University of BRISTOL

Estimating the prevalence of opioid dependence in New South Wales from multiple data sources:

case study application of a Bayesian modelling approach

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Acknowledgements & CoIs

- Bayesian modelling approach described in:

  Jones HE, Harris RJ, Downing BC, Pierce M, Millar T, Ades AE, Welton NJ, Presanis AM, De Angelis D, Hickman M. Estimating the prevalence of problem drug use from drug-related mortality data. Addiction. 2020 Dec;115(12):2393-404

- Co-authors of New South Wales case study:

  Downing BC, Hickman M, Jones NR, Larney S, Sweeting MJ, Xu Y, Farrell M, Degenhardt L

- I have no conflicts of interest related to this presentation

Background: multiplier methods

- Simple "*multiplier*" method:
  - If we observed *d* events, and we estimate that the probability of a person from the population of interest (e.g. opioid dependence/PWID) experiencing such an event is *p*…
  - then we can estimate the relevant population size is $N = d/p$
- Many limitations, including:
  - Assumes ***all*** of the *d* events used for estimation were among the population of interest
  - Assumes we have a ***really good*** (unbiased) estimate of *p*, that's relevant to the ***whole*** population, *N*

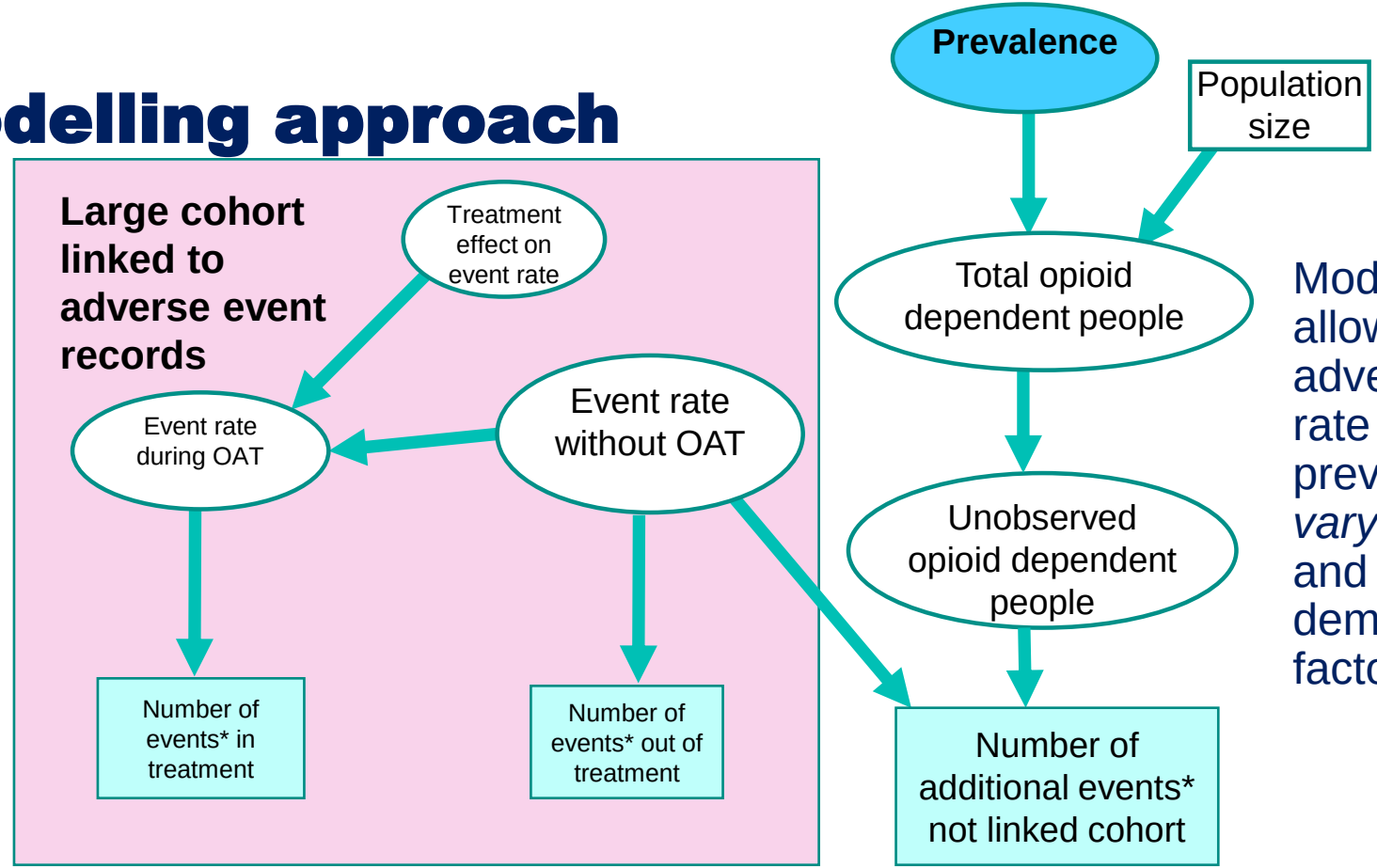
Tackling limitation 1

- Method attributes *all* events, e.g. drug-related deaths, modelled to the population of interest (e.g. people with opioid dependence)
- So it's **critical** to carefully *restrict events modelled to those that we're confident cannot occur outside of the population*
- It **doesn't matter** that we're "missing" some of the events: the "p" is just a tool to estimate prevalence
- i.e. specificity is crucial, sensitivity doesn't matter here

Tackling limitation 2

- Availability of data on a large cohort of individuals with opioid dependence – including everyone receiving OAT – linked to adverse event rate data, means we can get ***much*** better estimates of *p*:
  - Estimate of *p* is directly relevant to the time period of interest
  - …directly relevant to the country/region of interest
  - …is based only on the restricted (specific) event type that we carefully defined
  - We can allow for variation in *p*, in particular any *reduction in event rate while receiving OAT*
  - We only need to estimate the undercount of the large cohort - reducing our uncertainty in final prevalence estimates

Modelling approach



Model also allows both adverse event rate and prevalence to *vary* with year and demographic factors

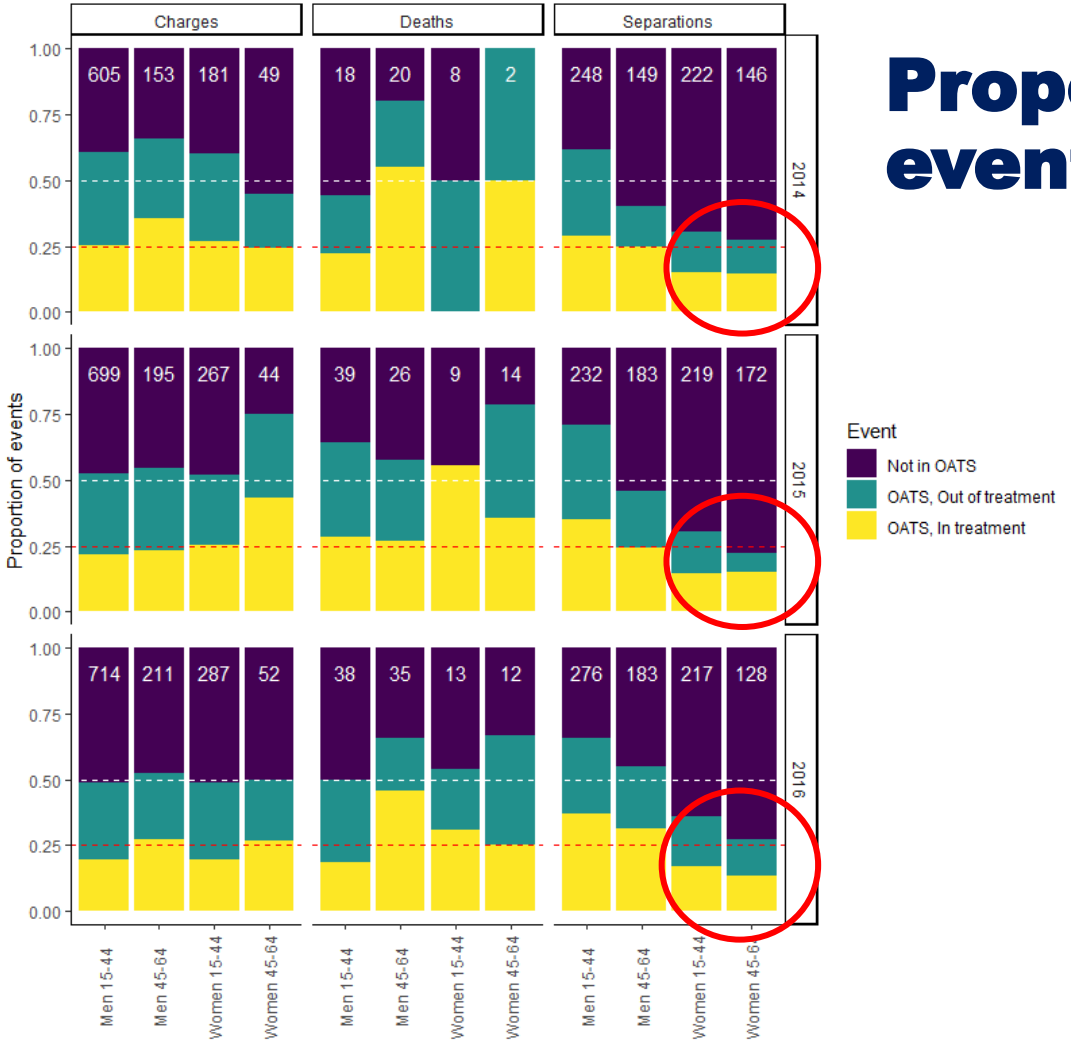
**Carefully selected subset of events believed to be specific to the population of interest*

Estimating the prevalence of opioid dependence in New South Wales, Australia

- Opioid Agonist Treatment and Safety (OATS) study: all people (n = 48,158) prescribed methadone/buprenorphine as opioid agonist treatment in NSW, 2001-2018: records linked to mortality, hospital and criminal justice records

- We applied the Bayesian modelling approach to 3 types of adverse event data and compared results:
  1) Opioid-related **mortality**: ICD10 codes F11.1, F11.2, F11.9 only
  2) Opioid-related **hospitalisations**: ICD10 T codes T40.0-T40.4, T40.6
  3) Opioid-related arrest **charges**: possession or use of illicit drugs AND opioid drugs specified

- Also extended the model such that prevalence is jointly estimated from all 3.

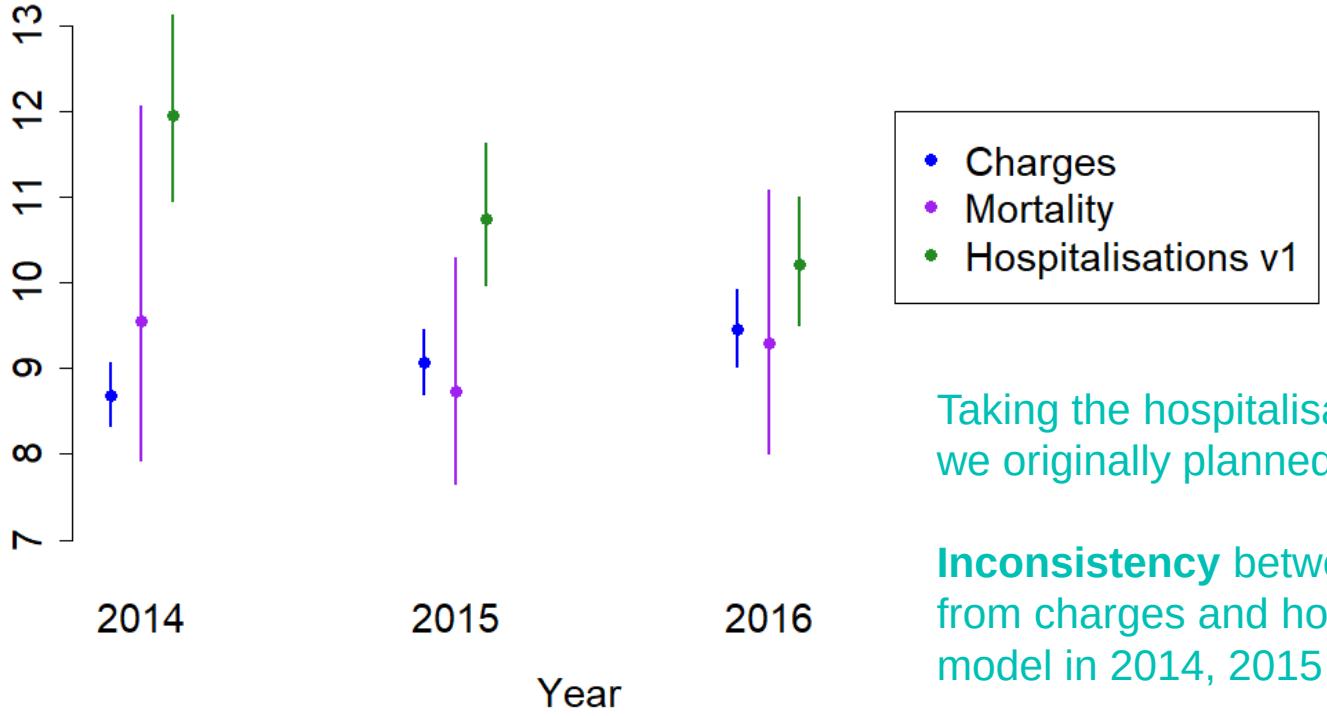


Proportion of each event linked to cohort

Unexpected pattern:

- Lower proportion of hospitalisations linked to the cohort than charges/deaths
- Particularly low in women: only 22-35% of hospitalisations among women were among the cohort
- On reflection, we were concerned hospitalisations modelled were not specific enough to opioid dependence

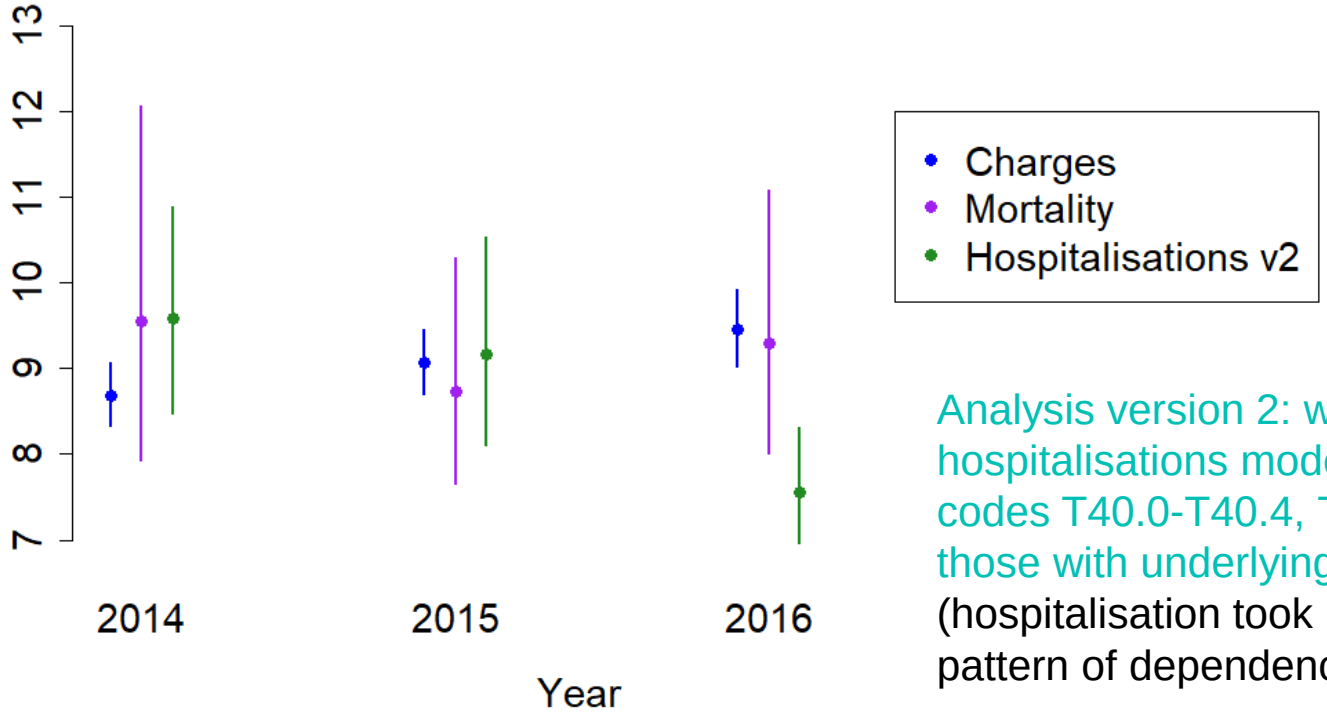
Prevalence per 1000 people aged 15-64



Taking the hospitalisations data as we originally planned:

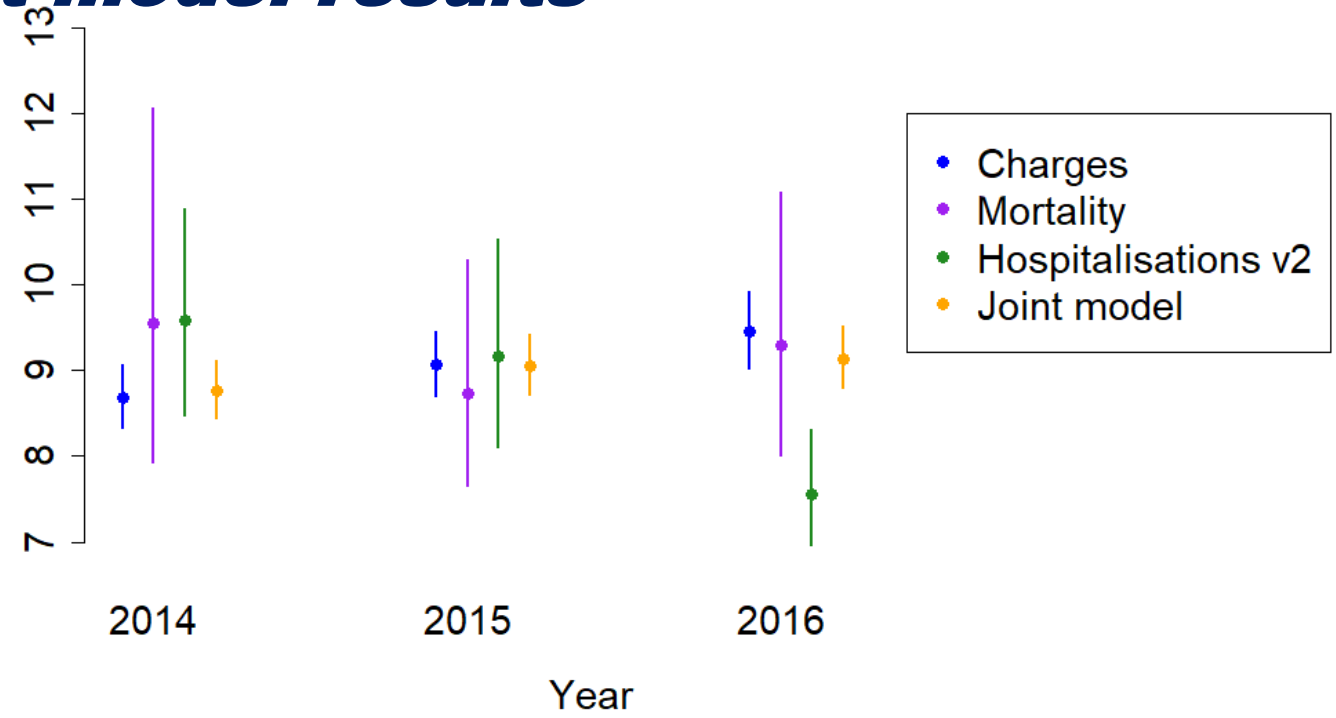
Inconsistency between estimates from charges and hospitalisations model in 2014, 2015

Prevalence per 1000 people aged 15-64

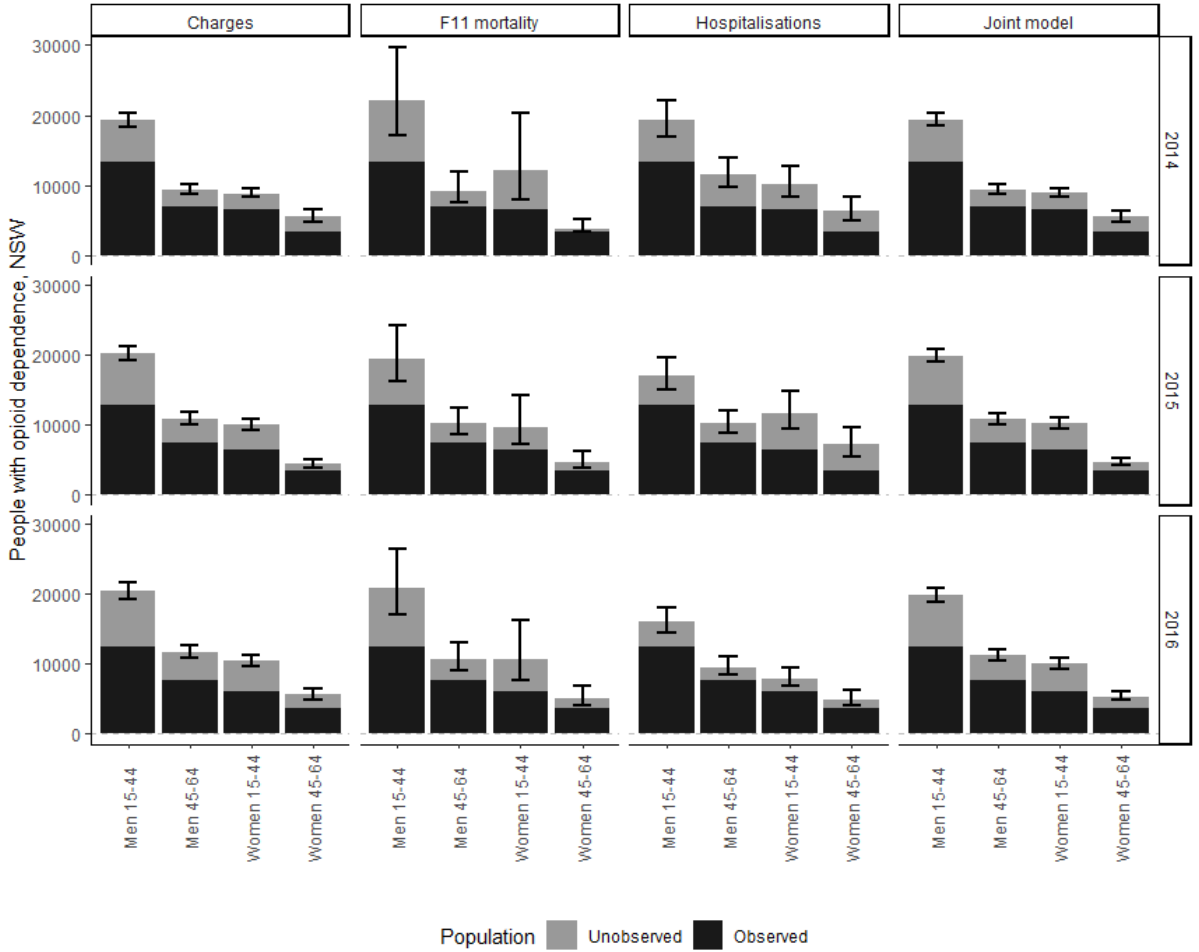


Analysis version 2: we restricted hospitalisations modelled (ICD10 codes T40.0-T40.4, T40.6) to only those with underlying F11.2 code (hospitalisation took place against pattern of dependence syndrome)

Prevalence per 1000 people aged 15-64: *joint model results*



Estimated number of people with opioid dependence – by age group and sex



Discussion

- Approach is an alternative to capture-recapture estimation for areas with rich, linked data sets but where the assumptions underlying capture-recapture are untenable
- Applying the approach to multiple types of adverse events allows for checking of consistency of evidence
- We also demonstrated an extension of our previously described approach to estimate prevalence jointly from multiple types of adverse event
- Case study reinforces the importance of high *specificity* of the adverse event modelled (100% specificity = impossible for the event to occur in anyone except the population we're trying to estimate the size of)