Excess registered deaths in England and Wales during the COVID-19 pandemic, March 2020 and April 2020

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Abstract

Official counts of COVID-19 deaths have been criticized for potentially including people who did not die of COVID-19 but merely died with COVID-19. I address that critique by fitting a generalized additive model to weekly counts of all registered deaths in England and Wales during the 2010s. The model produces baseline rates of death registrations expected in the absence of the COVID-19 pandemic, and comparing those baselines to recent counts of registered deaths exposes the emergence of excess deaths late in March 2020. Among adults aged 45+, about 38,700 excess deaths were registered in the 5 weeks comprising 21 March through 24 April (612 ± 416 from 21–27 March, 5675 ± 439 from 28 March through 3 April, then 9183 ± 468, 12,712 ± 589, and 10,511 ± 567 in April’s next 3 weeks). Both the Office for National Statistics’s respective count of 26,891 death certificates which mention COVID-19, and the Department of Health and Social Care’s hospital-focused count of 21,222 deaths, are appreciably less, implying that their counting methods have underestimated rather than overestimated the pandemic’s true death toll. If underreporting rates have held steady, about 45,900 direct and indirect COVID-19 deaths might have been registered by April’s end but not yet publicly reported in full.

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1 Introduction

The ongoing COVID-19 pandemic has killed tens of thousands of people [1, p. 1], including thousands in England and hundreds in Wales [2]. False negatives and false positives obstruct estimation of exactly
how many people COVID-19 has killed; false negatives are people who die of COVID-19 but whose deaths are wrongly attributed to something else, and false positives are people whose deaths are wrongly attributed to COVID-19. With official COVID-19 death counts booming, assorted commentators, some well credentialed and some well known, have stressed the possibility of false positives inflating the death count. Andrew Neil, host of BBC Television’s Politics Live and The Andrew Neil Show, former chairman of Sky TV, and chairman of The Spectator magazine, tweeted [3]:

Various headlines now hitting multiple websites with variations of: "UK death toll due to #Coronavirus now 766, an increase of 182 in last 24 hours"
BUT: what these stats don’t tell us us: [sic]
How many died FROM the virus?
How many died WITH the virus?

Forensic pathologist Raquel Fortun, of the University of the Philippines, tweeted [4]:

So covid-19 kills old people, and those sick of other things. In the Philippines are we really counting right? Or do we just say they’re old, or died of something else?[THINKING FACE emoji]

Bill Mitchell, Florida-based host of talk show YourVoice™ America, tweeted [5]:

I want to know how many who “died from COVID-19” were on ventilators prior to their death? Because if your COVID-19 wasn’t bad enough to put you on a ventilator, you died from something else.
Where are the numbers?

Mitchell also tweeted [6]:

I say the COVID-19 death counts are BULLSH*T. I say they are loaded with deaths from the flu and other co-morbidities and have been “dumped” into the COVID-19 column.
I demand a transparent international standard on what constitutes a COVID-19 death!
Retweet if you agree.

Professional boxer and former professional rugby player Anthony Mundine posted on Facebook [7]:

Corona virus [sic] is bogus for real ! There [sic] putting fear through media to set an agenda!All [sic] the deaths there [sic] saying that’s happening is true but then they add the corona virus [sic] when it was something else to scare everybody & market the corona ! The world order is happening peeps ! STAY WOKE NOT ASLEEP in what’s going on around you ! Mass vaccines will be introduced soon you will see !! To harm & control you more & could cause major effects on adults & children like autism & even death ! Then they will blame corona!

John P. A. Ioannidis, co-director of METRICS (the Meta-Research Innovation Center at Stanford) and editor-in-chief of the European Journal of Clinical Investigation, observed more temperately in an opinion piece for STAT [8] that

[i]n some people who die from viral respiratory pathogens, more than one virus is found upon autopsy and bacteria are often superimposed. A positive test for coronavirus does not mean necessarily that this virus is always primarily responsible for a patient’s demise.

Pundit Candace Owens tweeted to her two million Twitter followers [9]:

In other words: the death toll we are seeing is “people that tested positive for the the virus, and are now dead.” Not, people that have died FROM Coronavirus.
That number, when investigated, will be much lower. Italy determined only 12% of their death toll was FROM Covid

BBC News’s main UK Twitter account tweeted to 10.8 million followers [10]:

2
Deaths being reported daily are hospital cases where a person dies with the coronavirus infection in their body. But is the virus causing the death? It could be the major cause, a contributory factor or simply present when they die of something else.

Evidently the question remains open of how much false positives are inflating COVID-19 death counts. This paper contributes to answering that question with death data from the United Kingdom’s Office for National Statistics (ONS). The basic idea is simple. Instead of trying to count COVID-19 deaths directly and exclusively, I study how all known deaths, from any cause, have changed over time. A sufficiently large and rapid increase in COVID-19 deaths should appear as statistically detectable increases in all registered deaths, and increases in those registered deaths would be the same regardless of how many non-COVID-19 deaths were misregistered as COVID-19 deaths.

To try to detect those statistical signals, I fit a statistical model to the ONS’s pre-COVID-19 counts of all registered deaths, and generate baseline estimates of how many deaths would be expected absent the pandemic, given historical trends. I then compare the observed number of registered deaths in recent weeks against those baselines to see whether any excess registered deaths are evident; in the absence of an alternative explanation for them, such excess deaths may be attributed to COVID-19.

2 Data

2.1 Death counts

In this study I use the ONS’s provisional counts of deaths registered in England and Wales each week from week 1 (2–8 January) of 2010 onwards. Being only 11 days out of date when published, those provisional data are (as far as I know) the most up-to-date national counts of all deaths. While the ONS also publishes daily-resolution counts of all deaths registered in England, the daily-resolution counts appear only in the ONS’s quarterly death statistics, which have a far greater months-long publication delay.

In its provisional weekly counts the ONS decomposes the total counts in several ways. It tabulates each week’s deaths by respiratory disease separately from the all-cause totals (though the counts of respiratory-disease deaths are difficult to integrate with the other death counts, because respiratory-disease deaths overlap only partially with deaths associated with COVID-19). The ONS also breaks down the weekly counts by decedents’ region of usual residence (North West, Yorkshire and The Humber, Wales, etc.), and by sex and age group. My analyses use only the breakdown by age, but it would be possible to repeat them with an age-by-sex breakdown, and as COVID-19 deaths accumulate it should become feasible to build further analyses upon regional differences in COVID-19 incidence or fatalities.

Before April 2020, the weekly counts used 7 age bands when breaking down deaths by age: age 0, ages 1–14, ages 15–44, ages 45–64, ages 65–74, ages 75–84, and ages 85+. During the COVID-19 pandemic, however, the ONS updated the counts for 2020 to use a finer breakdown with 20 age bands: age 0, ages 1–4, then 17 contiguous 5-year age bands, and finally ages 90+. For consistency’s sake I aggregate the revised data for 2020 back to the original coarser age bands, reconciling them with the older data.

2.2 Central England temperatures

As well as the death counts themselves, I use the Met Office Hadley Centre for Climate Change’s time series of daily outdoor minimum temperatures and daily outdoor maximum temperatures in Central England. Outdoor surface temperatures might plausibly correlate with COVID-19 deaths and deaths in general, and Central England temperatures (CET) are a reasonable proxy for typical outdoor surface temperatures in England and Wales generally, because outdoor surface temperatures correlate reasonably well even at distances of hundreds of kilometres and different regions of England and Wales show similar year-to-year temperature changes.

I generate 6 weekly aggregates of CET (table) from the daily records as potential inputs to my models of death counts. Two (TMIN and TMAX) of the aggregates are a particular week’s extreme temperatures; a third, TMID, is the average temperature in a week; two more (TSD and TRAN) measure intra-week variability in temperature, and the last, TMDI measures the week-on-week change in temperature.
| aggregate | definition |
|-----------|------------|
| TMIN      | lowest daily minimum temperature |
| TMAX      | highest daily maximum temperature |
| TSD       | standard deviation of a week’s minimum and maximum temperatures |
| TMID      | mean of a week’s minimum and maximum temperatures |
| TMDI      | a week’s TMID minus the previous week’s TMID |
| TRAN      | TMAX minus TMIN |

Table 1: 6 weekly aggregates of daily Central England temperature measurements.

I also reformat the temperature observations, which the Hadley Centre presents as integers with units of tenths of a degree Celsius, by dividing them each by ten. The temperature-based parts of my analyses therefore use temperatures in units of degrees Celsius.

2.3 Air-quality indices

In the United Kingdom, Defra (the Department for Environment, Food and Rural Affairs) publishes a Daily Air Quality Index (DAQI) at individual air-monitoring sites [19] and for regions of the UK [20]. The DAQI is the highest of 5 indices of different pollutants: ozone, nitrogen dioxide, sulphur dioxide, PM_{2.5}, and PM_{10}. Research has correlated short-term changes in the concentrations of all 5 of these pollutants with short-term changes in mortality in developed countries [21, 22, 23, 24, 25] and in China [26, 27], and so I generate weekly aggregates of the DAQI to use as potential correlates of registered deaths.

Defra publishes a DAQI for each of 16 regions: one represents all of Northern Ireland, 4 represent Scotland (“Central Scotland”, “Highland”, “North East Scotland”, “Scottish Borders”), two Wales (“North Wales” and “South Wales”), and 9 England. I compute a national DAQI as the simple, unweighted mean of the 11 English and Welsh regional DAQIs. In theory, it may be better to use a weighted mean, such as a mean weighted by regions’ populations, but Defra’s DAQI regions do not comport to any single official scheme, which is an obstacle to precisely determining appropriate weights, and with the regional DAQIs all positively correlated with each other (during the 2010–2019 decade, the Pearson product-moment correlations between regions’ DAQIs ranged from +0.167 to +0.737, with a mean of +0.407), a weighted mean is unlikely to be a great improvement. I then define my weekly AQI aggregates AQIMIN, AQIMAX, and AQIMID, as the lowest, highest, and mean of a week’s 7 national DAQIs.

Unlike temperature, I define no aggregates representing AQI’s variability within or between weeks. Variation in temperature might cause thermal stress and hence mortality in itself; if people have adapted to the current temperature, then a change in temperature, even towards a more moderate temperature, could induce stress. There is no analogue for air quality: a lower (D)AQI should always tend to accompany lower mortality, and there is no basis to expect changes in (D)AQI to trigger deaths in their own right.

3 Modelling

3.1 Death-registrations data summary and formal model specification

Figure 1 shows the number of deaths registered in England and Wales by week. Deaths of middle-aged and older adults evince an annual cycle which becomes more pronounced with increasing age. The cycle peaks around January every year, sinks to a minimum every summer, and oscillates in April and May. A model is necessary to adjust for that seasonality (at least for adults) when calculating baselines for death rates during the COVID-19 pandemic.

I fit a generalized additive model (GAM) to all of the death counts from week 1 of 2010 through week 9 of 2020, the week ending 28 February 2020. When fitting the GAM I exclude March 2020 to avoid inflating the GAM’s baselines by contaminating them with COVID-19-associated deaths.

The model assumes that each registered-deaths count has a Poisson distribution, and uses the natural-logarithm function as its link function. My chosen GAM implementation is the `gamm` function in R’s
Figure 1: Weekly registered deaths, by age band, in England and Wales, 2010–2020. Labels on the plot’s right side denote age bands.

Using \texttt{mgcv} I fit the GAM

\[
\text{deaths registered for age band } \text{AGE} \text{ in the week ending } \text{WKEDAY} \sim \text{Po}(\exp(\alpha_{\text{AGE}} + \beta_{\text{SH}} + \gamma_{\text{LSH}} + \omega_1\text{ROY} + \omega_2\text{ESTR} + \omega_3\text{XMAS} + \omega_4\text{LROY} + \omega_5\text{LESTR} + \omega_6\text{LXMAS} \\
+ s_1(\text{WK}) + s_2(\text{WKEDAY}) \\
+ s_3(\text{TMID}) + s_4(\text{TMID}) + s_5(\text{TRAN}) + s_6(\text{AQIMIN})))
\]

where $\alpha$ accounts for the differences in average deaths across age bands; $\beta$, $\gamma$, and $\omega$ account for the impact of holidays, when register offices may be closed; and the smooths represented by $s$ account for how death registrations change with the annual cycle, any secular trend over the decade, CET, and AQI.

Specifically:
- $\alpha_{\text{AGE}}$ is the natural logarithm of mean weekly deaths for age band $\text{AGE}$; $\text{AGE}$ is an integer index from 1 through 7, with age 0 having index 1, ages 1–14 having index 2, etc.;
- $\beta$ represents the change in registrations if the week contains a particular secular holiday; $\text{SH}$ represents which (if any) secular holiday the week contains (an integer index from 1 through 5, representing no holiday, the first Monday in May, the last Monday in August, the spring bank holiday, and New Year’s Day);
- $\gamma$ represents the change in registrations if the previous week contained a particular secular holiday; $\text{LSH}$ is $\text{SH}$ with a 1-week lag (i.e. which secular holiday, if any, the previous week contained);
- $\omega$ represents the change in registrations for each Easter or Christmas holiday the week contains (or the previous week contained); $\text{ROY}$, $\text{ESTR}$ and $\text{XMAS}$ are the number of Royal Family-related holidays, Easter holidays (Good Friday or Easter Monday), and the number of Christmas holidays (Christmas Day and/or Boxing Day) respectively in the week; $\text{LROY}$, $\text{LESTR}$, and $\text{LXMAS}$ are $\text{ROY}$, $\text{ESTR}$, and $\text{XMAS}$ with a 1-week lag (i.e. how many Royal/Easter/Christmas holidays were in the previous week); $\text{WK}$ is the week of the year (an integer between 1 and 53); $\text{WKEDAY}$ is the date when the week ended, represented as the number of days since 1 January 2010; $\text{TMID}$, $\text{TMDI}$, and $\text{TRAN}$ are 3 of the temperature variables mentioned above; $\text{AQIMIN}$ is the weekly minimum AQI; and $s$ represents age-dependent smooths of week-of-year, of date, of temperature variables, and of $\text{AQIMIN}$.

1With the exception of the year 2020, for which the government is moving the first-Monday-in-May holiday to 8 May for the 75th anniversary of VE Day.
register offices fail to register some holiday-week deaths entirely. In a typical Christmas week, 34% fewer deaths would be registered. Christmas weeks include two public holidays (Christmas Day and Boxing Day), the model implies that holidays, but 19% fewer were registered for each Christmas holiday during a week — and because most equal. Over the decade of the 2010s, only 10% fewer deaths were registered on Royal Family-related holidays during week (\( \alpha_t \)).

Fitting the model to the time series of weekly death registrations produces a range of findings about the relationships registered deaths have with age, time of year, and CET (table 3, figs. 2, 3, and 4).

3.2 Fitted model of death registrations

The results reveal that, on average, when a public holiday occurs during a week, death registrations are 10%–19% lower in that week, but 2%–11% higher the week after (table 2). Those estimates comport with a naive back-envelope estimate that a one-day holiday might reduce a week’s registrations by one fifth to one seventh, because register offices would effectively lose one of the week’s 5–7 working days, but could partially compensate by registering slightly more deaths the week after. Not all holidays are equal. Over the decade of the 2010s, only 10% fewer deaths were registered on Royal Family-related holidays, but 19% fewer were registered for each Christmas holiday during a week — and because most Christmas weeks include two public holidays (Christmas Day and Boxing Day), the model implies that in a typical Christmas week, 34% fewer deaths would be registered.

Figure 2 plots \( s_{1, \text{age}}(\text{WK}) \), the annual cycles the model estimates for each age band. The GAM finds no statistically significant annual cycles in pre-adolescent children’s registered deaths. In teenagers and adults aged up to 45, a somewhat inscrutable cycle emerges which oscillates almost from month to month. Then, in all of the older age bands, death registrations have a broadly U-shaped relationship to time of year. Death registrations peak in the winter, trend downwards during spring, and reach a nadir in July and August, before increasing as winter approaches. That overall cycle also includes some subtler features: registrations tend to drop in November, between October’s rise and December’s rapid winter ramp-up, and the V-shaped mini-cycle in weeks 10–15 is consistently mirrored by an opposing mini-cycle in weeks 15–20.

The holiday multipliers and annual-cycle smooths account for the calendar cycle in registered deaths. Figure 3 moves on to \( s_{2, \text{age}}(\text{WKDAY}) \), which estimates the secular (non-cyclical) trends in registered deaths over the decade. That addresses the long-term trends in deaths due to slowly changing variables, most

Table 2: Average weekly death registrations by age band, and average holiday-associated changes in weekly death registrations, as estimated by the GAM in eq. [1]. “±” symbols denote approximate standard errors.

| factor                                                | parameter values on natural-log. scale | parameter values on original scale |
|-------------------------------------------------------|----------------------------------------|-----------------------------------|
| age 0 (\( \alpha_1 \))                                | 4.007 ± 0.006                          | 55.0 ± 0.6%                       |
| ages 1–14 (\( \alpha_2 \))                            | 2.980 ± 0.010                          | 19.7 ± 1.0%                       |
| ages 15–44 (\( \alpha_3 \))                           | 5.674 ± 0.003                          | 291 ± 0.3%                        |
| ages 45–64 (\( \alpha_4 \))                           | 7.099 ± 0.001                          | 1211 ± 0.1%                       |
| ages 65–74 (\( \alpha_5 \))                           | 7.399 ± 0.001                          | 1634 ± 0.1%                       |
| ages 75–84 (\( \alpha_6 \))                           | 7.964 ± 0.001                          | 2876 ± 0.1%                       |
| ages 85+ (\( \alpha_7 \))                             | 8.261 ± 0.001                          | 3870 ± 0.1%                       |
| first Monday in May during week (\( \beta_2 - \beta_1 \)) | -0.144 ± 0.004                         | (86.6 ± 0.4)%                     |
| last Monday in August during week (\( \beta_3 - \beta_1 \)) | -0.120 ± 0.004                         | (88.7 ± 0.4)%                     |
| New Year’s Day during week (\( \beta_4 - \beta_1 \))  | -0.155 ± 0.012                         | (85.6 ± 1.0)%                     |
| spring bank holiday during week (\( \beta_5 - \beta_1 \)) | -0.133 ± 0.004                         | (87.5 ± 0.4)%                     |
| Royal Family-related holidays during week (\( \omega_1 \)) | -0.105 ± 0.009                         | (90.0 ± 0.8)%                     |
| Easter holidays during week (\( \omega_2 \))          | -0.142 ± 0.003                         | (86.7 ± 0.3)%                     |
| Christmas holidays during week (\( \omega_3 \))       | -0.209 ± 0.002                         | (81.1 ± 0.2)%                     |
| first Monday in May during prev. week (\( \gamma_2 - \gamma_1 \)) | 0.023 ± 0.004                         | (102.4 ± 0.4)%                   |
| last Monday in August during prev. week (\( \gamma_3 - \gamma_1 \)) | 0.028 ± 0.004                         | (102.8 ± 0.4)%                   |
| New Year’s Day during prev. week (\( \gamma_4 - \gamma_1 \)) | 0.076 ± 0.004                         | (107.8 ± 0.4)%                   |
| spring bank holiday during prev. week (\( \gamma_5 - \gamma_1 \)) | 0.030 ± 0.004                         | (103.1 ± 0.4)%                   |
| Royal Family-related holidays during prev. week (\( \omega_4 \)) | 0.099 ± 0.008                         | (110.4 ± 0.9)%                   |
| Easter holidays during prev. week (\( \omega_5 \))     | 0.097 ± 0.003                         | (110.1 ± 0.3)%                   |
| Christmas holidays during prev. week (\( \omega_6 \))  | 0.054 ± 0.006                         | (105.6 ± 0.6)%                   |

2 That the compensation is only partial implies at least one of the following: (i) fewer people die in holiday weeks, (ii) register offices take multiple weeks to clear a typical backlog of yet-to-be-registered holiday-week deaths, and/or (iii) register offices fail to register some holiday-week deaths entirely.
Figure 2: Annual cycles in registered deaths estimated as relative registered deaths by week of year and age band, measured on the GAM’s natural-log. scale. Confidence bands represent ±2 standard errors around each estimated cycle. Age 0 is omitted because the GAM found no statistically significant cycle.

Figure 3: Secular trends in registered deaths by age band, measured on the GAM’s natural-log. scale. Confidence bands extend ±2 standard errors around fitted trends. The x axis is the date represented as the number of days since 1 Jan. 2010. Vertical dotted gridlines denote New Year’s Day, 2010–2020.
obviously England and Wales’s growing population. Registered deaths of young children consistently decreased throughout the 2010s, but trends were less encouraging at ages 15+. From 2010 through 2012, death registrations of those aged 15–64 steadily decreased, but changed little thereafter. Finally, there is some heterogeneity among the trends for people aged 65+ (the trend for people aged 75–84 is curiously muted relative to the trends for 65–74-year-olds and those at least 85 years old), but the graphs strongly suggest that they died in increasing numbers from 2010 until 2018. Those increases cannot be put down to winter influenza because the annual-cycle smooths already account for causes of death with a seasonal cycle (which include the average winter flu epidemic), and these long-term secular-trend smooths average out the impact of any one worse-than-average winter flu epidemic.

3 more sets of smooths capture the relationship between CET and registered deaths (fig. 4). The 3 temperature variables the GAM uses are \( T_{\text{MID}} \), which captures how hot each week was on average; \( T_{\text{MDI}} \), which captures how much hotter a week was than the week before it; and \( T_{\text{TRAN}} \), which indexes how variable temperature was during a week. The temperature during a week and inter-week shifts in temperature prove more important than intra-week temperature variability; \( T_{\text{MID}} \) and \( T_{\text{MDI}} \) show stronger relationships with registered deaths than \( T_{\text{TRAN}} \).

\( T_{\text{MID}} \) has a consistent negative relationship with death registrations; mortality appears to be lower in hot weeks, and that relationship is stronger in older adults than younger adults. \( T_{\text{MDI}} \), however, tends to have a positive relationship with death registrations, suggesting that mortality is higher when a week is warmer than the week before. \( T_{\text{TRAN}} \) is unusual in showing significantly different relationships at different ages: a high \( T_{\text{TRAN}} \) is associated with more registered deaths of those aged under 45 and fewer registered deaths of those aged 75+. The changing sign of the relationship between \( T_{\text{TRAN}} \) and death registrations across different ages is arguably anomalous, but since the relationship is consistently modest (and virtually nonexistent in those aged 65–74) the sign inconsistency would be a mild anomaly in practical terms.

The remaining pieces of the GAM are the age-dependent smooths of \( A_Q I_{\text{MIN}} \) (fig. 5). The statistically significant relationships between \( A_Q I_{\text{MIN}} \) and registered deaths (i.e. those for ages 1–14 and ages 45+) tend to be positive, consistent with earlier epidemiological studies: when average national air-pollution levels are elevated every day for a week, slightly more deaths of (pre)school-age children, middle-aged adults, and retirement-age adults are registered.

After reviewing each of the GAM’s individual components, the natural next step is to review the retrospective baselines that the whole GAM produces. Figure 6 plots the GAM’s retrospective baselines against all of the original data. The fits for each age band successfully reproduce each band’s overall rate of registered deaths, and each band’s overall secular trend during the 2010s. The assumption that death registrations are Poisson distributed implies that on the logarithmic-scale plot, the death counts should appear less scattered around higher baselines, and that prediction is borne out; visually, there is a lot of vertical scatter for children (where the baselines are lower), and less vertical scatter for older adults (where the baselines are higher).

Focusing on the most-recent data and fits for the older age bands (fig. 7) demonstrates that the model fails to precisely match every winter peak in registered old-age deaths. Checking this more systematically by plotting the GAM’s relative errors for older adults by week of year (fig. 8) confirms that the GAM has particular trouble fitting weeks 52–53 and 1–6. The most obvious explanation is that influenza epidemics each winter, and concomitant peaks in respiratory diseases such as pneumonia, are a major influence on old-age excess mortality in the winter, and the sizes of those epidemics are somewhat random and difficult to predict [28]. While influenza and pneumonia deaths correlate with the weather and the season, it remains the case that average national temperatures and air quality, and the time of year, do not fully account for all variation in influenza-related deaths, so the GAM cannot account fully for idiosyncratically small or large winter influenza epidemics. One must bear this limitation in mind if using the GAM to produce baselines for winter weeks, but it is unlikely to interfere much with estimating excess COVID-19 deaths because virtually all UK COVID-19 deaths have occurred in week 11 or later of 2020, after the worst of the influenza season.

### 3.3 Rationales for modelling choices

One could fit many slight variations on eq. 1 so I justify some of my modelling choices with my understanding of the data-generating process. A primary concern informing my modelling is balancing parsimony against the introduction of bias by failing to account for systematic variation in the data.
Figure 4: Registered deaths as a function of TMD (left), TMDI (centre), and TRAN (right) by age band, measured on the GAM’s natural-log. scale. Confidence bands extend ±2 standard errors around each fit.
Figure 5: Registered deaths as a function of AQIMIN by age band, measured on the GAM’s natural-log. scale. Confidence bands extend ±2 standard errors around each fit.

Figure 6: Weekly registered deaths, by age band, in England and Wales, with GAM fits superimposed as solid curves. Labels on the plot’s right side denote age bands.
Figure 7: Weekly registered deaths, for each older age band, with GAM fits superimposed as solid curves. Labels on the plot’s right side denote age bands.

Figure 8: Actual weekly registered deaths divided by the GAM’s expected weekly registered deaths, for the years 2010 through 2019. A ratio of 1 indicates that the GAM’s expectation was exactly correct; ratios under 1 represent GAM overestimates and ratios over 1 underestimates.
Parsimony leads me to minimize how many interactions among variables I include in the GAM. Crudely, the GAM takes 6 quantities as inputs: age, public-holiday status, week of the year (WK), overall date, temperature, and air pollution. Thus there are $2^6 - 6 - 1 = 57$ broad kinds of interaction the GAM could include in principle, but ultimately I use only 4: age’s interaction with each of WK, date, temperature, and air pollution.

I chose those 4 because the results make clear that they are necessary. Figures 2, 4, and 5 make plain that the relationships death registrations have with WK, date, temperature, and air pollution differ by age. By contrast, there is strong theoretical reason not to have age interact with holiday status. Death registrations dip on public holidays (and then rebound) because many register offices close on public holidays. Closed register offices register no deaths, regardless of the age of the deceased. As such, public holidays should have the same effect on death registrations regardless of age, and trying to account for different effects according to age is pointless (if not actively harmful, inasmuch as it wastes information in the data on superfluous parameters). I check this theoretical expectation with a test GAM by adding (linear, not smoothed) age-holiday interaction terms to the original GAM and refitting it to the death-registrations data. Most of the 84 newly added interaction terms are statistically insignificant ($p > 0.1$), and 6 of the 14 original holiday-status terms become statistically insignificant, with 5 of the 14 implausibly becoming positive (i.e. implying that death registrations increased on average on those holiday weeks). Those results support the dubiousness of putting interactions between age band and holiday status into a model of death registrations.

I exclude all three-way and higher-order interactions from the model because such many-way interactions are difficult (albeit not impossible) to justify a priori, and are less readily interpretable than two-way interactions and single regressors’ relationships, and threaten to exhaust the information in the dataset. As an example of the last risk, for each age band, there are only 10 observations of deaths registered on the last Monday in August, because that holiday occurs only 10 times in the period the ONS data covers. There would therefore be only limited information to fit any three-way interaction between age band and holiday status, and any other variable.

The remaining interactions the GAM could include are two-way interactions not involving age. I exclude two-way interactions between AQI and non-age variables because there is minimal basis to expect them to be practically or statistically significant. AQI’s age-dependent relationships to death registrations tend to be weak; at almost all ages, the highest observed values of AQIMIN accompany death-registration rates at most 3% higher than average. Prior research does not suggest a basis to expect AQI’s interactions with other variables to reveal a stronger relationship to registered deaths, except perhaps AQI-temperature interactions, but some provisional experiments with fitting GAMs including AQIMIN-temperature interactions have unimpressive results. I exclude the non-age, non-AQI two-way interactions because the non-age, non-AQI quantities are all closely related: WK and holiday status are direct functions of the date, and average temperatures have a roughly sinusoidal relationship to WK and date.

Parsimony also informs the maximum number of degrees of freedom (DOF) I allow gamm to use for each of the AGE-dependent smooths. I limit every smooth of TMID, TMDI, TRAN, and AQIMIN to 3 DOF, since it is implausible that those variables’ age-specific relationships to registered deaths are much more complex than S-shaped relationships, which 3 DOF suffice to represent. Each age band’s WKEDAY smooth can use at most 5 DOF, which permits one inflection point per two years in fitted secular death-registrations trend — enough flexibility to capture multiple shifts in the trend over time, but not so much flexibility as to erroneously absorb individual years’ seasonal cycles. Finally, unlike the other smooths, I force each age band’s WK smooth to be cyclic, since WK smooths represent annual cycles. I limit them to 12 DOF each, granting each WK smooth approximately monthly resolution. Alloting many more DOF to the WK smooths would risk having them absorb some of the effect of public holidays which fall in the same week each year.

Moving on from matters of parsimony, the residuals of a preliminary fit of the main GAM have slight autocorrelation for the young age bands and medium-sized autocorrelation for old-age adults. So I fit my model assuming AR(1) residuals within each combination of year and age band.

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3Ideally I would fit the model with AR(1) residuals within just each age band, but that proves computationally difficult for gamm. Fortunately, the autocorrelation is not overwhelming (the final model estimates $\phi = 0.3$), so slicing the data into year-long chunks when fitting the AR(1) residual structure does not unduly compromise the model.
### 3.4 Auxiliary models for imputing CET

The Hadley Centre publishes its daily CET data only for complete months, so temperature data for the current month (May at the time of writing) are unavailable. That is irrelevant when fitting the GAM, because I fit the GAM only to death counts for 2010 through 28 February 2020, over which period complete CET data are already available. However, the lack of May data shall become an obstacle when the ONS reports death counts for weeks 18–23 and the GAM has to generate baselines for those weeks, because the necessary current-month temperature data shall be missing.

Anticipating that problem, I fit additional simple GAMs to the known temperature data, GAMs which I can later use to impute \( \text{TMIN} \), \( \text{TMDI} \), and \( \text{TRAN} \) for the current month.

I fit a separate imputation GAM for all of the temperature variables except \( \text{TRAN} \) (because \( \text{TRAN} \) is the difference of \( \text{TMAX} \) and \( \text{TMIN} \), so imputing \( \text{TMIN} \) and \( \text{TMAX} \) with GAMs suffices to impute \( \text{TRAN} \) without fitting a specific \( \text{TRAN} \) GAM). Every GAM includes a linear date trend, to exploit any consistent secular trends over the 2010–2020 period, and a cyclic smooth of \( \text{WK} \), to account for annual temperature cycles. They also include smooths of the temperature variables \( \text{TMIN} \), \( \text{TMAX} \), \( \text{TSD} \), \( \text{TMDI} \), and \( \text{TMDI} \) with a 1-week lag, allowing the smooths only 3 DOF, enough to fit an S-shaped relationship. Finally, for parsimony, I manually prune extraneous regressors from each GAM and refit them: ultimately, I impute \( \text{TMDI} \), \( \text{TMDI} \), and \( \text{TRAN} \) as functions of lagged \( \text{TMDI} \) and lagged \( \text{TSD} \). The imputation GAMs are therefore analogous to regularized vector autoregression models, but gently nonlinearized and with a seasonal cycle also fitted.

This imputation process introduces some error, but the incorporation of seasonality and the relatively short period of imputation (at most 4 weeks if the current month is long, and only 3 weeks in the current study) limits it. A sensitivity analysis for weeks 14–16, presented in earlier versions of this preprint when April temperature data were unavailable, found that the GAM’s original April baselines might be wrong by at most about 10% due to the error arising from imputing temperatures. Fortunately, as of early May, all necessary temperature data have been published, and I do no imputation of temperature data, so my current results have no imputation error.

### 4 Estimation of excess registered deaths

I use the fitted GAM to generate baselines for each age band during this year, and compare the ONS’s recent counts to the baselines. Close-up visual comparisons of the ONS’s death counts to the GAM’s baselines for older ages are in figure 9. The observations, plotted as individual circles, run through week 17 of 2020.

The ONS reports 108 registered deaths “where COVID-19 was mentioned on the death certificate” in weeks 11 and 12 of this year, but registered deaths in those weeks were nonetheless close to the baselines in all of the older age bands. In week 13, death registrations consistently increased on week 12 and were above the baselines; moreover, for ages 75–84, registered deaths in week 13 were above the 95% confidence interval. In week 14, death registrations accelerated greatly, producing a statistically significant excess of deaths in each of the older age bands. Simple visual examination of the plots reveals about 600, 1000, 2000, and 2000 excess registered deaths in age bands 45–64, 65–74, 75–84 and 85+ respectively in week 14, for a total of approximately 5600 excess deaths. The numbers of excess deaths in each of weeks 15–17 were patently greater still.

Table 3 collects, for each of weeks 12 through 17 and every non-infant age band, the precise baselines from the GAM, the actual number of registered deaths, the implied number of excess registered deaths, and the ONS’s report of COVID-19-associated deaths. The precise numbers reveal that despite a modest number of their death certificates mentioning COVID-19, the number of excess registered deaths was negligible for children and young adults even into April, although excess registered deaths among 15–44-year-olds achieved statistical significance in week 15. More dramatically, among people aged 45 and up, there were \( 102 \pm 424 \), \( 612 \pm 416 \), \( 5675 \pm 439 \), \( 9183 \pm 468 \), \( 12,712 \pm 589 \), and \( 10,511 \pm 567 \) excess registered deaths in weeks 12 through 17 respectively.

Figure 10 illustrates the emergence of excess deaths in recent weeks differently, graphically stacking the older age bands’ weekly death counts to make them more comparable on the same scale. It demonstrates how much total (registered-)death rates have increased. Cruelly, in weeks 15 and 16 total registered

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4 To obtain the aggregate standard errors I do not sum the individual standard errors in quadrature, but rather sum them in the direct and conventional fashion, lest errors across age bands be correlated.
Figure 9: Registered deaths (circles) compared to the GAM’s baselines (solid lines) in older age bands, from August 2019’s public holiday to date. Inner, darker, grey bands cover ±1 standard error (SE), estimated as the GAM’s root-mean-squared log-scale error in 2010–2019 for the combination of age band and week of year. Outer, lighter, grey bands are 95% confidence intervals covering ±1.96 SEs.
| ages   | wk  | GAM baseline | obs'd | excess | ONS C19 deaths |
|--------|-----|--------------|-------|--------|----------------|
| 1–14   | 12  | 19 ± 7       | 12    | −7 ± 7 | 0              |
| 15–44  | 12  | 282 ± 17     | 275   | −7 ± 17| 1              |
| 45–64  | 12  | 1249 ± 50    | 1264  | 15 ± 50| 6              |
| 65–74  | 12  | 1717 ± 59    | 1780  | 63 ± 59| 20             |
| 75–84  | 12  | 3017 ± 94    | 3067  | 50 ± 94| 31             |
| 85+    | 12  | 4290 ± 221   | 4204  | −26 ± 221| 45         |
| 1–14   | 13  | 19 ± 4       | 13    | −6 ± 4 | 0              |
| 15–44  | 13  | 289 ± 20     | 283   | −6 ± 20| 8              |
| 45–64  | 13  | 1256 ± 39    | 1301  | 45 ± 39| 63             |
| 65–74  | 13  | 1718 ± 64    | 1805  | 88 ± 64| 99             |
| 75–84  | 13  | 2997 ± 108   | 3247  | 250 ± 108| 181        |
| 85+    | 13  | 4215 ± 205   | 4444  | 229 ± 205| 188        |
| 1–14   | 14  | 19 ± 5       | 21    | 2 ± 5  | 0              |
| 15–44  | 14  | 285 ± 26     | 288   | 3 ± 26 | 43             |
| 45–64  | 14  | 1257 ± 47    | 1860  | 603 ± 47| 412        |
| 65–74  | 14  | 1730 ± 78    | 2734  | 1004 ± 78| 626        |
| 75–84  | 14  | 3070 ± 109   | 5005  | 1936 ± 109| 1231      |
| 85+    | 14  | 4296 ± 205   | 6428  | 2132 ± 205| 1163      |
| 1–14   | 15  | 18 ± 3       | 14    | −4 ± 3 | 0              |
| 15–44  | 15  | 259 ± 16     | 332   | 73 ± 16| 74             |
| 45–64  | 15  | 1094 ± 46    | 2111  | 1017 ± 46| 742        |
| 65–74  | 15  | 1537 ± 78    | 2946  | 1409 ± 78| 1104      |
| 75–84  | 15  | 2622 ± 123   | 5613  | 2991 ± 123| 2210      |
| 85+    | 15  | 3696 ± 232   | 7462  | 3766 ± 232| 2083      |
| 1–14   | 16  | 17 ± 3       | 15    | −2 ± 3 | 2              |
| 15–44  | 16  | 288 ± 15     | 353   | 65 ± 15| 101            |
| 45–64  | 16  | 1162 ± 66    | 2294  | 1132 ± 66| 966        |
| 65–74  | 16  | 1618 ± 76    | 3380  | 1762 ± 76| 1442      |
| 75–84  | 16  | 2730 ± 139   | 6657  | 3927 ± 139| 2834      |
| 85+    | 16  | 3710 ± 280   | 9601  | 5891 ± 280| 3413      |
| 1–14   | 17  | 20 ± 4       | 12    | −8 ± 4 | 0              |
| 15–44  | 17  | 328 ± 30     | 404   | 76 ± 30| 103            |
| 45–64  | 17  | 1374 ± 54    | 2283  | 909 ± 54| 823            |
| 65–74  | 17  | 1893 ± 62    | 3238  | 1345 ± 62| 1189      |
| 75–84  | 17  | 3249 ± 129   | 6513  | 3264 ± 129| 2615      |
| 85+    | 17  | 4500 ± 322   | 9493  | 4993 ± 322| 3507      |

Table 3: Baseline versus observed counts of all registered deaths, and ONS counts of registered COVID-19-associated deaths, registered in England and Wales in weeks 12–17 of 2020. “±” symbols denote approximate standard errors. Age-0 results omitted for lack of C19 deaths (ONS-documented or excess).
deaths doubled in each older age band, so COVID-19 roughly doubled the hazard rate of death for people aged 45+. Closer inspection shows that the increase in risk itself increased with age: in weeks 16 and 17 excess registered deaths of the 85+ visibly outnumbered the baseline death count, but the ratio of excess registered deaths to baseline was somewhat less at ages 45–64. The diagram also shows that excess registered deaths were not only concentrated in the oldest of the old, but that their excess mortality accelerated the most.

Comparing the excess-deaths estimates to the ONS’s counts of COVID-19-associated deaths suggests that people who die with COVID-19 have been undercounted, and more undercounted in early April than in late March. The ONS reported 102, 531, 3432, 6139, 8655, and 8134 “[d]eaths where COVID-19 was mentioned on the death certificate” among people aged 45+ in weeks 12–17 respectively. Week 12’s count happens to match the relatively noisy GAM-based excess-death estimate, but the subsequent ONS counts are only 87%, 60%, 67%, 68%, and 77% respectively of the GAM-based excess-death estimates, although the 87% estimate for week 13 is very uncertain (due to the relatively large error attached to week 13’s excess-death estimates). Contrary to the commentators quoted in the introduction, counting the known deaths of those who died with COVID-19/SARS-CoV-2 has produced underestimates of those who died from COVID-19, not overestimates.

5 Conclusion

This study addresses the concern that COVID-19 has been blamed for too many deaths, an error which could occur if official COVID-19 death counts include too many false positives. To test for that putative error, I develop a statistical model of historical rates of registered deaths, and compare the baselines that model produces to the actual number of deaths registered during the COVID-19 pandemic. The comparison gives only a weak statistical signal of excess deaths in week 12 of 2020, but reveals that in weeks 13 through 17 — i.e. from 21 March through 24 April — of 2020, England and Wales registered 38,904 ± 2586 excess deaths of adolescents and adults, versus the 27,220 registered deaths the ONS reported “where COVID-19 was mentioned on the death certificate”. COVID-19 appears to have been blamed for too few deaths, not too many, at least over those 5 weeks. The true number of registered
deaths for which COVID-19 is (directly or indirectly) responsible is likely to be 42% ± 10% higher than the number of registered deaths where the death certificate mentions the disease.

The UK's Department of Health and Social Care provides more up-to-date counts of COVID-19-associated deaths than the ONS, though (until 29 April) their counts of such deaths in England included only people who died in NHS-commissioned medical facilities. The Department counted 5222 people with COVID-19 who died in England and 245 who died in Wales during week 17, for a total of 5467 deaths [2]. During that week, therefore, about \((76 + 909 + 1345 + 3264 + 4993) / 5467\) = 1.94 excess deaths were registered for each in-hospital COVID-19-associated death. If the same ratio obtains for the subsequent 3609 deaths the Department has reported for 25 April through 30 April [2], the true number of COVID-19 deaths in England and Wales from 25 April through 30 April may be closer to 7001 (3609 multiplied by 1.94). Adding that to the estimate of 38,904 excess registered deaths in the 5 weeks leading up to 25 April, the ultimate number of COVID-19 deaths registered (even if not all recognized as COVID-19 deaths) in England and Wales through the end of April could be about 45,900, if deaths have been underreported at a steady rate since mid-April.

My work has multiple limitations. Although it investigates one means of avoiding false-positive errors, it is susceptible to false-negative errors. My estimates of excess registered deaths can capture only net deaths due to the COVID-19 pandemic. If the response to the pandemic saves some Britons’ lives (perhaps by reducing air pollution [29] or motor accidents or attacks of non-COVID-19 infectious diseases) while the pandemic itself kills thousands, my approach would detect only the net effect of both taken together, which would underestimate the gross number of deaths due to COVID-19.

The geographical scope of my analysis is quite tightly bounded, confined exclusively to England and Wales, not the entire United Kingdom (although data exist in principle to extend it to the entire UK), nor a wider range of countries.

Another limitation of this study is that it estimates excess registered deaths only as a function of temperature, air quality, time, and approximate age, neglecting possible differences in mortality across sexes and regions of England and Wales. A more elaborate model which brings in region and sex as further regressors might generate more accurate baselines, and could be informative about disproportionate mortality burdens suffered by COVID-19 victims of a particular sex or region (or indeed class or ethnicity, inasmuch as region might serve as a proxy, however weak and inadequate, for class or ethnicity). Such a model could also include more localized weather conditions and other variables which differ substantially among regions, such as humidity, precipitation, and population density.

A last complication is mortality displacement, also known as “harvesting” [30], which is the phenomenon of a fatal condition killing people only slightly earlier than they otherwise would have died. In the specific case of COVID-19, it could be that even if all people who die with COVID-19 die because of COVID-19, some of them would not have lived much longer even if they had never caught COVID-19. If so, and if one blames COVID-19 only for killing those people whose lives it shortened by years, and not for killing people whose lives it shortened by days or weeks, then one can interpret my excess-deaths estimates as overestimates of people killed by COVID-19. Recent research [31] and actuarial commentary [32] suggest that such mortality displacement is minor, but longer-term data are necessary to exclude it entirely. If England and Wales suppress the spread of SARS-CoV-2 early in the summer, the weeks immediately after (or at least between waves of) the pandemic might have fewer deaths than the baselines, which would suggest mortality displacement: COVID-19 would have killed in the spring people who would otherwise have died in the summer. Also possible, perhaps even probable, is the opposite outcome — excess deaths could persist even beyond the pandemic’s acute phase, as they did, for example, after London’s Great Smog of 1952 [33].

## 6 Corrigenda

The 23 April version of this preprint (i) erroneously gave the reference to the DH&SC’s daily death counts [2] an access date of 21 April rather than the correct 22 April; (ii) referred in its conclusion to “the subsequent 8466 hospital deaths from 11 April through 20 April” when the end of the relevant period was actually 22 April, not 20 April; (iii) gave the ratio of excess registered deaths to reported

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5 unusually low death rates immediately after an acute phase of the pandemic might also reflect an ongoing lockdown, if the lockdown is maintained even when COVID-19 deaths are low, and the lockdown turns out to prevent a substantial proportion of non-COVID-19 deaths.
in-hospital deaths in week 15 as 1.91 rather than 1.90; and (iv) used an outdated caption for table 3 where “weeks 12–14” should have been “weeks 12–15”.

The 28 April version of this preprint included an outdated table 3 (of expected versus observed counts) where the baselines and standard errors and hence excess-death estimates came from the older GAM without AQI as an input. Its conclusion also asserted that this study “estimates excess registered deaths only as a function of time and approximate age”, omitting the additional (albeit also time-dependent) inputs of ambient temperature and AQI.

The 3 May version of this preprint wrongly opened section 4 with the clause “After imputing temperatures for April,”, a phrase mistakenly retained from the previous version.

References

[1] World Health Organization [2020]. Coronavirus disease 2019 (COVID-19): Situation Report – 72. Accessed at https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200401-sitrep-72-covid-19.pdf?sfvrsn=3dd8971b_2 on 2 April 2020.

[2] Department of Health and Social Care [2020]. coronavirus-deaths_latest.csv. Accessed at https://coronavirus.data.gov.uk/downloads/csv/coronavirus-deaths_latest.csv on 30 April 2020.

[3] Andrew Neil [2020]. Tweet dated 27 March 2020, accessed at https://twitter.com/afneil/status/1243550854315212801 on 2 April 2020.

[4] Raquel Fortun [2020]. Tweet dated 5 Mar 2020, accessed at https://twitter.com/Doc4Dead/status/1235533176031731712 on 2 April 2020.

[5] Bill Mitchell [2020]. Tweet dated 31 March 2020, accessed at https://twitter.com/mitchellvii/status/1244953210554646529 on 2 April 2020.

[6] Bill Mitchell [2020]. Tweet dated 31 March 2020, accessed at https://twitter.com/mitchellvii/status/1244943538565062656 on 2 April 2020.

[7] Anthony Mundine [2020]. Facebook post dated 11 March 2020, accessed at https://www.facebook.com/teammundine/posts/corona-virus-is-bogus-for-real-there-putting-fear-through-media-to-set-an-agenda/2754030061332745/ on 2 April 2020.

[8] John P A Ioannidis [2020]. A fiasco in the making? As the coronavirus pandemic takes hold, we are making decisions without reliable data. STAT; 17 March 2020, accessed at https://www.statnews.com/2020/03/17/a-fiasco-in-the-making-as-the-coronavirus-pandemic-takes-hold-we-are-making-decisions-without-reliable-data/ on 2 April 2020.

[9] Candace Owens [2020]. Tweet dated 4 April 2020, accessed at https://twitter.com/RealCandace0/status/1246557480106307589 on 7 April 2020.

[10] BBC News [2020]. Tweet dated 2 April 2020, accessed at https://twitter.com/BBCNews/status/124573285463949670 on 3 May 2020.

[11] Office for National Statistics [2020]. Deaths registered weekly in England and Wales, provisional. Accessed at https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/weeklyprovisionalfiguresondeathsregisteredinenglandandwales on 29 April 2020.

[12] Office for National Statistics [2020]. Quarterly mortality, England. Accessed at https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/quarterlymortalityreportsanalysis on 2 April 2020.

[13] Sarah Caul [2020]. Email from Health.Data@ons.gov.uk with subject line “COVID-19 deaths vs./as respiratory-disease deaths”. Received 10 April 2020.
[14] D E Parker, T P Legg, C K Folland [1992]. A new daily central England temperature series, 1772–1991. *International Journal of Climatology*, 12, 317–342. Accessed at [https://www.metoffice.gov.uk/hadobs/hadcet/Parker_etal13OC1992_dailyCET.pdf](https://www.metoffice.gov.uk/hadobs/hadcet/Parker_etal13OC1992_dailyCET.pdf) on 22 April 2020.

[15] Met Office Hadley Centre for Climate Change [2020]. Daily minimum HadCET, 1878 to date. Accessed at [https://www.metoffice.gov.uk/hadobs/hadcet/cetmindly1878on_urbadj4.dat](https://www.metoffice.gov.uk/hadobs/hadcet/cetmindly1878on_urbadj4.dat) on 3 May 2020 via [https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html](https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html).

[16] Met Office Hadley Centre for Climate Change [2020]. Daily maximum HadCET, 1878 to date. Accessed at [https://www.metoffice.gov.uk/hadobs/hadcet/cetmaxdly1878on_urbadj4.dat](https://www.metoffice.gov.uk/hadobs/hadcet/cetmaxdly1878on_urbadj4.dat) on 3 May 2020 via [https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html](https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html).

[17] Gerald R North, Jue Wang, Marc G Genton [2011]. Correlation Models for Temperature Fields. *Journal of Climate*, 24, 5850–5862.

[18] Geoff Jenkins, Matthew Perry, John Prior [2009]. The climate of the United Kingdom and recent trends. Revised edition, January 2009. Accessed at [https://ukcip.ouce.ox.ac.uk/wp-content/PDFS/UKCP09_Trends.pdf](https://ukcip.ouce.ox.ac.uk/wp-content/PDFS/UKCP09_Trends.pdf) on 3 April 2020.

[19] Department for Environment, Food and Rural Affairs [2020]. UK AIR: Data Selector. Accessed at [https://uk-air.defra.gov.uk/data/data_selector](https://uk-air.defra.gov.uk/data/data_selector) on 26 April 2020.

[20] Department for Environment, Food and Rural Affairs [2020]. UK AIR: DAQI regional data. Accessed at [https://uk-air.defra.gov.uk/data/DAQI-regional-data?action=](https://uk-air.defra.gov.uk/data/DAQI-regional-data?action=) on 26 April 2020.

[21] Anoop S V Shah, Jeremy P Langrish, Harish Nair, David A McAllister, Amanda L Hunter, Ken Donaldson, David E Newby, Nicholas L Mills [2013]. Global association of air pollution and heart failure: a systematic review and meta-analysis. *The Lancet*, 382(9897), 1039–1048.

[22] Anoop S V Shah, Kuan Ken Lee, David A McAllister, Amanda Hunter, Harish Nair, William Whiteley, Jeremy P Langrish, David E Newby, Nicholas L Mills [2015]. Short term exposure to air pollution and stroke: systematic review and meta-analysis. *British Medical Journal*, 350, h1295.

[23] R W Atkinson, S Kang, H R Anderson, I C Mills, H A Walton [2014]. Epidemiological time series studies of PM$_{2.5}$ and daily mortality and hospital admissions: a systematic review and meta-analysis. *Thorax*, 69, 660–665.

[24] Monica Chiusolo, Ennio Cadum, Massimo Stafoggia, Claudia Galassi, Giovanna Berti, Annunziata Faustini, Luigi Bisanti, Maria Angela Vigotti, Maria Patrizia Dessì, Achille Cernigliaro, Sandra Mallone, Barbara Pacelli, Sante Minerba, Lorenzo Simonato, Francesco Forastiere [2011]. Short-Term Effects of Nitrogen Dioxide on Mortality and Susceptibility Factors in 10 Italian Cities: The EpiAir Study. *Environmental Health Perspectives*, 119(9), 1233–1238.

[25] M L Williams, R W Atkinson, H R Anderson, F J Kelly [2014]. Associations between daily mortality in London and combined oxidant capacity, ozone and nitrogen dioxide. *Air Quality, Atmosphere & Health*, 7(4), 407–414.

[26] Hak-Kan Lai, Hilda Tsang, Chit-Ming Wong [2013]. Meta-analysis of adverse health effects due to air pollution in Chinese populations. *BMC Public Health*, 13, 360.

[27] Yu Shang, Zhiwei Sun, Junji Cao, Ximming Wang, Liuju Zhong, Xinhui Bi, Hong Li, Wenxin Liu, Tong Zhu, Wei Huang [2013]. Systematic review of Chinese studies of short-term exposure to air pollution and daily mortality. *Environment International*, 54, 100–111.

[28] M Hall, R Naqvi [2019]. Seasonal mortality at older ages in England & Wales 1993-2016. Institute and Faculty of Actuaries, November 2019. Accessed at [https://www.actuaries.org.uk/system/files/field/document/SeasonalMortality_EW_1993-2016_Mary_Hall_20191014.pdf](https://www.actuaries.org.uk/system/files/field/document/SeasonalMortality_EW_1993-2016_Mary_Hall_20191014.pdf) on 18 April 2020.

[29] Marshall Burke [2020]. COVID-19 reduces economic activity, which reduces pollution, which saves lives. Accessed at [http://www.g-feed.com/2020/03/covid-19-reduces-economic-activity.html](http://www.g-feed.com/2020/03/covid-19-reduces-economic-activity.html) on 21 April 2020.
[30] Anthony J McMichael, H Ross Anderson, Bert Brunekreef, Aaron J Cohen [1998]. Inappropriate use of daily mortality analyses to estimate longer-term mortality effects of air pollution. *International Journal of Epidemiology, 27*(3), 450–453.

[31] Peter Hanlon, Fergus Chadwick, Anoop Shah, Rachael Wood, Jon Minton, Gerry McCartney, Colin Fischbacher, Frances S Mair, Dirk Husmeier, Jason Matthiopoulos, David A McAllister [2020]. COVID-19 — exploring the implications of long-term condition type and extent of multimorbidity on years of life lost: a modelling study [version 1; peer review: awaiting peer review]. *Wellcome Open Research, 5*:75.

[32] Matthew Edwards [2020]. Are this year’s COVID-19 victims already ‘on death row’? Accessed at https://henrytapper.com/2020/04/07/ theres-life-in-the-old-dog-yet-let-no-one-be-abandoned-to-covid-19/ on 6 May 2020.

[33] M L Bell, D L Davis [2001]. Reassessment of the lethal London fog of 1952: novel indicators of acute and chronic consequences of acute exposure to air pollution. *Environmental Health Perspectives, 109*(S3), 389–394.