Hidden populations

Estimating the prevalence of opioid dependence in people aged 15-64 in NSW, 2014-16, from three indirect data sources.

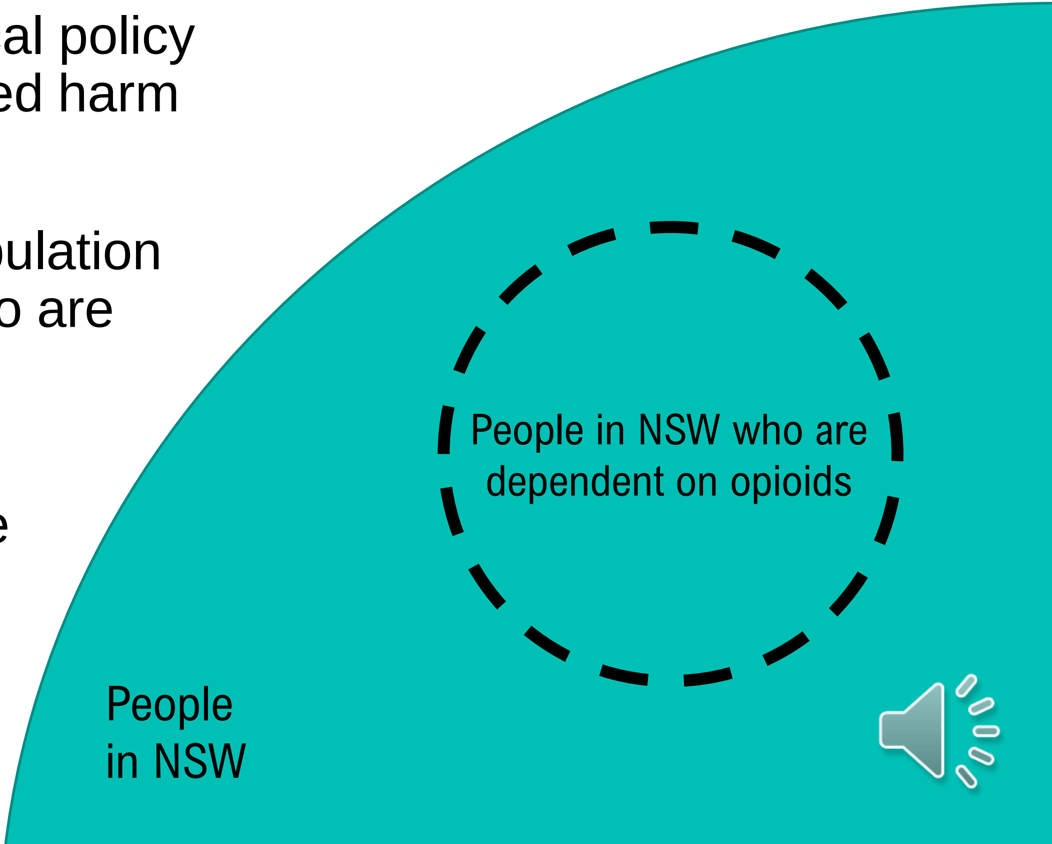
Dr Beatrice Downing
Beatrice.Downing@bristol.ac.uk

With thanks to the community

I would like to acknowledge everybody who took place in the Opioid Agonist Safety study, without which this research would not be possible.

Estimating the size of hidden populations

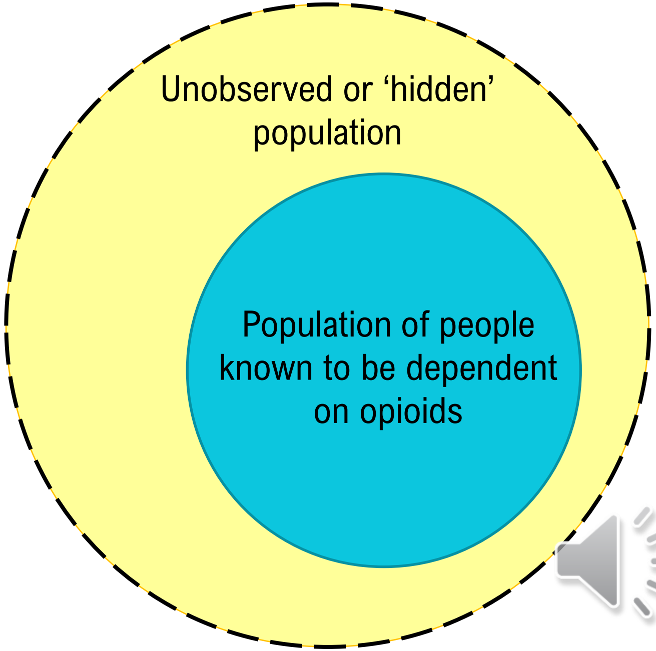
- Critical for public health and clinical policy and models evaluating drug related harm
- Direct data collection through population surveys will undercount those who are opioid dependent
- Indirect methods can estimate the number unobserved in different data sets



Estimating the size of hidden populations

- We do know how many people come forward for treatment or help – this is the number of 'known' people with opioid dependence

- We need to estimate the additional, unobserved population size to estimate the total number of people with opioid dependence and plan services effectively to support them

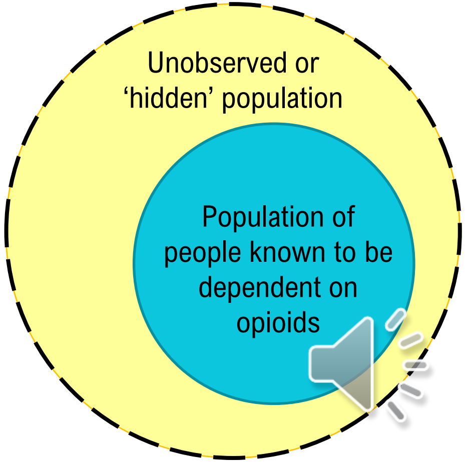


The data: Opioid Agonist Treatment and Safety (OATS) study, NDARC, UNSW

- A retrospective cohort study linking people who received or were receiving opioid-agonist treatment in NSW with adverse events

- Started in 2001, these models used finalised data from 2014-16 on the number of F11-coded deaths, finalised arrest charges and separations

- This study gives us the blue circle: the number of people *known* to be dependent on opioids

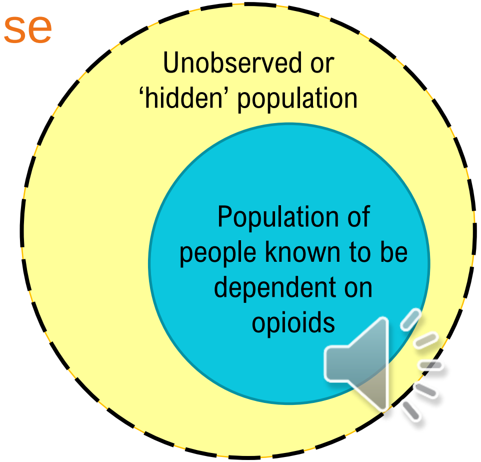


The data: state-level totals

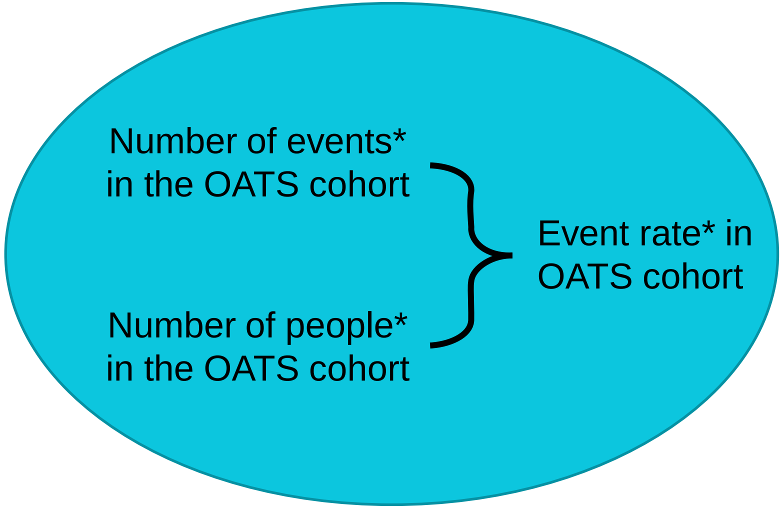
We also have counts of the total number of adverse events in New South Wales with exactly the same definitions as used for the OATS cohort:

- Number of opioid-related deaths specific to opioid dependence
- Number of opioid-related hospital separations
- Number of finalised arrest charges for opioid possession or use

We use the number of these that were ***not*** linked to the OATS cohort to estimate the size of the unobserved population



Mechanics of model

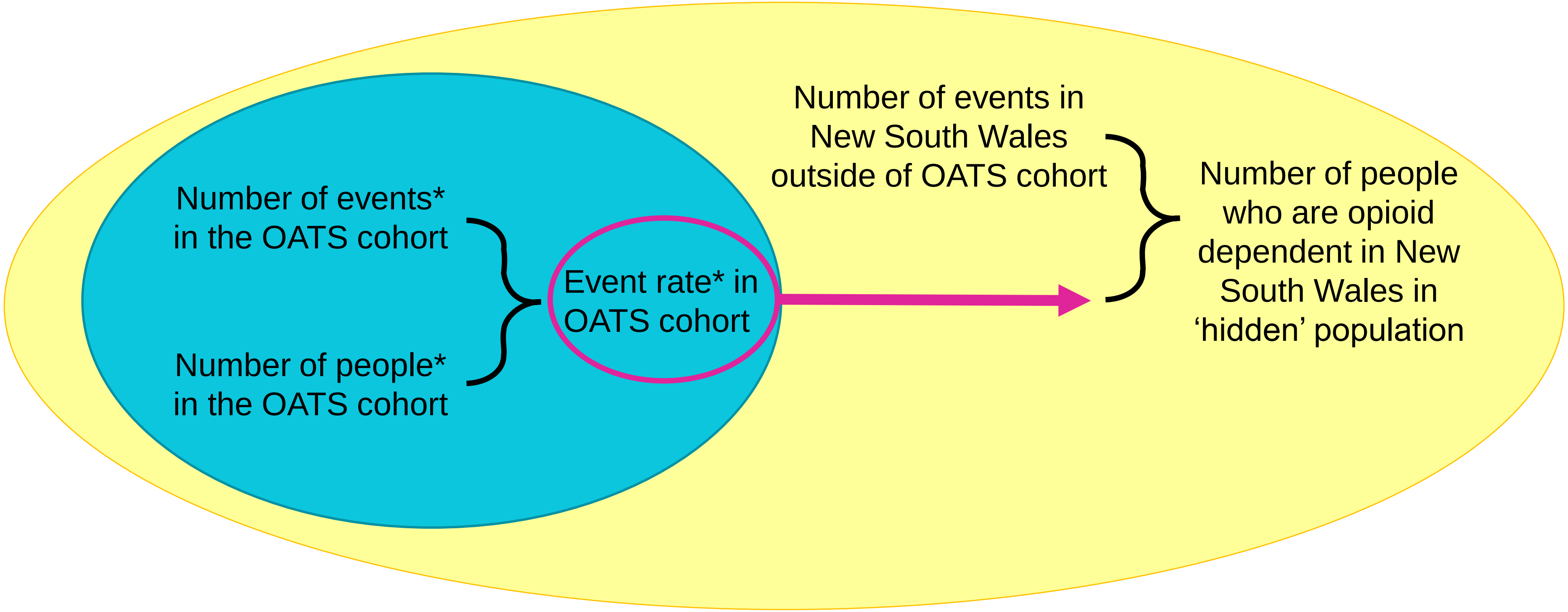


* Event rates are calculated for those *in* opioid-agonist treatment and for those *not* in treatment

The event rate for people **out of treatment** is used to estimate prevalence

For more details: *Jones HE et al. (2020) Estimating the prevalence of problem drug use from drug-related mortality data. Addiction, 115: 2393-2404. [DOI:10.1111/add.15111](https://doi.org/10.1111/add.15111).*

Mechanics of model



For more details: *Jones HE et al. (2020) Estimating the prevalence of problem drug use from drug-related mortality data. Addiction, 115: 2393-2404. [DOI:10.1111/add.15111](DOI:10.1111/add.15111).*

Mechanics of model

60 charges in women 15-44 in the OATS cohort out of treatment

2247 person-years at risk for women 15-44 in the OATS cohort out of treatment

Charge rate in women 15-44 in the OATS cohort out of treatment

Number of events in women 15-44 in New South Wales outside of OATS cohort
= 181 – (49 + 60) = 72

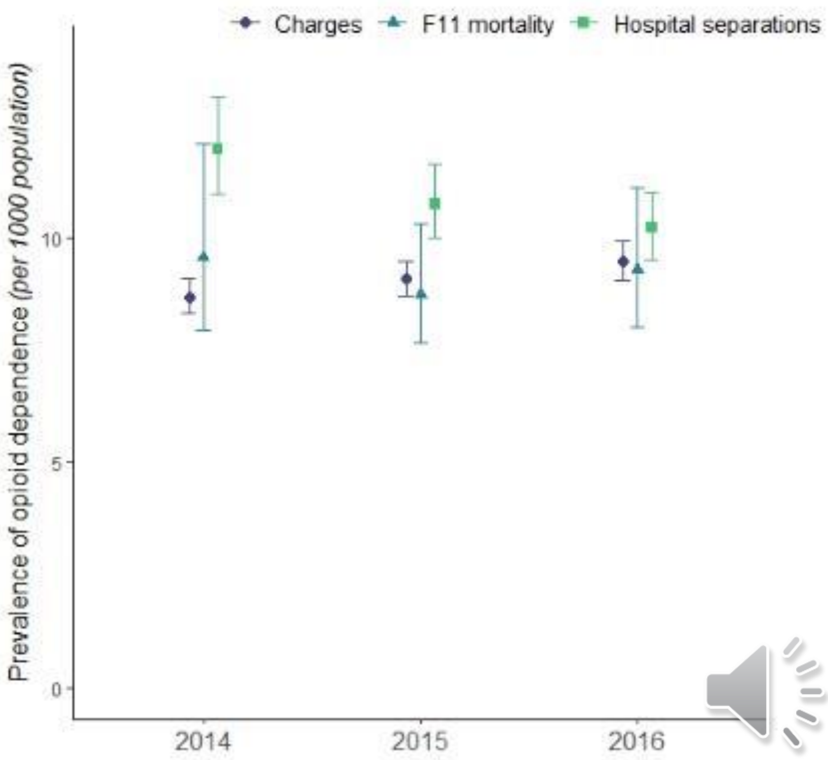
Number of women aged 15-44 who were opioid dependent in New South Wales in 'hidden' population

	A	B	C	D	E	F	G
1	group[]	pyr_in[]	events_in[]	pyr_out[]	events_out[]	events_NSW[]	populationNSW[]
2	W 15-44	3930	49	2247	60	181	1538434
3	W 45-64	2345	12	866	10	49	939655
4	M 15-44	7332	153	5336	213	605	1550677

Results: overall prevalence

- The three data sources – charges (●), mortality (▲) and separations (■) – gave similar estimates for the prevalence of opioid dependence

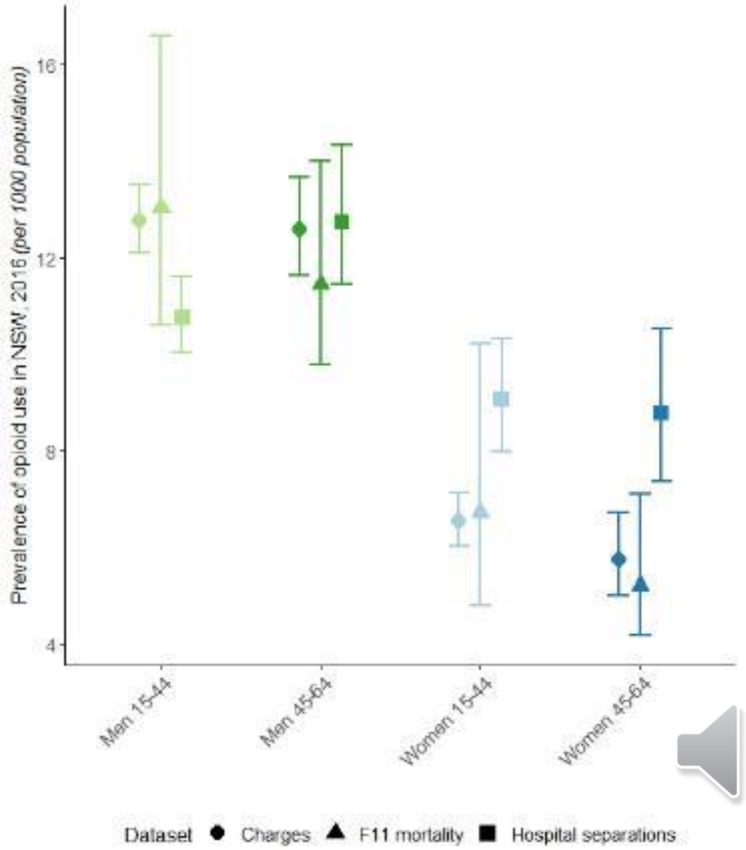
Year	Dataset	Prevalence per 1000 population (95% CrI)	
2014	Charges	8.68	(8.33, 9.07)
	F11 mortality	9.56	(7.93, 12.07)
	Separations	11.95	(10.96, 13.13)
2015	Charges	9.07	(8.70, 9.46)
	F11 mortality	8.73	(7.65, 10.29)
	Separations	10.74	(9.98, 11.63)
2016	Charges	9.46	(9.03, 9.92)
	F11 mortality	9.29	(8.01, 11.09)
	Separations	10.21	(9.51, 11.01)



Results: prevalence by demographic group

- The prevalence of opioid dependence was estimated to be higher in men than in women

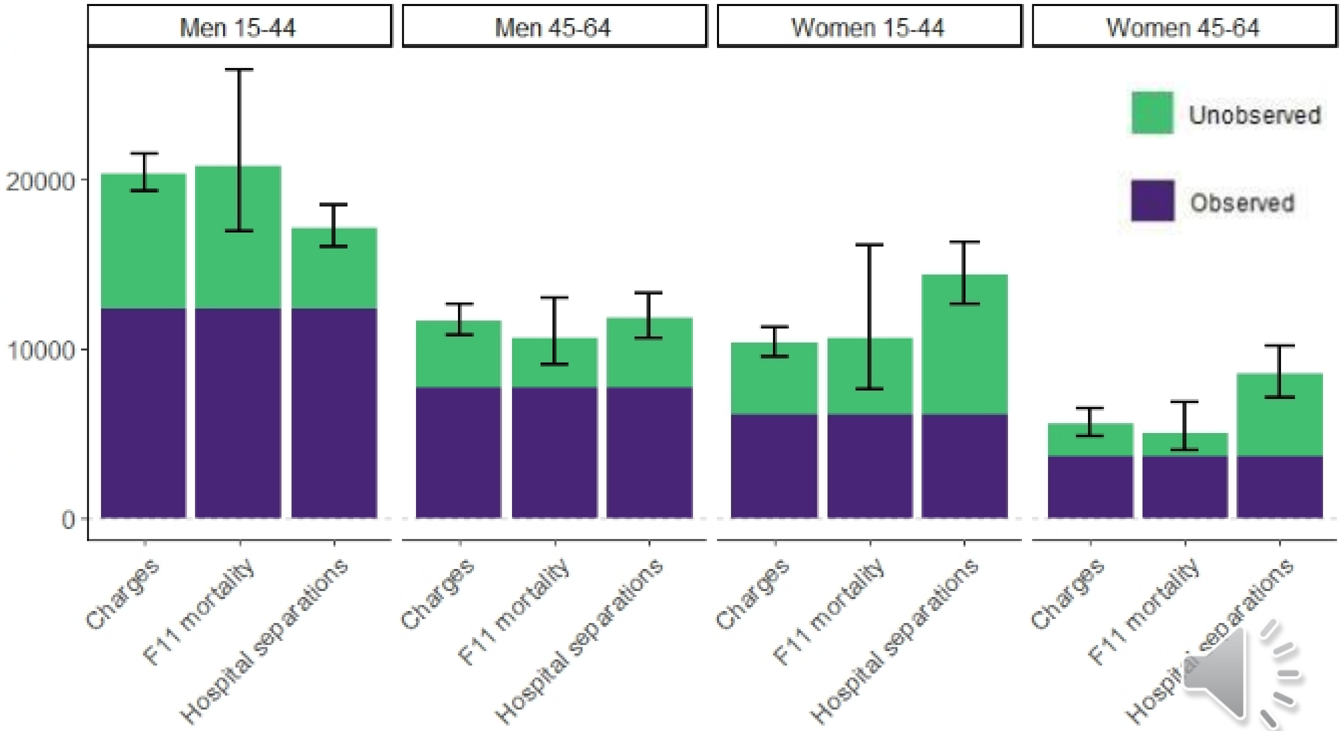
- Estimates from the model of charges data (●) differed from estimates from the model of separations data (■) for most demographic groups



bristol.ac.uk

Results: size of the unobserved population

- All models estimated that a large proportion of the population with opioid dependence is ‘hidden’ – i.e. not part of the OATS cohort
- The model of hospital separations estimated a relatively high number of unobserved women who were opioid dependent



bristol.ac.uk

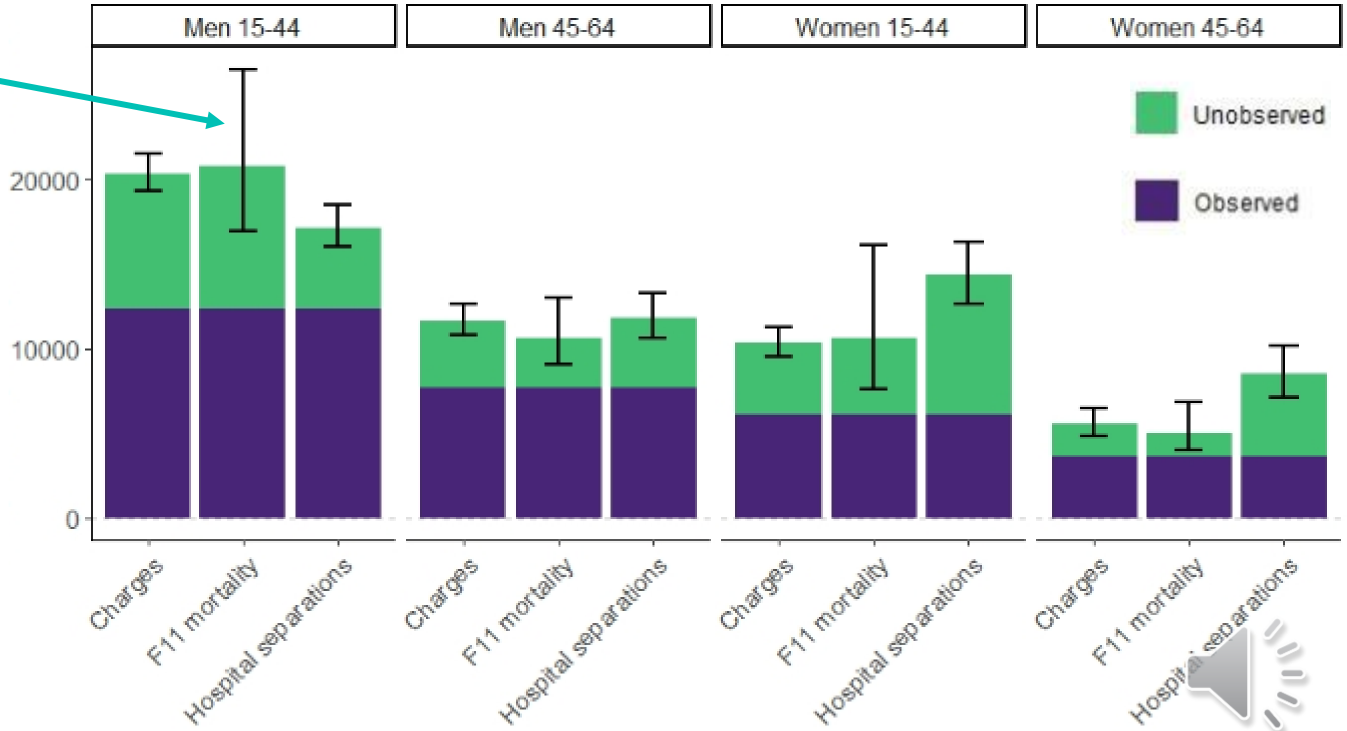
Assumptions and Strengths

Assumptions of this Model	Strengths of this Model
❖ Adverse events took place **at the same rate** in the OATS cohort (for those not in opioid-agonist treatment) and in the population of NSW for people with opioid dependence ❖ **All of the events** – charges, F11-coded deaths and hospital separations – took place in people who were opioid dependent	✓ Multiple data sources were used to estimate prevalence – and different, independent data sources gave similar answers ✓ Prevalence was estimated for each demographic group in each year, giving specific, tailored estimates

Can we do better?

There is a lot of uncertainty around some of our estimates

Can we use **multiple** data sources in the same model?

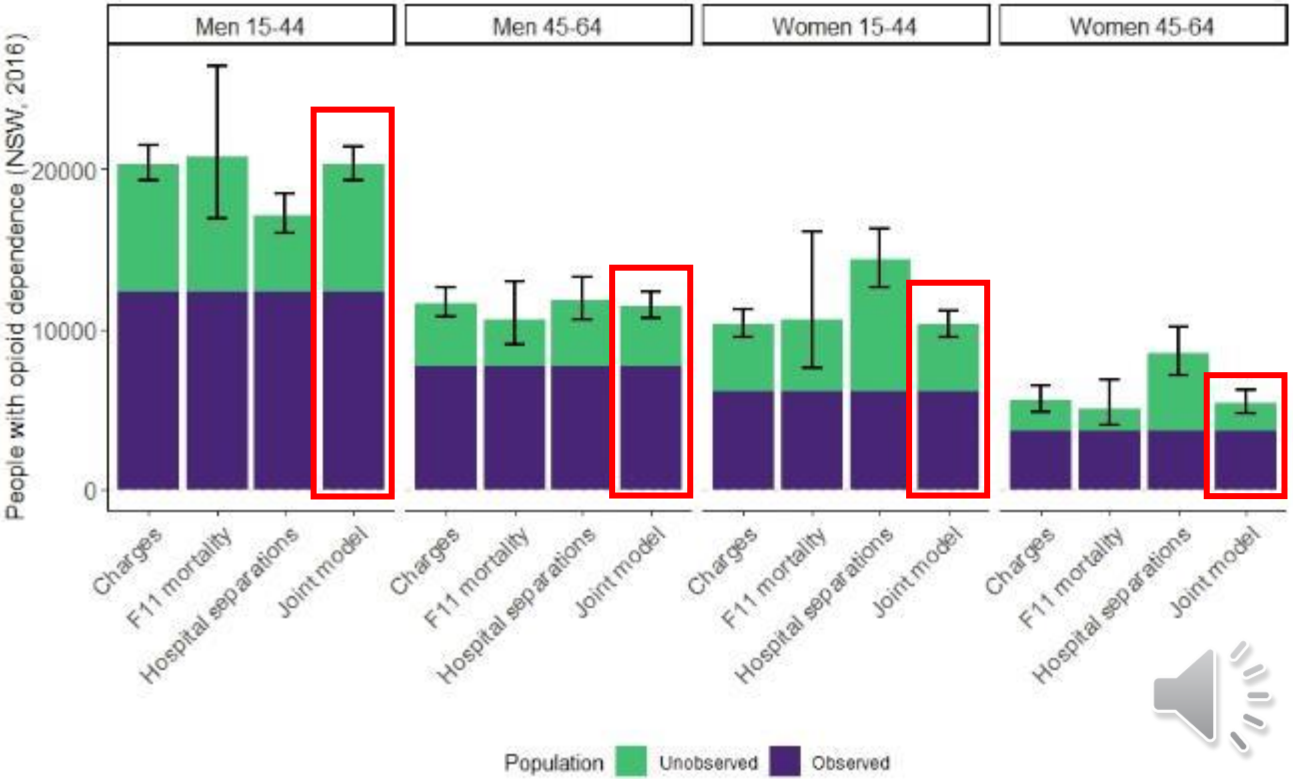


Methods: joint model

- We want to use multiple sources in our model, but the separations data may not be as specific to the OATS population
- Used arrest charges and mortality data
- Event rates were estimated **separately** for both the sources
- The number of hidden people with opioid dependence was estimated **jointly** from both data sources

Results: joint model

Demographic Group	Prevalence per 1000 population (95% CrI)	
Men 15-44	12.74	(12.09, 13.45)
Men 45-64	12.37	(11.52, 13.35)
Women 15-44	6.52	(6.02, 7.09)
Women 45-64	5.59	(4.93, 6.42)



bristol.ac.uk

Questions you might ask

- How do these estimates compare to previous estimates?
- Why not include all opioid-related deaths?
- Why not do joint model of all 3 estimates?
- Why not use capture-recapture (CRC) techniques?

Questions you might ask

- How do these estimates compare to previous estimates?

*These estimates are higher than previous estimates of the prevalence of **injecting** drug use (National Drug Strategy Household Survey 2016) and of **opioid use** (National Opioid Pharmacotherapy Statistics) because we also estimate the additional hidden population.*

- Why not include all opioid-related deaths?
- Why not do joint model of all 3 estimates?
- Why not use capture-recapture (CRC) techniques?

Questions you might ask

- How do these estimates compare to previous estimates?

- Why not include all opioid-related deaths?

We use a very specific definition of opioid-related deaths to make sure that we are modelling people with opioid dependence only. If we widen the definition, we may include opioid-related deaths from people who were not opioid-dependent, which would bias the event rate.

- Why not do joint model of all 3 estimates?
- Why not use capture-recapture (CRC) techniques?

Questions you might ask

- How do these estimates compare to previous estimates?
- Why not include all opioid-related deaths?

- Why not do a joint model of all 3 data sources?

Over 50% of the opioid-related deaths with F11 code and arrest charges that took place in NSW could be linked to the OATS cohort. However, a large proportion of opioid-related hospital separations took place in the unobserved population. This data source seems to cover a different population to that covered by the mortality and arrest data.

- Why not use capture-recapture (CRC) techniques?

Questions you might ask

- How do these estimates compare to previous estimates?
- Why not include all opioid-related deaths?
- Why not do a joint model of all 3 data sources?

- Why not use capture-recapture (CRC) techniques?

CRC techniques take two (or more) samples from the population of interest and use the number in each sample and the number of people in both samples to estimate the total population size. CRC makes several strong assumptions about the population, including that the sources are independent, that every person is equally likely to be recorded and that there is no movement in or out of the population. See Jones et al. (2016) Addiction, 111: 438-447. DOI:10.1111/add.13222

Thanks and acknowledgements

Project collaborators:

- Nikky Jones and Prof Louisa Degenhardt *(National Drug and Alcohol Research Centre, University of UNSW, Australia)*
- Dr Sarah Larney *(Université de Montréal, Research Centre of Centre Hospitalier de l'Université de Montréal and NDARC, UNSW)*
- Dr Hayley Jones, Yixin Xu and Prof Matt Hickman *(University of Bristol, UK)*
- Dr Mike Sweeting *(University of Leicester, UK)*

Competing interests: No potential competing interest was reported by the authors

With thanks to my funders: NIHR, UK and the HPRU, University of Bristol, UK

Questions or comments?

Dr Beatrice Downing, beatrice.downing@bristol.ac.uk