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Abstract

Seasonal infectious diseases can cause demand and supply pressures that reduce the ability of healthcare systems to provide high-quality care. This may generate *negative spillover effects* on the health outcomes of patients seeking medical help for unrelated reasons. Separating these indirect burdens from the direct consequences for infected patients is usually impossible because of a lack of suitable data and an absence of population testing. However, this paper finds robust empirical evidence of excess mortality among non-COVID-19 patients in an integrated public healthcare system: the English NHS. Analysing the forecast error in the NHS' model for predicted mortality, we find at least one additional excess death among patients who sought medical help for reasons unrelated to COVID-19 for every 42 COVID-19-related deaths in the population. We identify COVID-19 pressures as a key driver of non-COVID-19 excess mortality in NHS hospitals during the pandemic, and characterise the hospital populations and medical conditions that are disproportionately affected. Our findings have substantive relevance in shaping our understanding of the wider burden of COVID-19, and other seasonal diseases more generally, and can contribute to debates on optimal public health policy.

Externalities; spillovers; COVID-19; public health; seasonal diseases; excess mortality; prediction errors
JEL Classification: I1, I18

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1 Introduction

The spread of infectious diseases, caused by viruses such as the corona, influenza, noro or respiratory syncytial virus (RSV), is a feature of human civilization. As most recently evidenced by the COVID-19 pandemic, infection waves can create widespread disruption to daily life around the globe and pose a major burden for healthcare systems, with the possibility of large secondary effects (Moss et al. 2020). Most existing research has primarily focused on quantifying the *direct health and economic burden* that waves of infectious diseases exert on hospitals and healthcare systems (see e.g. de Courville et al. (2022)). However, it has typically not been possible to identify and measure the extent of any indirect *spillover effects* within the healthcare system. Spillover effects arise when infectious disease waves reduce the ability of the healthcare system to provide high-quality care for patients seeking medical help for reasons unrelated to the infectious disease itself. It is an empirical question whether such spillover effects exist and how far-reaching they are. This paper presents ample evidence suggesting that the COVID-19 pandemic produced negative spillover effects in English National Health Service (henceforth, NHS) hospitals and that these were a significant driver of non-COVID-19 excess mortality.

Past research has been unable to quantify spillovers from seasonal infectious diseases mostly due to data limitations. Being able to measure, for example, whether an influenza outbreak is affecting the quality of care for non-influenza patients necessitates that all patients are routinely tested for influenza upon admission and during their hospital stay. Further, qualifying the extent to which a hospital faces pressures due to an *unusually pronounced seasonal disease*, possibly a new virus strain, requires a good understanding of the population prevalence. For most seasonal diseases, no population testing programs exist to establish this. Lastly, in most instances, it is hard to *track* health outcomes of patients whose quality of care may have been compromised by the impact of seasonal diseases. Therefore, it is often simply not possible to determine to what extent health outcomes among patients seeking medical care for unrelated reasons may have been adversely affected by a seasonal disease.

The COVID-19 pandemic provides a unique natural experiment that can help to cast light on the extent to which infectious disease waves may cause such spillover effects. Many of the data constraints that previously made this kind of quantification exercise impossible have been relaxed. In this paper, we leverage data that is derived from the population of all hospital episodes within the English NHS during the first year of the pandemic.[1] This individual-level data has been linked to the population of COVID-19 testing data, allowing those patients in hospital with a COVID-19 diagnosis to be distinguished from those without a COVID-19 diagnosis. This is possible because the NHS adopted a standard operating procedure from the start of the pandemic whereby all hospital patients were routinely screened for COVID-19 upon admission and during their stay. Therefore, we can study the spillover effects of COVID-19 pressures measured *at the healthcare provider level* by analysing health outcomes among patients that were in hospital for reasons unrelated to COVID-19. In particular, we focus on excess mortality among non-COVID-19 patients.

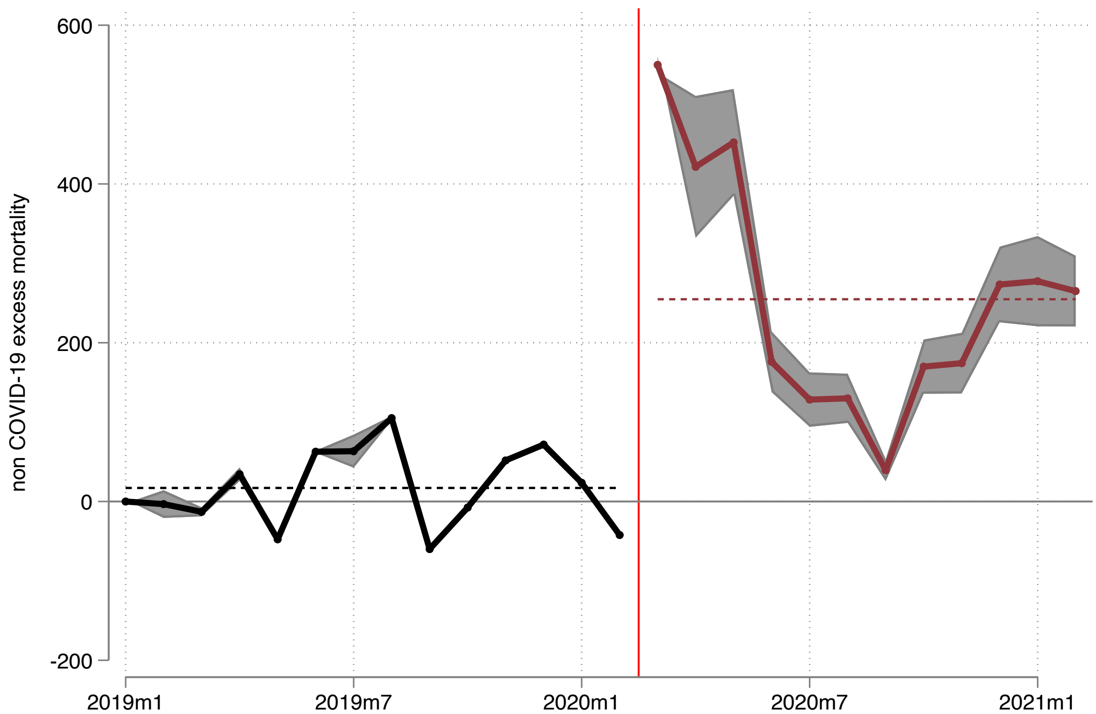
For each hospital episode, the NHS uses a statistical model to predict the probability of the admitted patient's death in the time window between admission and the 30th day after discharge. The mortality risk model is trained on *historic* patient-level NHS data, which includes a broad range of patient characteristics across all NHS providers. Since the statistical model is trained off historic data mostly from before the pandemic, it captures the expected mortality risk of a patient based on their individual characteristics and medical diagnosis *assuming pre-pandemic normal operating circumstances* across hospitals. We use the output from the NHS' mortality prediction model to construct a measure of the difference between the actually observed deaths and the expected number of deaths. Crucially, the data excludes all

[1]We focus on the first year of the pandemic, as in the later years cumulative effects of postponed treatment are more likely to confound the indirect effects of the immediate pandemic pressures.

patients with a positive COVID-19 test in the time between their admission to hospital and the 30th day after discharge as well as all deaths that mention a COVID-19 infection as a cause or contributing factor on the death certificate. This ensures that our analysis is not confounded by COVID-19 patients and that we can focus fully on consequences of the pandemic for patients that were seeking medical help for reasons unrelated to COVID-19.

Figure 1 presents the overall time-series patterns in our measure of non-COVID-19 excess deaths among patients who were in hospital for reasons unrelated to COVID-19 and whose deaths are not linked in any way to a COVID-19 infection. Our estimates capture the evolution of excess deaths up until February 2021 across NHS providers. On average, prior to the pandemic, the excess mortality measure is approximately centered around zero, suggesting that the individual-level mortality risk model has good out-of-sample predictive power. With the start of the COVID-19 pandemic in March 2020, there is a sharp upwards jump in the excess deaths measure to between 420 and 550 excess deaths in each of the first three months of the pandemic among patients in hospital for reasons unrelated to COVID-19. In the following months, there continue to appear systematic deviations in observed deaths from expected deaths, with observed deaths being significantly higher than expected deaths among non-COVID-19 patients. This suggests that the individual-level patient mortality risk estimate trained off historic data may produce expected mortality estimates that are downward biased due to a significant omitted variable: the impact of the pandemic on the ability of the healthcare system to provide high-quality care to non-COVID-19 patients.

Figure 1: Estimates of excess mortality across English NHS providers over time.



Notes: The figure plots the difference between the expected and the observed number of deaths among patients visiting an English NHS hospital in the time between admission to hospital and the 30th day after discharge. All individuals who either tested positive for COVID-19 or whose death certificate mentions COVID-19 are excluded, thereby focusing on non-COVID-19 excess mortality. The *expected* number of deaths is computed based on patient-level characteristics at the point of hospital admissions using a statistical model trained on data from mostly prior to the pandemic. The black solid line represents the pre-pandemic months and the red solid line the months during the pandemic. The black dashed line represents the mean of the excess mortality measure in pre-pandemic months, while the red dashed line represents this mean over pandemic months until February 2021. 90% confidence intervals are added in grey.

Taking the sum of the red dots in Figure 1, we estimate that, for the first twelve months of the pandemic from March 2020 to February 2021 alone, there were at least 3,058 (with a 90% confidence interval of [2,572, 3,543]) excess deaths of non-COVID-19 hospital patients in England who, if it were not for the pandemic disruptions, may not have died. This number stands significant in the context of COVID-19 deaths in the population: for every 42 deaths which mention COVID-19 on the death certificate, there was one excess death of a non-COVID-19 patient in hospital. Our estimates also indicate that the 3,058 excess deaths of non-COVID-19 patients between March 2020 and February 2021 make up a non-negligible 3.0% of all excess deaths in the population.

We document that a key omitted variable that can explain the systematic variation in non-COVID-19 excess mortality across healthcare providers is the extent to which different hospitals were exposed to pressures arising from COVID-19. We find that the number of excess deaths among non-COVID-19 patients rises sharply with the number of hospitalized COVID-19 patients in a given month. For every 100 new COVID-19 admissions, there are an additional 1.3 to 1.8 non-COVID-19 excess deaths among patients seeking medical help for reasons unrelated to COVID-19 in a month. Further, we find significant heterogeneity in these effects: the spillover effects from COVID-19 affecting excess mortality among non-COVID-19 hospital patients are increasing in hospitals serving catchment areas which are larger, have a higher share of ethnic minorities and have a lower share of old people. This result could reflect the fact that, prior to the pandemic, areas that structurally had higher levels of demand for healthcare (due to having an older, less healthy population) also had, on the margin, higher levels of resources devoted to them (Barr et al. 2014), potentially enabling them to cope better with COVID-19 disruptions. It also suggests that the indirect health burden of COVID-19 crowding out care may have been borne especially by younger and ethnic minority populations.

Our research contributes to a wider literature on the health-related effects and economic consequences of seasonal diseases. Much of this work has focused on studying the impact of influenza (see e.g. Bellia et al., 2013; de Courville et al., 2022; He et al., 2023). For seasonal diseases like influenza, data is often severely limited, making it impossible to distinguish between direct and indirect impacts of the disease. However, in this paper, we *can* actually study spillover effects on the health outcomes of non-COVID-19 patients by virtue of widespread COVID-19 testing in the population and in hospitals, and the centralised collection of rich patient-level data in the NHS. This provides a vital estimate of one aspect of the significant burden COVID-19 imposed on the healthcare system: excess mortality among non-COVID-19 patients. Our results are relevant to the issue of seasonal diseases more broadly and can contribute to debates on optimal healthcare policy such as, for example, vaccination provision. These debates are regularly held around seasonal waves of the flu, with those opposing vaccination mandates pointing to the lack of rigorous evidence of spillover effects (see e.g. Tilburt et al., 2008; Prematunge et al., 2012). We argue that, although the strain under which healthcare systems came during the first waves of the COVID-19 pandemic (de Oliveira Andrade 2020; Mahase 2021) was extraordinary, some parallels can, for example, be drawn to what may be expected in the case of a new potent influenza strain, with intensive-care units (ICU) and healthcare workers being forced to work at and above capacity (Mehta et al. 2021), raising concerns about the quality of healthcare that patients can receive (Mira et al. 2020).

Our paper also relates to previous work on attempting to measure the death toll that arose from the pandemic. This literature, similarly to that on other seasonal diseases, has typically also not been able to decompose excess deaths into the underlying drivers. Rather, it provides an aggregate estimate of excess mortality. For example, for India (Adam 2022; Jha et al. 2022), the UK (Laliotis et al. 2023) and the US (Ruhm 2021), numerous studies estimate that the true number of COVID-19 deaths may be notably larger than initially reported. Cronin and Evans (2021) also show for the US that non-COVID-19 excess mortality increased particularly among Black men. By quantifying excess deaths of patients seeking healthcare for reasons unrelated to COVID-19, this paper is able to document that there are notable negative spillovers to non-COVID-19-related care. This approach, combined with the administrative data we use, provides a quantification of spillover effects that are widely discussed around other seasonal diseases as well. We are able to provide a lower bound estimate on the likely number of deaths that may have been caused by the deterioration of care that patients could receive in hospital under COVID-19 stress. Our approach contrasts with existing work on excess deaths which relies on modelling studies of the likely increases, e.g. due to undetected or delayed treatment of cardiovascular diseases (Banerjee et al. 2021), cancer (Lai et al. 2020b), or lacking access to insurance (Galvani et al. 2022).

Finally, we contribute to an emerging literature which uses forecast errors for causal inference (Mueller and Rauh 2024; Fetzer and Yotzov 2023; Valente et al. 2023). As prediction models become more accurate, thanks to increasing computing power and the availability of better data, forecasts serve as benchmarks against which to compare actual outcomes. By providing a counterfactual scenario, they play a crucial role in detecting abnormal periods, especially when the treatment is omitted from the prediction model. In Figure 1, we observe that, before the onset of the COVID-19 pandemic, the NHS prediction model exhibited errors that were centered around zero, indicating a good model fit. However, we can attribute the substantial and systematic forecast errors during the COVID-19 pandemic to the heightened pressures associated with the treatment of COVID-19 patients.

The rest of this paper is structured as follows. Section 2 describes our data and how we measure non-COVID-19 excess mortality and provider-level exposure to COVID-19. Section 3 details our empirical strategy for analysing whether COVID-19 pressures are a driver of non-COVID-19 excess mortality, as well as for investigating heterogeneity across different diagnoses and trust population characteristics. Section 4 presents our results, and Section 5 provides a discussion.

2 Data and measurement

Measuring non-COVID-19 excess mortality

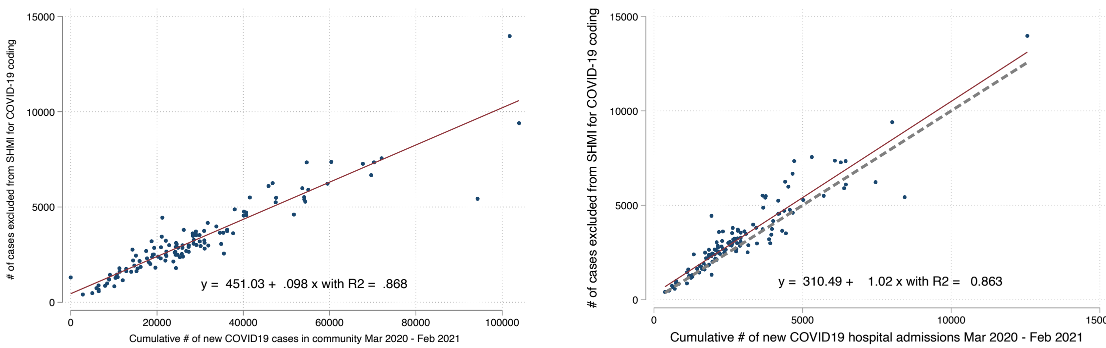
The Summary Hospital-level Mortality Indicator (SHMI) reports on mortality in NHS trusts across England and is produced as an official monthly statistic by NHS Digital. The SHMI is the trust-level ratio between the actual number of patients who die either while in hospital or within 30 days of discharge and the number of patients who would be expected to die in the same time window (NHS Digital 2023a). It is used by the English NHS to evaluate hospital performance and identify hospitals that produce substandard health outcomes in *normal times*. The data used to calculate the SHMI comes from the Hospital Episode Statistics (HES) dataset, which is linked to Office for National Statistics (ONS) death registrations data.[2] Crucially, the SHMI data removes any activity or death that is related to COVID-19: if any hospital episode within a provider spell mentions a COVID-19 diagnosis code (for example, if a patient tests positively for COVID-19) or if COVID-19 is recorded anywhere on the patient's death certificate, then the spell is excluded from the analysis. Since all admitted patients were routinely tested for COVID-19 during the pandemic, this implies that virtually all hospital episodes under consideration should exclude COVID-19 patients. This ensures that we focus exclusively on deaths in care settings that are not directly attributable to COVID-19, but may still be driven by COVID-19, due to its impact on the quality of care that can be provided.

Figure 2 shows that the exclusion of COVID-19 cases from the SHMI data at the provider level is very tightly correlated with the number of COVID-19 cases in the catchment areas of NHS providers (panel A) and with the number of patients admitted to hospital with a COVID-19 diagnosis (panel B). This suggests that our underlying data capturing hospital episodes of non-COVID-19 patients is doing well at removing COVID-19 patients, implying that the excess deaths estimates are likely very accurate.

[2] This data is available at `https://digital.nhs.uk/data-and-information/publications/statistical/shmi/`.

Figure 2: Comparison of COVID-19 cases in the community and admitted to hospital with cases being removed from the SHMI data product due to COVID-19

a) Community COVID-19 cases *b)* Cumulative COVID-19 hospital admissions



Notes: Figure shows the relationship between the number of COVID-19 hospital episodes that have been removed from the SHMI mortality modelling and COVID-19 cases in the community/catchment areas of NHS providers (panel A) or COVID-19 hospital admissions (panel B). The figure suggests a tight fit with a near one-to-one relationship between individuals admitted to hospital with a COVID-19 infection (panel B) and the number of hospital spells excluded for the estimation of non-COVID-19 excess mortality. The solid lines indicate the linear regression fit and the dashed line represents a 45-degree line. This suggests that the SHMI product is cleaned and fully focusing on patients that seek medical help for reasons unrelated to COVID-19.

The data on predicted and actual deaths, which is used to calculate the SHMI, is reported as twelve-month rolling cumulative totals. For example, the monthly publication for March 2020 includes the cumulative total number of hospital episodes or "spells", the number of observed deaths and the number of expected deaths over the twelve-month window ranging from April 2019 to March 2020 inclusive. That is, for every reporting month t, we capture the twelve-month cumulative totals $\sum_{\tau=t-11}^{t} \text{Obs}_{p,\tau}$, $\sum_{\tau=t-11}^{t} \text{Exp}_{p,\tau}$ and $\sum_{\tau=t-11}^{t} \text{Spells}_{p,\tau}$.[3]

We can compute the number of excess deaths in a twelve-month rolling window as reported in month t as

$$\sum_{\tau=t-11}^{t} \text{Excess}_{p,\tau} = \sum_{\tau=t-11}^{t} \text{Obs}_{p,\tau} - \sum_{\tau=t-11}^{t} \text{Exp}_{p,\tau}$$

which forms the basis of our analysis, as we discuss below.

[3]Descriptive statistics on these variables are provided in Table B.1.

Measuring provider-level exposure to COVID-19

We construct three measures to capture providers' exposure to COVID-19 pressures, observed directly at the healthcare provider level: (i) the number of new hospital admissions who tested positive for COVID-19 in the 14 days prior to hospital admission or who during their stay in hospital as inpatients were diagnosed with COVID-19, (ii) the number of COVID-19 cases in hospital measured as the number of people currently in hospital with confirmed COVID-19 through a positive PCR test for COVID-19 in the past 14 days, and (iii) the number of COVID-19 patients in beds which can deliver mechanical ventilation.[4]

3 Empirical strategy

In order to compute excess deaths, we rely on a statistical model used by the NHS leveraging historic individual-level patient data $x_{i,p,t}$, which is recorded for the individual hospital episode i and across healthcare providers p at time t. This data is linked to official mortality registers capturing whether a patient i died within 30 days of discharge. Let $y_{i,p,t}$ indicate the outcome taking the values:

$$y_{i,p,t} = \begin{cases} 1 & \text{if the patient died} \\ 0 & \text{if the patient survived.} \end{cases}$$

The model predicts $P(y_{i,p,t} = 1|x_{i,p,t})$, i.e. the probability of a patient's death while in hospital or within 30 days of discharge given their individual characteristics. These characteristics, among others, include age, sex and comorbidities. The predicted probabilities $P(y_{i,p,t} = 1|x_{i,p,t})$ are then summed to compute the expected number of deaths at the provider-diagnosis and provider level. More details on the estimation of expected mortality are given in Appendix A. Importantly, the model

[4]The data is available at `https://www.england.nhs.uk/statistics/statistical-work-areas/covid-19-hospital-activity/`.

does not include any variables measuring provider-level characteristics. This is intentional as the data was originally developed for performance monitoring whereby hospitals are flagged up if they have notably higher ratios of expected deaths to actual deaths relative to the pool of NHS providers as a whole.

We measure, for each provider p in a twelve-month rolling period ending in month t, the actually observed deaths in hospital and within 30 days of discharge $\sum_{\tau=t-11}^{t} Y_{p,\tau} = \sum_{\tau=t-11}^{t} \sum_i y_{i,p,\tau}$ along with the expected number of deaths from the predictive model $\sum_{\tau=t-11}^{t} \hat{Y}_{p,\tau} = \sum_{\tau=t-11}^{t} \sum_i P(y_{i,p,\tau} = 1 | x_{i,p,\tau})$ for the same time period. From this, as we describe in Appendix A, we derive a *monthly* proxy measure for excess deaths

$$\hat{\xi}_{p,t} = Y_{p,t} - \hat{Y}_{p,t}$$

which forms our dependent variable at the provider level p in month t.

Naturally, the above measure can be considered to be the residual of a regression that is the result of having aggregated the individual predicted mortality risk $h(x_{i,p,t})$ of patient i that is captured in a set of features x of the individual. If this model is unbiased, we would presume that the expected value of this measure $\mathbb{E}(\hat{\xi}_{p,t}|h(x)) = 0$. If, however, there is an *omitted variable* $z_{i,p,t}$ either at the individual, provider or time level that affects the number of observed deaths in a way that the statistical model to generate the expected deaths measure does not account for, we would expect the above condition to be violated. Thus, we would expect to see some structure in the residuals. In Figure 1, we document that up to February 2020, there is no structure in the residuals: the average excess deaths across providers and over time hover close to zero. Further evidence for this is depicted in Figures B.2, B.3 and B.4 in Appendix B, which show tight, one-to-one relationships between observed and expected deaths at the trust and trust-diagnosis levels. This implies that the model is indeed unbiased prior to the pandemic.

In contrast, from March 2020 onwards, Figure 1 shows how the residual, aggregated at the *monthly* level, jumps sharply with the onset of the pandemic and remains consistently elevated. This pattern suggests that there is indeed an important omitted variable in the risk model that is driving the notable divergence between the observed number of deaths and the expected number of deaths.

We now explore whether additional features that vary *at the provider level p* over time t can account for these systematic deviations in excess deaths. Specifically, we regress the measure of non-COVID-19 excess mortality $\hat{\xi}_{p,t}$ on provider-time specific pressures COVID-19$_{p,t}$, provider-level fixed effects α_p, month fixed effects ν_t and the excess deaths one year ago at the provider level $x_{p,t}$ using the following form

$$\hat{\xi}_{p,t} = \alpha_p + \nu_t + \beta \times \text{COVID-19}_{p,t} + \gamma \times x_{p,t} + \epsilon$$

while clustering standard errors at the provider level. The coefficient of interest, β, captures the impact of COVID-19 pressures on excess deaths.

We test the impact of three provider-time specific COVID-19$_{p,t}$ related to (i) new COVID-19 hospital admissions (flow), (ii) patients in hospital with COVID-19 (stock), and (iii) COVID-19 patients in beds which can deliver mechanical ventilation. We additionally investigate whether the transmission of COVID-19 pressures depends on certain characteristics c_p of the resident population that is served by a provider p using the same specification as above, while adding an interaction term between c_p and COVID-19$_{p,t}$ pressures. The characteristics c we look at are the deprivation score of the population served by a provider, the share of the population who are Black or Asian, the log of total population, and the share of people below age 65 in the catchment area of provider p. These characteristics of the catchment area are measured in 2019 and are features that commonly surface in the discussion of (unequal) health care and outcomes. More information on these characteristics is provided in Appendix A.

Finally, we also conduct some heterogeneity analysis in terms of excess mortality for different diagnoses. That is, we study which types of non-COVID-19 diagnoses were more likely to result in non-COVID-19 excess deaths. To do so, we compute whether for a specific diagnosis d, our excess deaths measure

$$\hat{\xi}_{p,t,d} = Y_{p,t,d} - \hat{Y}_{p,t,d}$$

varies systematically depending on the pressures COVID-19$_{p,t}$ experienced at the provider level p over time t. This data is much more sparse and subject to statistical data disclosure control. Given the granularity of the diagnosis codes, 142 in total, we limit our analysis to the 14 most common ones for which we have consistent non-suppressed data across at least 100 of the 124 main NHS providers. We provide more information on this empirical design in Appendix A.

To examine non-COVID-19 excess mortality in healthcare systems during the pandemic, studies in the medical literature have, for example, compared pandemic and pre-pandemic mortality rates by diagnosis group, adjusted for patient age and sex (e.g. Bodilsen et al. (2021)). We are using a different approach out of concern for a selection problem: the average non-COVID-19 patient admitted to hospital during the COVID-19 pandemic is likely to be different from the average patient admitted to hospital in pre-pandemic times. This is because we can expect people to have had a higher threshold for going to hospital, for instance due to lockdown policies or fear of catching COVID-19 in hospital.[5] Trusts were also asked to postpone *non-urgent* elective operations at the start of the pandemic. Therefore, differences in non-COVID-19 mortality before and during the pandemic could be driven by endogenous selection into hospital admission, rather than the excess burden of COVID-19 on the healthcare system.

Our approach of comparing actual deaths to predicted deaths, which are calculated using individual patient characteristics, can be seen as a selection-on-observables

[5]In some cases this might have caused patients to delay seeking treatment and therefore their health status might have deteriorated prior to going to the hospital. However, this should be accounted for by the SHMI estimations of mortality risk as this risk is predicted conditional on current health status.

solution to the selection problem. By factoring patient characteristics, including age, sex, comorbidities and admission method, into the measure of predicted deaths, we are accounting for observables that might otherwise be driving mortality patterns. In this way, our dependent variable $\hat{\xi}_{p,t} = Y_{p,t} - \hat{Y}_{p,t}$ is comparable for the pandemic and pre-pandemic period. Our analysis benefits from the size and richness of the NHS patient-level data, which means the prediction model can be estimated on the near-universe of non-COVID-19 episodes in non-specialist acute trusts over three-year rolling periods.

There are some limitations to our empirical approach. First, there is a concern that pressures exerted by the pandemic on the healthcare system could have reduced the accuracy of reporting of patient characteristics. For example, it could be possible that secondary diagnoses were generally underreported, leading to patients on average seeming less at risk of dying than they actually were – by biasing predicted deaths downwards, this could contribute to the increase in the residual $\hat{\xi}_{p,t} = Y_{p,t} - \hat{Y}_{p,t}$ we document in Figure 1. Reassuringly, however, the average number of secondary diagnoses reported, which is released over rolling twelve month periods like the SHMI data, is higher in all twelve-month periods which include any months of the pandemic than at any time before for both elective and non-elective admissions. This suggests that secondary diagnoses were at least not substantially under-reported. Another concern is that imperfections in COVID-19 testing and reporting may have led patients who had COVID-19 to be included in the dataset. This would confound the analysis and could additionally also induce an increase in the difference between observed and expected deaths by biasing predicted deaths downwards. However, as discussed above, Figure 2 shows that there is a tight relationship between COVID-19-related episodes excluded from the SHMI and COVID-19 cases in the community. This suggests that the data is likely doing well in excluding COVID-19-related episodes. Moreover, because problems with testing and reporting are plausibly most likely at the beginning of the pandemic, we also run the main specifications on data which excludes the first two months of the pandemic (Table B.5) as a robustness check. The results generally suggest a slightly stronger relationship between COVID-19 pressures and non-COVID-19 excess mortality than for the full dataset, providing further evidence that problems with COVID-19 testing, leading to COVID-19-positive patients being included in the analysis, are not likely to be driving the results.

4 Results

The results from our main analysis are presented in Panel A of Figure 3. Tables B.3 and B.4 in Appendix B show the regression estimates across varying specifications. In each case, the dependent variable is our proxy for the number of excess deaths.[6] The point estimates suggest that, depending on the specification, on average 1) 100 further new hospital admissions who tested positive for COVID-19 were associated with 1.3 to 1.8 additional non-COVID-19 excess deaths, 2) 100 further COVID-19-positive cases currently in hospital were associated with 4.4 to 6.6 additional non-COVID-19 excess deaths, and 3) 100 further COVID-19 patients on ventilators were associated with 19 to 30 additional non-COVID-19 excess deaths.

We find that, in particular, pressures from increases in the number of COVID-19 patients on ventilators are associated with significantly higher excess mortality for patients that were admitted to hospital for non-COVID-19 reasons. Appendix Figure B.5 also indicates that the effects of all three measures of COVID-19 pressures are strongest in hospitals that experienced the highest intensities of COVID-19 pressures.

Our results remain very robust across different specifications, including adding linear time trends and controlling for community infection rates at the provider level.[7] Further, Appendix Tables B.6, B.7 and B.8 find similar results for an adapted empirical design which uses the twelve-month rolling cumulative totals reported

[6]Details of how we calculate this are given in Appendix A.

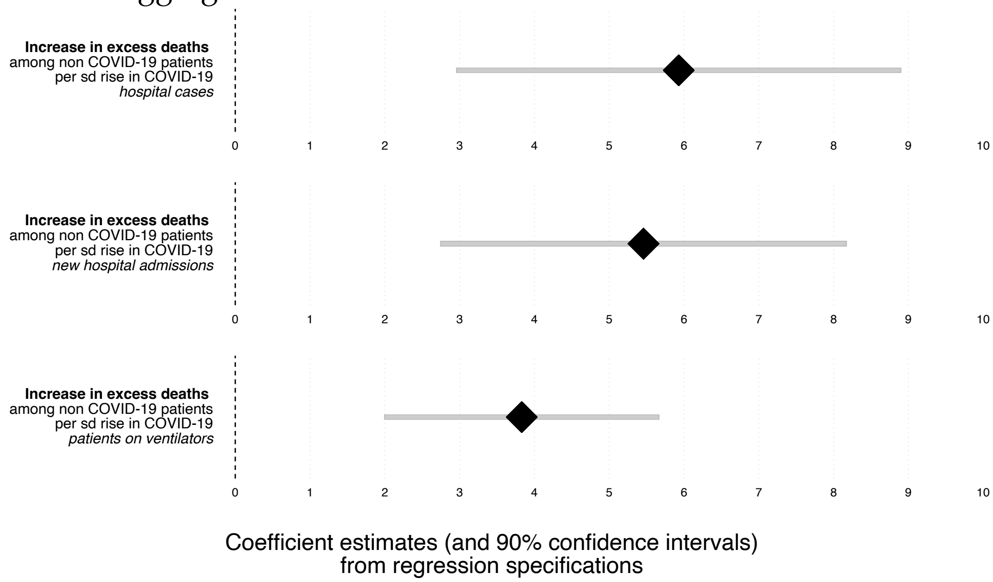
[7]We provide further information on how we construct the community infection rate measure in Appendix A.

by NHS Digital as the dependent variable, with the COVID-19 pressure variables adjusted to match the rolling data structure. This also indicates that our main results are robust.

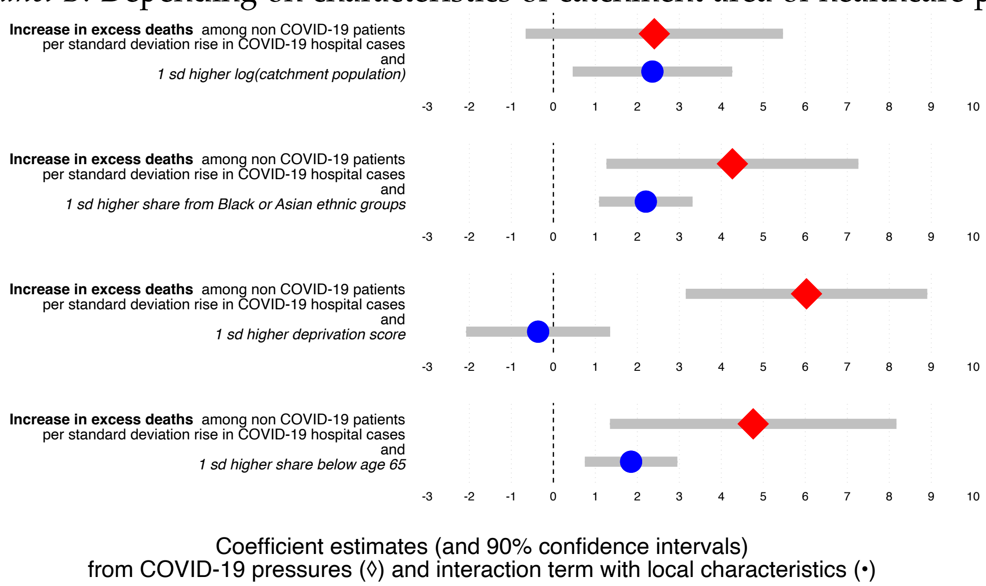
In Panel B of Figure 3, we present how characteristics of the hospital population relate to the impact of COVID-19 pressures on non-COVID-19 excess mortality. The plotted interaction coefficients indicate that a rise in COVID-19 cases currently in hospital was associated with higher non-COVID-19 excess mortality if the provider's catchment area featured a greater total population, a higher share of people from Black or Asian ethnic groups, and a greater share of younger people. In Figures B.6 and B.7 in Appendix B, we show that these patterns are similar when we measure COVID-19 pressures through the number of newly admitted COVID-19-positive patients and those on ventilators.

Figure 3: Impact of COVID-19 pressures across NHS healthcare providers on non-COVID-19 excess mortality.

Panel A: Aggregate



Panel B: Depending on characteristics of catchment area of healthcare providers

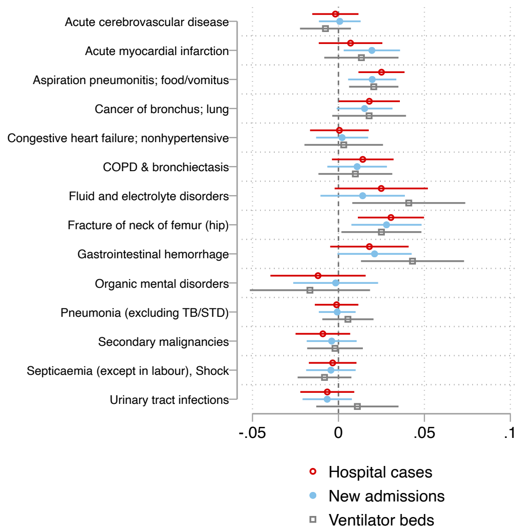


Notes: The figures plot coefficients and 90% confidence intervals from regression estimates at the NHS provider level. The point estimates capture the effect of a one-standard-deviation change in COVID-19 pressures on the number of excess deaths in a given month among patients seeking medical help for reasons unrelated to COVID-19. In panel A, we measure COVID-19 pressures either as the number of COVID-19 cases in hospital, the monthly average new daily COVID-19 hospital admissions, or the average number of cases on mechanical ventilation in a given month. In panel B, the figure plots the coefficients of regression estimates at the NHS provider level with the number of COVID-19 patients currently in hospital (red diamond) and the interaction term with catchment area characteristics (blue dot) as independent variables. The interaction term captures the effect of a one-standard-deviation increase in COVID-19 pressures combined with a one-standard-deviation increase in the catchment area characteristic on the number of excess deaths in a given month among patients seeking medical help for reasons unrelated to COVID-19. In panel B we measure COVID-19 pressures as the number of hospitalized COVID-19 patients in a given month. The catchment area characteristics are the deprivation score, the share of the population who are from Black or Asian ethnic groups, the log of total population, and the share of people below age 65 in the catchment area of the provider. All regressions control for NHS provider fixed effects and time fixed effects. Complete regression results are reported in Table B.3. 90% confidence intervals obtained from clustering standard errors at the provider level are indicated.

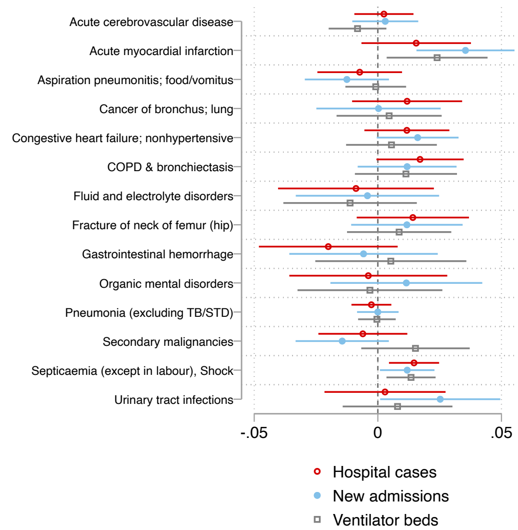
Finally, Figure 4 presents results from estimating the heterogeneous effects of the three different measures of COVID-19 pressures, focusing on 14 of the 142 diagnosis codes. The increase in mortality is notably higher for diagnoses requiring emergency treatment, such as fractures of the neck of femur (hip fractures), gastrointestinal hemorrhages, and acute myocardial infarctions (heart attacks). However, it is also elevated for aspiration pneumonitis, lung cancer, and chronic obstructive pulmonary disease (COPD). On the one hand, the latter may be patients competing with COVID-19 patients for resources. On the other hand, these may actually be undetected COVID-19 patients. However, in Panel B of Figure 4 we can see that even when dropping March and April 2020, i.e. the months during which testing was still less common and reliable, the patterns remain very similar, with particularly high spillovers on heart attacks and sepsis.

Figure 4: Impact of COVID-19 positive cases currently in hospital on diagnosis-specific excess mortality

Panel A: Full first year of pandemic



Panel B: Dropping March and April 2020



Notes: The figure presents heterogeneous treatment effects capturing the impact of COVID-19 pressures on diagnosis-specific non-COVID-19 excess mortality. The estimating equation explores variation in the log differences in observed minus expected deaths for hospital episodes and diagnoses for which data is available for the whole sample period and for diagnoses that are consistently included in the data across at least 100 of the 127 NHS providers for which the data is constructed. All regressions control for provider-by-diagnosis fixed effects as well as diagnosis-by-time fixed effects and control for the diagnosis-specific relationship between log(spells) and excess deaths. 90% confidence intervals obtained from clustering standard errors at the provider level are indicated. Panel A reports results for the full first year of the pandemic (March 2020 to February 2021 inclusive), while Panel B drops March 2020 and April 2020 from the sample.

5 Discussion

This paper provides robust evidence on the substantive *indirect* health burden of seasonal infectious diseases on the healthcare system. Due to data limitations and the absence of population testing, this is usually very difficult to study. Using the systematic effects of the COVID-19 pandemic as a natural experiment, we produce a first estimate of excess mortality among patients who were admitted to hospital for non-COVID-19-related health issues in the English NHS.[8]

We estimate that there were 3,058 *excess* deaths of patients seeking medical care for reasons unrelated to COVID-19 between March 2020 and February 2021. This is a large number of lost lives. It evidences the extent to which the pandemic overstrained the healthcare system, reducing its ability to provide high-quality healthcare for all patients. We can compare this estimate to measures of COVID-19-related mortality in the English population. In the same period, the most comprehensive measure of COVID-19 fatalities in England, deaths that mention COVID-19 on the death certificate, records 127,475 deaths, while the least comprehensive measure we use, the number of deaths within 28 days of a positive COVID-19 test, counted 108,754 deaths. Therefore, for every 36 to 42 deaths linked to COVID-19 during the first year of the pandemic, there was at least one excess non-COVID-19 death among hospital patients. This further emphasises the substantive indirect burden of the pandemic on the healthcare system. In Appendix A, we provide additional discussion of how our results relate to measures of COVID-19 deaths in England in the same time period.[9]

We document that a healthcare provider's exposure to COVID-19 pressures, in the form of COVID-19 hospital admissions, COVID-19-positive patients currently in hospital, and COVID-19 patients on ventilators, was a key driver of excess mortality

[8]In Fetzer and Rauh (2022) we made preliminary findings of this study on the deterioration of health care and the increase of excess deaths available as preprints.

[9]More information on comparisons of these measures to our estimate of non-COVID-19 hospital patient excess mortality and the time series of these measures is shown in Table B.2 and Figure B.1.

in non-COVID-19 patients. This is indicative of the fact that the elevated excess mortality of patients seeking healthcare for reasons unrelated to COVID-19 was indeed caused by the systemic pressures the pandemic exerted on the healthcare system.

However, it is important to recognise that there is significant heterogeneity in these estimates across multiple dimensions. First, COVID-19 did not have a uniform effect on all hospitals across England; rather, *additional* COVID-19 admissions, patients in hospital and patients on ventilators had the largest effects on non-COVID-19 excess mortality in hospitals that were *already* suffering the highest degrees of strain from the pandemic. Second, we find that excess mortality of non-COVID-19 patients was highest in trusts serving larger populations with a higher share of ethnic minorities and a higher share of younger people. This result could reflect the fact that areas with structurally high levels of healthcare demand due to an older, less healthy population may have had more facilities and structures in place that enabled them to cope better with COVID-19 disruptions and mitigate their impact on non-COVID-19 patients. Third, we identify that COVID-19 pressures often had an especially high impact on non-COVID-19 excess mortality in patients requiring emergency care and in patients with respiratory ailments. This suggests two possible reasons for why COVID-19 pressures were causing a notable increase in non-COVID-19 excess mortality: firstly, they may have impaired the quality and speed with which care could be provided and, secondly, they may have crowded out care for patients who required medical attention from the same specialists as COVID-19 patients.

We note that these estimates of excess deaths are, crucially, lower bounds of excess mortality in non-COVID-19 patients caused by the pandemic. They refer only to excess deaths among hospital patients between admission and the 30th day after discharge. It is, however, likely that in coming years, there will be more excess deaths arising from delayed care, or delayed detection of cancer and other diseases because of the pandemic (Lai et al. 2020a; Maringe et al. 2020; Fetzer and Rauh

2022). Moreover, it is also important to note that, by focusing on excess mortality, we are only capturing *one* dimension of the excess health burden of the pandemic on the healthcare system. By putting significant strain on the healthcare system, it is plausible that the pandemic also impacted other health outcomes, such as re-admission rates and lengths of stay, as well as quality of care received and patient experience more generally.

Our findings call attention to the wider burden of the COVID-19 pandemic, but they also have relevance for the impact of seasonal infectious diseases more broadly. Seasonal diseases exhibit strong and sometimes unpredictable patterns. They can cause demand and supply pressures which may impact the ability of healthcare systems to provide high-quality care across seasons. Although the COVID-19 pandemic had, especially in the first waves, particularly severe repercussions for healthcare systems, many of the mechanisms through which it did so are also present regularly as a result of common seasonal diseases. For example, influenza epidemics have also led to the flooding of emergency departments and ICUs with infected patients (Lane et al. 2022) and put large psychological strain on healthcare workers (Barello et al. 2020). Although our findings cannot speak to the magnitude of excess mortality in patients who seek medical care for reasons unrelated to the particular seasonal disease, they do suggest that this indirect burden is a very real concern. They also raise the question of how to deal with large-scale infectious outbreaks in order to limit spillover effects. Possible approaches could include for healthcare providers to specialize the provision of care in order to be able to isolate usual care from the care for a pandemic, or for healthcare systems to require more generous buffers in terms of staffing and facilities in order to accommodate large shocks.

Robust empirical evidence that quantifies the spillovers from infectious disease wave-induced pressures may be a vital input as policymakers weigh the costs and benefits of non-pharmaceutical interventions (Mitze et al. 2020; Abaluck et al. 2021; Fetzer and Graeber 2021; Fetzer 2021), vaccination mandates and the resourcing of healthcare systems more generally (Kruk and Pate 2020). Healthcare systems were already facing chronic issues coming into the pandemic. As the world has now moved to an equilibrium to live with the COVID-19 virus, it remains important to derive lessons learned from the pandemic not only for future pandemics, but also for the pressures that arise due to other peaks of infectious diseases. Our robust findings suggest that spillover effects are systematic and require more attention.

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Appendix

A Data and methods

Measuring provider-level exposure to COVID-19

NHS trusts are not defined spatially explicitly, but rather, can serve multiple regions. However, most NHS trusts are spatially quite concentrated. To allocate NHS trusts and providers to specific locations and to merge in additional data, we leverage an analysis of individual-level micro data from the Hospital Episodes Statistics dataset which breaks down all hospital visits to an NHS provider location by the location of residence of the patients at the granular middle layer super output area (MSOA) level. MSOAs have, on average, a population of 8,000 residents. We allocate MSOAs to NHS trusts on the basis of a first-past-the-post approach – that is, an MSOA is counted towards the catchment area of an NHS trust if that trust handles the most hospital episodes across all NHS trusts that serve residents from this MSOA. As illustrated in Appendix Figure A.1 there is, not surprisingly, ample spatial clustering implicit in this. Having this mapping of MSOAs that are spatially close to NHS trusts (which may operate out of several sites within an area) allows us to construct measures of the cumulative community exposure to COVID-19 as COVID-19 case figures are provided at the MSOA level.

Figure A.1: Allocation of spatial areas to NHS Trusts

Panel A: MSOAs across England *Panel B*: Visits to Barking, Havering and Redbrige NHS Trust

Notes: Map displays the residential address of visitors to the Barking, Havering and Redbrige University Hospital NHS Trust in 2019. The left figure plots the distribution across England's 6791 MSOAs. The hospital trust saw hospital visits from patients coming from 412 MSOAs. The right figure provides a zoom in on the spatial distribution of patients visiting the Barking, Havering and Redbrige University Hospital NHS Trust in 2019 and what share of visits are made up by residents from different MSOAs. The vast majority 83% come from 70 MSOAs that are immediately in the neighborhood of the trusts's main hospitals: the King George Hospital and the Queen's Hospital. The solid dark lines in the right panel indicate the MSOAs that are attributed to the NHS Trust by virtue of the trust's hospitals have been serving most of the patients that had a hospital spell in 2019 that reside in each MSOA. This data is available on `https://app.powerbi.com/view?r=eyJrIjoiODZmNGQ0YzItZDAwZi00MzFiLWE4NzAtMzVmNTUwMThmMTVlIiwidCI6ImVlNGUxNDk5LTRhMzUtNGIyZS1hZDQ3LTVmM2NmOWRlODY2NiIsImMiOjh9`.

NHS Digital's procedure to calculate expected deaths

Details on the exact methodology NHS Digital uses are provided in NHS Digital (2023a) and NHS Digital (2023b). Below we give a summary based on these guidance documents.

Expected deaths are calculated from the risk of death for a patient in the time between admission to hospital and the 30th day after discharge from hospital. The measure of expected deaths is estimated over rolling twelve-month periods using data from the Hospital Episodes Statistics (HES) dataset, which is linked to ONS mortality data to include information on deaths which happen up to 30 days after discharge.

NHS Digital calculates expected deaths in a three-step process. First, data on actual deaths and patient characteristics for NHS hospital spells from the last 36 months is used to calculate the probability of an individual patient's death in hospital or in the 30-day post-discharge window. Specifically, NHS Digital estimates a logistic regression model, by primary diagnosis group, to calculate the probability of death using the following covariates ('case-mix adjustment variables'):

- Age group
- Charlson Comorbidity Index, which is calculated based on secondary diagnoses
- Admission method (e.g. elective)
- Sex of the patient
- Year index, which indicates which year out of the three years included in the sample the patient was discharged in
- Admission month
- Birthweight group (for perinatal diagnosis groups only)

The data used includes almost all hospital spells at non-specialist acute trusts, and excludes spells at specialist trusts, community trusts, mental health trusts and independent sector providers. Importantly, it also excludes any spells which either have COVID-19 as a diagnosis code or which mention COVID-19 on the death certificate. In the second step, the model is used to *predict* the risk of death for every spell in the last of the three years included in the sample, using the same covariates as in step 1. In the third step, for every trust, the expected deaths in hospital and within the 30-day post-discharge window for the twelve-month period are calculated by summing over all the estimated risks for all diagnosis groups and covariates.

Transforming SHMI data to uncover monthly structure

As indicated, the data from NHS Digital (2021) provides us with an estimate of the expected mortality of patients admitted to hospital for different diagnoses based on a range of patient characteristics.[10] Importantly, this excludes all COVID-19-related cases and deaths. We study whether the structure of excess deaths changes with the start of the pandemic and further, to what extent month-on-month variation in COVID-19 pressures is affecting the excess deaths. As the data is reported at the monthly level but as twelve-month cumulative rolling totals this dampens the month-on-month variation. We carry out two complementary exercises that document however, that this is not an issue.[11]

The reported data in a given month t provides the cumulative totals of the observed and expected deaths $\sum_{\tau=t-11}^{t} \mathrm{Obs}_{p,\tau}$ and $\sum_{\tau=t-11}^{t} \mathrm{Exp}_{p,\tau}$. This implies we can compute the month-on-month changes as

$$\begin{aligned} \Delta\mathrm{Excess}_{p,t} &= \left[\sum_{\tau=t-11}^{t} \mathrm{Obs}_{p,\tau} - \sum_{\tau=t-11}^{t} \mathrm{Exp}_{p,\tau}\right] - \left[\sum_{\tau=t-12}^{t-1} \mathrm{Obs}_{p,\tau} - \sum_{\tau=t-12}^{t-1} \mathrm{Exp}_{p,\tau}\right] \\ &= \left[\mathrm{Obs}_{p,t} - \mathrm{Exp}_{p,t}\right] - \left[\mathrm{Obs}_{p,t-12} - \mathrm{Exp}_{p,t-12}\right]. \end{aligned} \tag{1}$$

If the statistical model to calculate expected deaths was unbiased (because there were no significant omitted variables), then $\mathbb{E}[\mathrm{Obs}_{p,t} - \mathrm{Exp}_{p,t}] = 0$. We would expect this to be so for all months t prior to the COVID-19 pandemic. We provide evidence that this is indeed the case in Figure 1 in the main body, as well as Figures B.2, B.3 and B.4 in Appendix B. Given that the difference between observed and expected deaths is mean zero before the pandemic, it must be the case that $\mathbb{E}[\Delta\mathrm{Excess}_{p,t}] = \mathbb{E}[\mathrm{Excess}_{p,t}]$ for t from March 2020 onwards. This implies that, for the pandemic era, we can, in expectation, capture the number of excess deaths in a given month t, rather than the twelve-month rolling window, using $\Delta\mathrm{Excess}_{p,t}$. If we denote the genuine monthly excess number of deaths as $Excess_{p,t} = \mathrm{Obs}_{p,t} - \mathrm{Exp}_{p,t}$,

[10] The Hospital Episode Statistics (HES) data linked to Office for National Statistics (ONS) death registrations data is available at `https://digital.nhs.uk/data-and-information/publications/statistical/shmi/`.

[11] A monthly rather than twelve-month rolling sum of the excess mortality data was requested by the researchers via email and via a Freedom of Information request – all communication relating to this FOI request can be tracked here `https://www.whatdotheyknow.com/request/shmi_data_by_provider_at_monthly`.

which we proxy for using $\Delta\text{Excess}_{p,t}$ as explained, we can exploit month-on-month variation in COVID-19 pressures at the hospital level by estimating variations of the below specification:

$$Excess_{p,t} = \alpha_i + \nu_p + \gamma_t + \beta \times \text{COVID-19}_{p,t} + \psi \times \mathbf{X}_{p,t} + \nu_{i,p,t} \tag{2}$$

Crucially, given the above transformation, the vector of additional control variables $\mathbf{X}_{p,t}$ should include $[\text{Obs}_{p,t-12} - \text{Exp}_{p,t-12}]$. We proxy for this using $\Delta\text{Excess}_{p,t-12}$, which contains $\text{Excess}_{p,t-12}$, and is therefore a valid proxy variable for it.

We also estimate alternative specifications that do not transform the data in the above fashion. Given the reporting in twelve-month cumulative totals this implies we also need to measure the COVID-19 pressures not month-on-month but similarly compute cumulative totals over a time window. For example, we can estimate the impact of COVID-19 pressures in the last ϕ months relative to the reporting month t on the log difference in observed vis-a-vis expected deaths cumulatively in the last twelve months as in

$$\log \sum_{\tau=t-11}^{t} \text{Obs}_{p,\tau} - \log \sum_{\tau=t-11}^{t} \text{Exp}_{p,\tau} = \nu_p + \gamma_t + \beta \times \log \sum_{\tau=t-\phi}^{t} \text{COVID-19}_{p,\tau} + \nu_{p,t} \tag{3}$$

Catchment area characteristics

The provider catchment characteristics are available at `https://digital.nhs.uk/`. We use the provider characteristics of the catchment areas for all admissions in 2019. All measures are standardized with mean zero and a standard deviation of one before interacted with the respective COVID-19 pressures. The English Indices of Deprivation 2019 are computed based on seven weighted domains of deprivation: income 22.5%, employment 22.5%, education 13.5%, health 13.5%, crime 9.3%, barriers to housing and services 9.3%, and living environment 9.3%. The information about the measure of deprivation is available at `https://www.gov.uk/governm` ent/statistics/english-indices-of-deprivation-2019. A higher deprivation score is associated with greater deprivation.

Diagnostic-specific empirical design

For the diagnostic-specific analysis we follow the same procedure as in equation 3, with $\phi = 3$, while splitting the sample by diagnosis code. The database features 142 diagnosis codes. Since we are analyzing provider-level data, the data becomes sparse when we split the sample for each of the diagnosis codes. Therefore, we limit our analysis to 14 of the 142 diagnosis codes which are consistently included in the data across at least 100 of the 127 NHS providers. Even when only focusing on the 14 most prevalent diagnosis codes, the diagnosis-specific data is too sparse to allow us to estimate the preferred specification exploiting month-on-month changes. Hence, we work with the cumulative twelve-month rolling window design to study to what extent COVID-19 pressures in the last three months affect the cumulative twelve-month rolling sum of excess death by diagnostic group.

Comparison of COVID-19 death measures and non-COVID-19 excess deaths

The analysis in Figure 1 suggests that cumulatively there were at least 3,058 excess deaths among patients who sought medical help for reasons unrelated to COVID-19 from March 2020 to February 2021 inclusive.

A natural question that arises is how large these quantities stand in comparison to deaths directly caused by COVID-19. This appendix section provides such a comparison. There are numerous methods used in the UK and across countries to measure the number of deaths that arise from COVID-19. The underlying accuracy of these approaches depends on a broad range of factors, such as the degree to which mortality and health registers are integrated and to what extent COVID-19 infections are indeed detected, which largely depends on the underlying test capacity (Kiang et al. 2020; Clark and Turner 2021).

While the primary focus of this paper is to study non-COVID-19 excess deaths that are a result of COVID-19 disrupting the healthcare system, we nevertheless aim to compare the indirect death toll of COVID-19 with a measure of the direct COVID-19 death toll in order to quantify the relative effect. We therefore express our main estimate of excess mortality among hospital patients seeking medical help for reasons unrelated to COVID-19 relative to estimates of COVID-19 deaths. For the estimates of COVID-19 deaths, we leverage various measures which have been derived from UK data; this provides us with an upper and a lower bound estimate.

In England, multiple measures of COVID-19 deaths were regularly constructed and reported. Table B.2 provides an overview of the cumulative deaths reported from March 2020 to February 2021. Figure B.1 provides the aggregate time series. In addition to measures of COVID-19 deaths, we also report the ONS' measure of total *excess deaths*, which includes both COVID-19 and non-COVID-19-related causes of death. The total excess deaths estimate sometimes lies below the COVID-19 deaths measures, implying that not all COVID-19 deaths were excess deaths and/or that some causes of death saw fewer deaths than expected in these periods.

We note that the measure capturing deaths through COVID-19 being mentioned on the death certificate is the most comprehensive COVID-19 death measure over the time period of interest, with an estimate 127,475 deaths.

The reason why the data based on COVID-19 mentioned on the death certificate produces notably larger death figures than, say, the number of deaths within 28 days or 60 days of a positive COVID-19 test, is due to the way the death certificate data can be coded. The death certificate is produced by a doctor or coroner certifying a death. They can record more than one health condition or event on the form which capture a sequence of health conditions or events leading directly to death or other health conditions that contributed to the death but were not part of the direct sequence. This may also include suspected diagnosis that may not have been confirmed. As a result, many deaths are coded as involving a COVID-19 diagnosis or suspected COVID-19 diagnosis either as a direct or indirect condition. This produces death figures that are notably larger.

Our estimates in Table B.2 imply that for every 36 to 42 deaths that can be linked to COVID-19 in the population, there is at least one excess death among hospital patients seeking medical help for reasons unrelated to COVID-19. We also find that one out of every estimated 34 excess deaths in the population was a non-COVID-19 death of a hospital patient. This suggests sizeable negative spillover effects, with COVID-19 overstraining the healthcare system, and care for COVID-19 patients likely crowding out care for non-COVID-19 patients. Indeed, as we documented, at the provider level, non-COVID-19 excess deaths were strongly increasing in times when hospitals were exposed to high pressures in the form of many hospital cases with COVID-19 or large increases in COVID-19 admissions.

B Additional tables and figures

Table B.1: Descriptive statistics

	Mean	Median	Min	Max	St.d.
Expected deaths	2187.25	2035	340	7647.29	984.37
Observed deaths	2187.2	2025.5	340	7468	991.53
Spells	69214	62735	7985	275335	34465.21

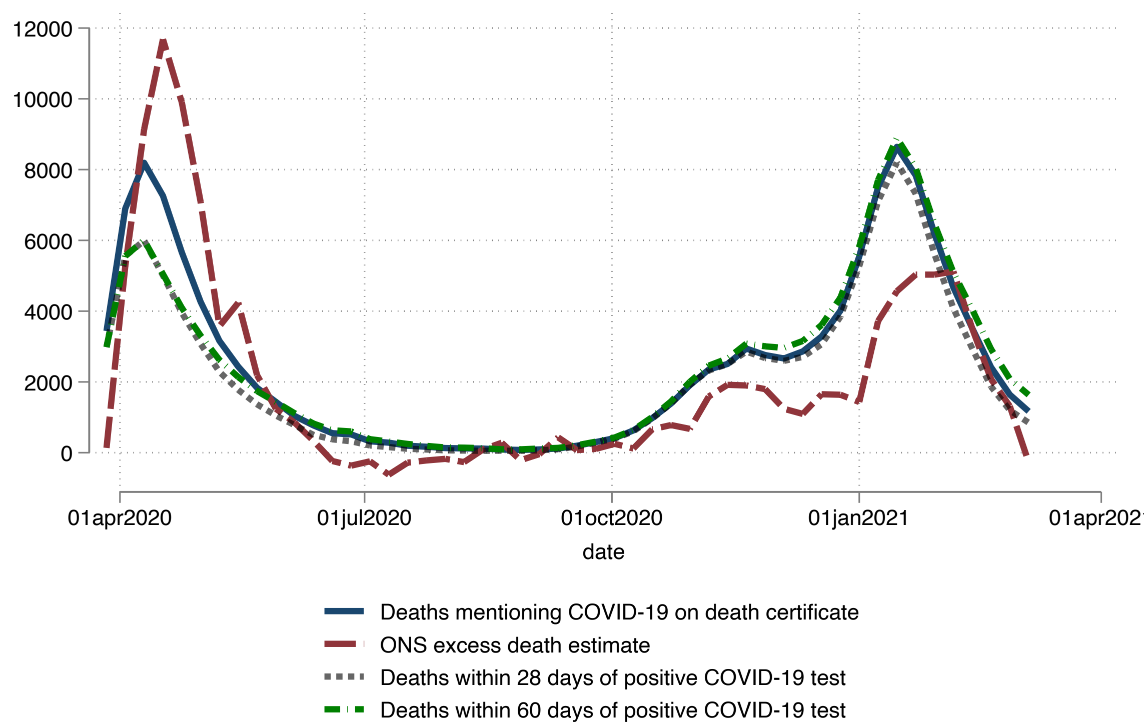
Notes: The table presents descriptive statistics across trusts at the monthly level in the twelve months preceding the pandemic and the first twelve months of the pandemic.

Table B.2: Estimated total COVID-19 deaths across measurement methods and estimated total excess deaths from March 2020 to February 2021

	Deaths	Number of deaths for every non-COVID-19 excess hospital death
Deaths mentioning COVID-19 on death certificate	127,475	41.69
Deaths within 28 days of positive COVID-19 test	108,754	35.56
Deaths within 60 days of positive COVID-19 test	124,210	40.62
ONS excess deaths	102,585	33.55

Notes: First column shows cumulative estimates of COVID-19 deaths reported across different data sources, as well as the Office for National Statistics' estimate of excess deaths, for England from March 2020 to February 2021 (inclusive). Second column compares these estimates to our estimate of 3,058 excess non-COVID-19 deaths by showing the number of COVID-19 or population excess deaths for every estimated excess non-COVID-19 death of a hospital patient in the NHS.

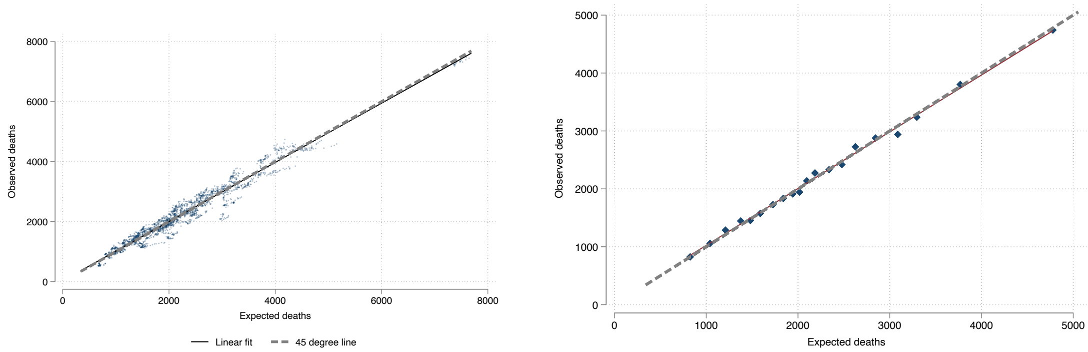
Figure B.1: Comparison of total excess deaths and COVID-19 deaths data across different data products



Notes: This Figure shows estimates by different data products of how COVID-19 deaths and total excess deaths evolved by week between April 2020 and March 2021 in England. All data products show peaks corresponding to the first and second waves of the pandemic around Spring 2020 and Winter 2020/21.

Figure B.2: Relationship between observed vs expected deaths in the SHMI data before the pandemic

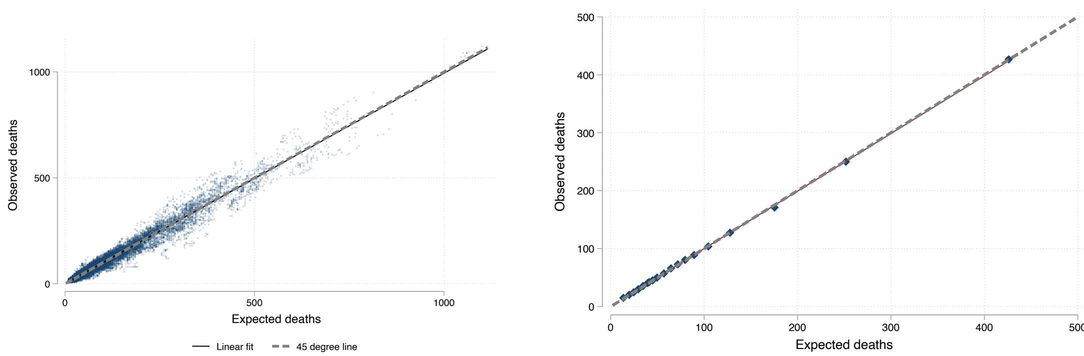
Panel A: Scatterplot *Panel B*: Binned scatterplot



Notes: Figure displays the relationship between observed and expected deaths in the SHMI data before the pandemic. We note that there is a tight relationship. In the left panel we plot a simple scatterplot with the solid line indicating the linear regression fit and the dashed line representing a 45-degree line. The linear regression fit and the 45-degree line coincide nearly. The right panel presents a binned scatterplot.

Figure B.3: Relationship between observed vs expected deaths in the SHMI data before the pandemic at the trust-diagnosis level

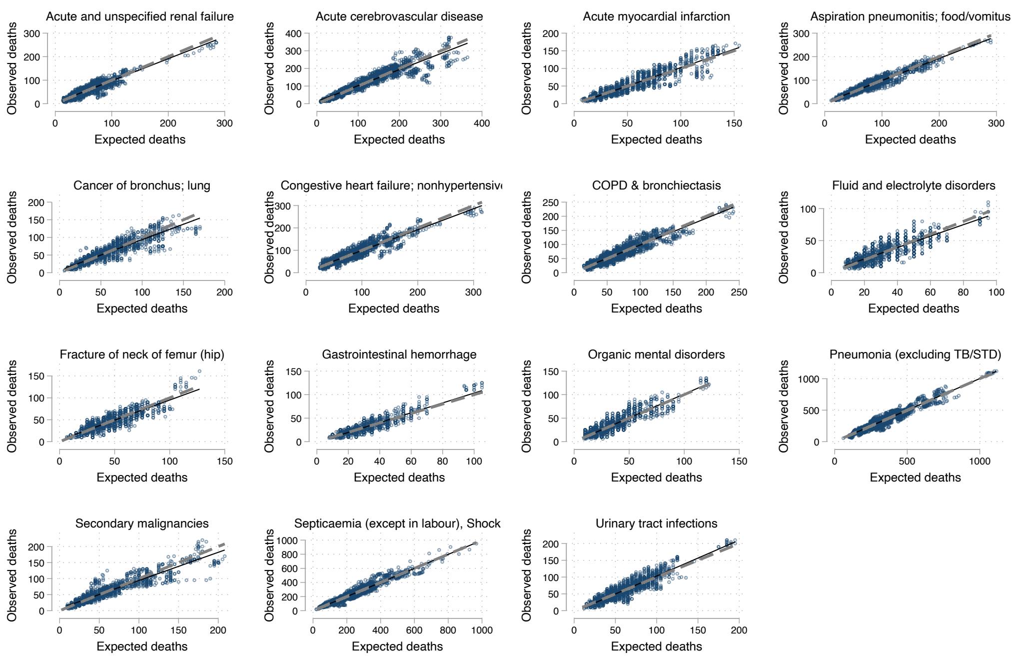
Panel A: Scatterplot *Panel B*: Binned scatterplot



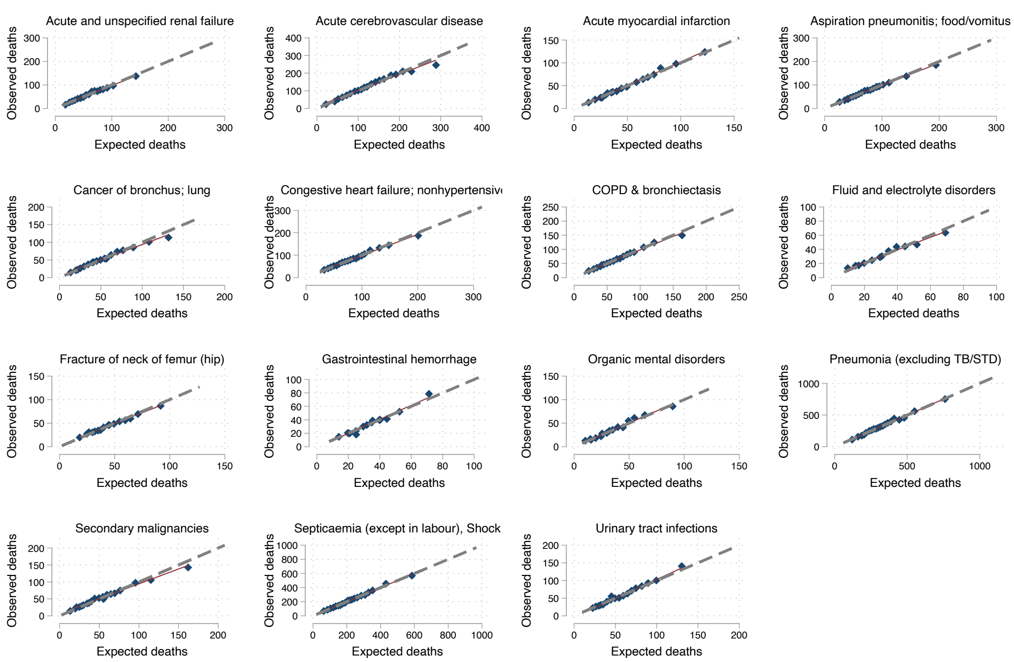
Notes: Figure displays the relationship between observed and expected deaths in the SHMI data before the pandemic at the trust-diagnosis level. We note that there is a tight relationship. In the left panel we plot a simple scatterplot with the solid line indicating the linear regression fit and the dashed line representing a 45-degree line. The linear regression fit and the 45-degree line coincide nearly. The right panel presents a binned scatterplot.

Figure B.4: Relationship between observed vs expected deaths in the SHMI data before the pandemic at the trust-diagnosis level, disaggregated by diagnosis

Panel A: Scatterplot



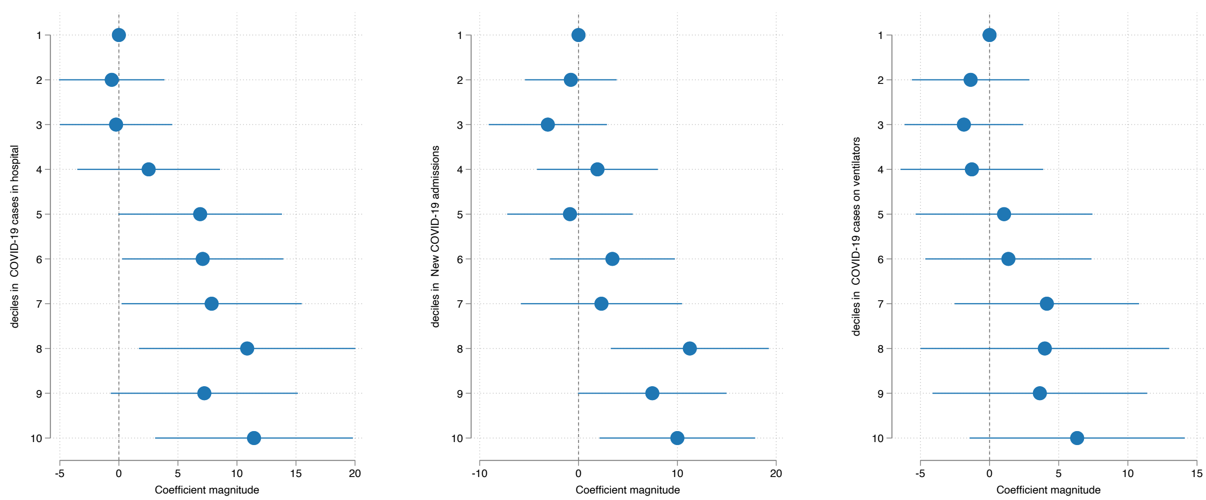
Panel B: Binned scatterplot



Notes: Figures display the relationship between observed and expected deaths in the SHMI data before the pandemic, broken down at the trust-diagnosis level. We note that there is a tight relationship. In the upper panel we plot simple scatterplots with the solid line indicating the linear regression fit and the dashed line representing a 45-degree line. The linear regression fit and the 45-degree line coincide nearly for the vast majority of specialties. The lower panel presents binned scatterplots.

Figure B.5: Impact of COVID-19 pressures on non-COVID-19 excess mortality: effect across different deciles of the COVID-pressure intensity

a) Hospital cases b) New admissions c) On ventilators



Notes: Figure presents heterogeneous treatment effects capturing the impact of COVID-19 pressures on excess mortality. The dependent variable measures the month-on-month changes in excess mortality to proxy month-specific excess mortality. All regressions control for provider fixed effects, time fixed effects and provider-specific linear trends along with as well as month-on-month changes in number of spells. 90% confidence intervals obtained from clustering standard errors at the provider level are indicated.

Table B.3: Impact of COVID-19 health care system pressures on non-COVID-19 excess deaths in levels *without controlling for community COVID-19 transmission*

	(1)	(2)	(3)	(4)	(5)
Panel A:					
COVID-19 cases in hospital	0.044***	0.065***	0.063***	0.064***	0.066***
	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	1480	1480	1458	1458	1458
Clusters	124	124	122	122	122
Panel B:					
New COVID-19 admissions	0.013**	0.018***	0.017***	0.017***	0.016**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.008)
Observations	1480	1480	1458	1458	1458
Clusters	124	124	122	122	122
Panel C:					
COVID-19 cases on ventilators	0.190**	0.265***	0.259***	0.259***	0.299***
	(0.083)	(0.073)	(0.075)	(0.075)	(0.083)
Observations	1480	1480	1458	1458	1458
Clusters	124	124	122	122	122
Provider FE	X	X	X	X	X
Time FE	X	X	X	X	X
ΔSpells$_{p,t}$		X	X	X	X
Excess deaths$_{p,t-12}$			X		
Obs$_{p,t-12}$ and Exp$_{p,t-12}$				X	X
Provider specific linear time trend					X

Notes: Regressions present results at the NHS provider level documenting the relationship between different measures of COVID-19 pressures at the provider level and overall excess deaths reported in a given month. The excess deaths measure proxies for month-on-month changes in excess deaths constructed from the twelve-month cumulative windows. Across columns subsequently more control variables are added that aim to capture the potential confounding effect that base effects could have on the estimates. Standard errors are clustered at the provider level with stars indicating *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.4: Impact of COVID-19 health care system pressures on non-COVID-19 excess deaths in levels *with controlling for community COVID-19 transmission*

	(1)	(2)	(3)	(4)	(5)
Panel A:					
COVID-19 cases in hospital	0.039**	0.061***	0.059***	0.060***	0.062***
	(0.017)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	1431	1431	1420	1420	1420
Clusters	123	123	122	122	122
Panel B:					
New COVID-19 admissions	0.012*	0.017***	0.016***	0.016***	0.015*
	(0.007)	(0.006)	(0.006)	(0.006)	(0.009)
Observations	1431	1431	1420	1420	1420
Clusters	123	123	122	122	122
Panel C:					
COVID-19 cases on ventilators	0.186**	0.262***	0.260***	0.260***	0.294***
	(0.087)	(0.078)	(0.079)	(0.079)	(0.086)
Observations	1431	1431	1420	1420	1420
Clusters	123	123	122	122	122
Provider FE	X	X	X	X	X
Time FE	X	X	X	X	X
Community Transmission	X	X	X	X	X
$\Delta \text{Spells}_{p,t}$		X	X	X	X
Excess $\text{deaths}_{p,t-12}$			X		
$\text{Obs}_{p,t-12}$ and $\text{Exp}_{p,t-12}$				X	X
Provider specific linear time trend					X

Notes: Regressions present results at the NHS provider level documenting the relationship between different measures of COVID-19 pressures at the provider level and overall excess deaths reported in a given month, controlling for community COVID-19 transmission. The excess deaths measure captures month-on-month changes in excess deaths constructed from the twelve-month cumulative windows. Across columns subsequently more control variables are added that aim to capture the potential confounding effect that base effects could have on the estimates. Standard errors are clustered at the provider level with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Table B.5: Impact of COVID-19 health care system pressures on non-COVID-19 excess deaths in levels *without controlling for community COVID-19 transmission* and dropping March and April of 2020

	(1)	(2)	(3)	(4)	(5)
Panel A:					
COVID-19 cases in hospital	0.057***	0.062***	0.060***	0.061***	0.052*
	(0.020)	(0.021)	(0.022)	(0.022)	(0.029)
Observations	1235	1235	1216	1216	1216
Clusters	124	124	122	122	122
Panel B:					
New COVID-19 admissions	0.018***	0.019***	0.018***	0.018***	0.014
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)
Observations	1235	1235	1216	1216	1216
Clusters	124	124	122	122	122
Panel C:					
COVID-19 cases on ventilators	0.307***	0.332***	0.322***	0.324***	0.343**
	(0.089)	(0.094)	(0.096)	(0.096)	(0.148)
Observations	1235	1235	1216	1216	1216
Clusters	124	124	122	122	122
Provider FE	X	X	X	X	X
Time FE	X	X	X	X	X
ΔSpells$_{p,t}$		X	X	X	X
Excess deaths$_{p,t-12}$			X		
Obs$_{p,t-12}$ and Exp$_{p,t-12}$				X	X
Provider specific linear time trend					X

Notes: Regressions present results at the NHS provider level documenting the relationship between different measures of COVID-19 pressures at the provider level and overall excess deaths reported in a given month, excluding March and April 2020. The excess deaths measure captures month-on-month changes in excess deaths constructed from the twelve-month cumulative windows. Across columns subsequently more control variables are added that aim to capture the potential confounding effect that base effects could have on the estimates. Standard errors are clustered at the provider level with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.6: Impact of COVID-19 health care system pressures and non-COVID-19 excess mortality

	COVID-19 pressures measured in the last ... months					
	0	1	2	3	6	9
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
log(COVID-19 patients in hospital)	0.005**	0.006**	0.007*	0.008*	0.005	0.003
	(0.002)	(0.003)	(0.004)	(0.005)	(0.009)	(0.012)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel B:						
log(New COVID-19 hospital admissions)	0.005**	0.009***	0.012***	0.016***	0.019*	0.020
	(0.002)	(0.003)	(0.004)	(0.006)	(0.011)	(0.014)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel C:						
log(# of COVID-19 cases in ventilator beds)	0.003*	0.005**	0.005**	0.006**	0.008*	0.009*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Provider FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Spells	X	X	X	X	X	X

Notes: Regressions present results at the NHS provider level documenting a positive relationship between COVID-19 pressures measured in different ways across Panels A - C and diagnostic-specific excess mortality for non-COVID-19 patients. The dependent variable measures the log difference in observed versus expected number of deaths. The expected number of deaths is constructed by NHS Digital (2021) based on case-level data. The right hand-side measures across columns are in logs measuring the COVID-19 pressures cumulative over the number of months indicated in the column head. That is, column (3) studies how COVID-19 pressures in the last two months, measured at the provider level, affect excess deaths over the last 12 months. Standard errors are clustered at the provider level with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.7: Impact of COVID-19 health care system pressures and non-COVID-19 mortality – controlling for expected mortality

	COVID-19 pressures measured in the last ... months					
	0	1	2	3	6	9
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
log(COVID-19 cases on ventilators)	0.003**	0.005**	0.005**	0.006**	0.008*	0.008*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
log(expected deaths)	0.856***	0.856***	0.857***	0.858***	0.860***	0.860***
	(0.079)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel B:						
log(New COVID-19 admissions)	0.005**	0.008**	0.012***	0.014**	0.016	0.018
	(0.002)	(0.003)	(0.004)	(0.006)	(0.011)	(0.014)
log(expected deaths)	0.857***	0.858***	0.860***	0.861***	0.861***	0.860***
	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)	(0.080)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel C:						
log(COVID-19 cases in hospital)	0.005**	0.006**	0.007*	0.008	0.004	0.002
	(0.002)	(0.003)	(0.004)	(0.005)	(0.009)	(0.012)
log(expected deaths)	0.856***	0.857***	0.858***	0.858***	0.858***	0.857***
	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)	(0.079)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Provider FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Spells	X	X	X	X	X	X

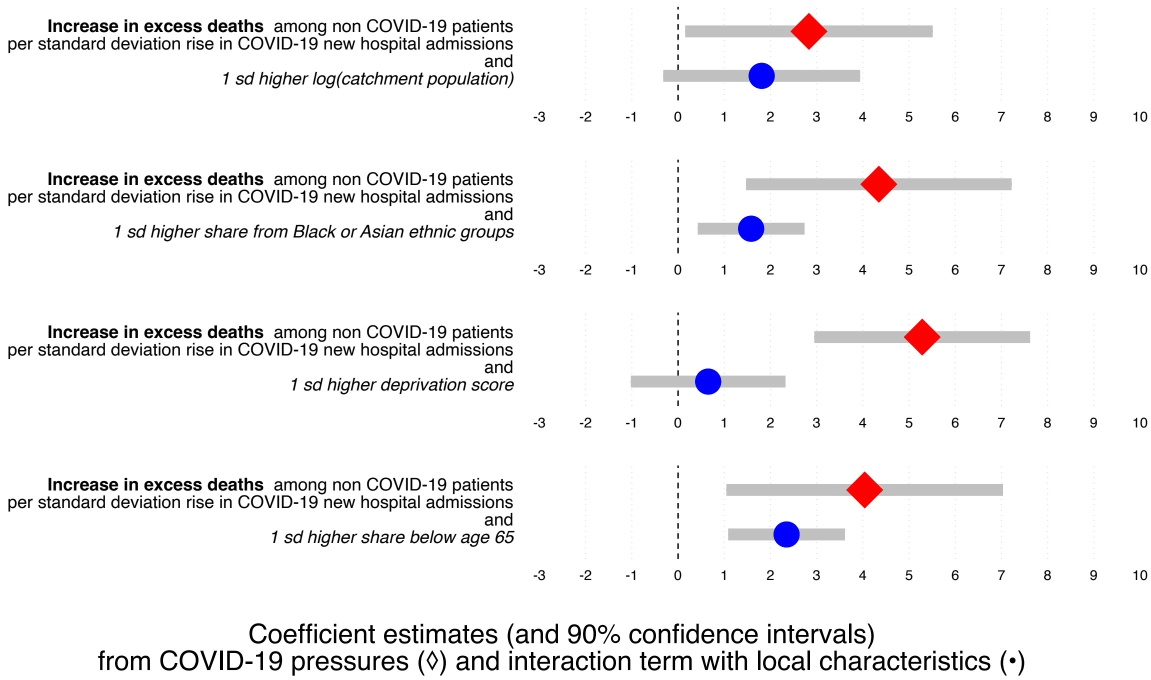
Notes: Regressions present results at the NHS provider level documenting a positive relationship between COVID-19 pressures measured in different ways across Panels A - C and mortality for non-COVID-19 patients. The dependent variable measures the log in observed deaths. The expected number of deaths is added as a control variable. The expected number of deaths is constructed by NHS Digital (2021) based on case-level data. The measures across columns are in logs measuring the COVID-19 pressures cumulative over the number of months indicated in the column head. That is, column (3) studies how COVID-19 pressures in the last two months, measured at the provider level, affect excess deaths over the last 12 months. Standard errors are clustered at the provider level with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Table B.8: Impact of COVID-19 health care system pressures and non-COVID-19 death rates

	COVID-19 pressures measured in the last ... months					
	0	1	2	3	6	9
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
COVID-19 cases in hospital	0.007**	0.008*	0.008*	0.008	0.009	0.009
	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)	(0.009)
Expected deaths / # of spells	0.957***	0.959***	0.959***	0.960***	0.960***	0.959***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel B:						
New COVID-19 admissions	0.007**	0.010**	0.011**	0.011**	0.012*	0.011
	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)	(0.008)
Expected deaths / # of spells	0.957***	0.960***	0.962***	0.963***	0.963***	0.961***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.112)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Panel C:						
COVID-19 cases on ventilators	0.007***	0.007***	0.008***	0.008**	0.010	0.011
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)
Expected deaths / # of spells	0.951***	0.951***	0.952***	0.952***	0.953***	0.954***
	(0.112)	(0.112)	(0.112)	(0.112)	(0.111)	(0.111)
Observations	1490	1490	1490	1490	1490	1490
Clusters	126	126	126	126	126	126
Provider FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X

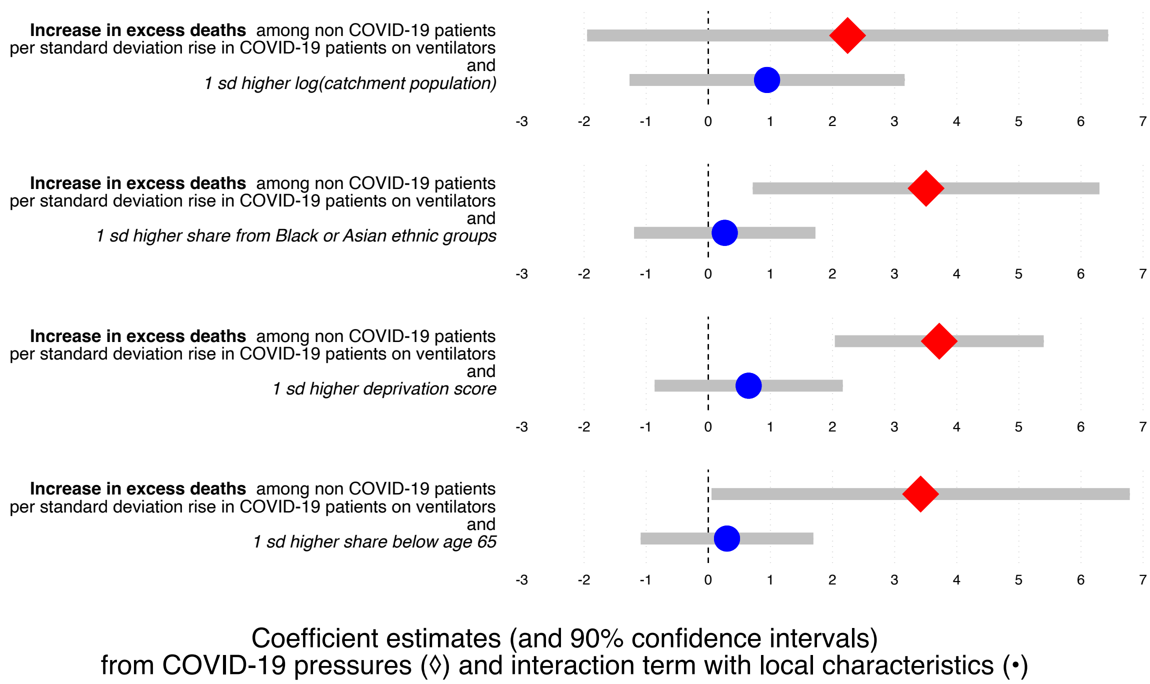
Notes: Regressions present results at the NHS provider level documenting a positive relationship between COVID-19 pressures measured in different ways across Panels A - C and mortality for non-COVID-19 patients. The dependent variable measures the share of hospital admissions that result in a death. The expected share of deaths per admission is added as a control variable. The expected number of deaths is constructed by NHS Digital (2021) based on case-level data. The measures across columns measure the COVID-19 pressures cumulative over the number of months indicated in the column head. That is, column (3) studies how COVID-19 pressures in the last two months, measured at the provider level, affect excess deaths over the last 12 months. Standard errors are clustered at the provider level with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B.6: Impact on non-COVID-19 excess mortality of average new daily COVID-19 hospital admissions depending on characteristics of the catchment area of NHS healthcare providers.



Notes: The figure plots the coefficients and 90% confidence intervals of the interaction term from regression estimates at the NHS provider level. The point estimate captures the effect of a 100% change in COVID-19 pressures combined with a one standard deviation increase in the catchment area characteristic on the number of excess deaths in a given month among patients seeking medical help for reasons unrelated to COVID-19. We measure COVID-19 pressures as the monthly average new daily COVID-19 hospital admissions in a given month. The catchment area characteristics are the deprivation score, the share of the population who are from Black or Asian ethnic groups, the log of total population, and the share of people below age 65 in the catchment area of the provider. All regressions control for NHS provider fixed effects and time fixed effects. 90% confidence intervals obtained from clustering standard errors at the provider level are indicated.

Figure B.7: Impact on non-COVID-19 excess mortality of beds with ventilator occupied by COVID-19 patients depending on characteristics of the catchment area of NHS healthcare providers.



Notes: The figure plots the coefficients and 90% confidence intervals of the interaction term from regression estimates at the NHS provider level. The point estimate captures the effect of a 100% change in COVID-19 pressures combined with a one standard deviation increase in the catchment area characteristic on the number of excess deaths in a given month among patients seeking medical help for reasons unrelated to COVID-19. We measure COVID-19 pressures as beds with ventilator occupied by COVID-19 patients in a given month. The catchment area characteristics are the deprivation score, the share of the population who are from Black or Asian ethnic groups, the log of total population, and the share of people below age 65 in the catchment area of the provider. All regressions control for NHS provider fixed effects and time fixed effects.