A Bayesian hierarchical framework to evaluate policy effects through quasi-experimental designs in a longitudinal setting

Marta Blangiardo

Environment and Health Statistics group | Imperial College London

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Policies are everywhere

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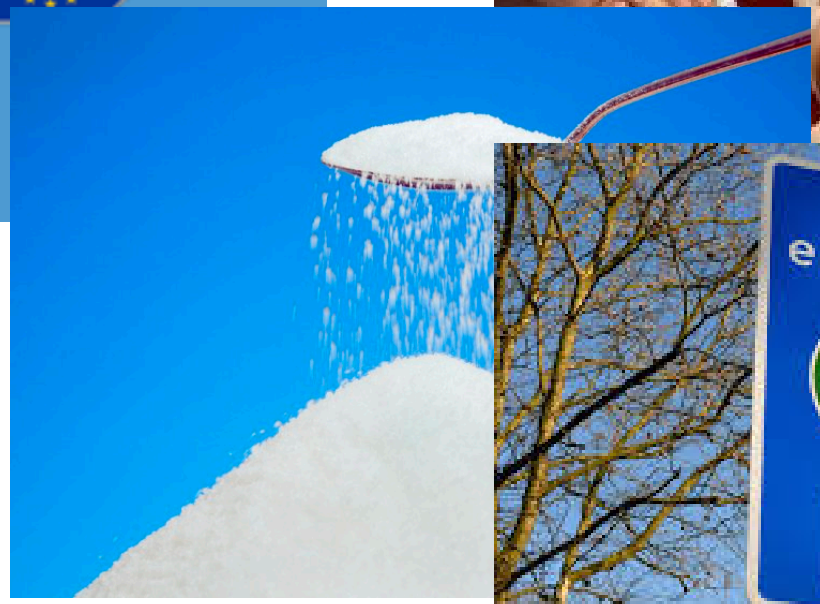

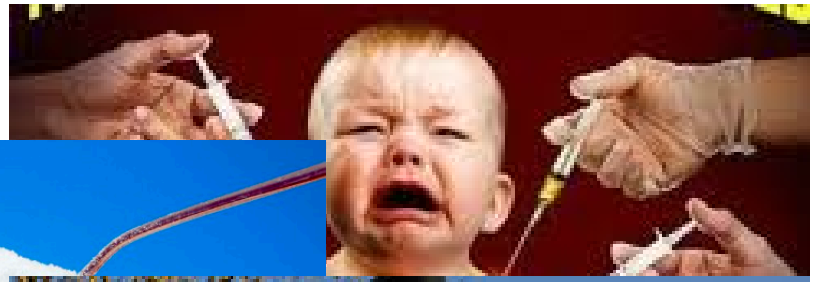

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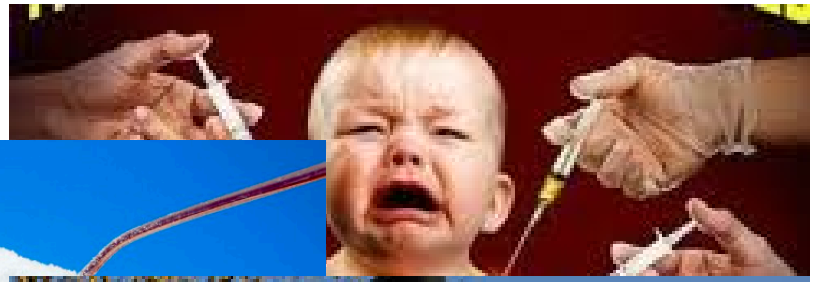

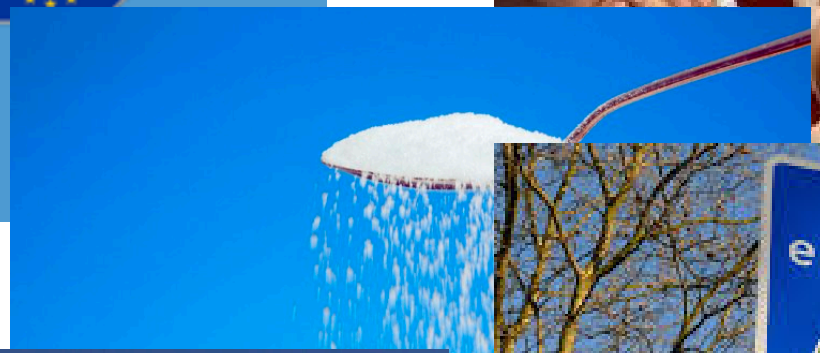

More policies = less evidence?

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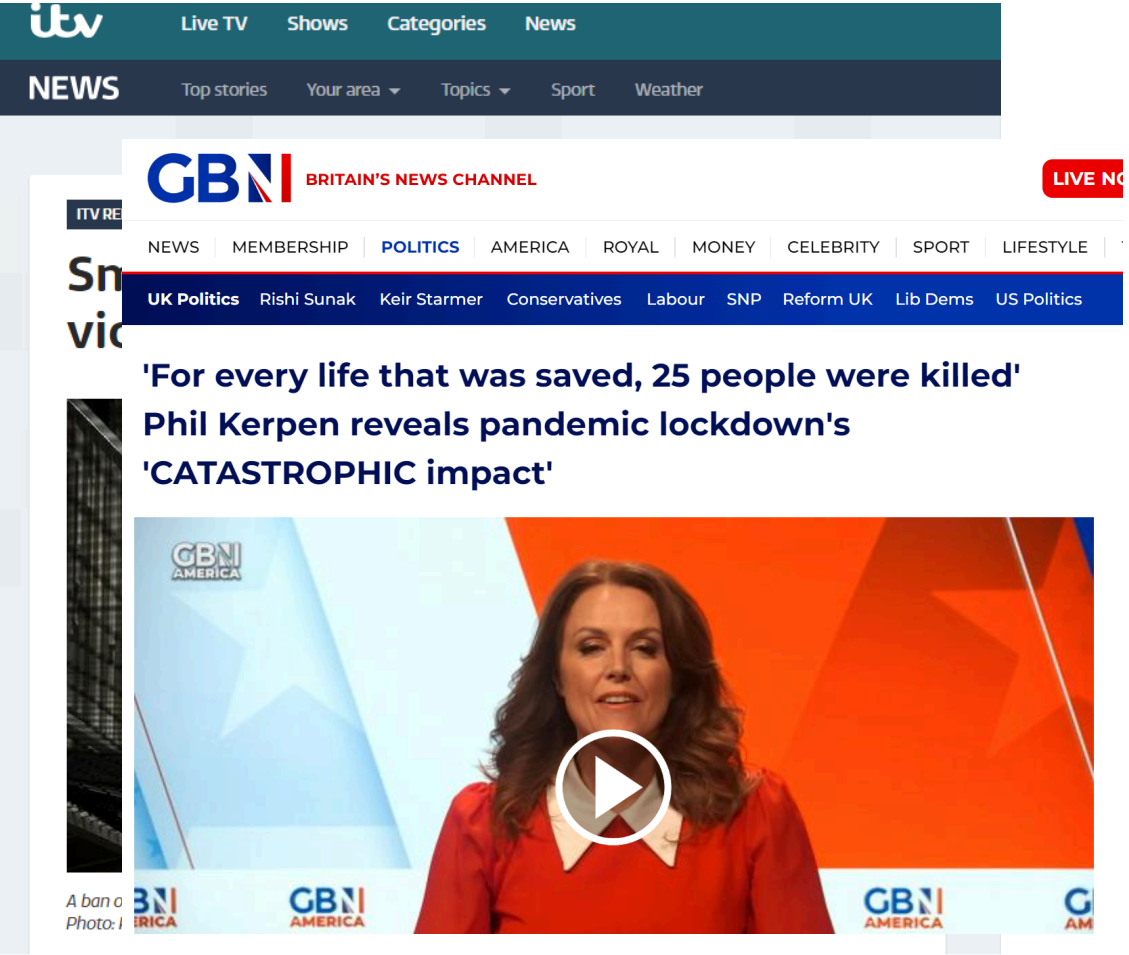
Smoking ban 'helped drive spike in violence at prison'

A ban on smoking in jails has been phased in since the beginning of 2016 (Anthony Devlin/PA)
Photo: PA Wire/PA Images

More policies = less evidence?



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More policies = less evidence?

- Evaluating the effects of policy interventions is of crucial importance.
- Robust statistical methods needed.

Can we infer causality?

- Randomised clinical trials are not viable

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Quasi-experimental designs

Research design used to estimate the causal impact of an intervention on its target population without random assignment.

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Quasi-experimental designs

Research design used to estimate the causal impact of an intervention on its target population without random assignment.

- How to deal with possible dependencies (presence of pre- and post-intervention trends, similarity across space/units)?
- Find comparable control groups to deal with residual confounding.

Outline

- Quasi-experimental design in a longitudinal setting.
- Adding dependency: hierarchical models as a general framework.

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- Examples: incinerators and infant health
- Examples: welfare policies in the UK and mental health

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- Quasi-experimental design in a longitudinal setting.
- Adding dependency: hierarchical models as a general framework.

- Examples: incinerators and infant health
- Examples: welfare policies in the UK and mental health

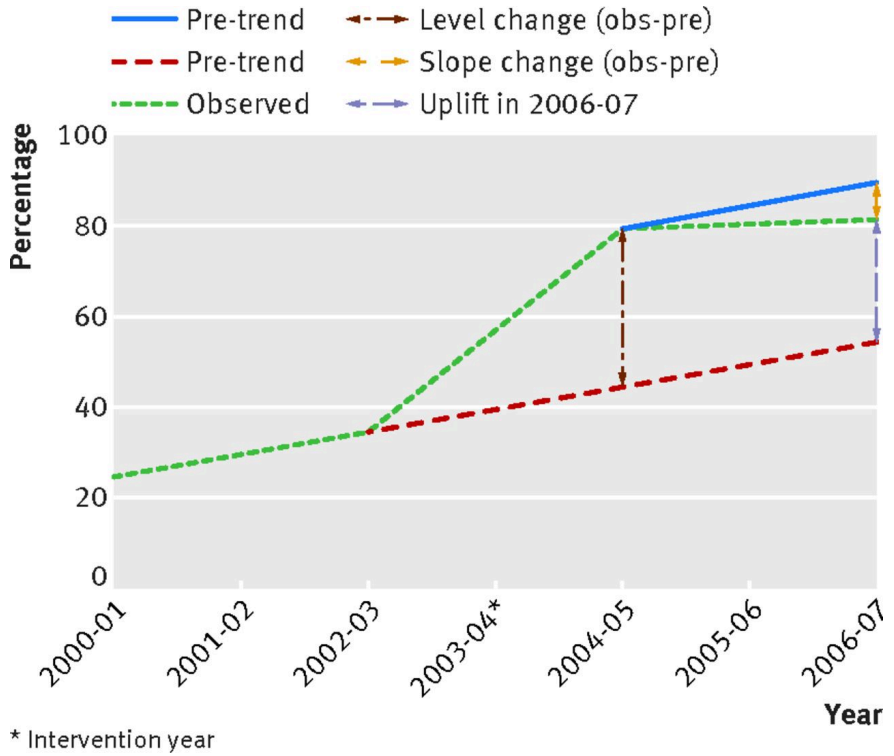
- Future directions: Spillover

Longitudinal setting: ITS

Interrupted Time Series (ITS)

A time series of a particular outcome of interest is "interrupted" by an intervention at a known point in time.

Particularly useful for "natural experiments" in real world settings.



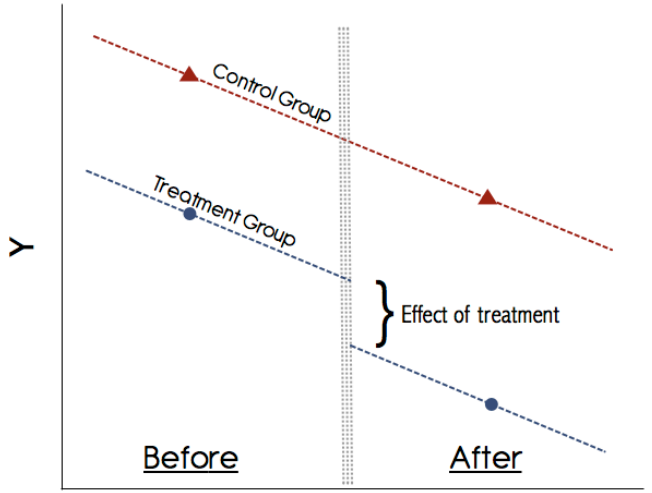
Kontopantelis et al., BMJ 2015; 350: h2750

In its general formulation:

- Linear effect of intervention.
- Do not account for external time varying effects or autocorrelation.
- Do not include controls.
- Causal effects: step and slope change.

Difference in difference

If controls are available the difference-in-difference approach (DID) is a popular choice:



D. Polsky, M. Baiocchi, in Encyclopedia of Health Economics, 2014

- Do not account for external time varying effects or autocorrelation
- Before-after approach
- Causal effects: step change

Other methods under this umbrella: segmented regression, change-in-change, regression discontinuity...

A general framework

These methods have been developed to perform causal inference on longitudinal data dealing with specific data availability

- They are similar!

AIM

- Build a general framework for quasi-experimental designs in a longitudinal setting
- Deal with a common limitation: lack of additional dependence (e.g. in space) & generally simplified assumptions on trends (computational reasons / to make life easy)

$\Rightarrow$ Bayesian Hierarchical Modelling Framework

Can we re-frame this?

For each unit $i = 1, \dots, I$ (areas or individuals) and time $t = 1, \dots, T \geq 2$, the data comprise:

- the outcome y_{it};
- a vector of K covariates (confounders) $\boldsymbol{X}_{it} = (X_{it1}, \dots, X_{itK})$;
- an indicator variable $z_t = 1$ if the intervention is being applied at time t and 0 otherwise;
- an indicator variable $w_i = 1$ if unit i is exposed and 0 if it is a control.

The generalised linear predictor for the average of the outcome μ_{it}:

$$E[y_{it}] = h(\mu_{it}) = \underbrace{\underbrace{\alpha_0 + \alpha_1 w_i + \delta_0 z_t + \delta_1 w_i z_t + \sum_{k=1}^{K} \beta_k X_{itk} + \gamma_i}_{\text{DID}} + \boldsymbol{\lambda}_t}_{\text{ITS}}$$

Can we re-frame this?

- Flexible structure - adapt to data availability:

$\Rightarrow$ Can include controls and non linearity in time trends.

- Account for dependencies in space / across units:

$\Rightarrow \boldsymbol{\gamma}$ can be modelled as exchangeable or spatially structured (neighborhood or distance based);

- δ_1 identifies the causal effect of the intervention. Additional time dependent causal effects can be obtained through λ_t if appropriate.

$$E[y_{it}] = h(\mu_{it}) = \underbrace{\underbrace{\alpha_0 + \alpha_1 w_i + \delta_0 z_t + \delta_1 w_i z_t + \sum_{k=1}^{K} \beta_k X_{itk} + \gamma_i}_{\text{DID}} + \boldsymbol{\lambda}_t}_{\text{ITS}}$$

Can we re-frame this?

- Can include relatively vague information in the priors, which can still help regularise the inference

→ Avoid inconsistent estimates because of small numbers/separation
→ Use Penalised Complexity (PC) priors

- Direct characterisation of full uncertainty in all model parameters

→ Can then rescale (e.g. from regression coefficients to original scores etc) and still obtain samples from the full posterior distributions
→ Particularly helpful for generalised linear models and for obtaining functions of original parameters
→ Can aggregate at any space-time resolution

Example: incinerators effects on health

- Recent increase in incineration of municipal waste in response to European Union (EU) legislation to divert waste from landfills.
- Few studies available, despite public concern about potential for adverse effects from this and other waste management processes on birth and other health outcomes.

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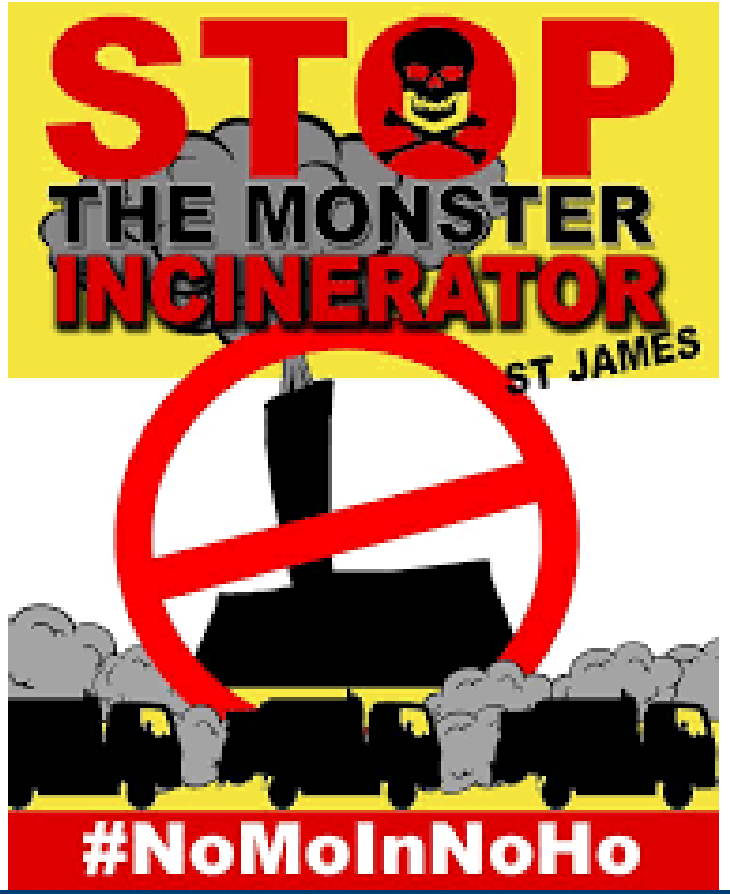
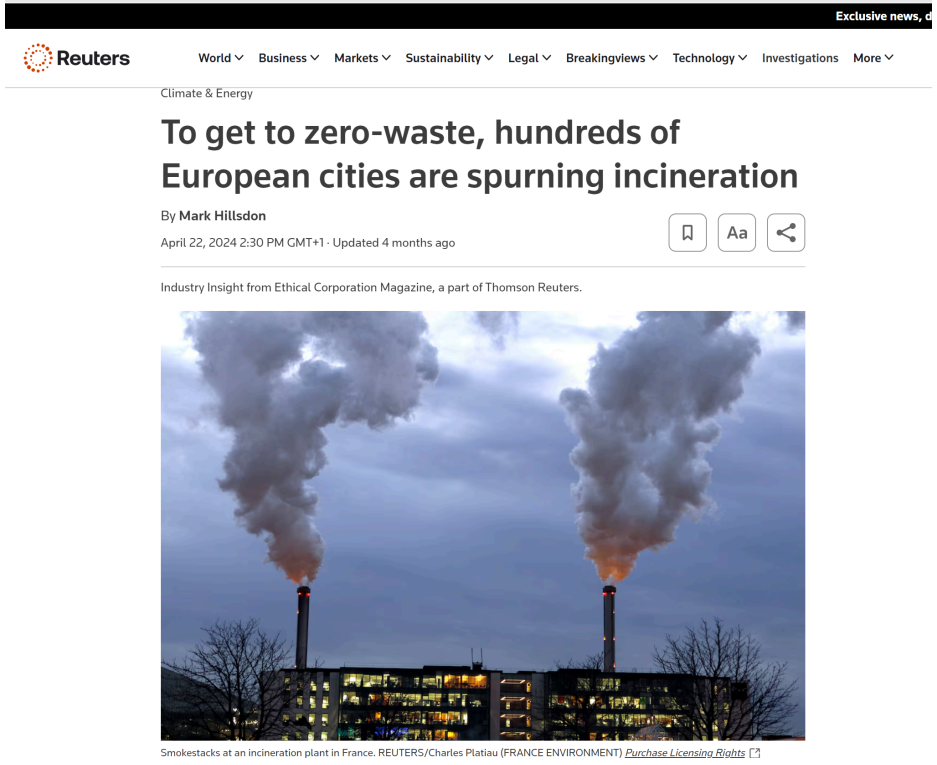




The project

Incinerators study

Frequently asked questions

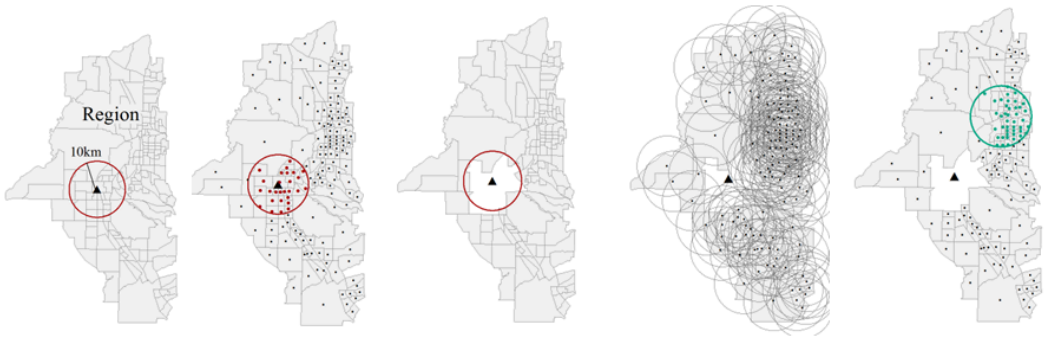
Project Background:

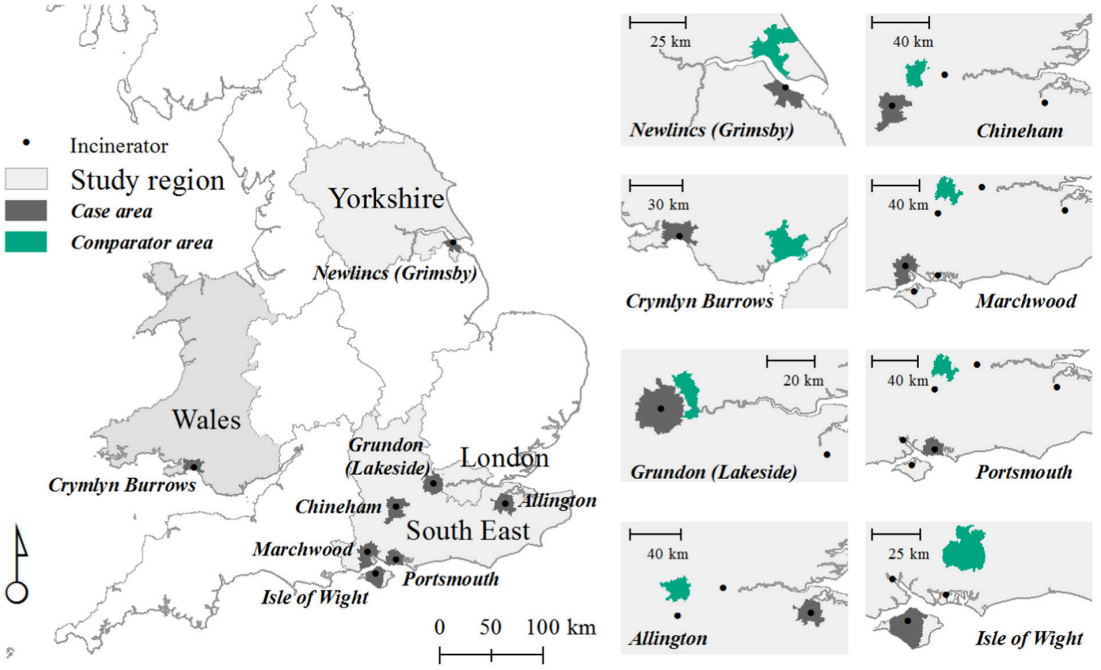
The use of incineration for waste disposal in the UK is increasing due to EU restrictions on the use of landfill. A number of new Municipal Waste Incinerators (MWIs) have been built and between 2003 and 2010 there were 22 operating in England, Scotland and Wales. The incineration process and emissions of modern MWIs are regulated by the Waste Incineration (England and Wales) Regulations 2002 which sets operational conditions, technical requirements, and emission limit values. However there is public concern over any possible health risks associated with modern incineration and this study has been commissioned to extend the evidence base and provide more information to the public on this subject.

This study investigating potential associations between reproductive and infant health and emissions from municipal waste incinerators (MWIs) in England, Scotland and Wales was announced in January 2012 by the Health Protection Agency, whose functions have since been transferred to Public Health England.

Data

- Eight Municipal Waste Incinerators (MWIs) opening within 2003-10; study period 1998-2012.
- Exposed areas as middle super output areas whose centroids lay within a 10km radius buffer of each of the eight MWIs.
- Matched 10km buffers as controls, based on live births, mean percentage of low social class, lack of car ownership, overcrowding, male unemployment, population density and non-white percentage ethnicity.





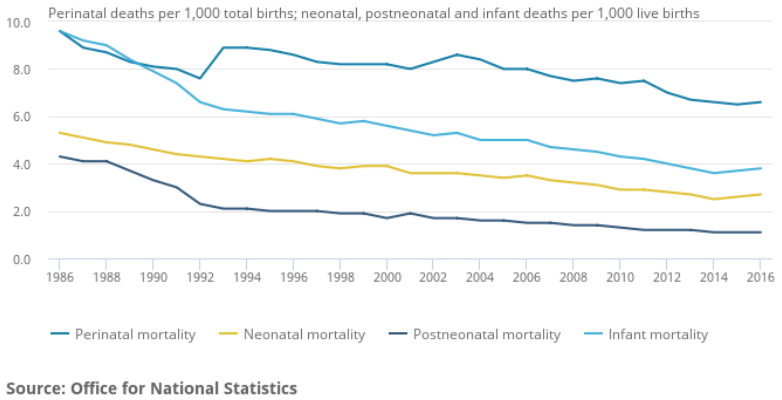
The model

$y_{it} \sim Bin(\mu_{it}, n_{it})$ for infant mortality;

$y_{it} \sim \mathcal{N}(\mu_{it}, \sigma^2)$ for sex ratio.

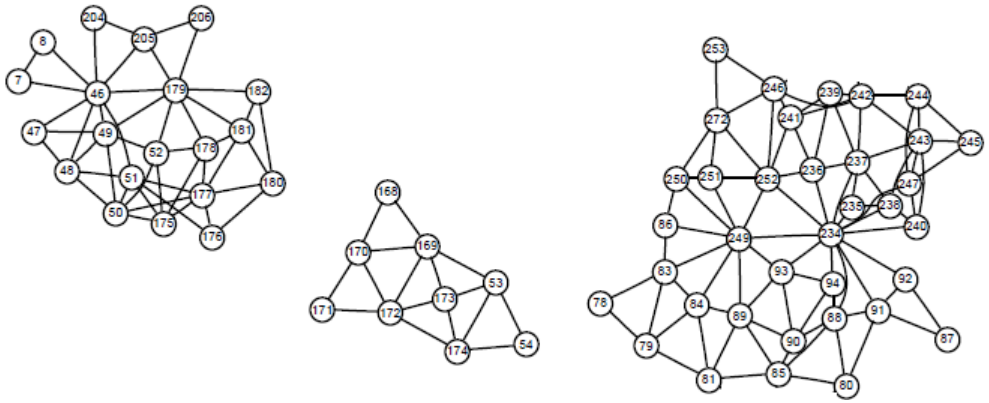
On the linear predictor

$$h(\mu_{it}) = \alpha_0 + \alpha_1 w_i + \psi_0 t + \psi_1 w_i t + \delta_0 z_t (t - t_0) + \delta_1 w_i z_t (t - t_0) + \sum_{k=1}^{K} \beta_k X_{ik} + \gamma_i$$



Source: Office for National Statistics

- Linear trends on λ_t and ψ_t
- On γ_i we assume a combination of spatial and unstructured random effects
- Disconnected spatial areas



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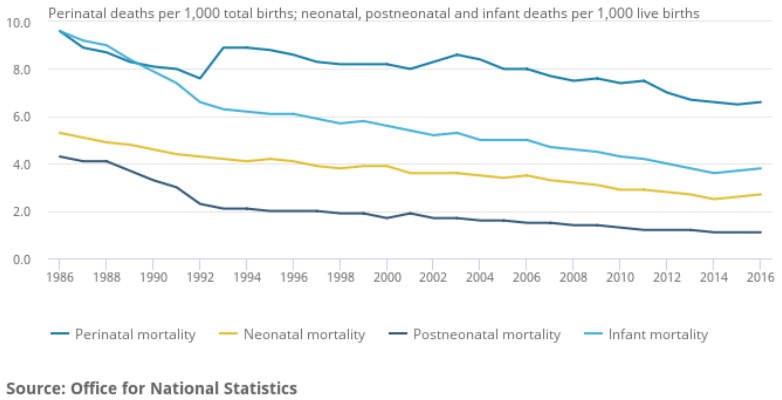

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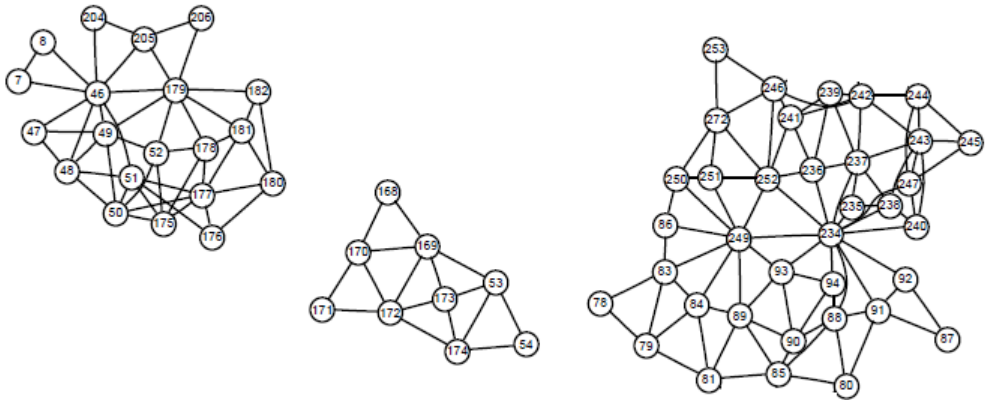

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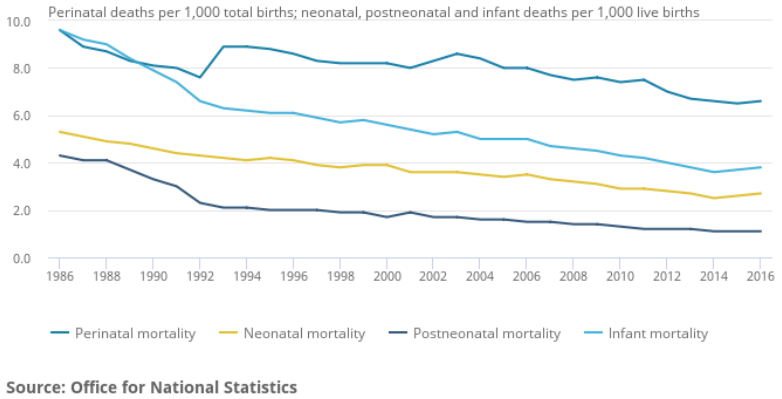

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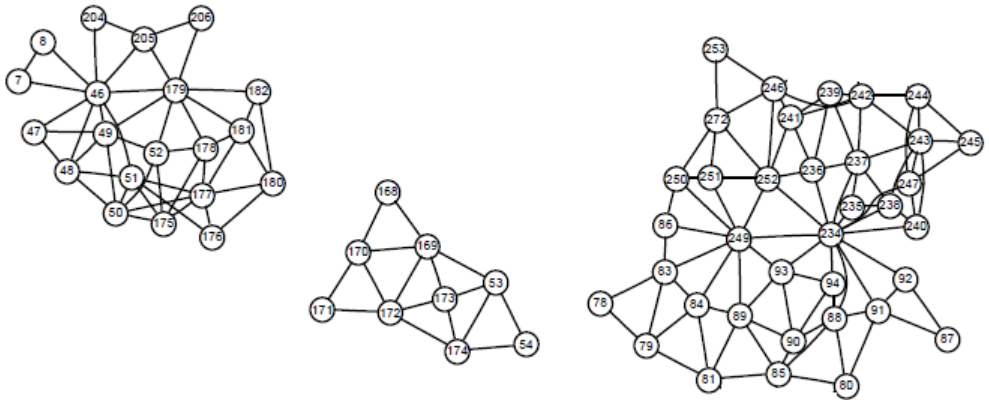

Interpretation

		Intervention indicator z_i		
		0	1	
Exposure group w_i	0	$\alpha_0 + \psi_0 t$	$\alpha_0 + \psi_0 t + \delta_0(t - t_0)$	$\delta_0(t - t_0)$
	1	$\alpha_0 + \alpha_1 + \psi_0 t + \psi_1 t$	$\alpha_0 + \psi_0 t + \psi_1 t + \delta_0(t - t_0) + \delta_1(t - t_0)$	$(\delta_0 + \delta_1)(t - t_0)$
		$\alpha_1 + \psi_1 t$	$\alpha_1 + \psi_1 t + \delta_1(t - t_0)$	

- δ_0: potential discontinuity in controls before-after intervention.
- δ_1: difference of differences before - after intervention between exposed and controls (at intervention time).

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		0	1	
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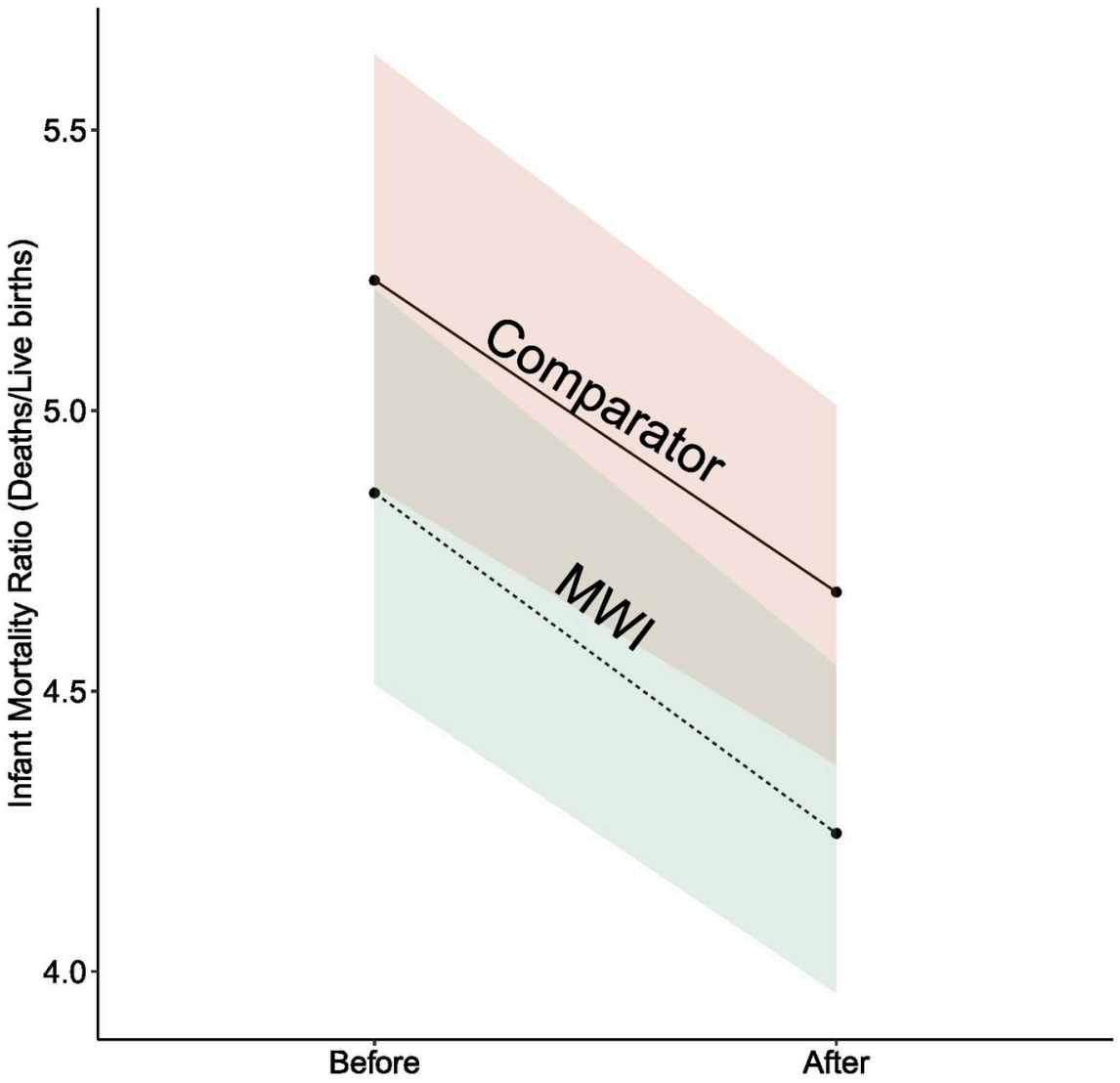
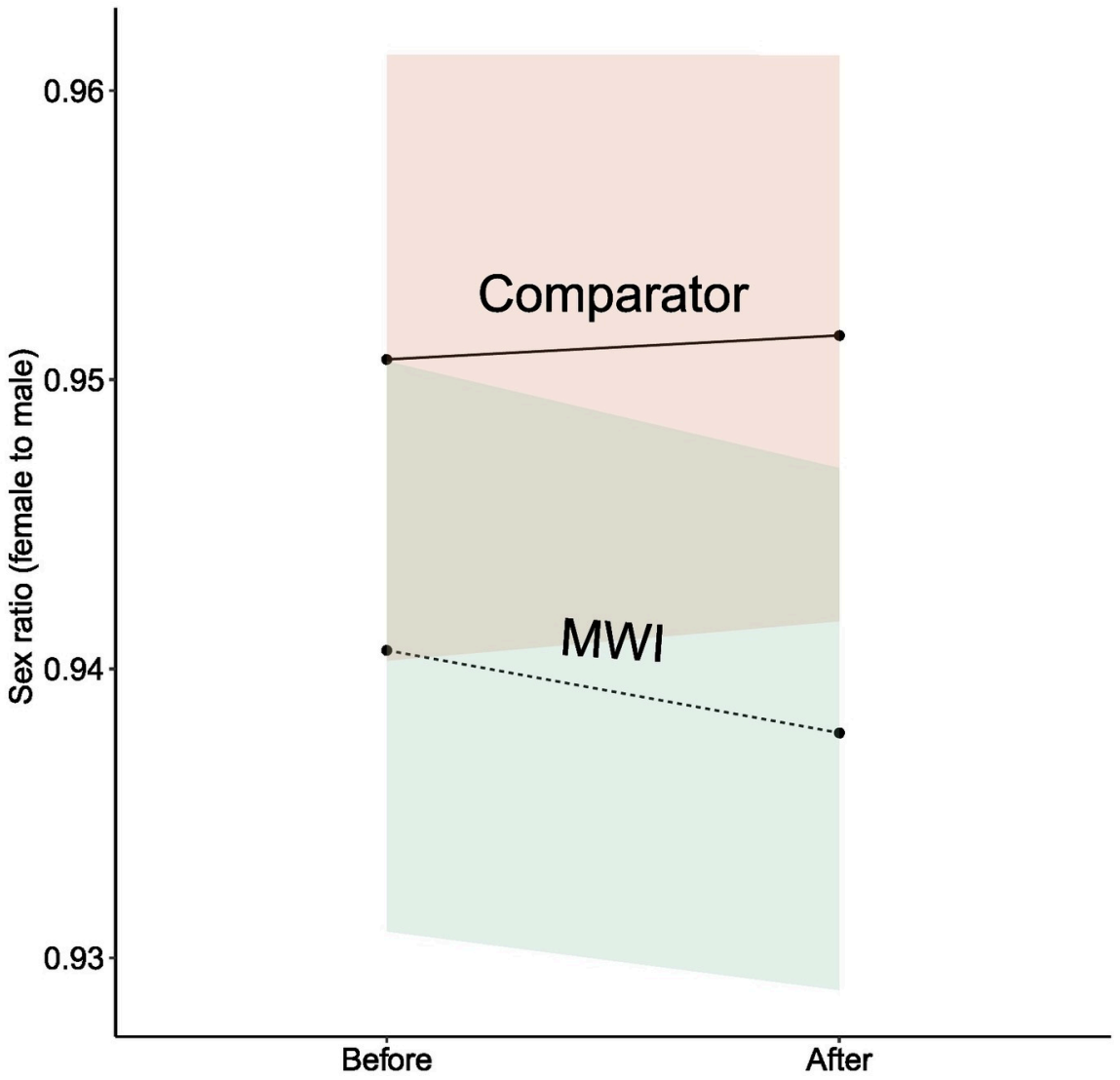
	1	$\alpha_0 + \alpha_1 + \psi_0 t + \psi_1 t$	$\alpha_0 + \psi_0 t + \psi_1 t + \delta_0(t - t_0) + \delta_1(t - t_0)$	$(\delta_0 + \delta_1)(t - t_0)$
		$\alpha_1 + \psi_1 t$	$\alpha_1 + \psi_1 t + \delta_1(t - t_0)$	

- δ_0: potential discontinuity in controls before-after intervention.
- δ_1: difference of differences before - after intervention between exposed and controls (at intervention time).

- Rich output means that we can easily look at differences for specific times before-after.
- Potential flexibility of the model traded-off with the difficulty in interpretation if a more flexible time trend is considered.

Results

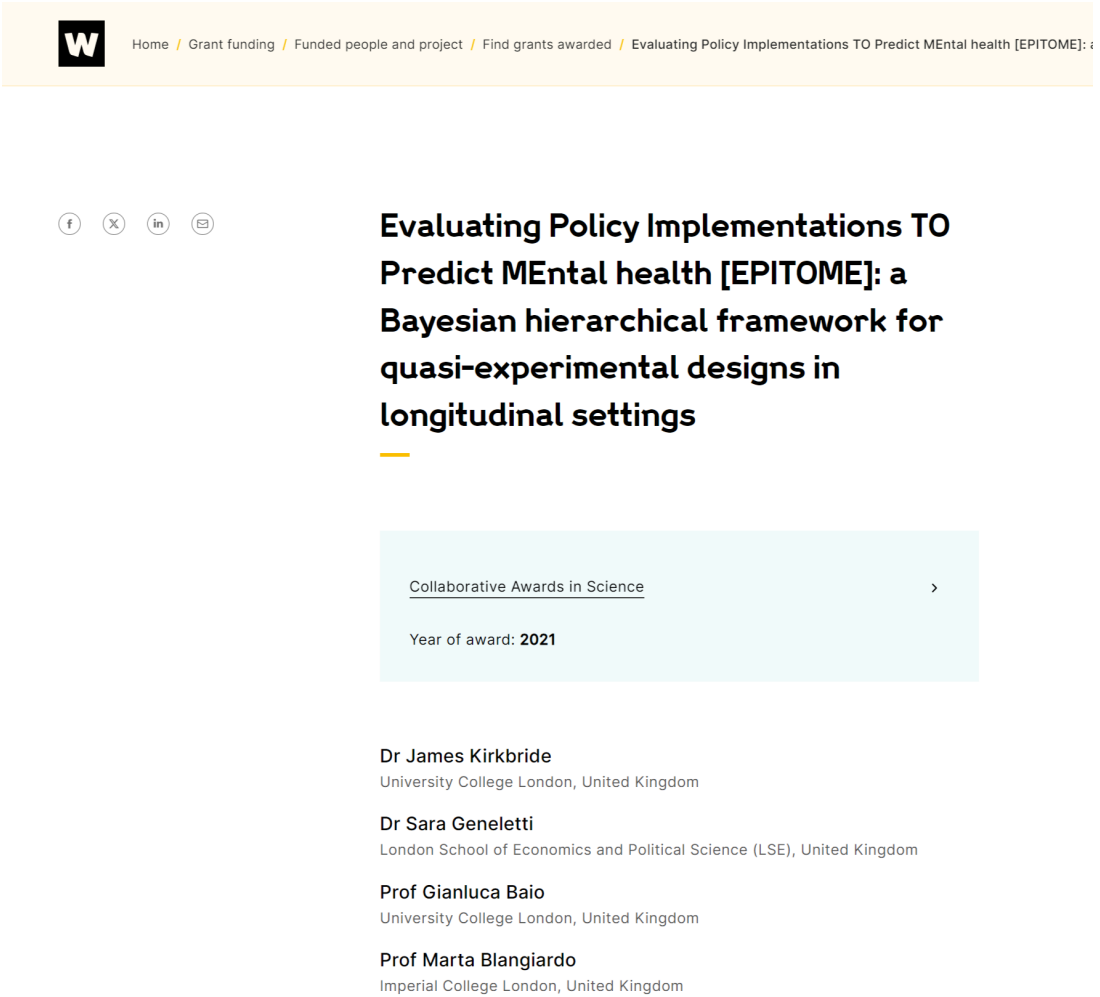




- No evidence of an effect on infant mortality and sex ratio

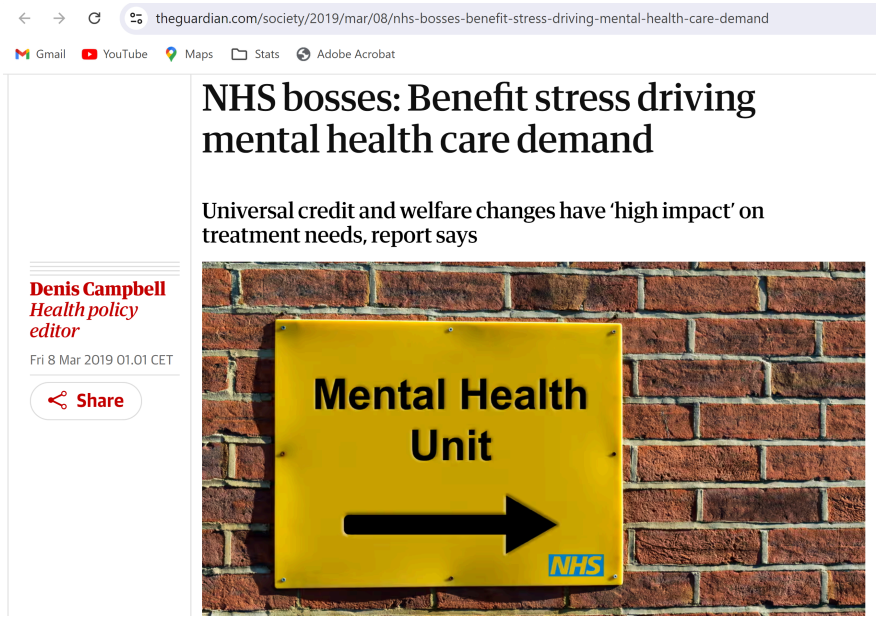
Example: Welfare policies and mental health

- As a modern welfare state, one of the core functions of Government is to promote equitable social and economic wellbeing for its citizens.
- Broad set of policy levers, ranging from taxation, welfare reform, migration policy to the provision of public health care
- Ineffective implementation of policy may result in negative consequences for population mental health, especially when intentionally or unintentionally generates or perpetuates social and economic inequities in society



Universal credit

- UC was introduced in the UK in the early 2010s by the coalition government led by the Conservatives
- Theoretical aim was to simplify and facilitate access and receipt of welfare according to need.
- In practice lengthy delay in payment and increased sanction with individuals receiving reduced amounts or no amount of welfare support at all for long periods



Data & Model

- UK Household Longitudinal Survey ("*Understanding Society*")

- Age 16-64 with
  – (i) employment status,
  – (ii) Lower Layer Super Output Area (LSOA) of residence,
  – (iii) responded at least once to mental health questionnaire - score from 0 - 36 derived from the GHQ-12 questionnarie where higher scores indicating more severe impairment

- **Exposure variable** was defined as unemployment status

- **Policy definition** contextual awareness using monthly statistics (Department of Work and Pensions) of UC - when it reaches 25% we assume the Local Authority has switched to UC.
- **Confounders** (individuals) age, education level, ethnicity, relationship sta- tus, and sex; (area level) social deprivation and ethnic diversity

$$
\begin{aligned}
E(Y_{it}) = h(\mu_{it}) = \\
&\alpha_0 + \alpha_1 w_{it} + \\
&\psi_0 t_i + \psi_1 t_i w_{it} + \\
&\delta_0^\star z_{it} + \delta_1^\star z_{it} w_{it} + \\
&\delta_0 z_{it}(t - t_{0i}) + \delta_1 z_{it}(t - t_{0i}) w_{it} + \\
&\sum_{k=1}^{K} \beta_k X_{itk} + \lambda_t + \gamma_i
\end{aligned}
$$

- γ_i includes individual, spatial random effect and strata/clusters coming from the survey design
- Start of the policy is not fixed

Results: fixed effects

	Parameter (95% Credible Interval)	$\Pr(\text{Parameter} > 0) \times 100$
Control:		
Intercept, α_0	10.6979 (9.5313, 11.7864)	100.00
Time, ψ_0	0.0089 (-0.0165, 0.0327)	80.90
Intervention, $\delta_0^\star$	-0.0222 (-0.285, 0.2413)	42.50
Time$^+$, δ_0	-0.0004 (-0.0019, 0.001)	27.30
Difference:		
Intercept, α_1	2.1617 (1.9858, 2.3503)	100.00
Time, ψ_1	0.0026 (0.0001, 0.0053)	97.80
Intervention, $\delta_1^\star$	0.5316 (0.1236, 0.9639)	99.70
Time$^+$, δ_1	-0.0011 (-0.002, -0.0003)	0.50
Exposed:		
Intercept, $\alpha_0 + \alpha_1$	12.8423 (11.7108, 13.9713)	100.00
Time, $\psi_0 + \psi_1$	0.0115 (-0.0142, 0.0355)	86.10
Intervention, $\delta_0^\star + \phi_1^\star$	0.507 (0.0414, 0.9603)	98.20
Time$^+$, $\delta_0 + \delta_1$	-0.0015 (-0.0031, 0.0002)	4.30

Standardised change

Standardised percent change

It estimates the change in the score in the exposed population before and after the intervention, while adjusting for what happens in the controls during the same period.

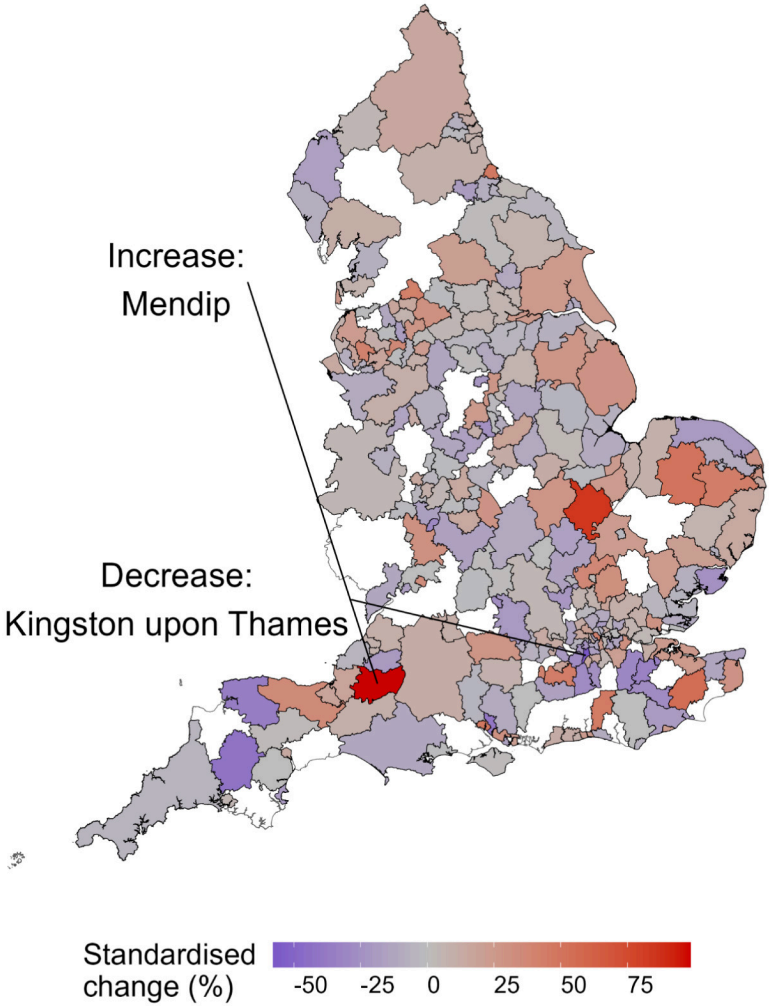
- E=exposed;
- C=non exposed;
- A= time points after the introduction of the policy;
- B=time points before the introduction of the policy

1. $p^{\mathrm{EA}} = \mu^{\mathrm{EA}}$ average of the posterior distribution of the linear predictor for all exposed individuals after the intervention only
2. $\tilde{p}^{\mathrm{EB}} = \mu^{\mathrm{EB}} \frac{\mu^{\mathrm{CA}}}{\mu^{\mathrm{CB}}}$ average of the posterior distribution of the linear predictor for all exposed individuals before the intervention only $\rightarrow$ rescaling using the controls
3. $\rho = (p^{\mathrm{EA}} - \tilde{p}^{\mathrm{EB}})/\tilde{p}^{\mathrm{EB}}$

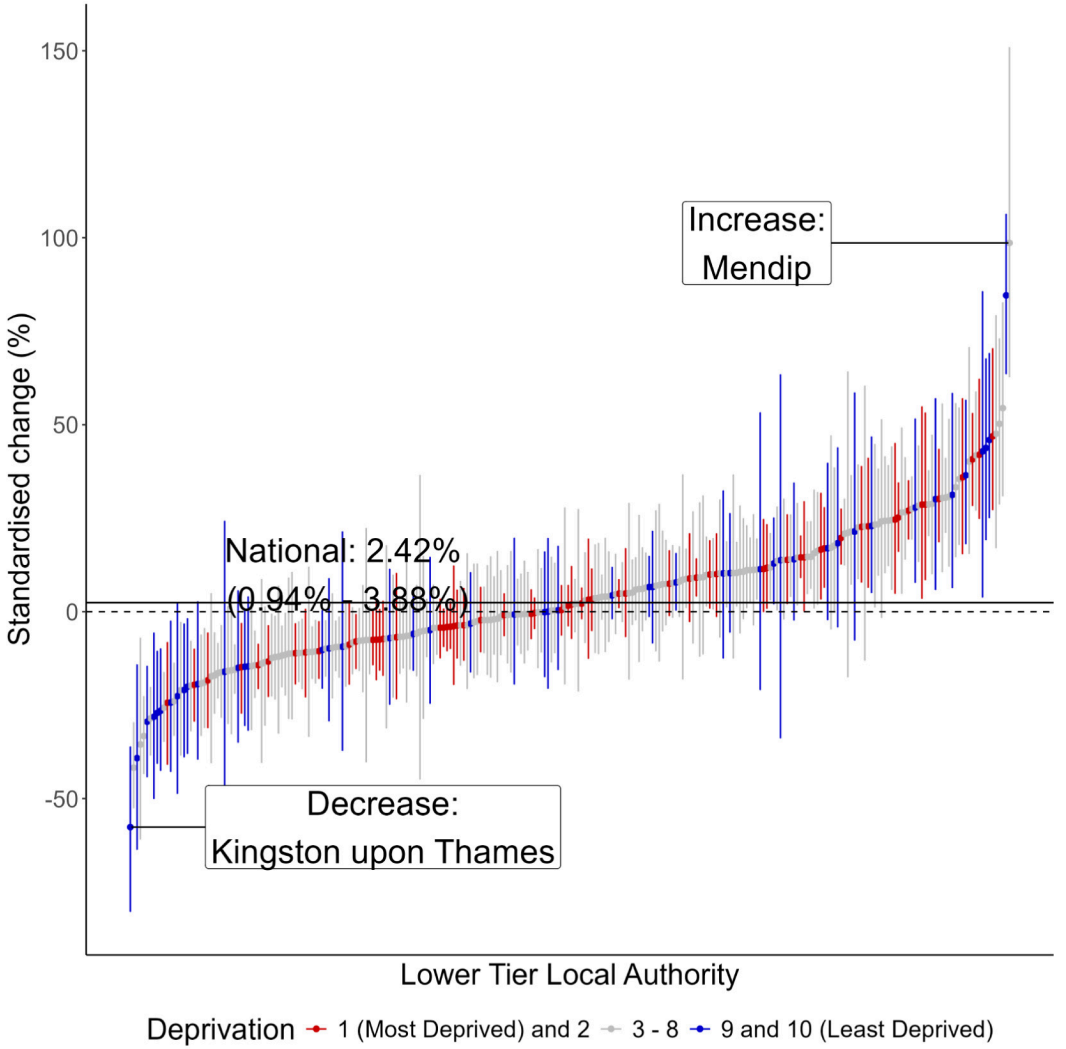
is a **standarsised change of the impact of UC on mental distress**

$\rightarrow$ Full posterior distribution

Results: standardised change



(a) Median standardised change



(b) Uncertainty of standardised change

The Windrush generation

- After the Second World War, the UK faced severe labour shortages. To make up for this they encouraged people from British Colonies to move to the UK, with the promise of jobs, a better standard of living, and British Citizenship
- Between 1948 and 1970, nearly half a million people moved from the Caribbean to Britain. These individuals became known as the **Windrush Generation**, after the ship which carried some of the first migrants
- The Immigration Act of 1971 meant that only commonwealth citizens who arrived before 1971 were allowed the right to stay in the UK
- However, in 2010 the British Home Office destroyed all migration records from the 1950s and 1960s
- This meant that many people who came to Britain as part of the Windrush Generation, and many of their children, no longer had evidence of their British Citizenship

Hostile environment and the Windrush scandal

- The UK government (under pressure from nationalist/populist parties pushing for brexit), started a series of immigration reforms, collectively known as the *hostile environment policy*, in **2012** followed by the Immigration Act in **2014**

- These policies deliberately aimed to make life difficult for migrants and operated on a "deport first, ask questions later" basis

- In **2017** the "Windrush scandal" hits the mainstream media headlines and cost her job to the new Home Secretary, Amber Rudd, but not to the one who actually enacted the policy...

Data and timeline

We use data from The UK Household Longitudinal Survey ("*Understanding Society*")

Participants

- Age 16+, responded at least once to mental health questionnaire

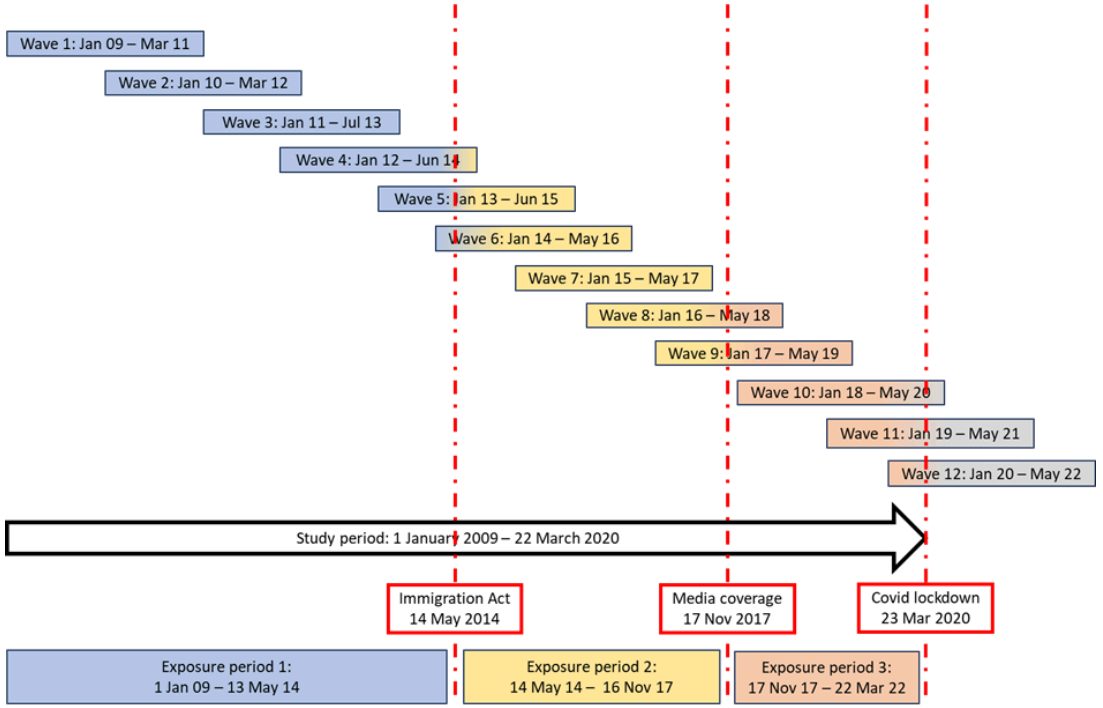
Timing

- 12x 24 month “waves”, January 2009 to March 2020
- Avoid "Covid" confounding...

Outcome & exposure

- Outcome: Mental ill health using the GHQ score
- Exposures:
  - Immigration Act 2014
  - Windrush media coverage 2017
  - Exposed ethnicities: Black African, Black Caribbean, Indian, Pakistani, Bangladeshi vs White
- Main confounders: age, sex, urban/rural, IMD, children, UK born, education, working condition

Study design



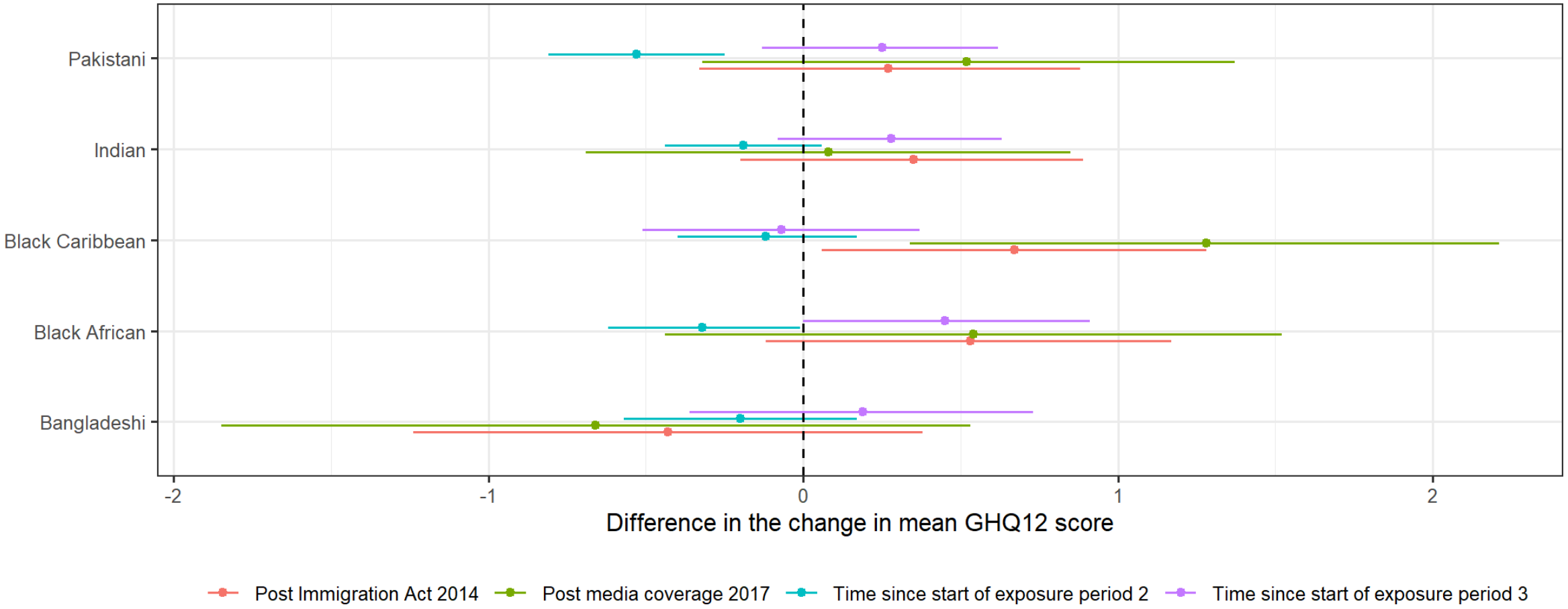
- More than one **policy**
- More than one **exposed groups**

For individual i, ethnical group j, month t

$$
\begin{aligned}
E(Y_{it}) = h(\mu_{ijt}) = \\
&\alpha_0 + \alpha_j w_{j_i} + \\
&\psi_0 t + \psi_j w_{j_i} t + \\
&\phi_0^\star z_t^1 + \phi_j^\star z_t^1 w_{j_i} + \\
&\phi_0 z_t^1 (t - t_0^1) + \phi_j z_t^1 (t - t_0^1) w_{j_i} + \\
&\delta_0^\star z_t^2 + \delta_j^\star z_t^2 w_{j_i} + \\
&\delta_0 z_t^2 (t - t_0^2) + \delta_j z_t^2 (t - t_0^2) w_{j_i} + \\
&\sum_{k=1}^{K} \beta_k X_{itk} + \gamma_i + \lambda_t
\end{aligned}
$$

- $\phi_0^\star$, $\phi_j^\star$, $\delta_0^\star$ and $\delta_j^\star$ immediate effect of first and second policies for control and j exposure groups
- ϕ_0 and ϕ_j, δ_0 and δ_j sustained effect of first and second policies for control and j exposure groups

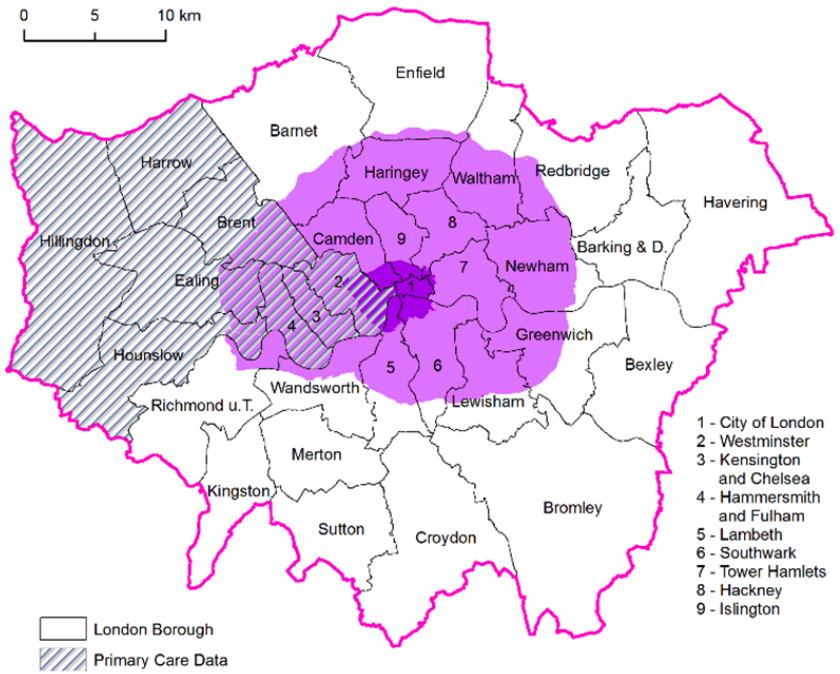
Results



- evidence of greater psychological distress in people from Black Caribbean backgrounds, which persists over time
- increase in mental distress between the two periods with post media coverage having a bigger effect across all ethnic groups

Spillover

A positive or a negative impact experienced in one place due to an independent event occurring in another place



	Population			
	Total	Age 0 - 15	Age 16 - 64	Over 64
ULEZ 2019	204,608	25,551	159,372	19,685
ULEZ 2021	3,834,718	736,535	2,734,505	363,690
Greater London	8,825,001	1,812,812	5,973,028	1,039,161

- Original policy implemented in 8/4/2019
- First extension in 2021
- Second extension in 2023 to cover the whole of Greater London

- Model framework can be extended so that the intervention effects are are specific
- Specified as function of space and/or covariates
- Synthetic controls can be added

Discussion

- Flexible robust framework which can be adapted to a range of questions at individual and aggregated level
- it naturally allows the construction of additional quantities of interest with their associated uncertainty
- Caveat: it cannot be framed in a traditional causality perspective entirely, but it allows to evaluate the effect of intervention in a regression-type model
- Still some assumptions are needed

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