UNIVERSITY OF LEEDS

SDAI
Secondary Data Analysis Initiative

Crime Surveys User Conference 2020

The impact of measurement error in police crime records

Recounting Crime

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  - These biases can be affecting estimates beyond the effect of crime
  - Their extent will be determined by the type of measurement error and outcome model
- In this paper (and project) we seek to tackle this problem
  - Identify the nature and prevalence of measurement error in police data
  - Illustrate the impact it has when used in regression models
  - Suggest methods for its adjustment

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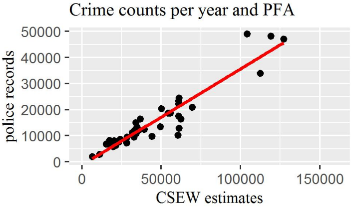
    additive error model: $X^* = X + U$, where $U \sim N(< 0, \sigma)$

    multiplicative error model: $X^* = X \cdot U$, where $U \sim N(\in (0,1), \sigma)$

Measurement Error in Police Data



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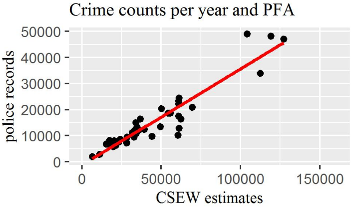

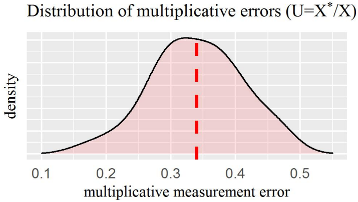

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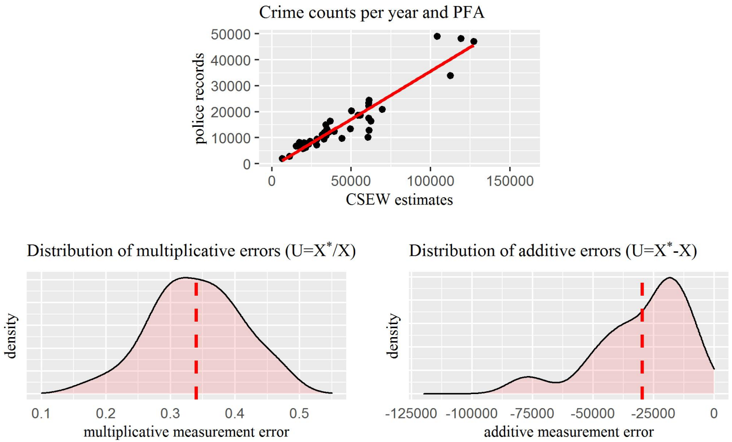

Impact of Multiplicative Errors

- The nature of the measurement error (not only its prevalence) defines its impact
- Let's assume systematic and random measurement error on the explanatory variable of a simple linear model

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- Using OLS we can estimate α and β solving the following system of equations

$$\hat{\alpha} = \bar{Y} - \hat{\beta}\bar{X}^*$$

$$\hat{\beta} = \frac{cov(X^*Y)}{var(X^*)}$$

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- Under-reporting will bias the slope upwards, while inconsistencies across PFAs will push it downwards

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  - Harder to trace out if using non-linear models
  - And we have not even consider how it affects measures of uncertainty too
- We recommend using Bayesian adjustments
  - We need to specify our outcome model of interest
  - Together with a measurement model for the variable affected by measurement error
  - Based on the estimated validity and reliability of that variable

Example of a Bayesian Adjustment

- We model the effect of acquisitive crime (X_1) and population density (X_2) on the % of white population (Y)
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  - $Y = \alpha + \beta_1 X_1^* + \beta_2 X_2 + \epsilon$
- The Bayesian adjustment, using police data and what we know about the validity and reliability of the measurement error
  - $Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \epsilon$
    $X_1 = X_1^* \cdot U$, where $U \sim N(1/0.29, 1/0.06)$

Example Using CSEW and Police Data

	outcome variable: % white in the area		
	true model	naive model	adjusted model
constant	0.977		
	(0.013)		
acquisitive crime	−0.073		
	(0.029)		
population density	−0.003		
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- Next steps
  - Small area estimation, synthetic data, multi-trait multi-method models, SIMEX
  - `http://recountingcrime.com`