ECCA 2022

Measurement Error in Police Recorded Crime Rates: Forms, Impact, and Adjustment

Recounting Crime

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- We are all aware of the problem, yet, we still use this data
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  - We normally include a few caveats and move on
- But can we really move on?
  - What are the specific implications of using this data?
  - How biased are our findings?
  - Should we keep publishing studies using police data?
  - Or are we simply polluting the evidence base?

The *Recounting Crime* Project

- In the *Recounting Crime* project, we seek to:
  - Explore the impact of measurement error in police data
  - I.e. how this types of errors can bias our findings
  - And suggest strategies to adjust for this problem
- We have started with a specific question
  - Police recorded crime rates used in linear regression models
  - We have not yet introduced a longitudinal or spatial dimension
  - Nor have we examined crime as individual events

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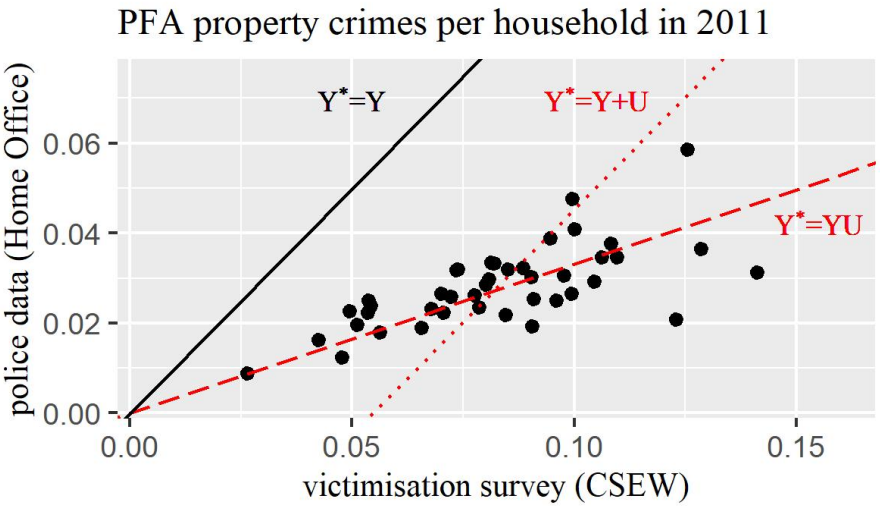
- To examine this proposition we compare police data (data.police.uk) and crime survey (CSEW) estimates
  - A flawed approach since it assumes the CSEW is a gold standard

Multiplicative Errors



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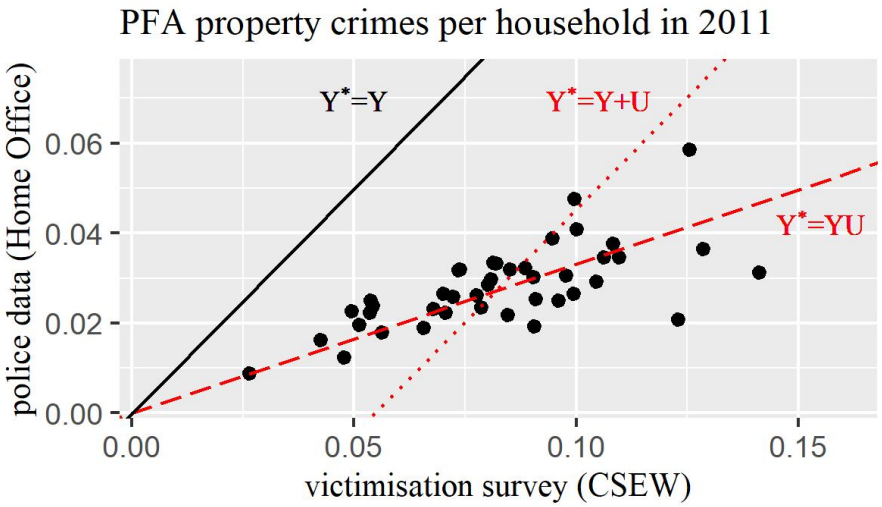

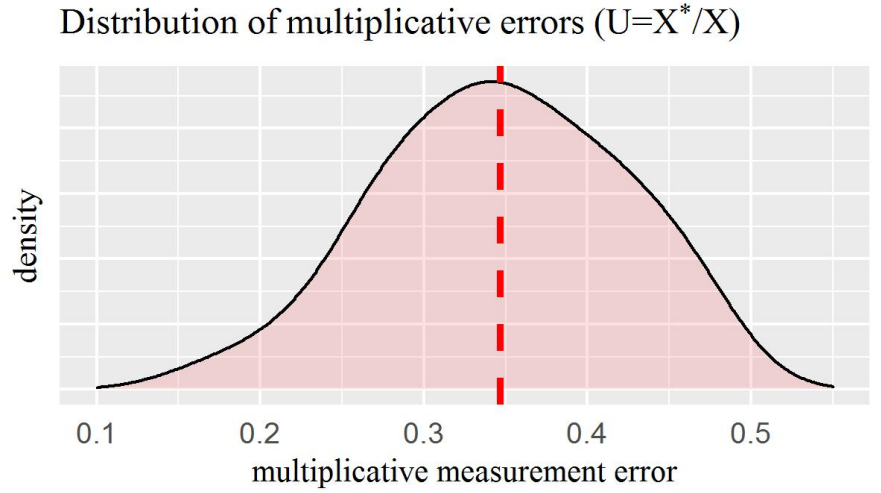

Impact of Measurement Error

- To estimate the impact of these errors we also need to consider how the error-prone variable is introduced in the model
- Let's take a linear model exploring causes of crime
  - $Y^* = \alpha + \beta_1 X_1 + \beta_2 X_2 + \epsilon$

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  - where, $Y^* = Y + U$, and $U \sim N(< 0, \sigma)$
  - $Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \epsilon - U$
  - Only the intercept is biased (upwards)

Hard to Anticipate Impacts

- When crime rates are used as the predictor we see different biases, harder to predict
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- In conclusion, it is hard to anticipate how the measurement error seen in police recorded crime rates will affect our findings
- Which is why we recommend employing sensitivity analysis

Sensitivity Analysis - *Recounting Crime*

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- Applicable to any outcome model over a wide range of measurement error mechanisms
  - Assumes multiplicative errors, but allows the user to define ranges of...
  - Systematic errors (S), i.e. under-recording
  - Random errors (R), i.e. recording inconsistencies
  - And differential errors (D), i.e. the correlation between measurement error and the variable of interest

Example of Sensitivity Analysis

- A linear model examining the effect of violent crime on perceptions of disorder, controlling for a few area characteristics
  - $Y = \alpha + \beta_1 X^* + \beta_k Z_k + \epsilon$
  - Variables referring to 345 English local authorities

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  - $Y = \alpha + \beta_1 X^* + \beta_k Z_k + \epsilon$
  - Variables referring to 345 English local authorities
- We estimate it first using police data (naive model), and we re-estimate it using adjusted crime rates (sensitivity analysis)
  - The adjusted crime rates: X^*/U
  - The measurement error term: $U = S + R + D \cdot Y$
  - We need to consider values for S (systematic error), R (random error), and D (differential errors)
  - which in some instances could be derived from victim surveys

The Naive Model

	outcome variable: perceptions of disorder	
	Using police data	Using adjusted data
constant	−0.67	
	(0.33)	
log(violent crime)	**0.27**	
	(0.13)	
% white British	−0.13	
	(0.06)	
% unemployment	0.28	
	(0.05)	
median age	−0.33	
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R^2	0.54	
N	345	

*Standard errors between parentheses

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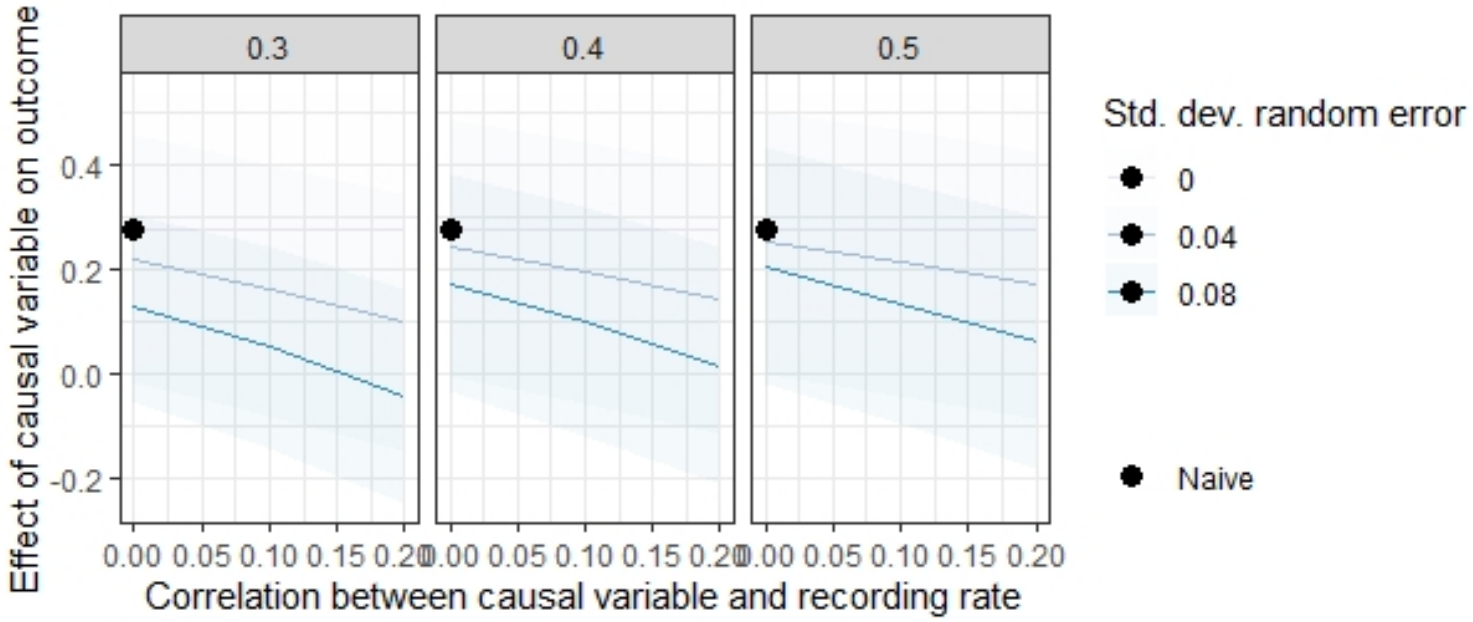
- Rather than using single measurement error parameters for the adjustment we suggest using ranges, e.g.
  - Range of systematic errors: $E(U) = (0.3, 0.4, 0.5)$
  - Range of random errors: $SD(U) = (0, 0.04, 0.08)$
  - Range of differential errors: $Cor(U, Y) = (0, 0.1, 0.2)$

The *Recounting Crime* Adjustment



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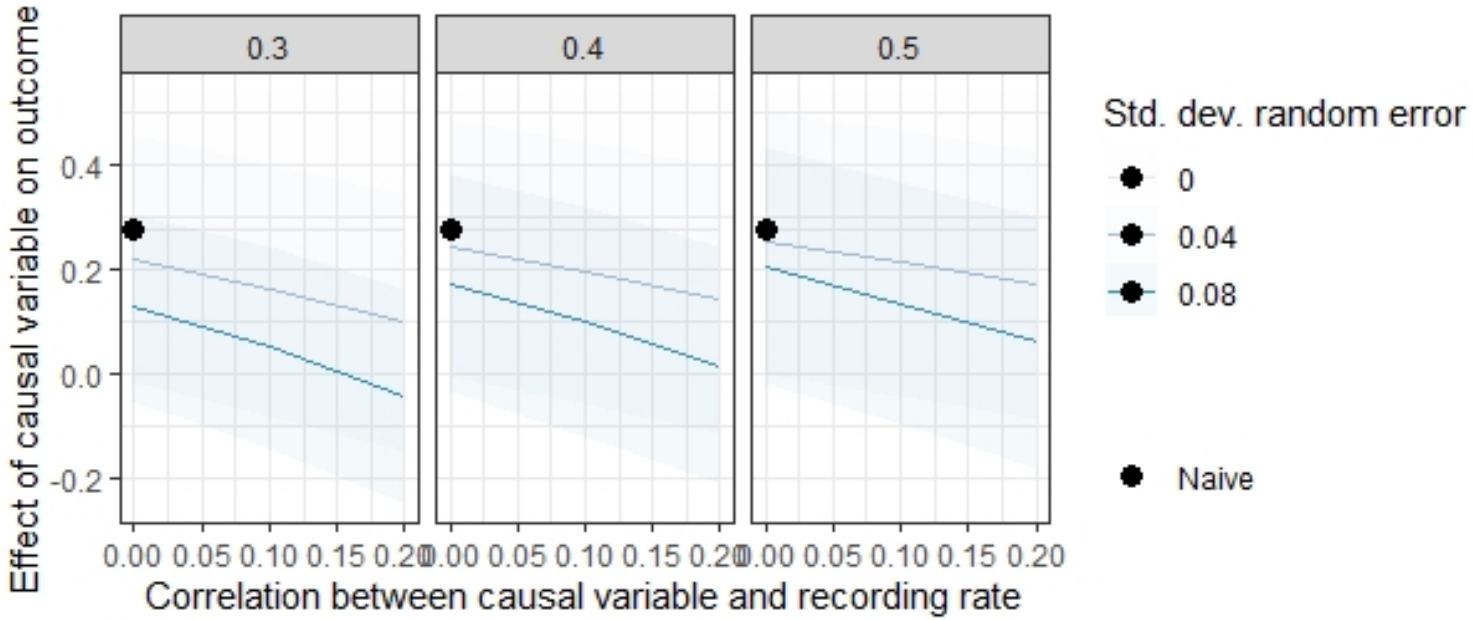

- The effect size attributed to violent crime on perceptions of disorder is likely overestimated
  - It is not too sensitive to the average under-recording rate
  - But it is affected by recording inconsistencies, and a positive correlation between recording and perceptions of disorder
  - If the recording rate is both moderately inconsistent across areas and positively correlated with perceptions of disorder, the effect attributed to violent crime is completely spurious

Discussion

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  - Inconsistencies in recording across areas also matter
  - And each of those mechanisms can operate in different directions
- When using police data we should undertake robustness checks
  - The *RecountingCrime* package can help with that
  - It can still be useful when all we have is an educated guess
  - We are also working on a synthetic crime dataset, which could be used to estimate some of those parameters

Thank You

- Future steps:
  - Estimate recording inconsistencies using expert elicitation techniques with police officers
  - Introduce longitudinal and spatial correlations
  - Expand the function for problems of misclassification in crime events as opposed to crime rates
- If you want to know more...
  - Project's website: `http://recountingcrime.com`
  - Short course at the British Society of Criminology conference (28^{th} June, Surrey)