The Role of Public Health Expenditures in COVID-19 control: Evidence from Local Governments in England

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ABSTRACT

For over 150 years the local health departments of England have been critical in controlling 19th and 20th century infectious epidemics. However, recent administrative changes have hollowed out their flexibility to serve communities. We use administrative data on past budgetary allocations per capita to public health departments at upper tier local areas (UTLAs) of England to examine whether public health funding levels were correlated with more rapid control of the first wave of the COVID-19 pandemic between March and July of 2020. The dependent variable was the number of days between a UTLA's 10th case of COVID-19 and the day when new cases per 100,000 peaked and began to decline. Our models controlled for regional socio-economic factors. We found no correlation between local public health expenditure and the speed of control of COVID-19. However, overall public expenditure allocated to improve local areas helped reduce time to reach peak. Contrary to expectation, more dense areas such as London experienced shorter duration. Higher income areas had more rapid success in accelerating the time of the first peak in the first wave of their local COVID-19 incidence. We contribute to understanding the impact of how public expenditure and socio-economic factors affect an epidemic.

Background and motivation

England has a glorious history of contributing to the practice of public health. The Public Health Acts of 1848 and 1874 conceived local health departments schools of public health where the establishment of a professional public health workforce was widely credited with England's remarkable health revolution (Szreter, 1988). England's local public services staff built the sewers and passed the local ordinances responsible for better housing, safer food, and ultimately dramatic control of regular cycles of contagious illnesses including cholera, typhoid, tuberculosis, diphtheria, etc. In the contentious debate over attributing causes to improvements in health, Szreter (1988) notes that the classic study by McKeown (McKeown et al., 1975) conservatively attributes to public health measures a mortality reduction of 25%.

Given its historical legacy and centuries' long lead in developing the profession and practice of public health, one would have expected that England would have successfully responded to the 2020 COVID-19 pandemic. Historically infectious disease outbreaks have been contained when local public health officials recognize cases, modify behaviors of close contacts, and take general measures in behavioral change among citizens and leaders. Therefore, variation in recent funding levels for local health departments may be correlated with the ability of health officials to execute outbreak control measures. If historical expenditures show little connection to the control of COVID, it should lead to renewed consideration of ways to spend funds on local public health operations in a way that makes them more prepared to control infectious outbreaks. We seek to understand local public health preparedness for containing infectious disease outbreaks by determining the extent to which variation in local-level public health expenditure contributed to shortening the number of days to reach the peak infection level during the first wave of the pandemic from March to July of 2020.

The period of 20 March to 31 July is recognized as the initial wave of

COVID-19 in England (Marmot et al., 2020). Restricting our focus to the first wave offers a more appropriate path to answer questions about how well prior investments in public health prepared local areas to control a new outbreak. As the pandemic in England continued, supplemental public health funding was released to local areas in patterns and amounts that have not yet been systematically made public. These funds would have given local areas a chance to upgrade their approach to outbreak control (Iabuci, 2020). The disbursement of public health funds in late 2020 is likely to have been correlated with both the prior public health investments as well as the early 2020 rates of COVID-19, thereby, making it counterproductive to use outcomes from the latter half of 2020 to examine the impact of pre-COVID era public health spending. [1]Therefore, looking at time to first peak and its relationship to public health spending at a geographic level is indicative of how well public health is (or not) working at the community level and how prepared public health was (or note) at the start of the pandemic. Extending the time horizon fundamentally shifts our focus from public health's ability to respond and react to the outbreaks to learning to do better over time conditional on new resources and experience.

We focus on the local areas of England known as upper-tier local authorities (UTLAs). Sub-national levels in the UK exhibited different levels of COVID-19 infection rates (Corona Virus Daily Data, 2020; Landler, 2020; The Office of National Statistics, 2020a). For the period where a clear bend in infections had taken place, we observe wide-spread local variations that persists when the data is aggregated to the nine English regions (see Fig. 1a & b) for the first wave (March to July 2020). Local health department functions are relevant to infectious disease control because the process of communicable disease control requires the capacity to collect and process local epidemiological data allied with informative local advocacy. Historically, local health departments played an immense role in data collection and policy formation that led to reforms such as the public financing of a sewer construction, a bully pulpit to promote hand hygiene, or a multi-sectoral consortium to change food production practices (Cutler & Miller, 2005). Local health departments can often succeed even without a national backing if they are politically astute and equipped with a trusted public health workforce.

For decades, preparedness for public health crises included local health departments in conjunction with national and regional public health officials. The local workforce's role wrested with rapid detection of outbreaks and rapid measures to stem the spread of infection (Middleton, 2017). Following the principles held in public health practice (Padamsee, 2018), local health departments are supposed to have built up channels of communication with citizens and local institutions such as schools, businesses, and politicians as part of the infrastructure of preparedness and community engagement. As such, local public health infrastructure is a source of potential variation in a pandemic's rate of spread within the area.

Citizens' capacity, willingness to isolate, and ability to observe public health measures are additional sources of variation. The capacity to comply with lockdown orders and follow recommendations for protective behavior depend on income, employment structure and local infrastructure such as accessibility of delivery services for necessary consumption. Economic conditions that would play a role in a pandemic's effect on health status are income-based poverty, employment status, and the stock of affordable housing. Population density and its age composition also matter.

In 2012, the UK's Health and Social Care Act (HSCA) moved the responsibility to commission public health services from the National Health Service (NHS) to 'upper tier' ('county council') or 'unitary' ('metropolitan') local authorities. The HSCA gave local authorities a statutory duty to improve their population's health and provided nearly 3 billion pounds in ring-fenced funds to enable them to implement their public health activities (Public Health England, 2015). These local health authorities received technical support from Public Health England (PHE) through its central office and 9 regional offices. Local authorities were to carry out prescribed and non-prescribed functions and track their own spending. Data suggests local public health expenditure per capita varies widely across UTLAs in England with a coefficient of variation at 36%. Local public health expenditure is separate (ring-fenced) from the NHS budget that pays for healthcare, where NHS spending per capita is relatively equal and delivered according to a standardized formula across the UK.

While there are reasons to expect that the geographical variations in local public health spending should be related to the variations in COVID-19 control, in the case of England, there are reasons to doubt the efficacy of the spending. Austerity measures since 2010 have cut local government and social welfare budgets by 40%. Local governments are stressed in addressing social determinants of health with diminished resources. In addition, the prescribed areas of public health spending in the HSCA give local health departments little latitude to spend funds on pandemic preparedness and cross-cutting engagement. As can be seen from the allocations to local public health in Fig. 2, the largest expenditures are in categorical programs in child health, substance use, and sexual health (Public Health England, 2015).

Even though local jurisdictions may have budgeted their public health funds in the past to other priorities besides pandemic preparedness, it is still plausible that having more public health assets offers a health department capacity to redirect or exhaust reserve funds. Many of the most successful responses to COVID-19 in East and Southeast Asia were staffed by health departments that had the administrative flexibility to draw public health nurses and sanitarians away from other duties (Tran BX, Hoang MT, Pham HQ, 2020; You, 2020). The additional capability, reflected in historically higher per capita sending, could and should have enabled a local health department to shift the resources into case detection, tracking, counseling, and communications for behavior change. This would result in a shorter interval between the epidemic's start and its first peak. One may expect that a quicker resolution of the epidemic would translate to a relatively lower peak daily new case per 100,000. Although COVID-19 requires multiple levels of specialized interventions, the existing pre-pandemic public health infrastructure should provide protection against the impact of the pandemic if structured adequately. The duration of time to reach peak incidence is an indicator of a UTLA's ability to respond quickly to control the outbreak of the pandemic. The hypothesis tested in this paper centers on the following precept: local-level public health infrastructure should influence the spread and impact of COVID-19 (Cole & Fielding, 2007; Middleton, 2017).

We thus hypothesize that higher public health expenditure can shorten the time to reach peak infection level over a local area. Our hypothesis will be tested for UTLAs in England and not for the entire UK due to 1998 devolution allowing various degrees of autonomy to Scotland, Wales and Northern Ireland over health and social services policies and the national variation in containment policies (Pope & Waters, 2016). Broad policies affecting NHS are mandated from the UK central government, but our data shows that variation in local health department spending occurs in England (Torrence, 2019).

We chose to study both size of the peak as well as duracation to peak instead of mortality for two reasons. First, the total number of deaths reflects both access to and outcomes of NHS funded hospital care. Second, dynamic changes in death rates in early 2020 were driven heavily

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[1] Analysis examining the second wave would be testing a different hypothesis than the one tested here. The dependent variable itself is harder to define as the pandemic seemed to have been peaking by end of 2020 after the first wave. We have examined the possible suggestion that consideration of data after July should be a robust test for our results here; we do not find anything that contradict the results of this paper (see Annex V).
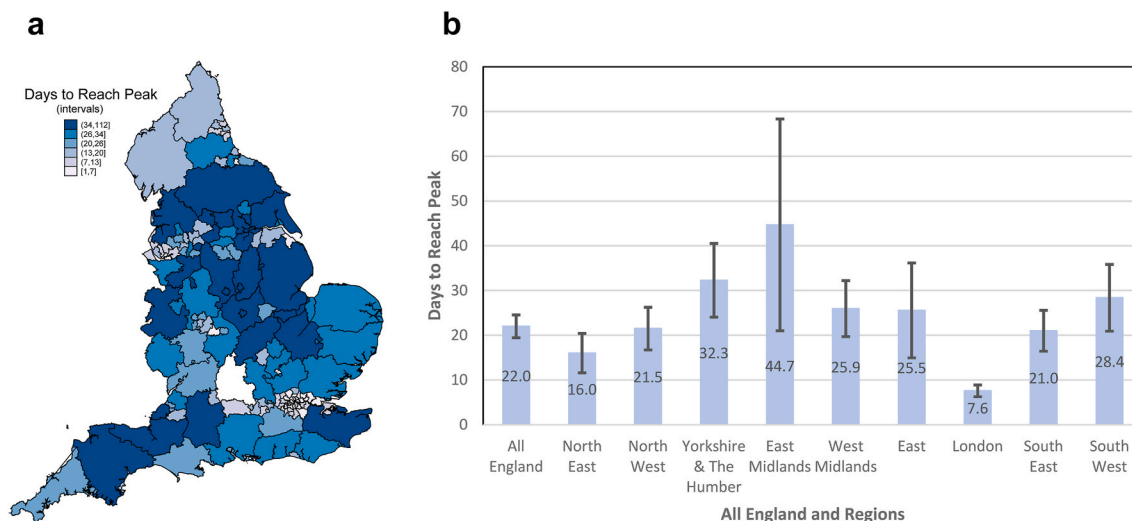
Fig. 1. a: Unadjusted Heat map of days to reach peak by UTLA[a], [a]This heat map shows variation in days to reach peak COVID-19 incidence across UTLAs in England. See Annex I for calculation of days to reach peak from incidence data. COVID-19 incidence data source: ONS, time period March–July 2020, (The Office of National Statistics, 2020a). Figure 1b: Variation in time to reach COVID-19 peak across England[a], [a]Data source, the same as 1a.
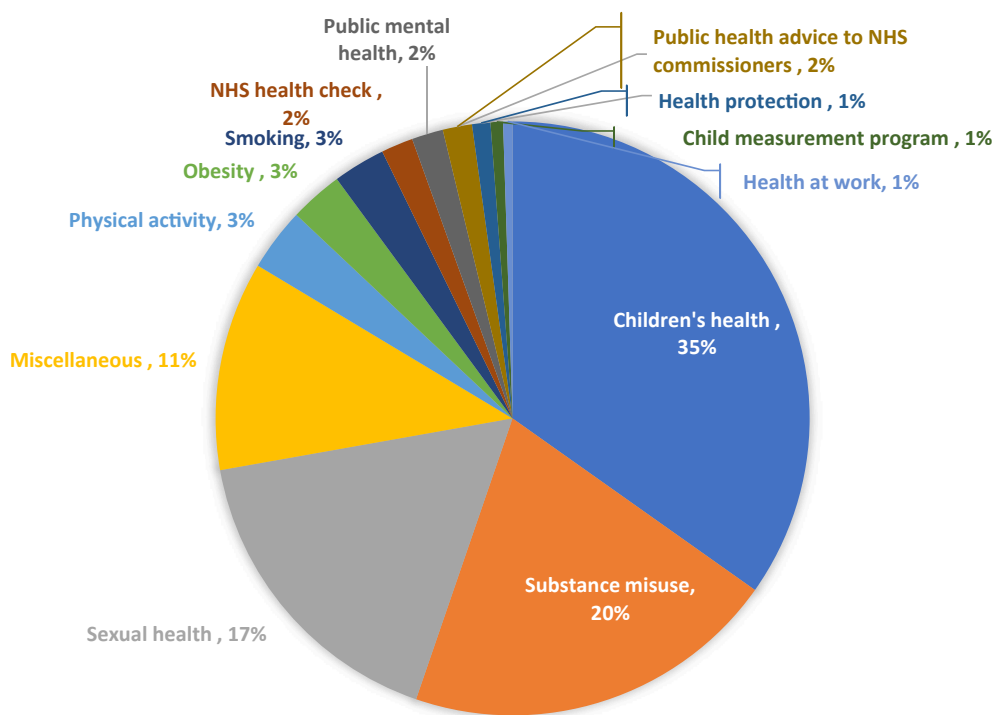
Fig. 2. Distribution of Local Public Health Expenditure by Types of Spending[a], [a]Source: Ministry of Housing, Communities & Local Government Revenue Account Budget (Public Health England, 2015).

by shifts in the age composition of cases as well as rapid improvements in the medical management of cases. Thus, the time to bend a mortality curve is less reflective of the local health department's ability to control cases.[2] Further, while deaths and health impacts of COVID-19 infections is related to comorbidity (Sorci et al., 2020) direct linkages between

becoming infected due to comorbidity has not been reported and can be ignored. We note that the incidence of deaths fell after the peak infection rate has been reached. For example, London areas reached their peak by late April 2020 and experienced the second lowest death rates after that having had the highest rate before that date. Thus, persistence of infections induced deaths from COVID-19.

Related work

This paper contributes to understanding geographical and ecological factors that affected the spread of COVID-19 in England. The UK Office

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[2] Deaths during the first wave indicate different relations to factors used in this paper. Marmot et al. (2020) show there is a great deal of difference between the first wave deaths and subsequent deaths by region and the overall case fatality rate.

of National Statistics (ONS) reported that England saw the second highest excess mortality—measured weekly against averaged values from the previous 5 years for the same period –during the week ending 21 February to the week ending 12 June, when compared with figures from 21 European countries (Aron & Muellbauer, 2020). Further, during spring and summer of 2020, England had the longest period of excess mortality of these countries after the onset of COVID-19 (Campbell and Morgan, 2020). Duration of the epidemic is a likely factor in excess mortality. By 24 April 2020, the COVID-19 death rate per 100,000 was shown to be higher in local areas with larger Black or Asian populations and worse levels of self-reported health in England (Sá, 2020). In other countries also, the impact of COVID-19 pandemic reflects prevailing socio-economic conditions (Borjas, 2020). Marmot et al. (2020) examine COVID-19 mortality related to deprivation in areas of England. A focus on England is important due to the high level of excess mortality; and explaining aspects of how the spread of COVID-19 occurred through socio-economic factors is a natural question.

Studies have examined the relation between the outbreak and health systems factors using cross-country data. Studies used varied geographical units: Allel et al. (2020) and Khan et al. (2020) use cross-country data from all regions of the world while Blondel, S. and Vranceanu, (2020) and Kapitsinis (2020) use data only from European countries or regions of a few European countries. The dependent variables used are deaths/100,000 (Kapitsinis, 2020), case fatality rate (Blondel & Vranceanu, 2020; Khan et al., 2020) and infection rate 5, 10, and 15 days after detecting the first case (Allel et al. 2020). Results show that the COVID-19 situation improved with some features of the health systems and measures taken to tackle the outbreaks across region/-countries. Improved situation was not related to health expenditure measures (Blondel & Vranceanu, 2020; Khan et al. 2020); additionally, Kapitsinis (2020) concludes that lockdown measures may have been less effective due to deterioration of health systems in Europe over the recent years.

These studies used COVID incidence rates from agreed upon sources at an earlier stage of the pandemic. The advantage for the current paper is that a focus on the regions within a country yields the use of data obtained through similar measurement methods. Incidence rates depend, even if adjustments are made, on testing which could not have been uniform across countries. Methods for attributing deaths to COVID could vary and be flawed although this data is important. Two studies report coefficient of variation greater than 1 for the dependent variable; this is not surprising and indicates that cross-country studies need cautious interpretation.

The article also contributes to discussions unrelated to COVID. Literature emphasizing the social determinants of health rests on the recognition of the influences of non-health sectors on health (Marmot, 2008); health can be affected by social factors including non-health social policy. Impacts of regional factors shaping general wellbeing has become a strong research subject in recent years (Chetty & Hendren, 2018).

Methods

In this paper we explain the association between duration to peak incidence of COVID-19 cases at the UTLA level and corresponding local public health expenditure adjusting for socio-economic factors. Daily COVID-19 cases were first smoothed using a locally weighted regression of cases on days for UTLAs that registered more than 10 cases since 30 January. The period between 1 and 10 cases may be long; however, never reaching 10 cases would make COVID a non-existent problem in the region in the period under consideration. Starting from a lower or higher number of cases does not change the results in the paper. We then used the smoothed time series of cases to compute daily incidence rates per 100,000 people (See Annex I). The peak is defined as the point where slope of the incidence curve is 0 signaling the rising incidence rate is followed by a declining incidence rate. A lower number of days to peak

and reaching the peak does not mean that the pandemic is over, rather that it has been controlled. The peak did not remain flat for any of the UTLAs for a sustained period, so we are able to define the time to reach the peak clearly in all ULTAs except Oxfordshire (see Annex I).

Covariates in our models are values reported after 2018 and chosen with considerations regarding collinearity and informed by the susceptible-infection-recovered (SIR) model. Our dependent and explanatory factors are measured at the UTLA level and can be categorized into five types. (1) Public Expenditure: Public health expenditure per capita (coded 390) was used for our main hypothesis. We also included an overall local expenditure per-capita (coded 799, Total Service Expenditure) to control for confounding with other expenditures at the UTLA level (Local authority revenue expenditure and financing, 2020; Public Health England-Government of United Kingdom, 2020). Health expenditure can offer messaging affecting the disease-spreading behavior of both infected and susceptible groups in the SIR. (2) Socio-economic-status (SES) factors: We include median household income at the UTLA level measured weekly in GBP, percentage of the population experiencing fuel poverty and unemployment, and affordability of homes in the area. SES status affects the susceptible population by affecting exposure to infection through employment or dwelling type.[3] (3) Density: Population density, measured as population per square kilometers, and infection disease would suggest that COVID-19 spreads more in denser areas. We used a London borough dummy to adjust for the disparate income inequality and high population density. (4) Demography: We capture demographic makeup of areas by adjusting for the percent of the population under 18 and over 65. Over 65 are less likely to be exposed outside home and younger people have been less susceptible to COVID. (5) Health: Our models proxy local measures of health and wellbeing through percent feeling or experiencing social isolation among caregivers or receivers over 18. This can be an indicator for physical and psychological conditions. Our indicators for health were limited; we deemed self-reports about health conditions unusable as the variations across the UTLAs were small. One can think of comorbidities to play a role in prolonging the outbreak through making people ill for a longer period thus more infectious; in Annex V, we tested to examine if comorbidity may have played role.

An epidemic would be clustered by regions; therefore, we sought to test whether there is geographical or spatial autocorrelation. We tested for spatial correlation through ordinary least square models (OLS) of the covariance in UTLA peak incidence (Drukker et al., 2013). We defined several alternative spatial weighting matrices based on contiguity and conducted Moran Tests to detect autocorrelation. We show in Annex III that spatial autocorrelation can be ignored.

Factors affecting time to reach peak COVID-19 incidence are examined through time to event models. The variations in time to reach the peak are hypothesized to be affected by variations in regional factors at the UTLA level through an accelerated failure time (AFT) model with log of time to peak as the variable to be explained by fixed time explanatory variables and a specified error term. Covariates act multiplicatively on the outcome of survival time. The baseline related hazard function was selected to be log-log distributed after finding the smallest Akaike Information Criterion (AIC, inverse of information matrix associated with the model) when judged against other specifications—exponential, Weibull, log-normal, and generalized gamma (Lee & Wang, 2003). As the Weibull distribution carries certain other advantages, results from models using the Weibull distribution are presented in Annex III.

As the dependent variable is not censored in completion of days to

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[3] Marmot (et al.) show a concave but positive univariate relation with percent of overcrowded household in local regions and age-adjusted Covid-19 death rate. As death affected London at the onset, there are multiple poorer regions of London which are crowded. The data for crowded household is from 2011; we note crowdedness is highly correlated with death from Covid. This result could be due to early deaths occurring in the London area.

peak and not far from normal, to understand the explanatory factors more intuitively, we run OLS models with log-dependent variables and used results to simulate policy scenarios (StataCorp LLC, 2019). These involved increasing the value of a single factor by one standard deviation for all UTLAs. We examined policy impact in cases only when a welfare improving policy would significantly reduce the COVID-19 impact. For example, if analysis suggested improving housing prices increased the number of days to reach peak, then this factor was not adjusted in the simulation exercise.

As many of the explanatory covariates may be correlated, we estimated the marginal contribution of each of the five clusters of factors toward the explained variation in the data. We examine the percentage of contribution to the R-square in the OLS model from each of the clusters. We use a Shapley decomposition method where the marginal contribution to the R-Square of each cluster is averaged over every permutated regression estimation using the five clusters (Lipovetsky & Conklin, 2001). Measures of the contributions for each cluster are adjusted for multi-collinearity (See Annex IV).

Data collected for the covariates at the UTLA level are not available from the same source or for the same year; they are all official and for years after 2018, fuel poverty is reported for the year 2017. Data on COVID-19 were made available by ONS (The Office of National Statistics, 2020a); data on socio-economic variables came from PHE (Public Health England-Government of United Kingdom, 2020). Population density data were obtained from ONS (The Office of National Statistics, 2020b); and finally the expenditure data were obtained from website of ministries of housing, communities & local government, published in June 2019 (House Pricing-Nat'l Statistics, 2020; Public Health England, 2015).

Results

As of July 26, 2020, there were 147 UTLAs in England that reported more than 10 cases of COVID-19. Twenty-five of these areas reached a peak infection incidence within a week, with a non-normal distribution (see Fig. 3a). The mean (standard deviation) number of days to a peak was 22 (15.76) in the full sample of 147 with a maximum of 112 days and a median of 20. However, not all 147 UTLAs could be used in the analyses due to results regarding the distribution of the data as explained below (See also Annex II). The final analytical sample was reduced to 136.

Table 1 summarizes the covariates for the analytical sample of 136 UTLAs that was used for the final analyses. Summaries for the larger sample are nearly the same. OLS models without any log forms were tested for contiguity and distance auto-correlation. Moran tests

Table 1
Summary values of days to reach peak and independent variables used in the analysis (days to reach peak > 3 days, analytical sample = 136).

Covariates, Year of Observation	Sample Description	Description of Fastest 10% to reach peak	Description of Slowest 10% to reach peak	P-Value Difference Fast and Slow
Days to Reach Peak	23.30 (15.24)	5.63 (1.09)	56.69 (17.26)	<0.001
Public Health Expenditure/ 1000 people (Local), 2019	62.96 (22.99)	79.82 (26.90)	52.27 (16.57)	<0.005
Public Expenditure/ 1000 people (Local), 2019	1705 (431)	2228 (485)	1360 (349)	<0.05
Median Weekly Income, GBP, 2018	582 (84.5)	628.45 (104.87)	488.08 (49.09)	<0.001
Ratio of Housing Cost to Income, 2018	11.29 (2.26)	13.88 (4.01)	6.87 (1.15)	<.001
Unemployment, 2018 (%)	4.37 (1.24)	5.16 (0.92)	4.21 (0.97)	<0.05
Fuel Poverty, 2017 (%)	8.77 (4.10)	12.18 (2)	10.44 (1.99)	<0.05
Population/Square KM, 2019	2774.60 (3298)	8315 (4395)	903 (1332)	<.001
London Burroughs, number	29	15	0	
Under 18, 2019 (%)	21 (2)	22.55 (2.72)	21.39 (2.63)	0.257
Over 65, 2019 (%)	17 (4)	11.76 (3.44)	20.21 (4.46)	<.001
Feeling of Social Isolation (%) among Care Givers, 18+, 2018 (%)	31.9 (6.8)	29.48 (8.46)	31.69 (4.82)	0.409
Feeling of Social Isolation Care Receivers, 18+, 2018 (%)	45.6 (4.6)	42.53 (4.5)	45.49 (2.21)	<0.05
Number of Observation	136	16	13	

(StataCorp LLC, 2019) for spatial correlation revealed weak contiguous correlation (p-value < 0.08) and strong distance correlation (p-value < 0.00). The adjusted spatial-weighted models did not reveal uniform divergence from OLS (Annex II). With logged dependent variable, and with logged continuous non-proportional independent variables, we
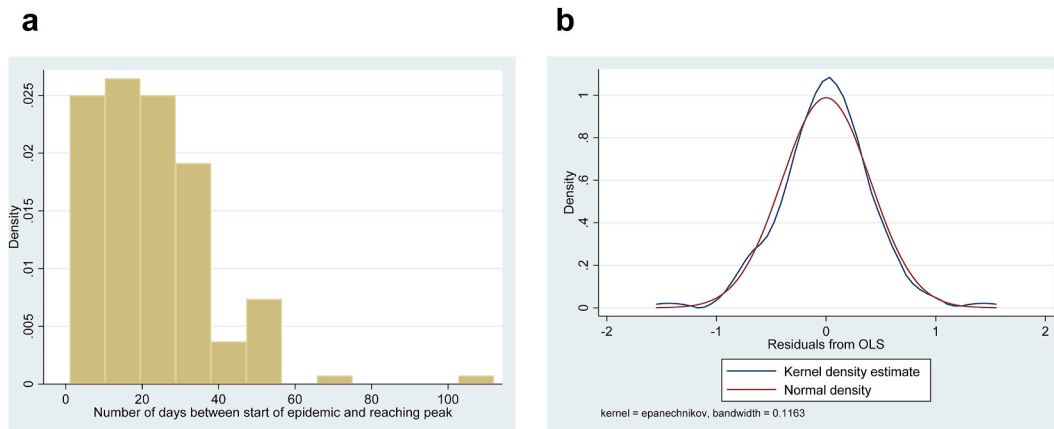
a

b

Fig. 3. a:Histogram: Days to reach peak, by UTLA (full sample = 147), Figure 3b: Density curve of errors from OLS, logged days to reach peak, (days to reach peak > 3 days, analytical sample = 136 to obtain normality).

ruled out both contiguous and distance spatial autocorrelation as a major source of bias. Our analyses showed that modeling the logged value of day to peak COVID-19 incidence produces a normal distribution for error terms and the dependent variable when low values of the dependent variable were eliminated (Fig. 3a–b, See also Annex II). We find that no spatial autocorrelation of any kind is present in the logged model with data from the analytical sample of 136 UTLAs.

The average time to peak was 23.3 days with a standard deviation of 15.24 for the analytical sample (See Table 1). There are considerable differences between those 10% of UTLAs that peaked fastest and those 10% that were slowest. Table 1 indicates that the slowest group of UTLAs spent less on local expenditure, experienced lower income, had a larger proportion of people over 65 and care recipients that felt more isolated in comparison to the fastest 10%. The slowest group also were less densely populated; and half of the London area UTLAs were among the fastest. Interestingly, the slowest regions, although having lower income, experienced lower unemployment and fuel poverty.

The results of survival models (See Table 2) provide the main relationships between the dependent variable and some transformations of the independent variables listed in Table 1; some were log transformed or divided into quartiles. Model 1 in Table 2 demonstrates that if on average a UTLA fell within Quartile 3 for per-capita public health expenditure it experienced a statistically significant increased time to reach peak compared to Quartile 1. These UTLAs required nearly 40 percent more days to peak in comparison to the average UTLA falling within the lowest quartile level of expenditure (TR 1.38, $p < 0.01$). The result is unexpected, we expected time to peak to be lower with higher

public health expenditure. However, the effects of public health spending on duration to peak become statistically insignificant for all 3 quartiles with the inclusion of measures of SES and other factors (models 2–5). Though insignificant, the direction of the coefficients for Quartiles 3 and 4 of local public health expenditure is in the hypothesized direction. One important policy factor to note is that the log of overall local expenditure per capita is significant; thus, higher overall local-level spending decreases the time to peak by as much as 50% in the full model (TR = 0.472, $p < 0.01$).

Higher median income for a UTLA is associated with significantly faster time to peak incidence in Model 2, though it does not remain significant after adjusting for density variables. Impact from unemployment is small but indicates that higher levels of unemployment increase the time to peak with statistical significance. UTLAs in London reached peak incidence nearly 60 percent faster in comparison to those not in London, holding other factors constant (TR = 0.429, $p < 0.001$). Additionally, higher population density (TR 0.82, $p < 0.001$) and a higher proportion of residents over the age of 65 years decreased the time to reach peak incidence for a UTLA, whereas the proportion of residents under age 18 had no significant impact on time to reach peak incidence. We do not observe any impact from health indicators used. The instability of some of the factors indicate correlations among the factors; our intuition of introducing them as clusters seem logical. The results from the Weibull survival model specification (Annex III) are similar to the logged OLS model discussed below (Table 3). The OLS model is presented as it clarifies intuitive policy implications.

The OLS models (See Table 3) used factors measured as continuous

Table 2
Survival model, log-log distribution, dependent variable: Logged days to reach peak (N = 136).

COVARIATES	Model 1	Model 2	Model 3	Model 4	Model 5
Local health expenditure per capita					
Quartile 2	1.091	0.895	1.043	1.049	1.033
	(0.15)	(0.12)	(0.13)	(0.12)	(0.12)
Quartile 3	1.381**	0.859	0.974	0.993	0.99
	(0.22)	(0.15)	(0.17)	(0.17)	(0.16)
Quartile 4	1.283	0.77	0.812	0.829	0.844
	(0.23)	(0.15)	(0.15)	(0.16)	(0.16)
Log net current expenditure per capita	0.153***	0.363***	0.517***	0.472***	0.472***
	(0.15)	(0.10)	(0.13)	(0.12)	(0.12)
Median Income					
Quartile 2		0.763**	0.855	0.875	0.887
		(0.09)	(0.09)	(0.09)	(0.10)
Quartile 3		0.714**	0.857	0.806	0.844
		(0.11)	(0.12)	(0.11)	(0.12)
Quartile 4		0.533***	0.827	0.779	0.8
		(0.10)	(0.15)	(0.14)	(0.13)
Housing price to income ratio		0.959**	1.016	1.02	1.014
		(0.02)	(0.02)	(0.02)	(0.02)
Unemployment		1.004	1.099**	1.078*	1.088**
		(0.05)	(0.05)	(0.05)	(0.05)
Fuel poverty		0.969	1.006	1.013	1.013
		(0.03)	(0.03)	(0.03)	(0.03)
London dummy			0.429***	0.419***	0.419***
			(0.07)	(0.07)	(0.07)
Log of population density			0.892**	0.825***	0.823***
			(0.05)	(0.05)	(0.05)
Percentage < 18 years				1.003	1.005
				(0.02)	(0.02)
Percentage > 65 years				0.966**	0.971*
				(0.02)	(0.02)
Social isolation: carers 18+					0.994
					(0.01)
Social isolation: care users 18+					0.992
					(0.01)
/lngamma	−1.15***	−1.30***	−1.42***	−1.44***	−1.44***
Constant	1.832e+07**	107,627***	4431***	26,176***	37,790***
AIC	247.5	218.9	192.3	191.3	193.4

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, Expenditure variable is measured as per capita. Standard errors in parentheses.

Table 3

OLS, logged Model, Dependent Variable: Logged Days to Reach Peak (N = 136).

Covariates	Model 1	Model 2	Model 3	Model 4	Model 5
Log of Local Health Expenditure per capita	0.187	−0.144	−0.287	−0.172	−0.159
	(0.197)	(0.202)	(0.189)	(0.200)	(0.204)
Log of Net Current Expenditure per capita	−1.708**	−1.059**	−0.687**	−0.802**	−0.780**
	(0.236)	(0.259)	(0.249)	(0.267)	(0.266)
Log Median Income		−2.210**	−1.079*	−1.171*	−1.049*
		(0.590)	(0.593)	(0.592)	(0.623)
Ratio of house price to earning		−0.00831	0.0283**	0.0310**	0.0239
		(0.0203)	(0.0136)	(0.0154)	(0.0173)
Unemployment		−0.0151	0.0743*	0.0545	0.0678
		(0.0443)	(0.0416)	(0.0425)	(0.0429)
Fuel poverty 2017		−0.0444	−0.00346	−0.00355	−0.00500
		(0.0291)	(0.0282)	(0.0280)	(0.0271)
London Dummy			−0.817**	−0.821**	−0.828**
			(0.128)	(0.135)	(0.139)
Log of people per square mile			−0.0584	−0.128**	−0.139**
			(0.0585)	(0.0581)	(0.0587)
Percentage < 18 years				0.0154	0.0168
				(0.0212)	(0.0214)
Percentage > 65 years				−0.0236	−0.0191
				(0.0152)	(0.0161)
Social isolation: carers 18 + 2018/19					−0.00755
					(0.00572)
Social isolation: care users 18 + 2018/19					−0.00844
					(0.00987)
Constant	14.84**	25.89**	16.04**	17.64**	17.27**
	(1.244)	(3.579)	(3.905)	(4.138)	(4.232)
R-square	0.345	0.541	0.623	0.634	0.642

Standard errors in parentheses, P-Values: *p < 0.1, **p < 0.05.

variables. Although there are some differences between the results from OLS and the survival models, the trends are similar; and they are more similar to the Weibull model (Annex III) than to log-log distribution model (Table 2). We mostly draw attention to the signs and significance of the coefficients in the OLS model. In the full OLS model a departure for the model corresponding to the one in Table 2 is that the public health expenditure contributes to lowering number of days to peak although is still insignificant. The level of overall local expenditure is significant at 0.05 level, consistent with Table 2. Higher population density lowers days to reach peak contrary to expectation. The indicators for ill health did not affect days to reach peak.[4] The results from Tables 1–3 are consistent.

The overall expenditure and the health expenditure variables are correlated at 0.698 level; and used separately (with all non-expenditure variables in place). The effect of the overall expenditure variable is stronger while both are significant (see Annex V). The impact of overall expenditure is twice as large and more strongly statistically significant. The interaction suggests the greater importance of non-health system expenditure while one would have suspected that health system factors would play a stronger role, and perhaps even the only role.

Tables 2 and 3 both report negative contribution to days to reach peak from density; less dense areas have longer peak time. This result can be questioned on epidemiological grounds because ordinarily population density increases human contact frequency and exacerbates the spread of infectious disease. We explored this as best as we can. Taking the linear model, we see that the coefficients for this variable move away from zero with additional variables contributing marginally toward the R-square value (Table 3 models 3–5). This is possible if the age variables (in the tail of the age distribution) and ill health variables in less dense areas contribute to increasing the days to reach peak. However, we

should not rule out omitted variable bias and that the density variable over-reports an impact due to its correlation with unobservable factors (Oster, 2019). The linear models helped us identify how much of the variation has been explained in this simple model; 62.3% of the variation has been explained by Model 3. Use of Shapley decomposition method for R-Square (Lipovetsky & Conklin, 2001) reveals marginal contribution of each of the clustered covariates to explaining the variations in days to reach the peak: Expenditure at 19.5%, SES factors at 25%, population density along with London factor at 38%, demographic factors at 13% and health factors at 4.5%. This is consistent with the survival model that density factor remains strongly significant when included in any specification.

The predicted value for days to reach peak COVID-19 incidence from the OLS logged dependent variable model yielded the baseline value at 21.45, nearly 2 days lower than the actual observed value (reported also in Table 1). This value differs from the actual values in Fig. 1b where the figures from all UTLA are used. This entails that there were many actual days to peak that were higher than predicted by the model, but not by a large amount. Confidence intervals overlap when comparing the basic prediction, the bar marked as baseline, with the actual average value of duration to peak. As the value predicted is not different, we show results from an exercise where we ask by how many days would time to peak be shortened if every UTLA had improved socio-economic and expenditure indicators by a single standard deviation? Fig. 4 shows the mean days to reach the peak and the confidence interval for improvements of a single covariate. Largest improvements come from rise in total local expenditure, yielding a reduction of nearly 4 days from baseline, and from increasing income, yielding a reduction of more than 3 days, at the UTLA level. Fig. 4 quantifies the contribution of socio-economic factors toward shortening the number of days to reach the COVID-19 peak infection level in the UTLAs of England.

Discussion

We note London is denser and richer. Much of Midlands and the northern parts of England are less dense and poorer on average (The

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[4] Other indicators of health status such as yearly averaged age-standardized cardiovascular death rates from 2015–17 or death rates from 2019 to 19 did not show significance in equation (5) of Table 3 either without the present health indicators or when added (see Annex V).
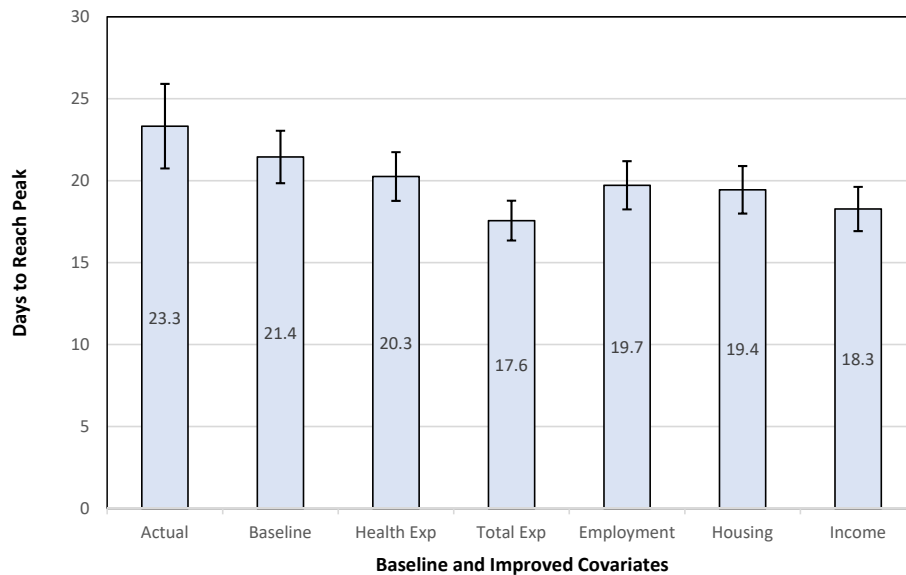
Fig. 4. Simulation, Covariates are improved by one standard deviation (N = 136), [a]Factors that can reduce the days to reach peak are improved by one standard deviation and are used in the OLS, Table 3 regression results to make predictions. Baseline bar is the prediction the regression makes with current data.

Office of National Statistics, 2020c). The London Dummy was a stable factor in all the models we estimated while population density was stable in many of the estimated models, but not in all specifications, and helped reduce days to peak. Regions with low income growth rate also have lower population density and lower housing price (House Pricing-Nat'l Statistics, 2020). The richer London areas managed a fast progression to bending the COVID-19 curve, while many of the regions in the north of England, poorer and less dense, experienced lengthier time to reach the peak. It is possible that public policy may have been more effective in denser areas or the population more effectively social distanced. Density may not always reflect the mass action (S x I) component in the SIR model, because viral exposure depends on behaviors that create proximity of less than 2 m of distance. The correlation between dense areas and income is positive. Congruent with Marmot's hypotheses regarding social determinants we note that the duration for a UTLA to achieve a bend in the infection level of COVID-19 is affected by the availability of non-health factors that enrich lives: public goods and amenities, and higher income.

Bending an outbreak curve to supress chains of infection during an infectious outbreak has been a fundamental role of public health departments. While one would expect a correlation between past investments in staff and capability from public health expenditure and quicker control of an outbreak we found that there is no statistically significant evidence that public health expenditure played a role when confounders are considered in our setting. Although public health expenditure is rather low at 63 GBP per 1000 people on average, with a farily high variance its inclusion is highly justified. The failure of local public health expenditure to have a detectable effect may have been due to insufficient power to detect what may have been a small effect. That still begs the question, why would local health department resources, devoted to protecting the population from disease have a small effect? Fig. 2 might offer insight, because it shows that local public health departments' budgetary allocations were not aligned *ex ante* with tasks related to rapid control of a contagious epidemic. It is common for staff in a public health department to become compartmentalized and super specialized in their various missions of children's health, substance misuse, and sexual health. Fig. 2 shows that only 1% of local public

health departments budgets were allocated to the cross-cutting area of health protection. This implies that many local health departments may have no full-time staff person assigned to cross-cutting health protection. Prior investments in community engagement and multi-sectoral coordination with schools, law-enforcement, transport, and commerce may have only occurred in the context of a compartmentalized public health unit assigned to substance use, or children' health, etc. However, being properly prepared for emerging health threats would require local public health departments to have standing relationships that could be leveraged to address a new problem like COVID-19.

Public health experts in the UK are divided on assigning responsibility for pandemic preparedness (Iabuci, 2020). In August 2020, England's health secretary directed a change toward forming institutions whose only job is to "prepare for and respond to external threats like the pandemic." This would reshape PHE's successor, the National Institute for Health Protection (NIHP) to work locally and focus on infectious disease control capacity. This may swing the pendulum away from compartmentalized programs to address non-communicable disease to compartmentalized programs to address communicable disease and biosecurity. A focus on building the capability to execute the essential elements of a public health system would avoid the dysfunctional fragmentation from compartmentalized programs, but it is too soon to know how the new NIHP will evolve.

There are limitations in this study. First, it may be possible to unpack local-level public expenditure to examine the type of expenditure that aided in achieving more rapid time to peak COVID-19 incidence. The hypothesis to examine first the impact of local-level public health expenditure along with over-all expenditure is a natural one. The low level of expenditure may have reduced the effect size making it too small to detect given the sample of 136 jurisdictions. Second, we may ask whether the multiple specifications of explanatory factors were correct although models had a reasonably high R-square. It is possible that a better variable for ill health prior to the epidemic would have improved the models; we did not find any useful one. Further, there may be omitted variables, such as crowded living quarters, although some of them could be reflected through variables that are already used. Third, our estimates provide evidence that regional socio-economic conditions

mattered in explaining the duration to peak along with local government expenditure on public goods. We have not provided causal mechanisms or pathways through which median income, housing or general local public expenditure affected days to reach the peak. Such pathways have been provided as supplemental explanations regarding persistent associations between gradients in health outcomes and those observed for socio-economic conditions (Braveman & Gottlieb, 2014). It is, of course, a topic for policy debates as to how social policies can effectively contribute to improving population health; in the literature the range of policy factors examined are wide, from ones that are obvious to ones that seem very indirect: improving the health system, environmental conditions, and growth rate of average income to ensuring political freedom (Varbanova & Beutels, 2020).

A modest interpretation of our findings would be that local expenditure can reduce the days to reach the peak incidence of a novel epidemic (Fig. 4). Perhaps factors associated with higher expenditure, such as being able to work from home, confounded this finding, even though we controlled for the median income of a UTLA. The contribution here should be seen as initial exploration into the association of regional socio-economic factors and the duration to achieving control of an epidemic of COVID-19.

Ethical statement

Only institutional data openly available from UK Government is used. No ethical concerns regarding any information.

Acknowledgments

ANNEX.

The Role of Public Health Expenditures in COVID-19 control: Evidence from Local Governments in England.

Annex I: Calculating Days to Peak
Annex II: Checking for Spatial Autocorrelation and Normality
Annex III: Selecting the specification for the Survival Model
Annex IV: Shapley Decomposition of R-Square
Annex V: Further Analyses, Confirming the Results

Annex I. Calculating Days to Peak

The first step in obtaining days to peak was to smooth out COVID-19 cases after 10 cases were observed. The method for smoothed path for COVID incidences was the following.

Smoothing the Curve

Let $C(d_j)$ be the incidence level for a UTLA for the observed for the jth day. As each UTLA is treated individually we have no subscript for UTLAs. Let $j = \{1,\ldots,\ldots,D\}$; then d_1 is 30 January 2020 $j = 1$, and d_D is 27 July 2020 A smoothed value $\widehat{C(d_j)}$ for the day d_j is created the following way: For the given specific day d_j, a weighted lowess smoothed value is generated using the incidence levels for all days of the period for every single UTLA with decreasing weights assigned to days further away from d_j. Thus, for a given d_j, the weight is inversely related to $|d_j - d_k|$ for all $k = \{1,\ldots,\ldots,D\}$ and $j \neq k$. The smoothing uses both past and lead values.

Calculating the days to reach peak

The smoothing result could be thought of as yielding a function $C(d, D_o)$ that maps calendar date d to COVID incidences with D_o denoting the date when cumulative number of infections reached 10. Define d^* - D_o, for some $d > D_o$ as the number days to reach the peak, where the global maximand d^* meets the requirements:

(1) $C(d^*, D_o) \geq C(d, D_o)$, for all $d > d^*$

and further following two conditions are met

(2a) $\exists\, d_1 > d^*$ such that $C(d_1, D_o) \leq \frac{1}{2} C(d^*, D_o)$

and

(2b) $\nexists\, d_2 > d_1$ such that $C(d_2, D_o) \geq \frac{3}{4} C(d^*, D_o)$

In all UTLAs except one the plateau fell sufficiently to meet 2 a-b in all UTLA within the period where we examine the data. Graphically we should observe figures similar to Figure Annex I, Fig. 1 for each UTLA. The figure is drawn for Herfordshire. Although the peak is reached in less than a month,

it does not come down slowly; reaching the ¾ of the peak rate takes longer than a month.

Herefordshire
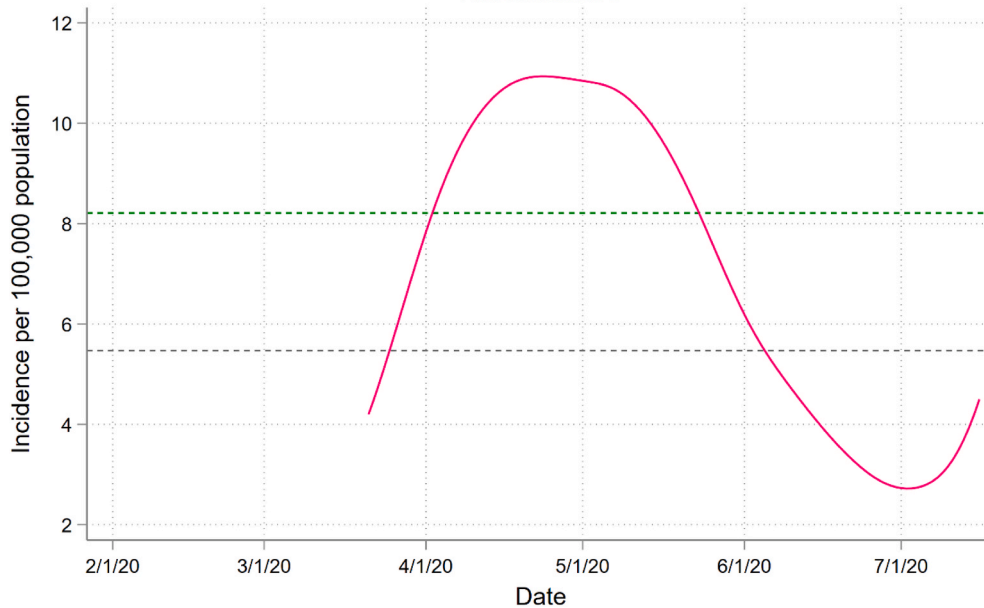
Annex I, Fig. 1. Example of a bending UTLA. The smoothed curve dips below ½ the peak level, below 6 per 100,000, and never reaches the ¾ of the peak level, incidence rate of 8

Days to Reach Peak by UTLA.

Below we present the days to reach the peak by UTLA used in this analysis. The period covered is from January to July. The table is sorted by UTLA code.

Annex I Table 1
Number of days to reach apex since the epidemic started by UTLA

UTLA	UTLA code	Total Cases	Date when epidemic started	Date when apex was reached	Days between apex and epidemic
Hartlepool	6000001	594	3/28/2020	4/17/2020	20
Middlesbrough	6000002	958	3/25/2020	3/31/2020	6
Redcar and Cleveland	6000003	702	3/24/2020	4/14/2020	21
Stockton-on-Tees	6000004	969	3/20/2020	4/17/2020	28
Darlington	6000005	605	3/26/2020	November 4, 2020	16
Halton	6000006	692	3/24/2020	3/27/2020	3
Warrington	6000007	1327	3/23/2020	April 4, 2020	12
Blackburn with Darwen	6000008	1137	3/24/2020	4/25/2020	32
Blackpool	6000009	1031	3/25/2020	November 4, 2020	17
Kingston upon Hull, City of	6000010	1547	3/26/2020	4/25/2020	30
East Riding of Yorkshire	6000011	1645	3/16/2020	February 5, 2020	47
North East Lincolnshire	6000012	208	3/25/2020	3/28/2020	3
North Lincolnshire	6000013	724	3/26/2020	4/15/2020	20
York	6000014	912	3/19/2020	4/20/2020	32
Derby	6000015	1302	3/15/2020	3/16/2020	1
Leicester	6000016	4488	3/18/2020	August 7, 2020	112
Rutland	6000017	93	October 4, 2020	March 5, 2020	23
Nottingham	6000018	1187	3/13/2020	June 4, 2020	24
Herefordshire, County of	6000019	862	3/20/2020	4/23/2020	34
Telford and Wrekin	6000020	612	3/23/2020	4/22/2020	30
Stoke-on-Trent	6000021	1472	3/22/2020	4/28/2020	37
Bath and North East Somerset	6000022	338	3/19/2020	February 4, 2020	14
Bristol, City of	6000023	1297	3/15/2020	October 4, 2020	26
North Somerset	6000024	912	December 3, 2020	June 5, 2020	55
South Gloucestershire	6000025	746	3/13/2020	December 4, 2020	30
Plymouth	6000026	663	3/19/2020	December 4, 2020	24
Torbay	6000027	276	3/20/2020	April 4, 2020	15
Swindon	6000030	758	3/22/2020	September 4, 2020	18
Peterborough	6000031	1361	3/21/2020	October 5, 2020	50
Luton	6000032	1465	3/18/2020	3/27/2020	9
Southend-on-Sea	6000033	680	3/22/2020	3/23/2020	1
Thurrock	6000034	556	3/18/2020	3/19/2020	1
Medway	6000035	1065	3/15/2020	3/28/2020	13
Bracknell Forest	6000036	382	3/21/2020	3/30/2020	9
West Berkshire	6000037	478	3/19/2020	January 4, 2020	13
Reading	6000038	778	3/17/2020	April 4, 2020	18
Slough	6000039	652	November 3, 2020	February 4, 2020	22
Windsor and Maidenhead	6000040	410	December 3, 2020	3/29/2020	17

(continued on next page)

Annex I Table 1 (*continued*)

UTLA	UTLA code	Total Cases	Date when epidemic started	Date when apex was reached	Days between apex and epidemic
Wokingham	6000041	599	3/15/2020	April 4, 2020	20
Milton Keynes	6000042	862	3/18/2020	May 4, 2020	18
Brighton and Hove	6000043	784	3/13/2020	February 4, 2020	20
Portsmouth	6000044	503	3/16/2020	June 4, 2020	21
Southampton	6000045	937	3/18/2020	September 4, 2020	22
Isle of Wight	6000046	422	3/25/2020	4/23/2020	29
County Durham	6000047	3330	3/20/2020	4/16/2020	27
Cheshire East	6000049	2213	3/15/2020	4/19/2020	35
Cheshire West and Chester	6000050	1996	3/17/2020	4/20/2020	34
Shropshire	6000051	1409	3/18/2020	June 5, 2020	49
Cornwall and Isles of Scilly	6000052	899	3/15/2020	May 4, 2020	21
Wiltshire	6000054	1258	3/13/2020	4/23/2020	41
Bedford	6000055	1284	3/22/2020	4/18/2020	27
Central Bedfordshire	6000056	1244	3/15/2020	November 4, 2020	27
Northumberland	6000057	1578	3/22/2020	May 4, 2020	14
Bournemouth, Christchurch and Poole	6000058	819	3/18/2020	September 4, 2020	22
Dorset	6000059	605	3/18/2020	September 4, 2020	22
Bolton	8000001	1885	3/16/2020	August 4, 2020	23
Bury	8000002	1294	3/18/2020	March 4, 2020	16
Manchester	8000003	3004	3/13/2020	4/13/2020	31
Oldham	8000004	1897	3/16/2020	May 4, 2020	20
Rochdale	8000005	1692	3/17/2020	March 4, 2020	17
Salford	8000006	1355	3/17/2020	February 4, 2020	16
Stockport	8000007	1646	3/14/2020	July 4, 2020	24
Tameside	8000008	1540	3/14/2020	April 5, 2020	51
Trafford	8000009	1273	3/13/2020	April 4, 2020	22
Wigan	8000010	2143	3/21/2020	4/14/2020	24
Knowsley	8000011	997	3/22/2020	March 4, 2020	12
Liverpool	8000012	2478	3/13/2020	3/30/2020	17
St. Helens	8000013	1198	3/21/2020	March 4, 2020	13
Sefton	8000014	1534	3/19/2020	3/30/2020	11
Wirral	8000015	2039	3/19/2020	3/30/2020	11
Barnsley	8000016	1927	3/18/2020	4/17/2020	30
Doncaster	8000017	2012	3/19/2020	September 5, 2020	51
Rotherham	8000018	1952	3/19/2020	4/13/2020	25
Sheffield	8000019	4076	August 3, 2020	January 4, 2020	24
Newcastle upon Tyne	8000021	1532	3/15/2020	3/30/2020	15
North Tyneside	8000022	920	3/18/2020	3/30/2020	12
South Tyneside	8000023	948	3/24/2020	August 4, 2020	15
Sunderland	8000024	1772	3/20/2020	3/30/2020	10
Birmingham	8000025	4946	November 3, 2020	3/27/2020	16
Coventry	8000026	1345	3/16/2020	October 4, 2020	25
Dudley	8000027	1310	3/14/2020	April 4, 2020	21
Sandwell	8000028	1682	3/14/2020	3/31/2020	17
Solihull	8000029	901	3/20/2020	3/23/2020	3
Walsall	8000030	1498	December 3, 2020	February 4, 2020	21
Wolverhampton	8000031	1391	November 3, 2020	June 4, 2020	26
Bradford	8000032	4520	3/17/2020	5/22/2020	66
Calderdale	8000033	733	3/25/2020	December 4, 2020	18
Kirklees	8000034	2222	3/18/2020	4/22/2020	35
Leeds	8000035	3704	November 3, 2020	4/17/2020	37
Wakefield	8000036	1753	3/20/2020	4/19/2020	30
Gateshead	8000037	1282	3/24/2020	January 4, 2020	8
Barking and Dagenham	9000002	718	3/14/2020	3/21/2020	7
Barnet	9000003	1621	September 3, 2020	3/16/2020	7
Bexley	9000004	1068	December 3, 2020	3/25/2020	13
Brent	9000005	1749	November 3, 2020	3/16/2020	5
Bromley	9000006	1525	December 3, 2020	3/19/2020	7
Camden	9000007	708	November 3, 2020	3/17/2020	6
Croydon	9000008	1861	December 3, 2020	3/20/2020	8
Ealing	9000009	1571	October 3, 2020	3/22/2020	12
Enfield	9000010	1194	December 3, 2020	3/26/2020	14
Greenwich	9000011	961	December 3, 2020	3/20/2020	8
Hackney	9000012	853	November 3, 2020	3/16/2020	5
Hammersmith and Fulham	9000013	760	November 3, 2020	3/24/2020	13
Haringey	9000014	764	November 3, 2020	3/17/2020	6
Harrow	9000015	1296	November 3, 2020	3/20/2020	9
Havering	9000016	953	3/15/2020	3/22/2020	7
Hillingdon	9000017	1117	December 3, 2020	3/24/2020	12
Hounslow	9000018	1077	November 3, 2020	3/24/2020	13
Islington	9000019	556	December 3, 2020	3/13/2020	1
Kensington and Chelsea	9000020	560	May 3, 2020	3/16/2020	11
Kingston upon Thames	9000021	744	3/16/2020	3/28/2020	12
Lambeth	9000022	1370	October 3, 2020	3/14/2020	4
Lewisham	9000023	1205	December 3, 2020	3/18/2020	6
Merton	9000024	943	November 3, 2020	3/19/2020	8

Annex I Table 1 (*continued*)

UTLA	UTLA code	Total Cases	Date when epidemic started	Date when apex was reached	Days between apex and epidemic
Newham	9000025	1290	3/14/2020	3/17/2020	3
Redbridge	9000026	1129	3/15/2020	3/20/2020	5
Richmond upon Thames	9000027	536	3/16/2020	3/17/2020	1
Southwark	9000028	1451	August 3, 2020	3/16/2020	8
Sutton	9000029	1011	3/13/2020	3/25/2020	12
Tower Hamlets	9000030	821	November 3, 2020	3/17/2020	6
Waltham Forest	9000031	1030	3/14/2020	3/18/2020	4
Wandsworth	9000032	1170	October 3, 2020	3/14/2020	4
Westminster	9000033	785	July 3, 2020	December 3, 2020	5
Buckinghamshire	10000002	1704	October 3, 2020	November 4, 2020	32
Cambridgeshire	10000003	2235	3/13/2020	4/25/2020	43
Cumbria	10000006	2726	November 3, 2020	3/26/2020	15
Derbyshire	10000007	3359	September 3, 2020	4/28/2020	50
Devon	10000008	1213	March 3, 2020	September 4, 2020	37
East Sussex	10000011	1552	3/17/2020	4/14/2020	28
Essex	10000012	5483	November 3, 2020	October 4, 2020	30
Gloucestershire	10000013	1841	3/13/2020	March 4, 2020	21
Hampshire	10000014	5034	September 3, 2020	August 4, 2020	30
Hertfordshire	10000015	4177	April 3, 2020	May 4, 2020	32
Kent	10000016	7843	October 3, 2020	4/18/2020	39
Lancashire	10000017	6810	December 3, 2020	4/19/2020	38
Leicestershire	10000018	3127	December 3, 2020	May 5, 2020	54
Lincolnshire	10000019	2472	December 3, 2020	4/30/2020	49
Norfolk	10000020	2864	3/15/2020	4/13/2020	29
Northamptonshire	10000021	3329	November 3, 2020	February 5, 2020	52
North Yorkshire	10000023	2542	3/14/2020	4/19/2020	36
Nottinghamshire	10000024	2997	November 3, 2020	4/17/2020	37
Oxfordshire	10000025	3138	September 3, 2020	a	
Somerset	10000027	1288	3/13/2020	March 5, 2020	51
Staffordshire	10000028	3752	3/13/2020	November 4, 2020	29
Suffolk	10000029	2634	3/15/2020	4/16/2020	32
Surrey	10000030	4626	September 3, 2020	March 4, 2020	25
Warwickshire	10000031	2514	November 3, 2020	November 4, 2020	31
West Sussex	10000032	2729	3/13/2020	4/13/2020	31
Worcestershire	10000034	2374	December 3, 2020	May 4, 2020	24

Note: (a) Apex was not reached.

Annex II. Checking for Spatial Autocorrelation and Normality

As we examine in this paper local level infectious disease patterns we should suspect spatial autocorrelation. Spatial autocorrelation makes estimation of non-linear relations such as survival model difficult. For policy analysis, we further examined ordinary least square results. OLS requires normality of the error terms. In this Annex we show that we can ignore spatial auto-correlation and are assured that OLS result with results with logged-transformed dependent variables are valid.

Spatial Correlation

Consider the basic model with day to reach peak within each UTLAs in England being related to socio-demographic factors.

Day to Reach Peak $= \alpha + \beta_1 * (Public\ Expenditure) + \beta_2 * (SES\ Factors) +$

$\beta_3 * (Population\ Density) + \beta_4 * (Age\ Demography) + \beta_5 * (Base\ Health) + Error$

Associated spatial correlation tests are reported as Moran statistics for the basic model above that is run without any adjustments (See Annex II, Table 1). Model 1 offers the results of the basic relation with 145 UTLAs. When a simple continuous relation is tested there is considerable spatial autocorrelation when measured by distance of 1/6th size of England, which is around 115 km (See Moran Test for Model 1, Distance p-value = 0.029). When the model is tested for contiguous spatial autocorrelation a test indicates some spatial auto-correlation (See Moran test for Model 1, Contiguous p-value = 0.080).

Model 2 shows the results of adjusted distanced correction; Model 3 shows the results for corrections for spatial correction due to correlation through contiguous relations. Correcting for spatial correlation does not show uniform trends; the method used for detecting contiguous correlation uses the command spmatrix for the weights in STATA and for correlation related to distance the available estimation method from spatwmat in STATA is used.

Although coefficient values differ across the three models; the models do not differ much across as to what factors play a role in shaping the day to peak Covid value. The adjustments do not show any directions as to whether the coefficients are larger or smaller regarding any singular factors across the two correction. We then test for spatial correlation using a logged transformation for the dependent variable. As spatial correlation of either type is not significant in the logged model, we can ignore spatial correlation to estimate non-linear models such as survival analysis to reaching the peak. Model 4 shows a basic log model using continuous explanatory variables. When some of the variables are made into categorical variables the spatial correlation tests do not show different results. The Moran tests for confirming non-correlation shows a p-values of 0.61 contiguous correlation and 0.287 for distance correlation. Ruling out spatial correlation allows us to use the survival model without adjustments.

Annex II, Table 1

Spatial Model, Dependent Variable: Number of days to reach the peak Covid −19 infections (n = 145)

COVARIATES	Model 1 Unadjusted Full Model	Model 2 Adjust Spatial Distance	Model 3 Adjust Spatial Contiguity	Model 4 Unadjusted Log Model
Local health expenditure per capita	−121.8	−106.0	−132.5	−0.650+
Log for Model 4	(96.75)	(87.37)	(90.91)	(0.340)
Net Current Expenditure per cap	−11.33*	−7.507+	−8.863*	−0.416
Log for Model 4	(4.617)	(4.276)	(4.493)	(0.387)
Median Income	−0.0791*	−0.0617*	−0.0642*	−2.157*
Log for Model 4	(0.0230)	(0.0212)	(0.0220)	(0.740)
	0.789	0.950*	0.791	0.0451+
	(0.511)	(0.463)	(0.514)	(0.0254)
Unemployment	0.825	0.357	0.948	0.0962
	(1.404)	(1.272)	(1.346)	(0.0756)
Fuel poverty 2017	−0.627	−0.497	−0.188	0.00775
	(0.736)	(0.665)	(0.710)	(0.0403)
London Dummy	−10.83*	−7.575	−11.94*	−0.698*
	(5.421)	(4.959)	(5.469)	(0.269)
People per sq kilometers	0.0003	0.000035	0.00032	−0.226*
Log for Model 4	(0.000933)	(0.000845)	(0.000907)	(0.0987)
% under 18 years	−25.79	−7.490	−20.16	−3.262
	(71.46)	(64.63)	(67.81)	(3.372)
% 65 years +	−39.88	−39.85	−27.55	−4.494+
	(52.94)	(47.76)	(49.05)	(2.672)
Social isolation: carers 18 + 2018/19	−0.232	−0.208	−0.251	−0.00677
	(0.168)	(0.152)	(0.157)	(0.00887)
Social isolation: care users 18 + 2018/19	0.0734	0.115	0.104	−0.00354
	(0.302)	(0.272)	(0.285)	(0.0159)
Constant	106.5*	72.31*	84.27*	17.47*
	(32.02)	(30.15)	(30.75)	(5.047)
Adj R-Square	0.3196			0.4137
rho_cons		0.471***		
		(0.119)		
sigma constant		11.72***		
		(0.691)		
W e.dayevent			0.466*	
			(0.203)	

Standard errors in parentheses, Level of significance + p < 0.1 * p < 0.05.
Moran Test, Model 1: Contiguity p-value 0. 0795, Distance p-value 0.029.
Moran Test, Model 4: Contiguity p-value 0.61 Distance p-value 0.287.

Normality

Estimating the factors influencing day to peak Covid 19 infection level can be modeled through Ordinary Least Square if the estimations produce error terms that are normal. There are a few UTLAs that have zero and or near zero Covid infections; some local governance units reached peak within 4 days. There are also some UTLA that reached peak at a late date. Logged value regressions lowers the impact of outliers. Non-logged value produced error terms that consistently failed normality tests. Further, logged-value model failed normality tests when UTLAs with lower values of day to peak were retained. Fig. 1 shows the distribution of error terms for the logged value regressed on factors slightly different from those reported in Model 4, Table 1 using OLS methods with robust error terms. The error terms come from a model where health expenditure and median income variable are divided into quartile levels and from the full model similar to Model 4 in Annex II, Table 1. The error terms are almost normal as shown in Fig. 1; the skewedness test shows the hypothesis of normality cannot be rejected at 0.05 p-value. Lower levels outliers (days to peak < 4) were eliminated which yielded a sample size of 136. Showing normality allows us to use the OLS model; thus Table 3 in the main text is justified.

Annex III. Selecting the specification for the Survival Model

Accelerated failure time (AFT) is an approach to survival analysis that models time as the outcome. Covariates act multiplicatively on the outcome of survival time. In this study, such an approach allows for the quantification of whether differences at the UTLA level are associated with increased or decreased time to reach peak incidence. AFT is a parametric model that requires specification of a distribution for the baseline hazard function. The baseline related hazard function was selected to be log-log distribution after finding the smallest Akaike information criterion (inverse of information matrix associated with the model) when judged against other specifications (exponential, Weibull, log-normal, and generalized gamma). Goodness of fit was confirmed using Cox-Snell residual plots.

With time invariant covariates accelerated failure time model with the assumption of Weibull distribution produces the same results as the proportional hazard model. Thus, the results are less dependent on the underlying assumptions. For these reasons we present the Weibull model. The coefficients are time ratios. Thus, for example, London dummy reduces the time to reach peak by 60% according Model 5. Some of the coefficients are similar to those in Table 2 of the text. A notable difference is the resilience of the income categories. They consistently reduce the time to reach peak as income rises, nearly the same impact as London dummy in Model 5 for the 4th Quartile.

Annex III Table 1

Survival Model, Weibull Distribution, Dependent Variable: Log Time to Reach Peak, (n = 136)

COVARIATES	Model 1	Model 2	Model 3	Model 4	Model 5
Local health expenditure per capita					
Quartile 2	1.13	0.921	1.093	1.12	1.105
	(0.18)	(0.13)	(0.15)	(0.15)	(0.14)
Quartile 3	1.586***	0.947	1.105	1.152	1.112
	(0.28)	(0.18)	(0.20)	(0.21)	(0.21)
Quartile 4	1.980***	1.131	1.139	1.26	1.224
	(0.40)	(0.29)	(0.27)	(0.30)	(0.29)
Log net current expenditure per capita, local level public spending	0.155***	0.348***	0.518**	0.449***	0.462***
	(0.05)	(0.10)	(0.15)	(0.12)	(0.13)
Median Income					
Quartile 2		0.507***	0.524***	0.626***	0.619***
		(0.07)	(0.07)	(0.09)	(0.09)
Quartile 3		0.511***	0.583***	0.589***	0.599***
		(0.09)	(0.10)	(0.10)	(0.10)
Quartile 4		0.345***	0.514***	0.464***	0.485***
		(0.07)	(0.11)	(0.10)	(0.11)
Housing price to income ratio		0.978*	1.014	1.032**	1.027
		(0.012)	(0.02)	(0.02)	(0.02)
Unemployment		0.92	1.016	0.978	0.984
		(0.05)	(0.06)	(0.05)	(0.06)
Fuel poverty		0.993	1.028	1.006	1.01
		(0.03)	(0.03)	(0.03)	(0.03)
London dummy			0.461***	0.442***	0.423***
			(0.09)	(0.08)	(0.08)
Log of population density			0.867**	0.784***	0.782***
			(0.06)	(0.06)	(0.06)
Percentage < 18 years				1.056*	1.054*
				(0.03)	(0.03)
Percentage > 65 years				0.959**	0.961*
				(0.02)	(0.02)
Social isolation: carers 18+					1.002
					(0.01)
Social isolation: care users 18+					0.989
					(0.01)
/ln_p	0.45***	0.68***	0.77***	0.81***	0.81***
Constant	1.908e+07***	217,491***	9343***	42,966***	53,657***
Observations	3371	3349	3349	3349	3349
AIC	299.8	259.1	239.3	231.3	234.4

***p < 0.01, **p < 0.05, *p < 0.1, Expenditure variable is measured as per capita. Standard errors in parenthesis.

Annex IV. Shapley Decomposition of R-Square

Shapley decomposition of R-Square examines the marginal contribution of each covariate (or a cluster of covariates) makes to the R-Square of the regression involving all covariates. It extracts the marginal contribution of a particular covariate from the R-Squares of all possible combinations of regression estimation in which a covariate can be involved, from having a univariate regression to those involving all covariates $k = \{1, ..., K\}$, K the number of total covariates. The marginal contributions are then averaged by weights for each marginal contribution. The weights are determined by inverse of number marginal values obtained through the k covariates used. For example, when 2 of 3 variables are used with $K = 3$, 6 marginal values are obtained. The marginal contributions add up to the total R-Square. We illustrate with three covariates used in the text: log of per-capita health expenditure (SPENDING), log median income (INCOME) and population density per square mile (DENSITY) which will be used to explain days to reach peak in the local area. There are seven regressions, from which we obtain 7 R-Squares. There is likely to be some multicollinearity, the approach shows a clearer contribution to the explained variations of these two variables.

Regression, Independent Variable: Days to Reach Peak.

Covariates	R-Square	From the R-Square column the specified value is subtracted to obtain the marginal value			Weights/Totals
		SPENDING Marginal Value	INCOME Marginal Value	DENSITY Marginal Value	
1. SPENDING, INCOME and DENSITY	0.496	R-Square (4) 0.014	R-Square (3) 0.099	R-Square (2) 0.07	1/3
2. SPENDING, INCOME	0.426	R-Square (6) 0.229	R-Square (5) 0.299		1/6
3. SPENDING, DENSITY	0.397	R-Square (7) 0.0041		R-Square (5) 0.27	1/6
4. INCOME, DENSITY	0.482		R-Square (7) 0.0891	R-Square (6) 0.285	1/6
5. SPENDING	0.127	0.127, none			1/3
6. INCOME	0.197		0.197, none		1/3
7. DENSITIY	0.392			0.392, none	1/3

(*continued*)

Covariates	R-Square	From the R-Square column the specified value is subtracted to obtain the marginal value			Weights/Totals
		SPENDING Marginal Value	INCOME Marginal Value	DENSITY Marginal Value	
Summed Weighted Value		0.0858	0.1633	0.2468	Total 0.496
Explained Variation by a Covariate. %		17	33	50	100

Annex V. Further Analyses, Confirming the Results

In this section we examine how well the main results stand up to changing the model specifications slightly. First, a set of different independent variables is used to test the robustness of the results; then an alternate dependent variable is used. We use the OLS model which is easier to understand.

Impact of public health expenditure as the sole public action: Our results are based on the hypothesis that public health expenditure is vital to controlling the outbreak along with other public expenditures. However, given that the health expenditure is correlated with overall expenditure, it is worth comparing multivariate models with models of the isolated effect of public health expenditure as the only included policy factor. Model 2 in Annex 5, Table 1 shows that public health expenditure by itself reduces days to reach peak; however, Model 3 shows that local overall expenditure has a larger impact. Model 3 has an R-Square equaling the Model 1 results below. Comparison of results across Models 1 to 3 shows that public health expenditure contributes little to reduce the days to peak is supported.

Using different variables for health conditions: Comorbidities can affect infectivity. Past measures of health conditions across UTLAs could be highly correlated with current comorbidities at the local level for which we had no exogenous data. As noted in the paper self-reported health condition surveys from England showed little variation across UTLAs. We used past age-standardized death rates from all causes and, separately, cardio-vascular diseases. Models 4–6 show that these variables were not significant. Comorbidity measures did not play a role in determining the time to reach the peak level of infections in the local areas.

Dependent variable duration: Our central question in this paper is what factors affected the first wave, specifically, what governance factors affected time to reach peak in the first wave. How prepared was England at the local level to bring down the infection rates? The first wave was clearly defined as the pandemic receded for a time being and remained flat. By July as there was a period where incidence rates were low, one could ask how the public sector shaped to reduce the infection rate. As noted in the paper there were changes made to Public Health Expenditure during the first wave. Thus, our main independent variable of interest, local public health expenditure, should not be a factor in determining the local outbreak trajectories after the first wave. Nonetheless, we test to see how the trajectory of the pandemic might have been affected by the factors we had chosen in explaining the days to reach peak during the first wave.

After July, a second wave was not easy to define technically. In none of the UTLAs do we find smoothed incidence to be lower than 10. Thus, the starting point from which we could measure days to reach peak was no different from the starting point of the first wave. When incidence for start of the outbreak from 10 cases is considered the average number of days to reach peak for the UTLAs is 322 with coefficient of variation to be a low of 7.8%. Annex V, Table 2 presents the results. The dependent variable is log of days to reach peak from 30 January to March of 2021. We find that local health expenditure does impact days to reach peak at a p-value < 0.10 level. However, as we noted, it is doubtful that the public expenditure variables, measured in 2019, remain relevant past summer of 2020 because supplemental fundings were made.

Annex-V, Table 1

Alternate Specifications Independent Variables to the Main Analyses, Dependent Variable: Log of Days to Reach Peak, 30 January to July 31, 2020 (n = 136)

COVARIATES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of Local Health Expenditure per capita	−0.159	−0.420*		−0.142	−0.160	−0.317
	(0.204)	(0.180)		(0.224)	(0.222)	(0.222)
Log of Net Current Expenditure per capita	−0.780**		−0.849**	−0.779**	−0.800**	−0.758**
	(0.266)		(0.228)	(0.267)	(0.268)	(0.265)
Log Median Income	−1.049+	−0.987	−1.020+	−1.087	−1.197+	−0.968
	(0.623)	(0.656)	(0.613)	(0.681)	(0.659)	(0.671)
Ratio of house price to earning	0.0239	0.0208	0.0234	0.0222	0.0298+	0.0530*
	(0.0173)	(0.0177)	(0.0167)	(0.0171)	(0.0157)	(0.0213)
Unemployment	0.0678	0.0812+	0.0530	0.0674	0.0543	0.0507
	(0.0429)	(0.0465)	(0.0446)	(0.0433)	(0.0430)	(0.0415)
Fuel poverty 2017	−0.00500	−0.0170	−0.00956	−0.00395	−0.00285	−0.00222
	(0.0271)	(0.0295)	(0.0277)	(0.0273)	(0.0280)	(0.0273)
London Dummy	−0.828**	−0.922**	−0.801**	−0.825**	−0.819**	−0.801**
	(0.139)	(0.144)	(0.138)	(0.137)	(0.131)	(0.135)
Log of people per square mile	−0.139*	−0.157*	−0.153**	−0.140*	−0.129*	−0.133*
	(0.0587)	(0.0682)	(0.0550)	(0.0588)	(0.0583)	(0.0591)
Percentage < 18 years	0.0168	0.00667	0.0235	0.0173	0.0157	0.0140
	(0.0214)	(0.0211)	(0.0197)	(0.0222)	(0.0220)	(0.0217)
Percentage > 65 years	−0.0191	−0.0124	−0.0183	−0.0209	−0.0248	−0.0186
	(0.0161)	(0.0171)	(0.0159)	(0.0197)	(0.0192)	(0.0165)
Social isolation: carers 18 + 2018/19	−0.00755	−0.00822	−0.00750	−0.00754		
	(0.00572)	(0.00559)	(0.00573)	(0.00573)		
Social isolation: care users 18 + 2018/19	−0.00844	−0.00937	−0.00898	−0.00855		
	(0.00987)	(0.0102)	(0.00975)	(0.00982)		
Log of age adj CVD death rate, avg 15-17				−0.0753	−0.0511	
				(0.384)	(0.398)	
Log of age adj death rate, avg 17-19						0.973

(continued on next page)

Annex-V, Table 1 (*continued*)

COVARIATES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
						(0.836)
Constant	17.27**	12.59**	17.03**	17.79**	17.99**	9.741
	(4.232)	(4.383)	(4.194)	(5.327)	(5.379)	(8.926)
R-square	0.642	0.613	0.641	0.642	0.634	0.638

Standard errors in Parentheses, P-Values: $+ \, p < 0.1$, $*p < 0.05$, $**p < 0.01$.

Annex V, Table 2
Dependent Variable, Log of Days to Reach Peak, From 30 January to March 2021 (n = 127)

COVARIATES	Model 1
Log of Local Health Expenditure per capita	−0.0688+
	(0.0377)
Log of Net Current Expenditure per capita	−0.0221
	(0.0340)
Log Median Income	0.0813
	(0.0698)
Ratio of house price to earning	0.00881**
	(0.00277)
Unemployment	−0.0102
	(0.00870)
Fuel poverty 2017	0.00895+
	(0.00492)
London Dummy	0.00453
	(0.0233)
Log of people per square mile	0.00364
	(0.0108)
Percentage < 18 years	0.000283
	(0.00399)
Percentage > 65 years	−0.00003
	(0.00339)
Social isolation: carers 18 + 2018/19	−0.00166*
	(0.00081)
Social isolation: care users 18 + 2018/19	0.00208
	(0.00180)
Constant	5.497**
	(0.545)
R-square	0.416

Standard errors in Parentheses.
P-Values: $+ \, p < 0.1$, $*p < 0.05$, $**p < 0.01$.

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