

# Utilising Data and Knowledge for Policy Impact

## A Case Study Using Bayesian Approach

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# Rationale for New Estimates

- Potential for inaccurate results
- More new data generated
- Potential for better sample representation
- Importance of choosing a suitable method

# Purpose & Context

- Purpose
  - \* To produce valid & credible estimate.
- Context
  - \* Previous attempts
  - \* Political sensitivity
  - \* Money/policies
  - \* Legal issues
  - \* Law enforcement
  - \* There are also data issues
  - \* Will be carefully scrutinised

# What is available?

## DATA

- National Administrative Data
  - \* Large sample size
  - \* Intensive information
  - \* Lack of data entry validation
  - \* Considerable data-mining is required
  - \* Need to establish communication with the data vendor

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## DATA

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- National Survey:
  - \* Fill in the gaps
  - \* Provide useful information on unpaid travel time
  - \* Can't be linked directly to the administrative data

## KNOWLEDGE

- Previous Estimates

- \* **Authoritative** government organisations
- \* Others from market research and small surveys
- \* **Wide ranging** estimates based on different sample sizes

## KNOWLEDGE

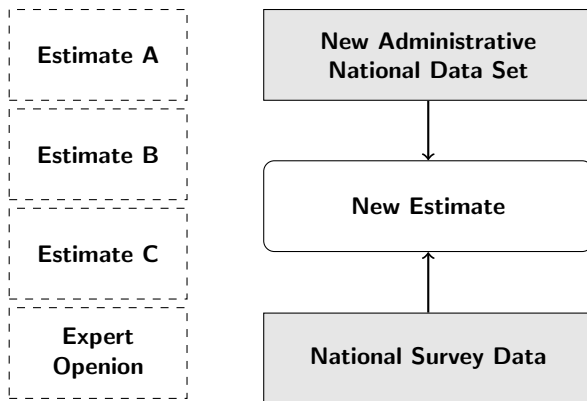
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- Expert Opinion:

- \* Different from previous estimates
- \* Based on related research

# Information summary





# Accounting for prior knowledge

- Previous point estimates that varies
- All previous samples are drawn from same population
- Researcher's opinion based on observations
- We need full distribution estimate that account for all the above
- A Bayesian approach is most suitable for this job

# How can we make use of all the above?

## Bayes' Theorem

$$P(A | B) = \frac{P(B | A) P(A)}{P(B)}$$

$$P(\text{Parameter} | \text{Data}) \propto P(\text{Parameter}) \times P(\text{Data} | \text{Parameter})$$

### PROS

- A formal approach for including prior knowledge in the analysis
- Flexibility in constructing appropriate model for the data
- Transparent, all modelling decisions are clear
- Full distributions instead of point estimates
- CI have more intuitive meaning

### CONS

- Tailored estimation could be challenging to implement
- Computationally intensive
- Need defense of decisions

# Hierarchical Bayesian Model

- A framework for capturing dependencies between parameters
- Treating all estimates as arising from a random process governed by hyperparameters
- More accurate than treating previous estimates as fixed prior
- Full posterior distributions for all parameters including previous estimates

# Model specifications

- All estimates are based on samples drawn from same population

$$P(\theta_i|y_i) \propto P(y_i|\theta_i) \times P(\theta_i)$$

- $\theta_i$  are drawn from a distribution with unknown parameter vector  $\phi$
- $\phi$  is an unknown hyperparameter with its own posterior distribution

$$P(\theta_i, \phi|y_i) \propto P(y_i|\theta_i, \phi) \times P(\theta_i, \phi)$$

$$\underbrace{P(\theta, \alpha, \beta|y)}_{\text{Posterior}} \propto \underbrace{P(y|\theta)}_{\text{Likelihood}} \times \underbrace{P(\theta|\alpha, \beta)}_{\text{Prior}} \times \underbrace{P(\alpha, \beta)}_{\text{hyperprior}}$$

# Model implementation

- All posterior densities could be derived, for example:

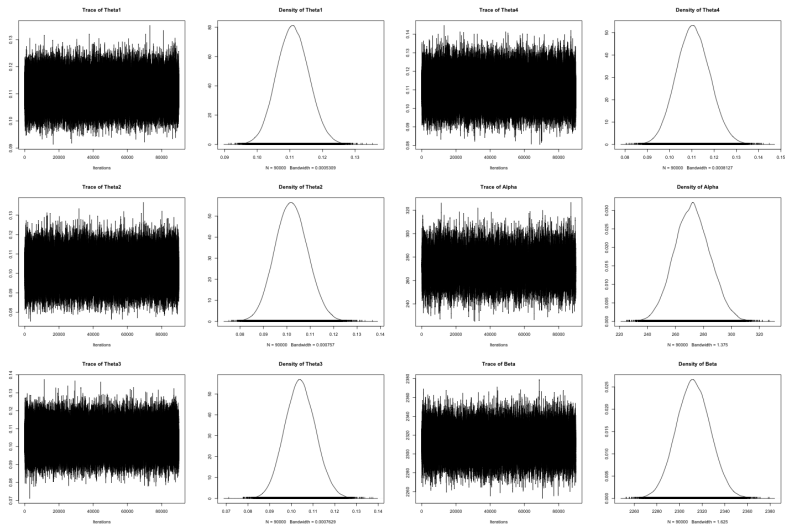
$$P(\theta_i | \alpha, \beta, y_i) \propto$$

$$(1 - \theta_i)^{\beta + n_i - y_i - 1} \prod_{i=1}^I \theta_i^{y_i} (1 - \theta_i)^{n_i - y_i} \times$$

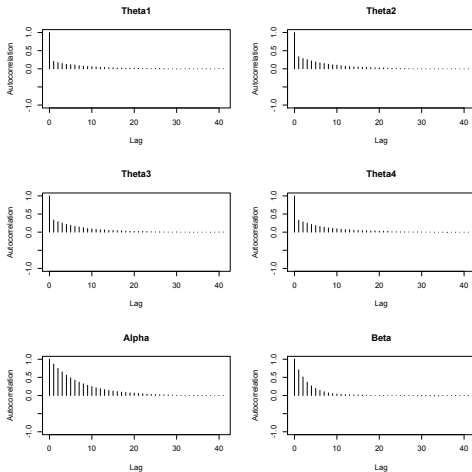
$$\prod_{i=1}^I \frac{\Gamma(\alpha + \beta) + n_i}{\Gamma(\alpha + y_i) \Gamma(\beta + n_i - y_i)} \theta_i^{\alpha + y_i - 1}$$

- Stochastic integration via Markov Chain Monte Carlo
- A hyper Metropolis-Hasting/Gibbs sampling algorithm
- Estimated densities of  $\theta_i$ ,  $\alpha/(\alpha + \beta)$
- R-Unix environment

# Output 1



# Output 2



# Communication & Interpretation

- Visualisation
- Communication process
- Providing tools for researchers to make decision



# Reflection

- This is just an example
- Focusing on the suitability rather than convenience could be rewarding
- Recent developments offer new opportunities
  - \* New algorithms for stochastic integration
    - \* Sampling instead of numerical approximation
  - \* Choice of programming languages
    - \* C/C++, R, Stan
  - \* Significant hardware advancement
  - \* Availability of big data
- Skills Matrix
  - \* Subject matter expert
  - \* Mathematical statistics
  - \* Quantitative programming

# Further Reading



Adrian E. Raftery (2000)

Statistics in Sociology, 1950-2000

*Journal of the American Statistical Association* 95(450): 654 – 661.



Bruce Western (1999)

Bayesian Analysis for Sociologists

*Sociological Methods & Research* 28(1): 7 – 34



Bruce Western (2001)

Bayesian Thinking about Macrosociology

*American Journal of Sociology* 107(2): 353 – 378



Bob Carpenter, et all (2016)

Stan: A Probabilistic Programming Language

*Journal of Statistical Software* (in press)

Thank You for Listening

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