The association between the Referral to Treatment backlog and all-cause mortality in England

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# Health, Morbidity, and Mortality Annual Meeting 2024 Bilbao September 25-27, 2024



• Aims



- The Data
- The Model



- Lag effects
- RRs
- AFs



Conclude

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Outline	Motivation	Model	Results	<b>Conclude</b>
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Motivation				

• Treatment (and diagnostic) delays within the National Health Service (NHS) have been increasing in recent years but since the emergence of COVID-19 the backlog has grown enormously.

Outline	Motivation	<b>Model</b>	Results	<b>Conclude</b>
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- Treatment (and diagnostic) delays within the National Health Service (NHS) have been increasing in recent years but since the emergence of COVID-19 the backlog has grown enormously.
- The NHS is under massive strain and many believe if the status quo continues, the backlogs are likely to contribute to worsening morbidity and mortality.

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- Treatment (and diagnostic) delays within the National Health Service (NHS) have been increasing in recent years but since the emergence of COVID-19 the backlog has grown enormously.
- The NHS is under massive strain and many believe if the status quo continues, the backlogs are likely to contribute to worsening morbidity and mortality.
- The current state of the NHS will continue to engage politicians, policymakers and the general public for years to come.

Outline	Motivation	Model	Results	<b>Conclude</b>
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Aims				

• To explore the association between all-cause deaths and the delay in NHS treatment in England.

Outline	Motivation	Model	Results	<b>Conclude</b>
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Aims				

- To explore the association between all-cause deaths and the delay in NHS treatment in England.
- To estimate the attributable risk of deaths due to NHS treatment delay.

Outline	Motivation	Model	Results	<b>Conclude</b>
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In the news				

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Health								

### England's hospital waiting lists rise to 7.57m



Nick Triggle > Health correspondent @nicktriggle >

13 June 2024 - 📮 155 Comments

Outline	Motivation	Model	Results	<b>Conclude</b>
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In the news				

## 'National tragedy': figures show large rise in people dying while on NHS waiting list

Figures obtained by Labour show an estimated 120,695 people died in England while awaiting treatment



Hospital bosses say deaths reflect a 'decade of underinvestment' that has left the NHS with too few staff and beds. Photograph: Victoria Jones/PA

More than 120,000 people in England died last year while on the <u>NHS</u> waiting list for hospital treatment, figures obtained by Labour appear to show.

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In the news				

Home UK **Politics** World Israel-Hamas War US Climate Science & Tech Business Ents & Arts

# Record number of GP appointments to have four-week waits this year

Data shows the number of lengthy waits for appointments is set to be more than 17.6 million this year.



Alix Culbertson Political reporter @alixculbertson

() Sunday 15 September 2024 22:54, UK

<b>Outline</b>	Motivation	Model	Results	<b>Conclude</b>
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UK NEWS WEBSITE OF THE YEAR													

# Hospital waiting list deaths double in five years

More than 120,000 died waiting for NHS treatment, as backlog hits all-time high

*By* Laura Donnelly, HEALTH EDITOR 31 August 2023 • 12:01am

### Related Topics

NHS waiting lists, NHS strikes, NHS, Rishi Sunak, Labour Party, Wes Streeting

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The number of NHS patients dying <u>while waiting for treatment</u> has doubled in five years, new figures suggest.

More than 120,000 people died while on waiting lists last year, according to an analysis of health service data. The total is even higher than it was in lockdown, with health leaders saying the pandemic and <u>NHS strikes</u> have made clearing backlogs more difficult.

Waiting lists are at an all-time high despite Rishi Sunak's pledge to cut them as <u>one of his five priorities</u> ahead of a general election.

Matthew Taylor, the chief executive of the NHS Confederation, said: "These figures are a stark reminder about the potential repercussions of long waits for care. They are heartbreaking for the families who will have lost loved ones and deeply dismaying for NHS leaders, who continue to do all they can in extremely difficult circumstances.

Outline	Motivation	<b>Model</b>	Results	Conclude
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# Waitlist growth month-by-month

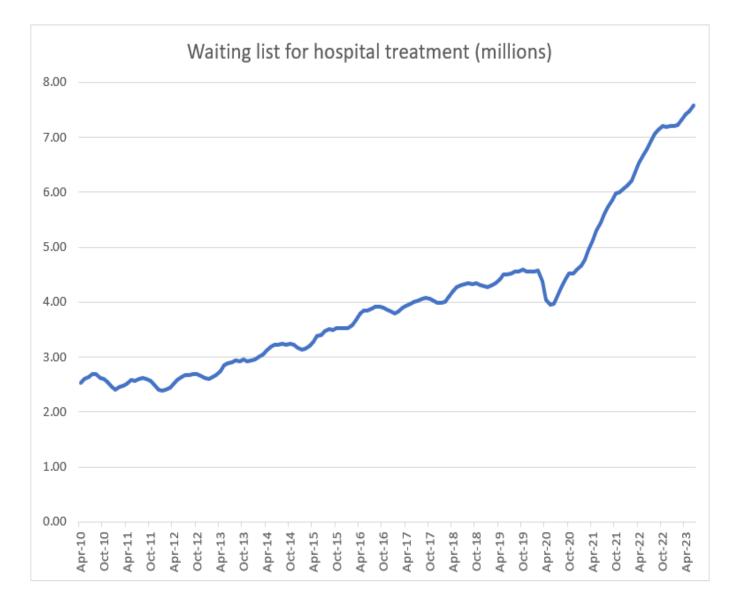


Figure: Median RTT wait time (weeks). Source: https://www.england.nhs.uk/statistics/statistical-work-areas/rtt-waiting-times/

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# Deaths vs monthly waitlist

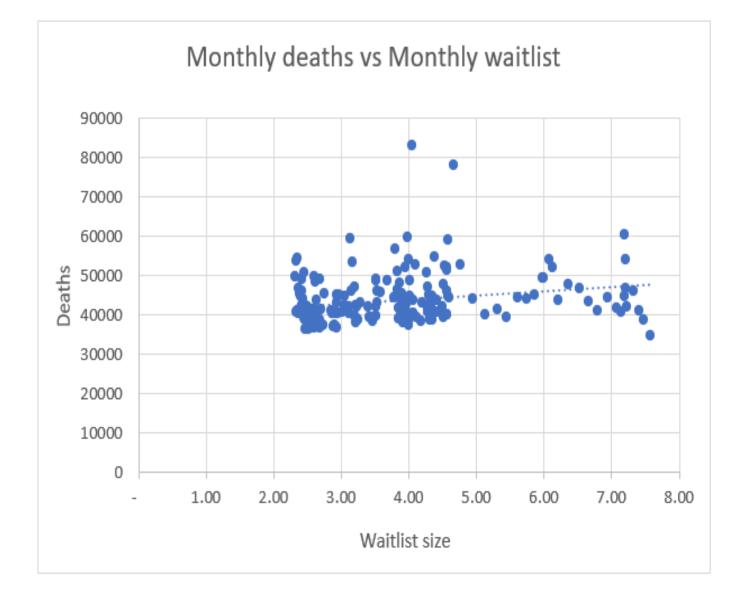


Figure: Deaths vs Waitlist. Source: https://www.england.nhs.uk/statistics/statistical-work-areas/rtt-waiting-times/

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Data				

Outline	Motivation	Model	Results	<b>Conclude</b>
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• Daily death occurrence data from the ONS

Outline	Motivation	Model	Results	Conclude
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Data				

- Daily death occurrence data from the ONS
- Referral to Treatment (RTT) Waiting Time data:
  - We convert monthly RTT to daily RTT data by assuming a linear change in RTT over each month

Outline	Motivation	Model	Results	<b>Conclude</b>
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Data				

• Daily death occurrence data from the ONS

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- Referral to Treatment (RTT) Waiting Time data:
  - We convert monthly RTT to daily RTT data by assuming a linear change in RTT over each month
- Data from Aug 1, 2007 June 30, 2023

Outline 0	Motivation	Model o●oooo	Results	Conclude 00
The Distribu et al., 2010)	ted Lag N	Jon-linear Model	(DLNM)	(Gasparrini

- Distributed Lag: The effects of a variable can be spread out over future time periods rather than just being immediate and concentrated at a single time point.
- Why DLNM?
  - Health impacts can persist for some time after "exposure" to delay in treatment.
  - DLNM captures both the delay-mortality relationship and its temporal structure.
- DLNM can be viewed as a special case of generalised additive models.

Outline	Motivation	Model	Results	<b>Conclude</b>
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Model				

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Outline	<b>Motivation</b>	Model	Results	<b>Conclude</b>
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 Assume 90-day lag to account for the delayed effect of waiting for treatment on mortality i.e today's waitlist for treatment can not only impacts mortality today but also future mortality outcomes.

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- This statistical approach is borrowed from environmental epidemiology and is considered state-of-the-art for modelling the association between mortality and temperature, air pollution, etc.

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- See e.g. Gasparrini, 2014

Outline	Motivation	Model	Results	<b>Conclude</b>
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Model				

# $Y_t \sim Poisson(\mu_t)$

$$log(\mu_t) = \alpha + cb + ns(time, 7df per yr) + DoW$$

- $Y_s$  daily death counts assumed to be overdispersed poisson dictributed
- $\alpha$  intercept term
- *cb* cross-basis matrix for the bi-dimensional functional space of predictor and lags produced by DLNM
- *ns* natural cubic spline with 7 degrees of freedom per year to control for seasonal and long-term trends

Outline	Motivation	Model	Results	<b>Conclude</b>
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Model				

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Outline	Motivation	Model	Results	<b>Conclude</b>
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Model				

•  $D_{x,t}, \mu_{x,t}$ : death counts and mortality rate for age x at time t

Outline	Motivation	Model	Results	<b>Conclude</b>
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Model				

- $D_{x,t}, \mu_{x,t}$ : death counts and mortality rate for age x at time t
- Using a log link with overdispersed Poisson distribution for DLNM, we model  $D_{x,t}$  as follows

$$\ln E(D_{x,t}) = \alpha_0 + v(t) + \sum_{l=0}^{L} s_l(T_{t-l}, l, n_l)$$

<b>Outline</b>	Motivation	Model	Results	<b>Conclude</b>
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•  $v_t$ : a smoothing function of time t capturing the time trend and seasonality of mortality.

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- $v_t$ : a smoothing function of time t capturing the time trend and seasonality of mortality.
- $T_{t-1}$ : a predictor (e.g. delay) at lag /

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- $v_t$ : a smoothing function of time t capturing the time trend and seasonality of mortality.
- $T_{t-1}$ : a predictor (e.g. delay) at lag /
- $s_l(T_{t-l}, I, n_l)$ : a cross-basis function between  $T_{t-l}$  and l parameterised by coefficients  $n_l$ , capturing the nonlinear and lagged effect of the predictor

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- L : the maximum considered lag

Outline	Motivation	Model	Results	Conclude
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# Practicalities

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Outline	Motivation	Model	Results	<b>Conclude</b>
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Practicalities	5			

 We fitted a natural cubic spline function with three internal knots placed at the 10th, 75th, and 90th percentiles of the local temperature distribution to model the exposure-response curve.

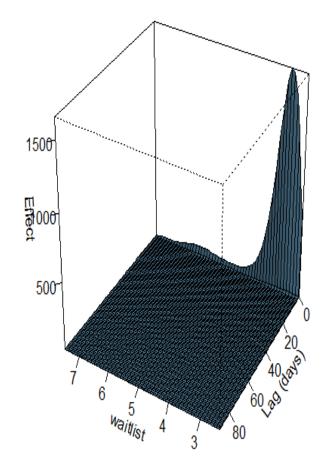
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Practicalities	S			

- We fitted a natural cubic spline function with three internal knots placed at the 10th, 75th, and 90th percentiles of the local temperature distribution to model the exposure-response curve.
- The lag-response curve was modelled with a natural cubic spline with an intercept and three internal knots equally distributed in the log-space

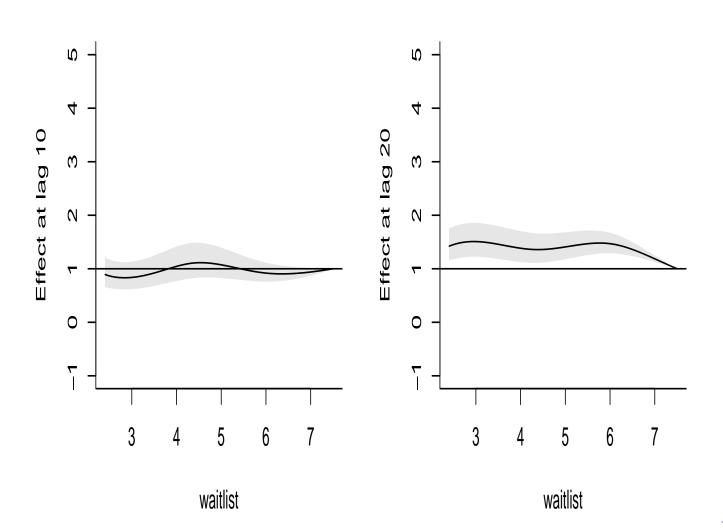
Outline	Motivation	Model	Results	<b>Conclude</b>
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Practicalities	S			

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- The lag-response curve was modelled with a natural cubic spline with an intercept and three internal knots equally distributed in the log-space
- Assumed up to for up to 90 days of lag in line with literature
- We controlled for day of the week with an indicator, and for seasonal and long-term trends with a natural cubic spline of time with 7 degrees of freedom per year.

Outline	Motivation	Model	Results	<b>Conclude</b>
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Lag-Expo	osure-Response			

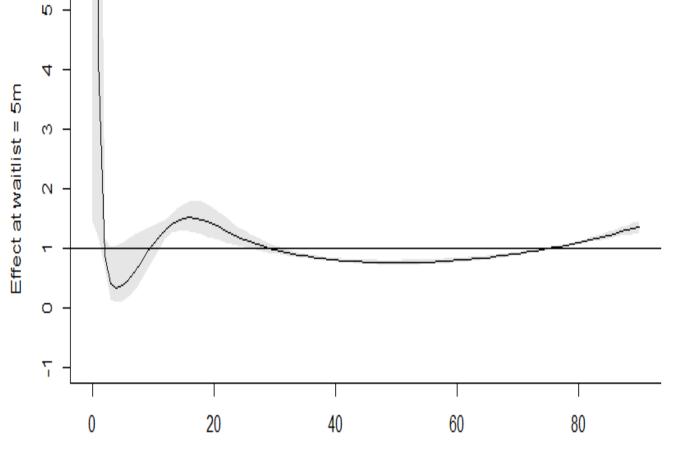


Outline	Motivation	Model	Results	<b>Conclude</b>
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Lag effects				



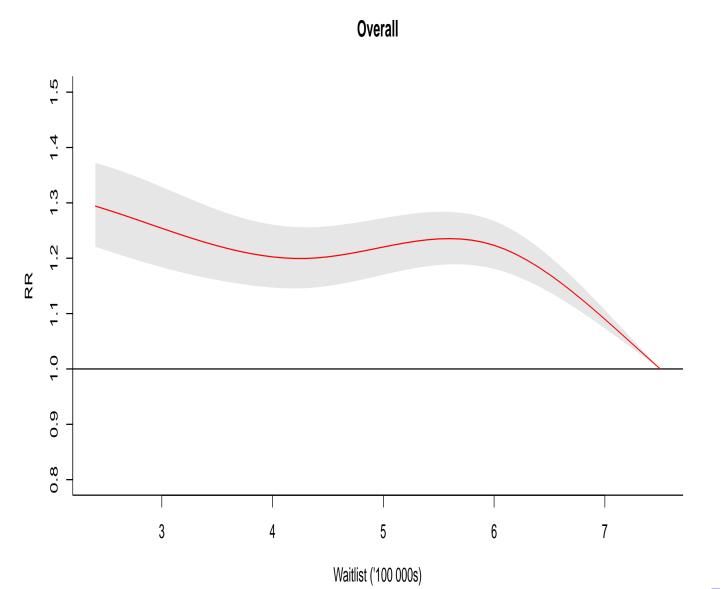
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Effect by lag for specific waitlist



Lag (days)

Outline	Motivation	Model	Results	<b>Conclude</b>
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Relative Ri	sks			



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Outline	Motivation	Model	Results	<b>Conclude</b>
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Attributa	ble fractions			

• Let AFx be the attributable fraction for exposure x, then

•  $AF_x = 1 - exp(-\beta x)$ ,

- where βx is the risk associated with the exposure, and it usually corresponds to the logarithm of a ratio measure e.g. relative risk, relative rate, etc.
- For binary variables reporting presence/absence of the exposure, formula simplifies AF = (RR 1)/RR

Estimated AF = 15.7% (12%, 19%)

<b>Outline</b>	Motivation	<b>Model</b>	Results	Conclude
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## Discussion

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<b>Outline</b>	Motivation	Model	Results	Conclude
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Discussion				

 Presented a way to model association between mortality and NHS treatment delays which accounts for the lag between waiting for treatment and mortality.

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Discussion				

- Presented a way to model association between mortality and NHS treatment delays which accounts for the lag between waiting for treatment and mortality.
- (Excessive) waiting lists may be contributing a non-trivial proportion of all-cause mortality in England.

Outline	Motivation	Model	Results	Conclude
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Discussion				

- Presented a way to model association between mortality and NHS treatment delays which accounts for the lag between waiting for treatment and mortality.
- (Excessive) waiting lists may be contributing a non-trivial proportion of all-cause mortality in England.
- The shape of the RR suggests that beyond a certain point, the excess mortality risk from the treatment backlog wears off. Why?

Outline	Motivation	<b>Model</b>	Results	Conclude
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## Further Work

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Outline	Motivation	Model	Results	Conclude
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Further Wo	ork			

• Can data on most serious conditions identified? Delays more crucial for serious conditions vs minor ones.

Outline	Motivation	Model	Results	Conclude
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Further W	′ork			

- Can data on most serious conditions identified? Delays more crucial for serious conditions vs minor ones.
- Improvements to model needed for identified weaknesses (account for exposure, testing smoothing approach, etc.)

Outline	<b>Motivation</b>	Model	Results	Conclude
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Further W	/ork			

- Can data on most serious conditions identified? Delays more crucial for serious conditions vs minor ones.
- Improvements to model needed for identified weaknesses (account for exposure, testing smoothing approach, etc.)
- Investigate ways to sense check RR shape and estimated AFs.

Outline	Motivation	Model	Results	Conclude
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- Can data on most serious conditions identified? Delays more crucial for serious conditions vs minor ones.
- Improvements to model needed for identified weaknesses (account for exposure, testing smoothing approach, etc.)
- Investigate ways to sense check RR shape and estimated AFs.
- Introduce other predictors, e.g. age, sex.

Outline	Motivation	Model	Results	Conclude
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- Can data on most serious conditions identified? Delays more crucial for serious conditions vs minor ones.
- Improvements to model needed for identified weaknesses (account for exposure, testing smoothing approach, etc.)
- Investigate ways to sense check RR shape and estimated AFs.
- Introduce other predictors, e.g. age, sex.
- Explore the lag structure.