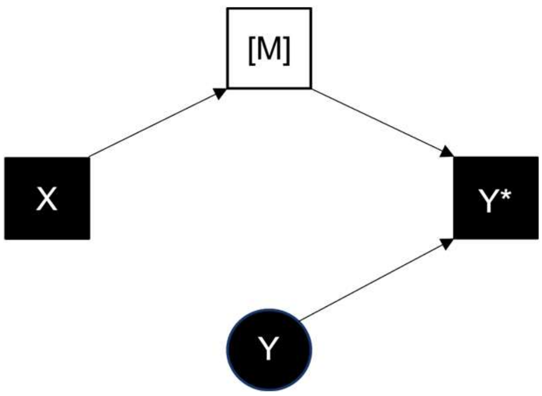
Statistical control – Example 1



Spurious association between X and Y* due to M.

63

Statistical control – Example 1



Regress Y* on X **controlling for M**.

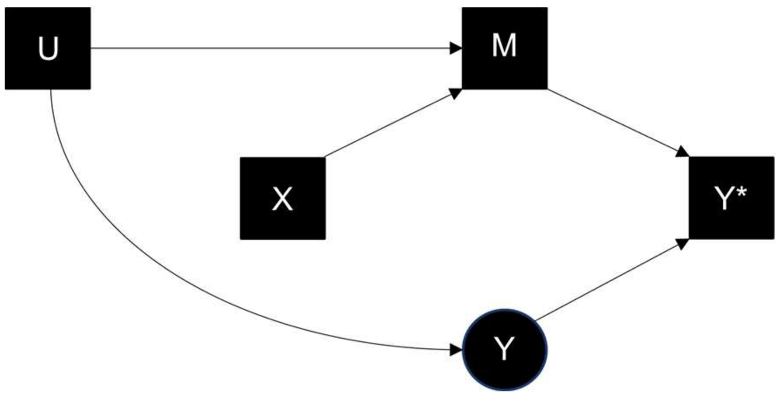
64

Statistical control

- However, where there is mode selection according to a relevant variable, accounting for mode alone may not be sufficient and could even increase bias.
- In this case, a larger set of control variables may be required.

65

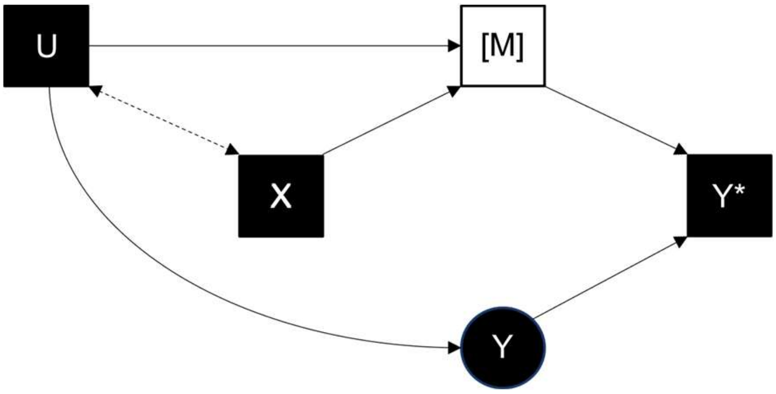
Statistical control – Example 2



Spurious association between X and Y* due to M.

66

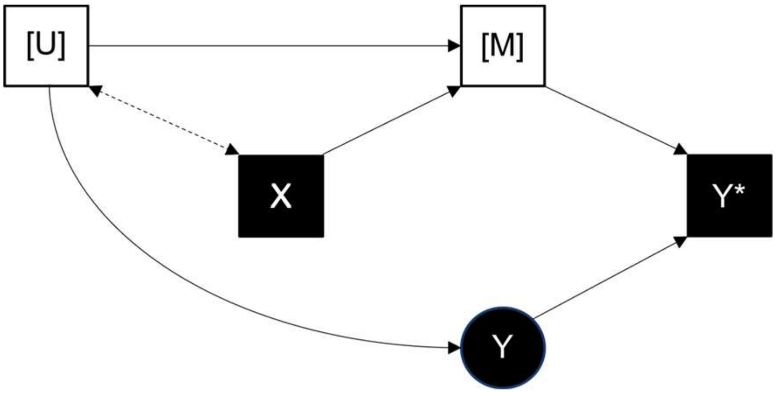
Statistical control – Example 2



Regress Y* on X controlling for M?

67

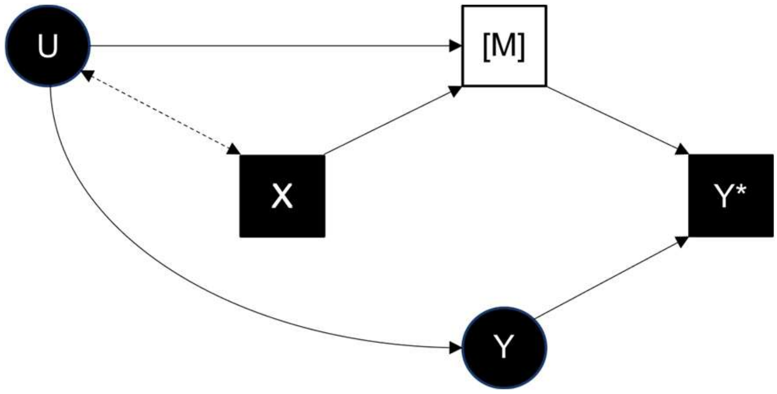
Statistical control – Example 2



Regress Y* on X controlling for M **and also U**.

68

Statistical control – Example 2

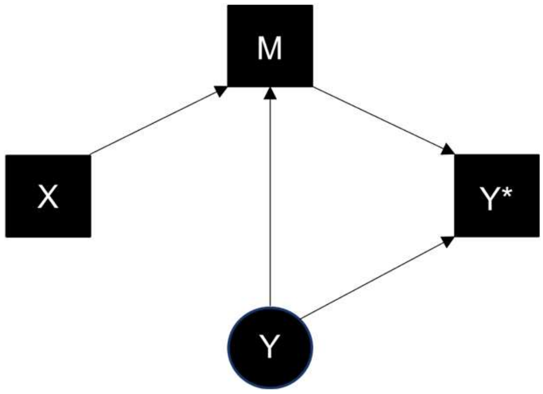


But what if U is **unobserved**?

Statistical control

- It is possible that the required set of control variables does not or could not exist in the data (e.g. if Y is both subject to mode effects and a source of mode selection).

Statistical control – Example 3



Regression of Y* on X biased whether controlling for M or not.

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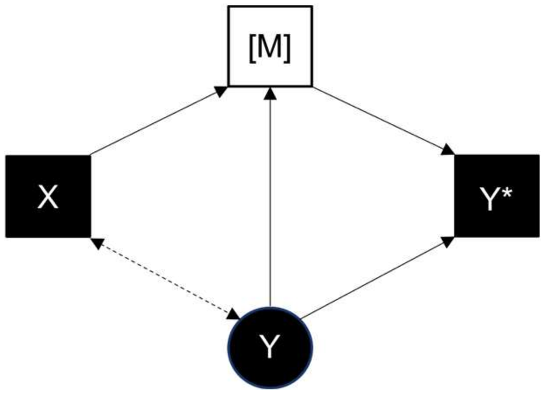
Statistical control – Example 3



Regression of Y* on X biased whether controlling for M or not.

72

Statistical control

- Can instead estimate the mode effect and use this to predict counterfactuals for those observed in the alternate mode.
- Then analyse as if observed.
- (Bootstrap the whole thing to appropriately incorporate uncertainty.)

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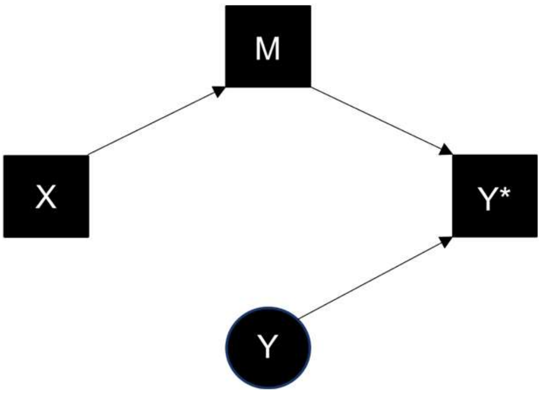
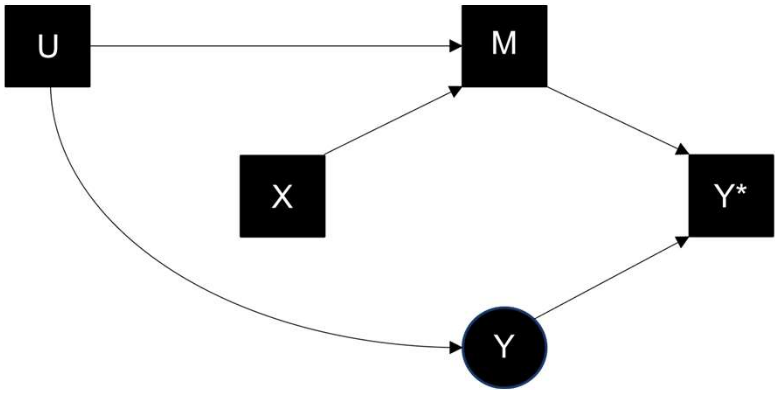
Statistical control – Example 1



Regressing Y* on M gives an unbiased estimate of the mode effect.

74

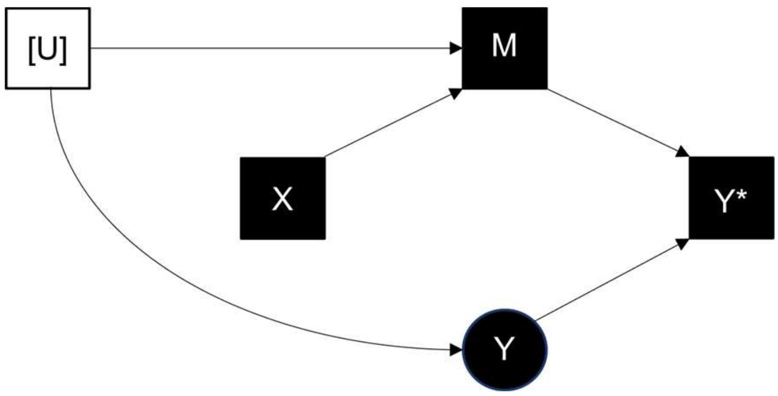
Statistical control – Example 2



Estimated mode effect now confounded by U.

75

Statistical control – Example 2



Regress Y* on M **controlling for U**.

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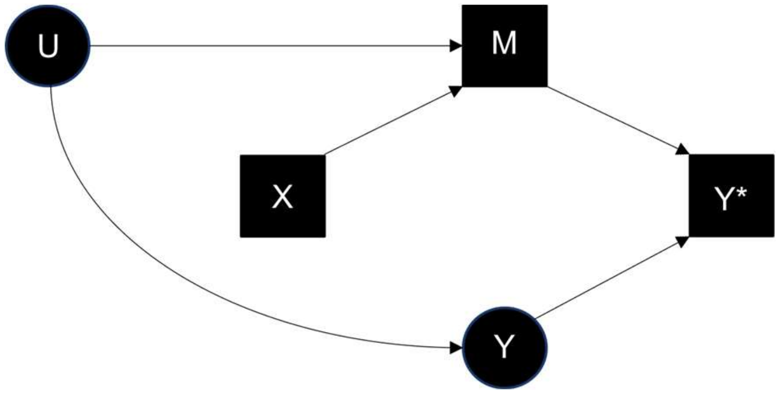
Statistical control – Example 2



If U **unobserved** then can't remove confounding.

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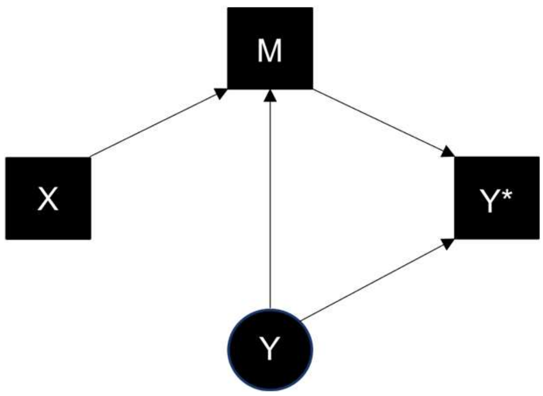
Statistical control – Example 3



Regression of Y* on M confounded by (unmeasured) Y.

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Statistical control

Advantages	Disadvantages
• Straightforward method, easily understood and implemented. • Given the richness of variables captured in large social surveys, the required set of control variables (or something sufficiently approximating it) may be available.	• Strong assumption that mode selection correctly accounted for. • Required set of control variables may be unknown, unmeasured, or poorly measured, meaning bias persists. • Adjusting for causes of mode selection may change the interpretation of the estimate being produced.

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Multiple imputation

- Values of variables hypothesized to exhibit mode effects are artificially set to missing for individuals in the alternate survey mode(s).
- Predictive models are developed based on data from those in the reference survey mode.
- Predictive models applied to data for those in the alternate survey mode to generate counterfactuals.
- ‘Completed’ dataset then used to provide descriptive statistics or analysed in substantive regression models.

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Multiple imputation

- Multiple imputed datasets generated by this procedure.
- Each imputed dataset analysed using the substantive model then estimates pooled to obtain standard errors that account for uncertainty inherent in the imputation process.

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Multiple imputation - Example

- A battery of mental health questions were asked by telephone (which used an interviewer) and web (which was anonymous).

id	mode	sum
1	tel	9
2	tel	17
3	web	14
4	web	22
5	tel	15
...	...	...

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Multiple imputation - Example

- Develop imputation model for sum score among web respondents.

sum ~ gender + social class + health + education + cognitive ability

id	mode	sum	gender	sc	health	ed	cog
1	tel	9	1	3	2	2	-0.5
2	tel	17	1	1	2	1	0.7
3	web	14	2	2	3	1	0.4
4	web	22	2	2	4	2	1.4
5	tel	15	1	4	5	3	-0.8
…	…	…	…	…	…	…	…

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Multiple imputation - Example

- Values of sum score artificially set to missing for telephone respondents.

id	mode	sum	gender	sc	health	ed	cog
1	tel	.	1	3	2	2	-0.5
2	tel	.	1	1	2	1	0.7
3	web	14	2	2	3	1	0.4
4	web	22	2	2	4	2	1.4
5	tel	.	1	4	5	3	-0.8
…	…	…	…	…	…	…	…

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Multiple imputation - Example

- Apply predictive model to data for telephone respondents, imputing counterfactual sum score.

id	mode	sum	gender	sc	health	ed	cog
1	tel	11	1	3	2	2	-0.5
2	tel	18	1	1	2	1	0.7
3	web	14	2	2	3	1	0.4
4	web	22	2	2	4	2	1.4
5	tel	18	1	4	5	3	-0.8
…	…	…	…	…	…	…	…

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Multiple imputation - Example

- Repeat process to create multiple imputed datasets.

id	mode	sum	gender	sc	health	ed	cog
1	tel	8	1	3	2	2	-0.5
2	tel	16	1	1	2	1	0.7
3	web	14	2	2	3	1	0.4
4	web	22	2	2	4	2	1.4
5	tel	14	1	4	5	3	-0.8
…	…	…	…	…	…	…	…

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Multiple imputation - Example

- Analyse each imputed dataset using the substantive model of interest.
- Pool estimates using standard rules to obtain appropriate standard errors.

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Multiple imputation

Advantages	Disadvantages
• Increasingly commonly used so may already be familiar to researchers. • Easy-to-use functionality in major statistical software. • Straightforward to implement for a wide variety of variable types. • Can combine with MI for missing data handling.	• Does not use information from the observed values in the alternate mode(s) – potentially very wasteful. • Strong assumption that data are 'missing at random' (MAR): conditional on the variables used, answering in the alternate mode is not informative about the value of the variables to be imputed – equivalent to requiring that mode selection is correctly accounted for.

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Quantitative Bias Analysis for Mode Effects

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Quantitative Bias Analysis (QBA)

- QBA refers to a collection of methods designed to incorporate or output **quantitative** information on sensitivity of an estimate to bias.
- QBA methods span:
  - Application to summary statistics (e.g., regression coefficients) or to record-level data (i.e., observations)
  - Provide bounds on bias to explain an association or generate bias-corrected estimate
  - Account for information, confounding and/or selection biases
  - Use deterministic or probabilistic and single- or multi-dimensional inputs.
- For more, see (e.g.): Fox et al. (2021), Keogh et al. (2020), Shaw et al. (2020), Cinelli & Hazlett (2020)

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Counterfactual Simulation

- Counterfactual Simulation: Correct observed data for assumed mode effect
- Advantages:
  - Uses information that's available
  - May not require assumptions about mode selection
  - Lots of experimental evidence to use (Tomova et al., 2026)
  - Implausible assumptions also useful!

ID	Mode	CASP-6	Degree
1	TEL	4	0
2	WEB	5	1
3	TEL	5	1
4	WEB	7	0
5	TEL	3	0
6	WEB	6	0
...	...	...	...

Tomova, G., et al., 'Mode Effects on Survey Item Measurement', Survey Futures Working Paper 12, 2016.
https://surveyfutures.net/wp-content/uploads/2026/01/working-paper-12-mode-effects-on-survey-item-measurement.pdf

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1	TEL	4	0	
2	WEB	5	1	
3	TEL	5	1	
4	WEB	7	0	
5	TEL	3	0	
6	WEB	6	0	
...	...	...	...	...

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ID	Mode	CASP-6	Degree	Sim
1	TEL	4	0	
2	WEB	5	1	**5**
3	TEL	5	1	
4	WEB	7	0	**7**
5	TEL	3	0	
6	WEB	6	0	**6**
…	…	…	…	**…**

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ID	Mode	CASP-6	Degree	Sim
1	TEL	4	0	***3***
2	WEB	5	1	**5**
3	TEL	5	1	***4***
4	WEB	7	0	**7**
5	TEL	3	0	***2***
6	WEB	6	0	**6**
…	…	…	…	…

Tomova, G., et al., 'Mode Effects on Survey Item Measurement', Survey Futures Working Paper 12, 2016.
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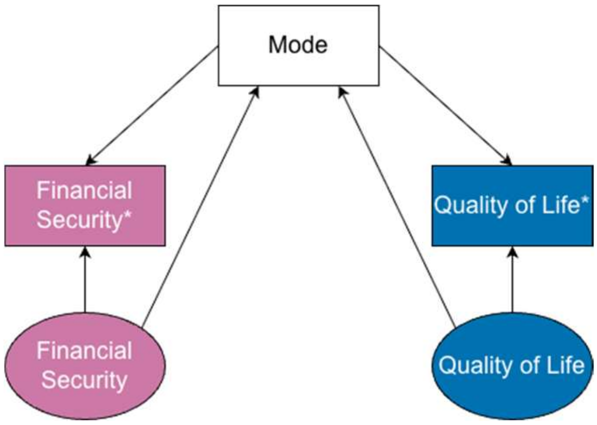

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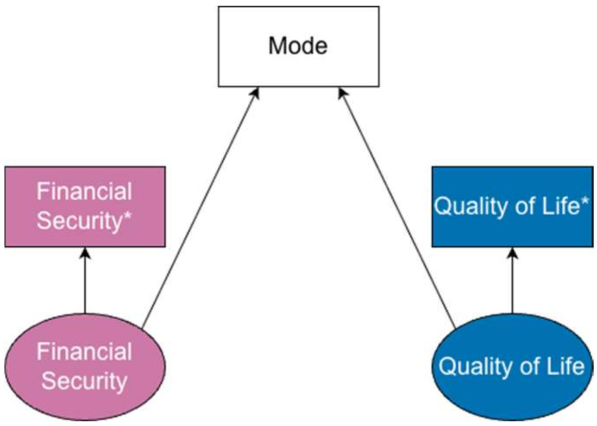

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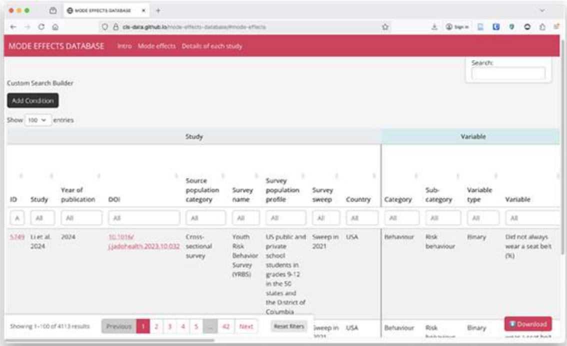

https://cls-data.github.io/mode-effects-database/

Tomova, G., et al., 'Mode Effects on Survey Item Measurement', Survey Futures Working Paper 12, 2016.
https://surveyfutures.net/wp-content/uploads/2026/01/working-paper-12-mode-effects-on-survey-item-measurement.pdf

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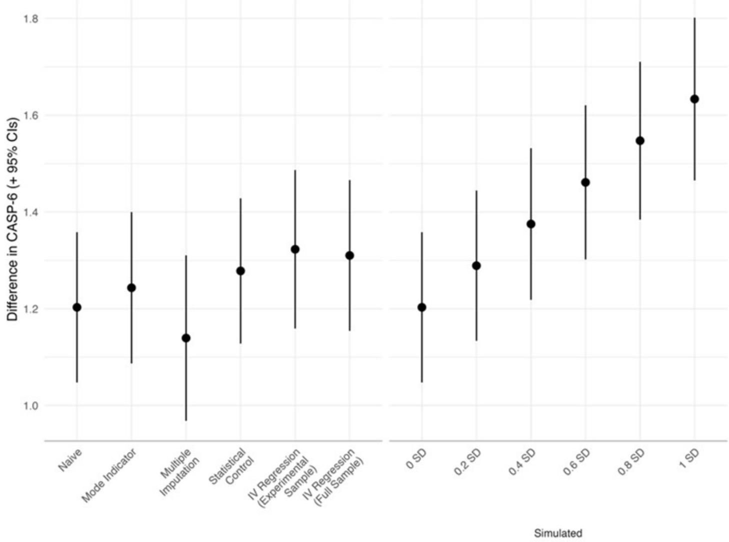
Counterfactual Simulation: Example



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Counterfactual Simulation: Limitations

- Doesn't work easily for non-continuous variables
  - e.g., for binary variables, may need negative predictive value (NPV) or similar, which require assumptions about underlying prevalence.
- But ...
  - Can assume implausible values for these, too.
  - VanderWeele & Li (2019) develop simple sensitivity analysis for differential measurement error in binary variables.

$$NPV = P(Depressed = 0 \mid Depressed^{*} = 0)$$

$$= \frac{Specificity\,(1-Prevalenc\ \ )}{(1-Sensitivit\ \ )\cdot Prevalence + Specificity\cdot(1-Prevalenc\ \ )}$$

VanderWeele, T. J., & Li, Y. 'Simple Sensitivity Analysis for Differential Measurement Error'. American Journal of Epidemiology, 2019. https://doi.org/10.1093/aje/kwz133

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Simple Sensitivity Analysis

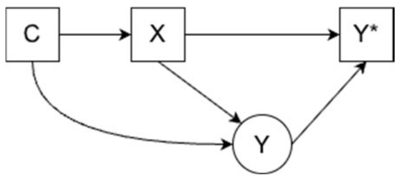
VanderWeele & Li (2019) observe ...

Where $RR_{XY^*} \geq 1$, to explain association:

- $RR_{XY^*} \leq$ Sensitivity(X = 1)/ Sensitivity(X = 0)

OR ...

- $RR_{XY^*} \leq$ False Positive Probability(X = 1)/ False Positive Probability(X = 0)



VanderWeele, T. J., & Li, Y. 'Simple Sensitivity Analysis for Differential Measurement Error'. American Journal of Epidemiology, 2019. https://doi.org/10.1093/aje/kwz133

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Where $RR_{XY^*} \geq 1$, to explain association:

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OR ...

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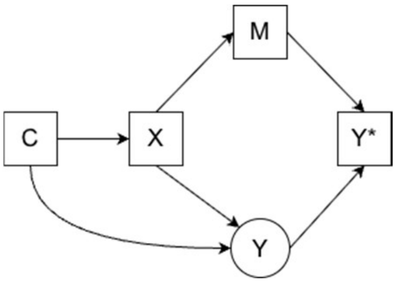

VanderWeele, T. J., & Li, Y. 'Simple Sensitivity Analysis for Differential Measurement Error'. American Journal of Epidemiology, 2019. https://doi.org/10.1093/aje/kwz133

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Simple Sensitivity Analysis

Sensitivity(X = 1) =

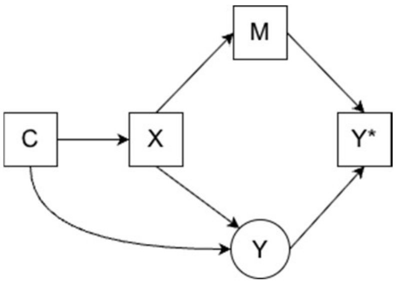
Sensitivity(M = 1) · Prob(M = 1 | X = 1) +

Sensitivity(M = 0) · Prob(M = 0 | X = 1)

Sensitivity(M = 0) ≤

Sensitivity(X = 1) ≤

Sensitivity(M = 1)



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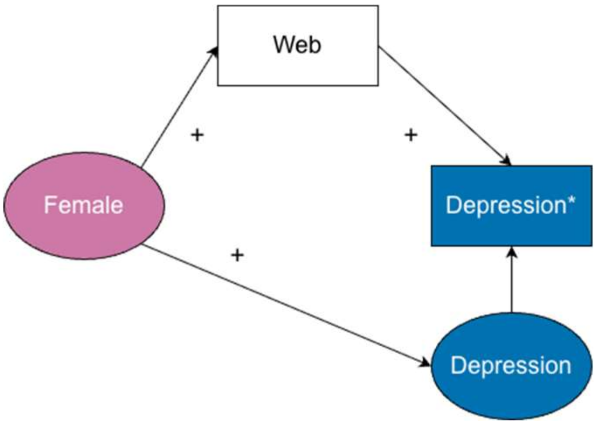
Worked Example: Next Steps Sweep 9

- RR(Depression* | Female) = 1.57 (95% CI = 1.45 – 1.71)
- RR(Web | Female) = 1.09
    - P(Web | Female) = 0.904
    - P(Web | Male) = 0.826
- Goodman et al. (2022): RR(Depression | Web) = 1.23
    - Sensitivity | Web = 1.00 (Assumption)
    - Sensitivity | Telephone = 1 / 1.23 = 0.813 (Corollary)
- Ratio of Sensitivities = 1.015
    - Sensitivity | Female = 1 * 0.904 + 0.813 * (1 – 0.904) = 0.982
    - Sensitivity | Male = 1 * 0.826 + 0.813 * (1 – 0.826) = 0.967



Goodman, A., et al. 'The Impact of Using the Web in a Mixed-Mode Follow-up of a Longitudinal Birth Cohort Study: Evidence from the National Child Development Study'. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 2022, https://doi.org/10.1111/rssa.12786.

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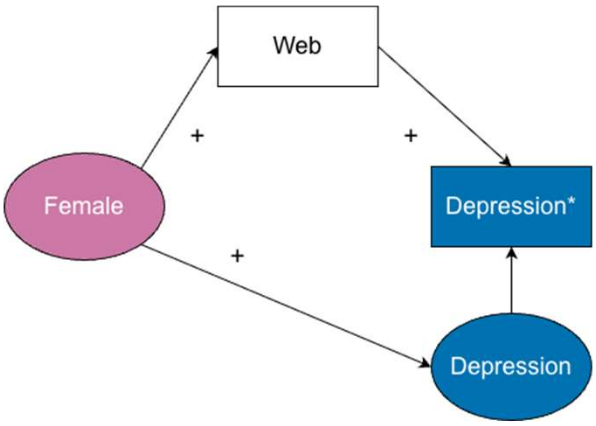
- RR(Web | Female) = 1.09
    - P(Web | Female) = 0.904
    - P(Web | Male) = 0.826
- Tipping Point: RR(Depression | Web) = ∞
    - Sensitivity | Web = 1.00 (Assumption)
    - Sensitivity | Telephone = 0.00 (Assumption)
- Ratio of Sensitivities = 1.094
    - Sensitivity | Female = 1 * 0.904 + 0 * (1 – 0.904) = 0.904
    - Sensitivity | Male = 1 * 0.826 + 0 * (1 – 0.826) = 0.826



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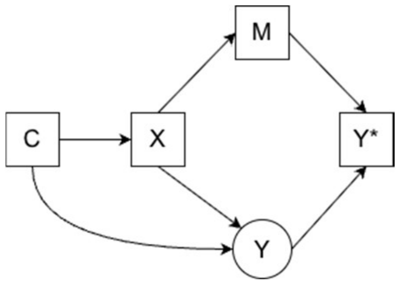
Mode Effects in Practice

- (Relative) bias depends on:
    - Association between X and Y absent mixed-mode
    - Prevalence of alternate mode
    - Extent of mode effect
    - Strength of mode selection



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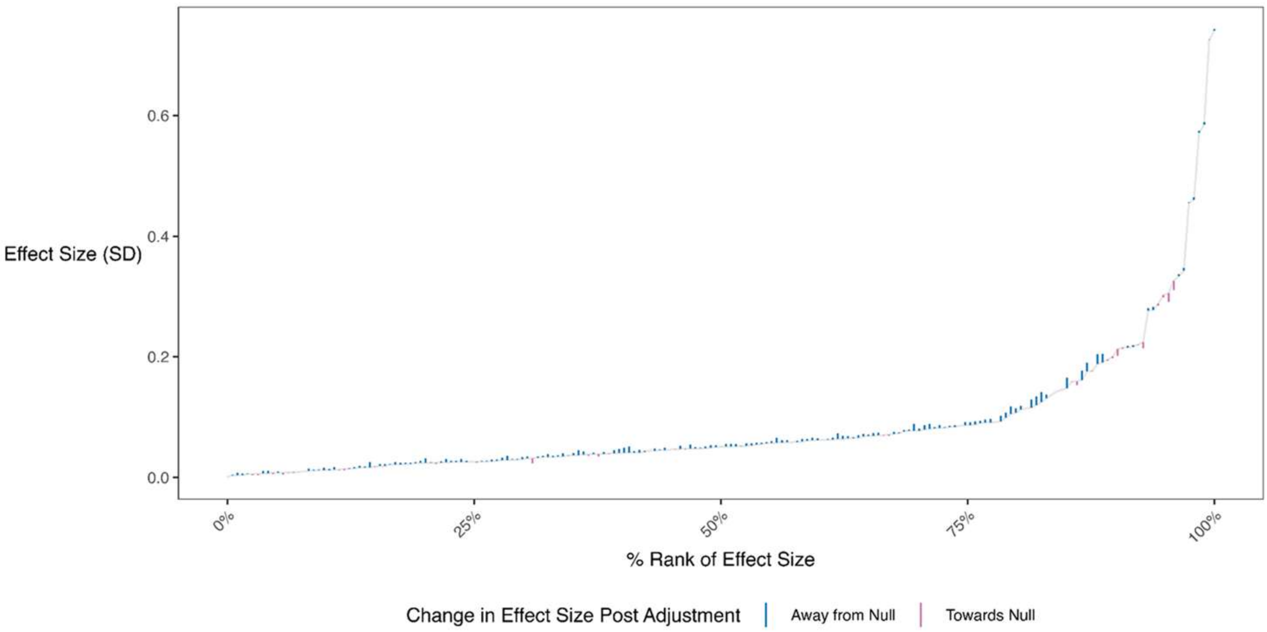

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Quantitative Bias Analysis: Advantages

- Detailed understanding of mode selection may not be required.
- Can sometimes use all available information, unlike MI.
- Flexible approach, e.g., heterogeneity in mode effects, multiple variables subject to mode effects, mixing modes between sweeps, multiplicative errors
- Simple sensitivity analysis can be performed *post hoc*

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Quantitative Bias Analysis: Disadvantages

- Plausible mode effects for a given situation may not be known (though, implausible *might* be).
- Estimation of mode effects from non-experimental data (if necessary) requires appropriate modelling of mode selection.
- No simple out-of-the-box functionality for performing general sensitivity analysis.

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Further Questions? liam.wright@ucl.ac.uk

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SURVEY FUTURES
SURVEY DATA COLLECTION METHODS COLLABORATION

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