The Cost of Lies

Assessing the human and financial impact of COVID-19 related online misinformation on the UK

LE London Economics

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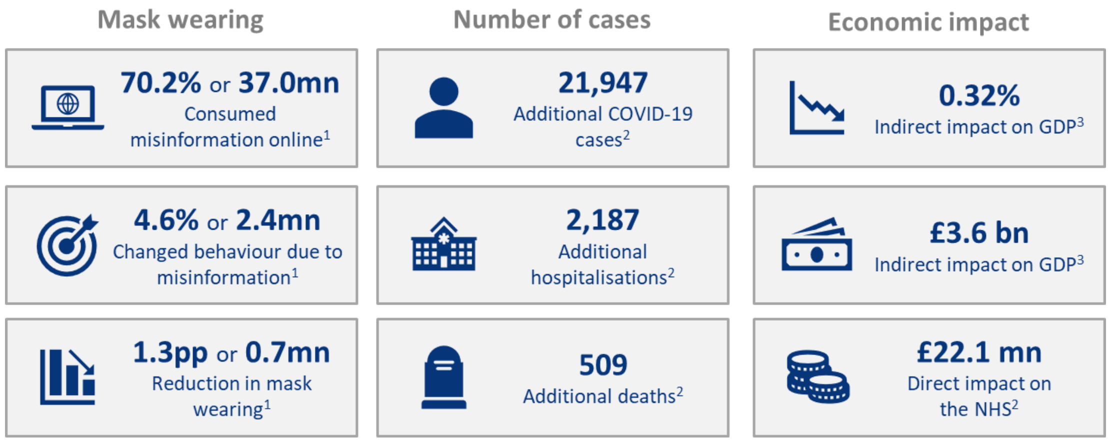
Executive Summary

Online misinformation relating to face masks and the coronavirus is **widespread in the UK** and has a **significant impact on individuals' health, the NHS and the economy** by affecting people's mask wearing behaviour.

21,947 COVID-19 cases, 2,187 hospitalisations and 509 deaths are attributable to misinformation online from 01 April to 10 November. As a result, the NHS is facing **additional health costs of £22.1 million**. The **indirect impact** of misinformation on the UK economy **totals £3.6 billion** in quarter 2 and quarter 3 of 2020. Figure 1 summarises the findings of the study. These results highlight that misinformation can have a **significant effect on people's health, which results in additional financial stress on the NHS, and on the overall economy**. This study focusses on the misinformation relating to coronavirus and face masks. But, misinformation in relation to other related topics, such as vaccination, is likely to have a similar if not larger effect.

Figure 1 The impact of misinformation on mask wearing and the UK economy



Note: 1 - The figure is based on results of a YouGov survey, commissioned by London Economics for the purpose of this study for the UK. The study ran between the 12-13 November 2020. 2 - The figure refers to 01 April to 10 November 2020. 3 - The figure refers to quarter 2 and quarter 3 2020.

Source: London Economics' analysis

A representative survey of UK adults carried out on 12-13 November 2020 found that **70.2% of the population (37.0 million people) have read misinformation on social media** or other online sources (other than traditional news websites). This includes false statements, such as 'Face masks can be harmful to wearers, even healthy adults' and 'COVID-19 is no more dangerous than the flu'. By analysing self-reported mask wearing behaviour and reasons given for not wearing a face mask in certain situations, the survey found that **4.6% of the population (2.4 million people) are impacted by misinformation** and **change their mask wearing behaviour** as a result of it. These figures imply that the **share of people wearing face masks** in public would be **1.3 percentage points higher in the absence of online misinformation**. **This is equivalent to an additional 0.7 million people wearing face masks.**

When people do not wear masks, this results in a higher level of infection. Over the period from 01 April until 10 November 2020, **21,947 of confirmed COVID-19 cases, 2,187 of hospitalisations and 509 fatalities** in the UK can be **attributed to online misinformation** relating to face masks. These figures have been estimated by modelling the share of the total number of confirmed COVID-19 cases that originate from a) situations, in which face masks should be worn; b) people not wearing face masks in these situations; and c) the share of these people who do not wear face masks because of misinformation.

These additional cases create direct costs for the healthcare services, as more people require medical treatment, such as hospitalisations. Drawing on official government figures, the academic literature and survey results, it has been estimated that the incremental costs to the NHS were **£9.6 million in quarter 2, £2.6 million in quarter 3 and £9.9 million in quarter 4** (until 10 November 2020). The additional health costs due to mask-related misinformation equals **£22.1 million** over the entire period of observation.

In addition to the financial stress on the NHS, misinformation can also cause **indirect costs to the economy** due to a higher transmission of the virus. Both, face masks and government restrictions are aimed at reducing the spread of COVID-19. The negative effect of a lower share of mask wearers due to misinformation can, therefore, be offset by additional government restrictions. However, **government restrictions have a negative impact on the economy**. The economic impact of the government restrictions that would be required to offset the impact of misinformation online amounts to **£2.379 billion in the second quarter of 2020 (0.426% of GDP)** and to **£1.185 billion in the third quarter of 2020** (**0.212% of GDP).** In total, the indirect costs were **£3,564 million or 0.319% over the half-year period**.

1 Introduction

The spread of false information, also commonly known as misinformation, on social media platforms **has become a widespread issue.** This has **harmful effects** that go beyond simply what individuals perceive to be true or false. It may also impact their actions and behaviours.

This study aims to bring a new perspective to the debate around online harms in the UK. This is done by identifying how widespread online misinformation in relation to face masks and the coronavirus is in the UK and identifying the economic impact that misinformation may have on the NHS and the economy. The analysis presented in this report is structured in three parts:

- Chapter 2: Survey analysis on the spread of misinformation in the UK
- Chapter 3: Estimating the direct impact of misinformation on health costs
- Chapter 4: Estimating the indirect economic costs of misinformation in terms of GDP

A **survey** has been conducted to gain information on misinformation in the UK. This survey sheds light on the **contact that people have with misinformation** online, their **mask wearing behaviour** and **reasons for not always wearing a face mask** in certain situations. This information is used to calculate the impact of misinformation on mask wearing behaviour in the UK.

In a second step, the direct impact of misinformation is estimated. While the direct economic costs can occur in different forms and may affect various stakeholders, this study focusses on the **direct effect on health costs**. In order to do so, the **additional number of people affected by COVID-19** due to misinformation have been estimated. Subsequently, the health **costs for each COVID-19 patient** have been calculated.

In addition, the **indirect economic costs** of misinformation are analysed. This impact is called 'indirect' because it refers to the economic costs of **government restrictions that would offset the negative impact of misinformation**. This approach is based on a study published by Goldman Sachs (2020), which looks at the impact of mask wearing on GDP in the USA.

2 Survey results

In order to evaluate the impact of misinformation in the UK, a survey has been conducted to evaluate the spread of misinformation in relation to face masks and to identify its impact on people's mask wearing behaviour. A representative sample of 2,120 adults was surveyed in the UK on 12-13 November 2020. As the sample is representative of the UK adult population it is possible to draw conclusions for the entire population.

In the survey, individuals were asked whether they had seen any of the below statements on social media or on other online sources (other than traditional news websites):

- Face masks do not help reduce the transmission of COVID-19;
- Face masks can be harmful to wearers, even healthy adults; or
- COVID-19 is no more dangerous than the flu.

These statements are common cases of misinformation in relation to face masks and coronavirus[1]. Just over **70% of survey respondents** reported to **have seen at least one of these stories online**.

This result is similar to the result of a Eurobarometer survey from 2018[2], which asks respondents how often they come across news or information which they believe misrepresents reality or is even false. The results from the Eurobarometer showed that **84% of adults in the UK report seeing some form of misinformation** at least once a month. This Eurobarometer figure is slightly higher, as it covers a more diverse type of misinformation than mask wearing, but the similarity of the results supports the reliability of the survey.

The survey conducted for this study also asked about respondents' mask wearing behaviour in different situations, such as in shops, public transport or moving around inside pubs and restaurants, over the last four months. Respondents were asked to select the degree to which they wear face masks in each of these situations[3]. If somebody did not answer 'always', they were asked about the reason for not always wearing a face mask in any of the situations. The reasons provided included the statements mentioned above, in addition to a number of other reasons that are not considered to be misinformation. Of all respondents, 6.0% said that one or more of the false statements were a reason for not wearing a face mask. The statement most frequently reported as being seen online is that COVID-19 is no more dangerous than the flu[4].

Figure 2 shows that the intersection of the people who have consumed misinformation online and the people who report that **misinformation had an impact on their mask wearing behaviour is 4.6% of the population.** This proportion translates to **2.4 million UK adults** who changed their mask wearing behaviour in response to online misinformation about mask wearing.

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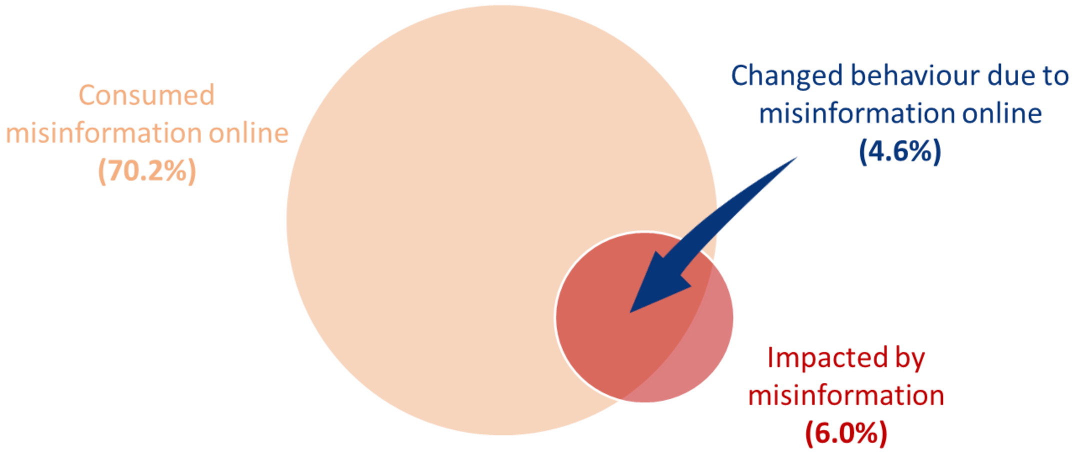
[1] The statements were not identified as misinformation in the questions. However, respondents were informed at the end of the survey that these statements are not true.

[2] European Commission, Brussels (2018): Flash Eurobarometer 464 (Fake News and Disinformation Online). TNS opinion, Brussels [producer]. GESIS Data Archive, Cologne. ZA6934 Data file Version 1.0.0, https://doi.org/10.4232/1.13019

[3] The answer options included Always, Most of the time, Sometimes, Rarely, Never, Not applicable, Prefer not to say.

[4] While this misinformation may affect mask wearing behaviour, it is also likely to have an impact on any other COVID-19 related behaviour, such as vaccinations.

Figure 2 Impact of online misinformation on face mask wearing



Source: London Economics' analysis

While 4.6% of individuals are affected by misinformation[5], it is reasonable to assume that they do not all stop wearing masks altogether, but they might wear them less often. In order to account for the change in behaviour Table 1 reports the difference in the proportion of individuals who 'always' wear face masks between the total sample and those who are influenced by misinformation. On average, there is a **decrease of 27.7 percentage points**[6] in the proportion of individuals **who 'always' wear a face mask** in public indoor spaces.

Table 1 Reduction in the proportion of the UK population that 'always' wear face masks[7]

	Shops	Public transport	Inside pubs and restaurants	Average
Total sample[8]	87.4%	88.2%	61.7%	79.1%
People impacted by misinformation online	55.4%	59.6%	39.2%	51.4%
Difference	32.0%	28.6%	22.5%	27.7%

Source: London Economics analysis

This means that the sub-sample of people who are impacted by misinformation online (4.6% of the population) reduce their face mask wearing by 27.7 percentage points. The total impact of

[5] Throughout this report, an individual is defined as being 'affected' (or 'impacted') by misinformation if they have seen any one of the three false statements covered in the survey, and they report that particular piece of misinformation as a reason for not wearing a face covering. This applies to all mentions of people impacted or affected by misinformation in the remainder of the report.

[6] Percentage points refers to the absolute difference between one percentage figure and another. For example, the difference between 79.1% and 51.4% (79.1-51.4) is 27.7 percentage points. This is equivalent to saying that the share in the total sample decreases by 35% (27.7/79.1).

[7] This sample does not include respondents who are exempt from wearing face masks, who prefer not to say or report that the question is not applicable to them.

[8] The 'total sample' in the first row also excludes respondents who report wearing face masks 'always' in every situation. This makes the sample more comparable to the sub-sample of people who are impacted by misinformation. Namely, if people report always wearing a face mask in every situation then it is reasonable to assume that they are not impacted by misinformation online regarding face coverings.

misinformation on mask wearing in the UK is, therefore, the product of these two figures. Thus, the share of the **population wearing masks would be 1.3 percentage points higher** in the absence of misinformation from online sources.[9]

In addition to the mask wearing behaviour, the survey also asked about the respondents' likelihood to self-isolate in different situations. **13% of all respondents reported that they would not self-isolate if they tested positive for COVID-19**. The share rises to **30% for the people who are impacted by misinformation**. A more detailed analysis of the survey results can be found in Annex 1.

[9] This step ensures that the variable used to measure the impact of misinformation on the share of face masks is aligned with the variable used in a study by Goldman Sachs (2020), which feeds into the indirect model in Chapter 4.

3 Estimating the direct economic costs of misinformation

3.1 Background

The survey analysis has shown that **misinformation has an impact on mask wearing in the UK**. In addition, the wider medical literature agrees that face masks reduce the transmission of the coronavirus, which helps to decrease the number of infected people (Mills et al., 2020[10]; Chu et al., 2020[11]; Wang et al.; 2020[12]; Wu et al., 2004[13]; Lau et al., 2004 [14]). Consequently, **misinformation results in more COVID-19 cases** by decreasing the number of people wearing face masks.

These additional COVID-19 cases create economic costs, as **every case has a direct impact on the economy**. This impact can take different forms and may affect various stakeholders. Some of the direct economic impacts include:

- COVID-19 patients create **health costs** for the NHS, as they might require testing and medical treatment.
- Infected people might get too ill to work, which has an impact on their **workplace** by reducing the economic output.
- Infected people are likely to reduce their consumption affecting the revenue of **businesses** because they must isolate and cannot take part in normal life. This includes expenditures, such as costs for entertainment, commuting, eating out or other recreational activities, etc.
- Fatalities due to COVID-19 will decrease the economic **output of the UK economy** as a whole if the affected people have been part of the workforce.

The direct modelling in this study focusses on the **incremental health costs** due to the additional COVID-19 cases caused by misinformation. Incremental cost refers to the additional costs that are directly related to the additional COVID-19 cases. The analysis does not include costs related to the wider response to the pandemic, such as structural changes in the NHS or a reduction in mental health due to lockdowns and working from home. As a result, the analysis does not reflect the total economic impact of COVID-19 on the NHS. Instead the analysis provides an estimate for the additional financial burden on the NHS due to the additional COVID-19 cases arising from misinformation.

[10] Mills, M., C. Rahal, and E. Akimova (2020). *Face masks and coverings for the general public: behavioural knowledge, effectiveness of cloth coverings and public messaging*. The Royal Society & The British Academy. Available at: https://royalsociety.org/-/media/policy/projects/set-c/set-c-facemasks.pdf?la=en-GB&hash=A22A87CB28F7D6AD9BD93BBCBFC2BB24

[11] Chu D, Duda S, Solo, K, Yaacoub S, and Schunemann H, (2020), 'Physical Distancing, Face Masks and Eye Protection to Prevent Person-to-Person Transmission of SAS-COV-2 and COVID-19', Journal of Vascular Surgery, 72(4), 1500. Available: https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(20)31142-9/fulltext

[12] Wang, Y., Tian, H., Zhang, L., Zhang, M., Guo, D., Wu, W., Zhang, X., Kan, G. L., Jia, L., Huo, D., Liu, B., Wang, X., Sun, Y., Wang, Q., Yang, P., & MacIntyre, C. R. (2020). Reduction of secondary transmission of SARS-CoV-2 in households by face mask use, disinfection and social distancing: a cohort study in Beijing, China. BMJ global health, 5(5), e002794. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7264640/pdf/bmjgh-2020-002794.pdf

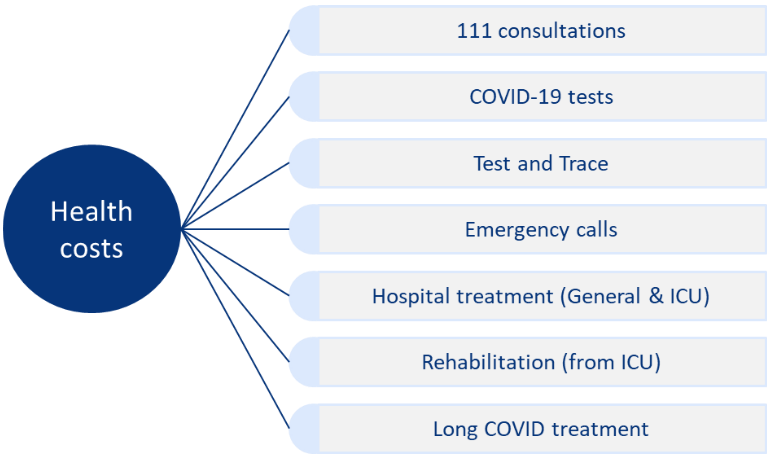
[13] Wu, J., Xu, F., Zhou, W., Feikin, D. R., Lin, C. Y., He, X., Zhu, Z., Liang, W., Chin, D. P., & Schuchat, A. (2004). Risk factors for SARS among persons without known contact with SARS patients, Beijing, China. Emerging infectious diseases, 10(2), 210–216. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3322931/pdf/03-0730.pdf

[14] Lau JT, Lau M, Kim JH, Tsui HY, Tsang T, Wong TW. Probable secondary infections in households of SARS patients in Hong Kong. Emerg Infect Dis. 2004;10(2), 235-243. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3322902/

3.2 Methodology

Figure 3 shows the health cost elements considered in this model. These categories are generally in line with the ones that Bartsch et al. (2020)[15] used to estimate the costs per COVID-19 case in the USA. Their study, however, does not include Test and Trace and the treatment of long COVID.

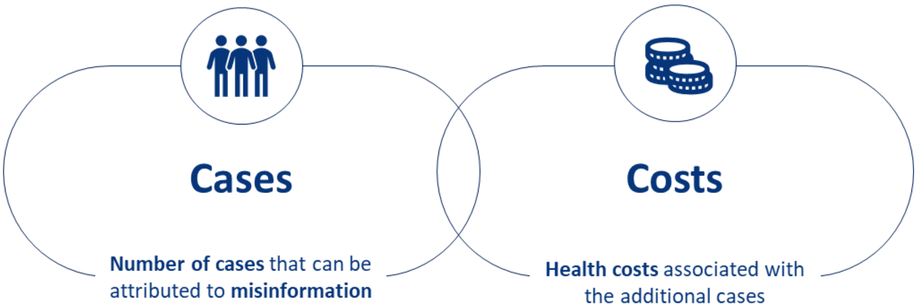
Figure 3 Health cost elements included in the direct economic costs



Source: London Economics

The modelling of the direct health costs involves two components (see Figure 4). First, the number of COVID-19 cases that are attributable to misinformation has to be estimated. Second, the health costs associated with each case are calculated.

Figure 4 Components in estimating the direct health costs



Source: London Economics

The number of COVID-19 **cases attributable to misinformation** is based on official health data and on a number of assumptions based on insights from government sources and survey data. The official health data provides information on the number of COVID-19 related infections, 111 calls, contacts reached by Test and Trace, 999 calls, hospital admissions, days spent in hospital and ICU,

[15] Bartsch, S. M., Ferguson, M. C., McKinnell, J. A., O'Shea, K. J., Wedlock, P. T., Siegmund, S. S., & Lee, B. Y. (2020). The Potential Health Care Costs And Resource Use Associated With COVID-19 In The United States: A simulation estimate of the direct medical costs and health care resource use associated with COVID-19 infections in the United States. Health Affairs, 10-1377. Available at: https://www.healthaffairs.org/doi/full/10.1377/hlthaff.2020.00426

etc. The full list of data and sources that feed into this estimation are presented in Annex 2. However, only a subset of these figures can be attributed to misinformation. In order to identify the share of COVID-19 cases that arise from misinformation, a number of parameters have to be applied. These parameters make it possible to estimate:

- the number of cases that originated from situations, in which people should have worn a face mask ('**face mask situations'**);
- the number of cases related to people who **did not wear a face mask**;
- the number of cases that **could have been avoided** by wearing a face mask; and
- the number of cases that can be **attributed to misinformation online**.

The parameters used for these estimations include the share of face mask wearers; the relative likelihood of contracting the virus with and without a face mask; the share of situations, in which face masks are generally worn ('face mask situations'); the R number and the impact of misinformation. Applying these parameters yields the share of cases attributable to misinformation. Annex 2 provides a detailed description of the steps involved.

The estimated number of attributable cases is then used to calculate the **number of COVID-19 related treatments and services**. For example, the number of COVID-19 tests is estimated by assuming that each person who has been confirmed positive for COVID-19 has done one coronavirus test, whereas COVID-19 patients who have been admitted to hospital have undergone two tests (Public Health England, 2020[16]). This yields the number of COVID-19 tests that can be attributed to misinformation.

The **direct health costs** are subsequently calculated by multiplying the number of COVID-19 treatments and services by the cost per treatment or service. The services and treatments are those presented in Figure 3 above. The unit costs that feed into these calculations are generally based on official NHS figures or estimates from the academic literature. Annex 3 provides a list of sources used for the different costs per treatment/service.[17]

Most of the underlying health data is available on a daily basis so that the attribution of cases has also been estimated for each day. This level of granularity provides more accurate estimates, as it reflects changes in some of the underlying modelling parameters over time. For example, the share of face mask wearers and the share of hospitalisations vary significantly over time.

Modelling the direct costs on daily figures also enables flexibility in terms of the modelling period. The results presented in this chapter refer to the **period from 01 April to 10 November 2020** as a whole and are also presented on a quarterly basis. The first quarter of 2020 has not been included in the model because some of the data sources are only available from mid-March onwards and because there was more uncertainty about the benefits of face masks in society at the beginning of

[16] Public Health England, (2020), 'Guidance for stepdown of infection control precautions and discharging COVID-19 patients', GOV.UK. Available: https://www.gov.uk/government/publications/covid-19-guidance-for-stepdown-of-infection-control-precautions-within-hospitals-and-discharging-covid-19-patients-from-hospital-to-home-settings/guidance-for-stepdown-of-infection-control-precautions-and-discharging-covid-19-patients#:~:text=People%20who%20are%20discharged%20from,adult%20social%20care%20plan.

[17] For a few elements, including Test and Trace, there was no published figures on the unit costs. London Economics has applied conservative estimates in these situations.

the pandemic. In the UK, face masks have been recommended by the government from the 09 June 2020 onwards and have been mandatory in certain public indoor spaces since 27 July 2020.[18]

3.3 Results

Table 2 shows the number of COVID-19 cases, hospital admissions and deaths attributable to misinformation. In all of these three categories, which are estimated to account for between **1.1-1.7% of all cases in the UK** over the period of investigation occurred **because of the effect that misinformation had on mask wearing**.

The number of **attributable COVID-19 cases are by far the largest in quarter 4 at 15,766**, even though data has not been available for the whole quarter. In quarter 2, the number of attributable hospital admissions and deaths (906 and 258 respectively) are relatively high compared to the number of reported cases. Part of this difference can be explained by less testing at the beginning of the pandemic resulting in fewer cases being identified; and, because the medical community has gained valuable insights after the first wave of the pandemic in the second quarter leading to improved management and recovery.

Table 2 Number of COVID-19 cases attributable to misinformation

Variables	Misinformation cases	Share of total		Q2	Q3	Q4[19]
Start date	01/04/2020	01/04/2020		01/04/2020	01/07/2020	01/10/2020
End date	10/11/2020	10/11/2020		30/06/2020	30/09/2020	10/11/2020
COVID-19 cases	21,947	1.73%		2,510	3,672	15,766
Hospital admissions	2,187	1.31%		906	276	1,005
Deaths	509	1.09%		258	40	210

Source: London Economics' analysis

Table 3 presents the results for the health costs associated with each cost element considered in the model (as shown Figure 3). In total, the additional COVID-19 cases due to misinformation result in an **incremental cost of just under £22.1 million for the NHS**.

The breakdown of the costs shows that **hospital treatments make up most of** the health costs (£18.01 million), while COVID-19 tests are the second most expensive category with £2.41 million. The remaining categories make up under a million pounds each.

The analysis of the cases attributable to misinformation has shown that the number of hospital admissions was lowest in the third quarter. Given that the hospital costs are driving the overall results, the total costs are relatively low in quarter 3. The number of hospital admissions were significantly higher in quarter 2 and quarter 4, which led to a total incremental cost of £9.58 million and £9.90 million respectively.

[18] European Centre for Disease Prevention and Control (2020). 'Data on country response measures to COVID-19' Available: https://www.ecdc.europa.eu/en/publications-data/download-data-response-measures-covid-19

[19] The figures only include a third of quarter 4, as the analysis has been conducted before the end of the quarter.

Table 3 Additional health costs attributable to misinformation (in £)

Cost element	Q2	Q3	Q4	Total
111 consultations	173,485	142,045	109,779	425,309
COVID-19 tests	341,550	394,759	1,677,098	2,413,408
Test and Trace	16,853	57,059	147,810	221,722
Emergency calls	79,614	34,251	24,672	138,537
Hospital treatment	8,574,228	1,863,078	7,576,969	18,014,276
Rehabilitation	368,532	62,800	232,618	663,950
Long COVID treatment	21,339	31,216	134,042	186,596
Total health costs	9,575,602	2,585,208	9,902,988	**22,063,798**

Source: London Economics' analysis

3.4 Sensitivity analysis

This section conducts a sensitivity analysis of the results. A sensitivity analysis is conducted due to the **large number of parameters and assumptions** feeding into the model. In these cases it is best practice to undertake sensitivity analyses to determine how the modelling estimates may change if key parameters change.

Dividing the total health costs of £22.1 million by the number of additional COVID-19 cases due to misinformation (21,947, Table 2) suggests that one case creates an average cost of £1,005.3 over the entire modelling period. The total health costs per COVID-19 case were highest in the second quarter (£3,815.2) compared to the third quarter (£704.1) and fourth quarter (£628.1). These figures compare to a health cost estimate of £2,280 ($3,045) for every COVID-19 case in the USA (Bartsch et al., 2020). It should be also noted that Bartsch et al. (2020) do not include any elements related to testing, Test and Trace or long COVID in their analysis.

The fact that the model **estimates are very comparable** to the ones published for the USA strengthens the results. Given that the UK estimates are lower than the ones for the US, it also highlights that the **results and model inputs are of a conservative nature**. One possibility for the difference in the results is that the share of COVID-19 patients that required hospital treatments, which make up most of the health costs, might be different across the two countries and that medical treatments are more expensive in the USA. Moreover, Bartsch et al. (2020) published their estimates in April, which means that their assumptions are likely to be influenced by the costs and case numbers from the first and second quarter, which were higher compared to the third and fourth quarter included in the study's model.

As the model requires the use of many parameters whose values are uncertain, **Monte Carlo simulations** have also been used to **determine the likely range of the cost estimates**.

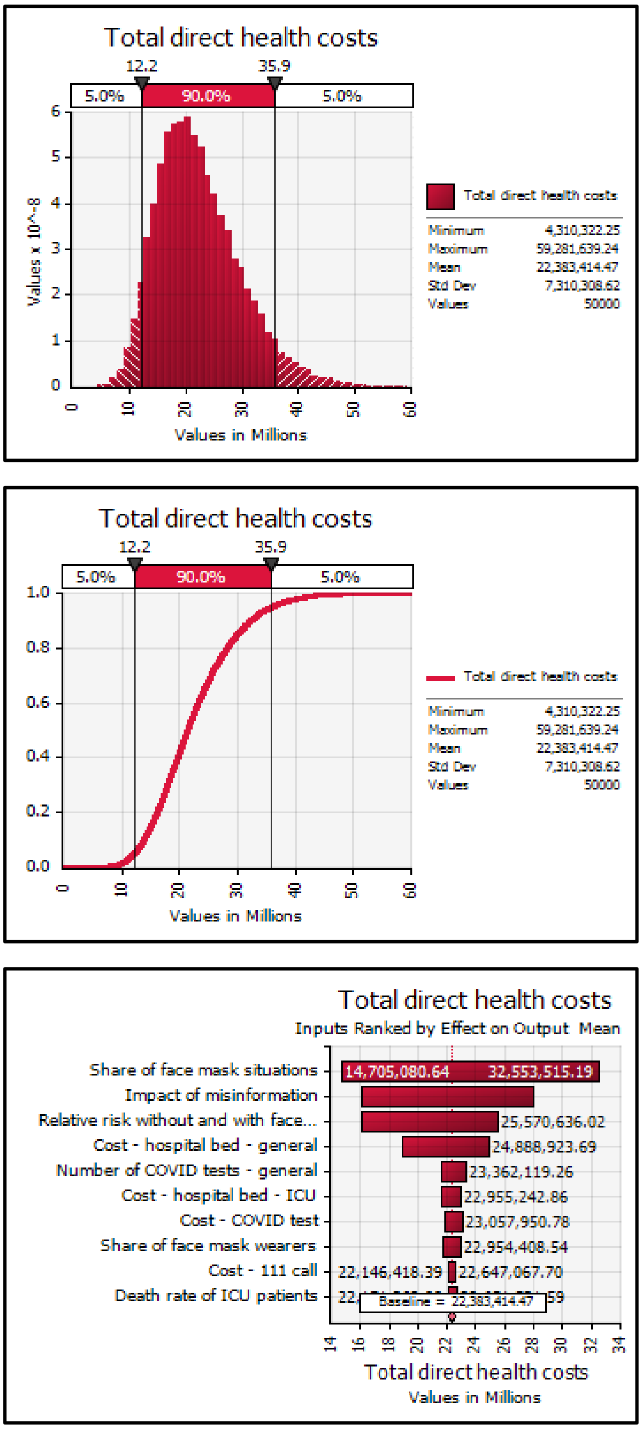
A Monte Carlo simulation produces results for a high number of iterations, during which different input values are used for each variable in the model. These input values are picked randomly from a defined range of values for each model run. The random draws of the input values are generated based on an underlying probability distribution. The assumed distribution of the input values takes the form of a triangle, which is often used when the true distribution of the values is unknown. The horizontal line of the triangle represents the range of the input value and the height of the triangle at each point of the horizontal line defines the likelihood assigned to a particular value. Values that lie towards the sides of the triangle are, thus, less likely to occur and will therefore be picked in fewer simulations to account for their 'outlier-status'. The value used in the main model constitutes the baseline case and has the highest probability assigned to it (the tip of the triangle). The simulation yields a distribution of the outcome variable, as every iteration provides an outcome estimate. This distribution can be used to gain an understanding of the likely range and an expected value of the model's estimates as different parameters change.

Figure 5 presents the results of the Monte Carlo simulation, which is based on 50,000 simulations. The ranges for the input values are based on the same sources used to estimate the costs for the COVID-19 treatment and services as presented in Figure 3. The published sources these costs are based on are presented in Annex 3.

The graph at the top left corner of the figure shows the distribution of the estimated total direct health costs of each simulation. 90% of the simulated results lie within a **range from £12.2 million to £35.9 million**. This provides a likely range for the direct health costs of misinformation. The graph also shows that the distribution is skewed to the right (i.e. the tails of the curve are skewed to the right). This means that in some cases, the simulation estimates very high values that exceed the 90% range by a large amount. However, these outcome scenarios are very unlikely. Nonetheless, it shows that there is the **possibility of outlier scenarios, which involve a significantly higher direct health cost**.

Figure 5 also provides information on the model inputs that have the highest impact on the results. This is shown in the lower left-hand panel of the figure. The variable that causes the **largest change in the estimated total health cost** is the **share of 'face mask situations'**. The second most influential variable is the impact of misinformation, which is based on the survey results. Both of these variables feed into the estimation of the number of cases that are attributable to misinformation related to face masks and COVID-19.

Figure 5 Monte Carlo simulation of the additional health costs



Simulation Summary Information	
Number of Simulations	1
Number of Iterations	50000
Number of Inputs	27
Number of Outputs	1
Sampling Type	Latin Hypercube
Random # Generator	Mersenne Twister
Random Seed	2054604563

Summary Statistics for Total direct health costs			
Statistics		**Percentile**	
Minimum	4,310,322	5%	12,206,031
Maximum	59,281,639	10%	13,852,906
Mean	22,383,414	15%	15,096,016
Std Dev	7,310,309	20%	16,132,828
Variance	5.34406E+13	25%	17,044,767
Skewness	0.724873914	30%	17,930,703
Kurtosis	3.580663996	35%	18,794,767
Median	21,372,850	40%	19,665,594
Mode	20,085,158	45%	20,493,076
Left X	12,206,031	50%	21,372,850
Left P	5%	55%	22,290,188
Right X	35,852,278	60%	23,235,523
Right P	95%	65%	24,311,049
Diff X	23,646,247	70%	25,453,388
Diff P	90%	75%	26,747,947
#Errors	0	80%	28,205,294
Filter Min	Off	85%	30,036,634
Filter Max	Off	90%	32,310,515
#Filtered	0	95%	35,852,278

Change in Output Statistic for Total direct health c			
Rank	**Name**	**Lower**	**Upper**
1	Share of face mask	14,705,081	32,553,515
2	Impact of misinform	16,127,454	27,995,618
3	Relative risk withou	16,081,024	25,570,636
4	Cost - hospital bed	18,947,119	24,888,924
5	Number of COVID t	21,627,430	23,362,119
6	Cost - hospital bed	21,594,772	22,955,243
7	Cost - COVID test	21,855,557	23,057,951
8	Share of face mask	21,785,482	22,954,409
9	Cost - 111 call	22,146,418	22,647,068
10	Death rate of ICU p	22,151,262	22,651,532

Source: London Economics' analysis

3.5 Caveats

It is important to consider that the modelling approach is subject to a couple of caveats and limitations.

This analysis is not an epidemiological study, which simulates the spread of the virus in different situations. Instead, it attempts to attribute COVID-19 cases to different situations and to people who did not wear a face mask because of misinformation. This attribution is very difficult because it is very hard to track the specific situation, from which a person has contracted the coronavirus. The modelling approach outlines a structure that provides estimates for these figures based on government data. For example, the government's publication on 'Events and activities reported by people testing positive, prior to symptom onset' and on 'Common locations reported by people testing positive' have been used to identify the situation, in which a person has contracted the virus. In addition to the high level of uncertainty surrounding the data, additional assessments had to be made in order to identify, which activity/location should be considered a 'face mask situation'. The **sensitivity analysis reflects the uncertainty of these parameters**.

The attribution of cases to misinformation also draws on the relative likelihood of contracting the coronavirus when wearing a face mask versus not wearing a face mask. This is based on the fact that face masks help to reduce the spread of a virus. While some isolated studies do not find a strong effect of face masks (Bundgaard et al., 2020[20]), the majority of the academic research points to a reduced risk of spreading a virus. For example, a review of the existing evidence in a July 2020 study from Oxford University[21] concluded that cloth face coverings are effective in protecting the wearer and those around them. The World Health Organization, UK government and US Centers for Disease Control and Prevention all recommend their use.

This study draws on a meta-analysis (Chu et al., 2020), which includes 10 adjusted and 29 unadjusted studies, for the coefficient of the relative risk. Chu et al. (2020) conclude that "the use of both N95 or similar respirators or face masks (e.g. disposable surgical masks or similar reusable 12–16-layer cotton masks) by those exposed to infected individuals was associated with a large reduction in risk of infection". However, the study attributes a low certainty to the point estimates and highlights that the effect of face masks is stronger for N95 or similar respirators and in health care settings. A range of the relative risk of face masks has been applied in the Monte Carlo analysis in order to reflect the uncertainty around the exact point estimate.

Due to the attribution approach of the study and to the coefficients used, the modelling only considers the protective effect of face masks for the wearer. Given that face masks are not only worn to protect the wearer but also the people around them, the cost estimates will be higher if the benefits to others beside the wearer were included in the modelling. However, as previously mentioned this would require a complex understanding of epidemiology which is beyond the scope of this study. In other words, the modelling estimates are expected to be towards the lower bound of impact.

[20] Bundgaard, H., et al. (2020). Effectiveness of adding a mask recommendation to other public health measures to prevent SARS-CoV-2 infection in Danish mask wearers: a randomized controlled trial. *Annals of Internal Medicine*. Available at: https://www.acpjournals.org/doi/10.7326/M20-6817

[21] Mills, M., C. Rahal, and E. Akimova (2020). *Face masks and coverings for the general public: behavioural knowledge, effectiveness of cloth coverings and public messaging*. The Royal Society & The British Academy. Available at: https://royalsociety.org/-/media/policy/projects/set-c/set-c-facemasks.pdf?la=en-GB&hash=A22A87CB28F7D6AD9BD93BBCBFC2BB24

Due to the limited amount of data over time, some of the parameters and assumptions had to be treated as constant over time. This includes the impact of misinformation, as the estimate is based on one representative survey that collected information on self-reported behaviour over the last four months. The survey analysis cannot infer causality in the identified relationships, as other variables, such as income or political affiliation, might be correlated with the consumption of misinformation and mask wearing. But, the findings are consistent across reported mask wearing and self-isolation behaviour, which strengthens the results. Furthermore, the identified impact of misinformation is expected to be larger because people are likely to underreport socially undesirable behaviour, such as not wearing face masks and not self-isolating.[22]

The lack of data and information also means that **not every economic cost element could be considered in the model**. For example, there is no reliable information on the costs associated with displacing routine treatments and long-term health impacts. These exclusions mean that the direct health costs should, in fact, be higher than reported. The lack of information but also the constantly changing knowledge of the coronavirus, medical treatment and government response means that some of the model estimates, for example for Test and Trace and long COVID treatment, have to rely on a number of assumptions with a high degree of uncertainty. In order to reflect this uncertainty, conservative cost estimates have been produced.

[22] The risk of underreporting behaviour was taken into account when designing the survey questions. See for example Tourangeau.R and Yan.T (2007) *Sensitive questions in Surveys.* Psychological Bulletin American Psychological Association. Available here: https://www.learnlab.org/research/wiki/images/a/a8/Tourangeau_SensitiveQuestions.pdf

4 Estimating the indirect economic costs of misinformation

4.1 Background

In addition to the direct costs of COVID-19 cases, the economic burden of misinformation can also be **expressed as an indirect cost**.

The UK government has taken many steps and introduced a number of restrictions to reduce the spread of the virus and to prevent the NHS from being overwhelmed. The government decides on these restrictions based on multiple criteria, including the number of cases, the rate of infections and the capacity of hospital beds. The previous analysis has shown that **misinformation** had a direct effect on the number of cases and hospitalisations, which means that they **contributed to the need for introducing government restrictions**.

Wearing face masks and government restrictions both aim to reduce the transmission of the virus so that they can be seen as alternative measures with the same objective. As a result, the costs of misinformation can also be expressed in indirect terms by looking at the **economic costs of the government restrictions** that had to be taken to offset the effect on the infection growth rate that is attributable to misinformation in the UK.

4.2 Methodology

Figure 6 illustrates the approach for estimating the indirect economic costs of misinformation. Each of the four steps yields a coefficient, which can be used to calculate the indirect impact on GDP.

The first step aims at identifying the **impact of misinformation** on the share of people wearing face masks. The second and third step look at the **impact of face masks and government restrictions** on the daily infection growth rate.

The ratio between the estimated effect of face masks and the estimated effect of government restrictions can be used as a multiplier to identify the amount of government restrictions needed to offset a particular change in the share of people wearing face masks. By combining the results from the first three steps, it is possible to estimate the incremental change in the government restrictions, which achieves the same impact on the infection rates as the change in face mask wearing due to misinformation online.

Step 4 draws on this result in order to estimate the impact **of these additional government restrictions on GDP**.

This approach is based on a study published by Goldman Sachs (2020)[23] that estimates the economic impact of face masks on GDP in the USA.

Government restrictions are measured using an index published by the University of Oxford[24]. The index is called the Stringency Index and "records the strictness of 'lockdown style' policies that primarily restrict people's behaviour" (Oxford, 2020). It draws on multiple indices, such as school

[23] Hatzius, J., Struyven, D., Rosenberg, I. (2020). *Face masks and GDP*. Goldman Sachs Research. Available at: https://www.goldmansachs.com/insights/pages/face-masks-and-gdp.html

[24] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

closing, cancellation of public events and stay at home requirements, and combines them into a number from 1 to 100.

Figure 6 Approach for estimating the indirect economic costs of misinformation

Source: London Economics

The data and parameters used in the model vary across the steps outlined above:

- The first step draws on the **survey results** presented in Chapter 1. The results are representative for the UK population and are expressed in a way that is **comparable with the variables used in the step 2**. The compatibility is described in more detail in Annex 1.
- The coefficients for step 2 and step 3 are taken from the **country panel analysis** in the Goldman Sachs (2020) study[25]. The country panel analysis provides regression estimates based on a broad international dataset.
- Step 4 involves an in-depth analysis of the relationship **between the government restriction index and the percentage change in GDP**. The analysis, which is presented in Annex 4, is based on monthly UK data from the Office of National Statistics (ONS)[26] and on quarterly international data from the OECD[27]. Similar to the face mask variable, the **government restriction variable is aligned** as much as possible with the one used by Goldman Sachs in step 3 (see Annex 4).

The model estimates the impact of GDP in the UK for quarter 2 and quarter 3. The first quarter is excluded from the analysis because there was no clear advice yet by the UK government on the use of face masks. This indicates that there was a genuine political debate about the use of face masks, which is not considered to be misinformation by this study[28]. Quarter 4 is not included, as there was no complete data available at the time of the analysis.

[25] The impact of a one percentage point difference in the share of people wearing face masks on the daily growth rate of confirmed cases is 0.08. The impact of a one-point difference in Goldman Sachs' Effective Lockdown Index (ELI) is 0.07.

[26] https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpmonthlyestimateuk/previousReleases

[27] https://data.oecd.org/gdp/quarterly-gdp.htm#indicator-chart

[28] It should be noted that the false statement, which has been seen most often by survey respondents, was that COVID-19 is no more dangerous than the flu. There has been no uncertainty around the falsehood of this statement in the political debate.

4.3 Results

The analysis of the survey results has shown that 1.3% of the UK population do not wear face masks due to misinformation.

In the **absence of misinformation**, the **share of people wearing face masks would be 1.3 percentage points higher**, which would reduce the infection growth rate by 0.102 percentage points. In order to achieve the same reduction in the infection growth rate, the UK government would have to introduce restrictions that raise the government stringency index by 1.456 points.

The analysis of the impact of government restrictions on GDP has shown that the relationship between the two variables varies across quarters. Restrictions had a stronger relative impact on GDP in the second quarter compared to the third quarter. Consequently, a change in the government stringency index of 1.456 points would have led to a **reduction in GDP of 0.426% in quarter 2** and of **0.212% in quarter 3**. This is equivalent to **£2,379 million in quarter 2 and £1,185 million in quarter 3**. In total the impact would have been **£3,564 million or 0.319% over the half-year period**.[29]

Table 4 presents the impact of misinformation for the different steps over the modelling period.

Table 4 Indirect economic costs arising from misinformation

	Variables	Q2	Q3	Total
Step 1	Total impact of misinformation on **face mask wearing**	1.3pp		
Step 2	Total impact of wearing face masks on the **infection rate**	0.102pp		
Step 3	Required change in **government restrictions**	1.456 points		
Step 4	Impact of government restrictions on **GDP**	£2,379 mn	£1,185 mn	**£3,564 mn**
		0.426%	0.212%	**0.319%**

Source: London Economics' analysis

The impact on GDP is evaluated relative to the UK GDP in Q4 of 2019[30], which was £558,417 million at November 2020 current prices[31]. Given that the expectation before the pandemic was for GDP to increase in 2020 compared to 2019, the estimated impact of misinformation would be larger if the potential output gap was used in the analysis.

[29] The parameters used from Goldman Sachs (2020) for their estimations refer to the daily infection growth rate. The study also presents regression coefficients for the daily growth rate of fatalities. When drawing on these coefficients, the estimated indirect impact for the UK is £2.339 billion.

[30] Q4 of 2019 has been used as a reference point because there have already been government restrictions in place in Q1 2020, which are likely to have impacted the GDP at the time.

[31] https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/realtimedatabaseforukgdpybha

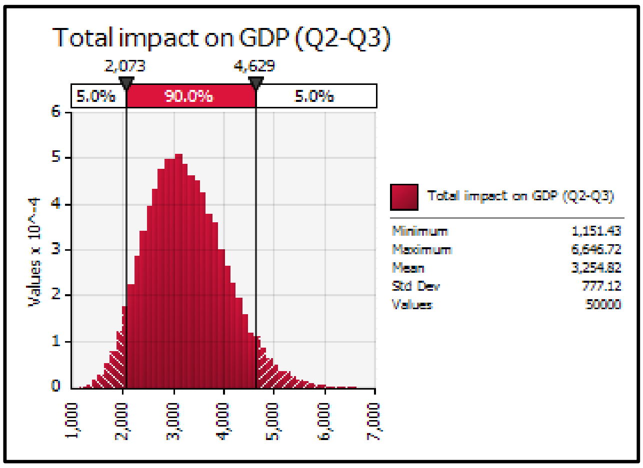
4.4 Sensitivity analysis

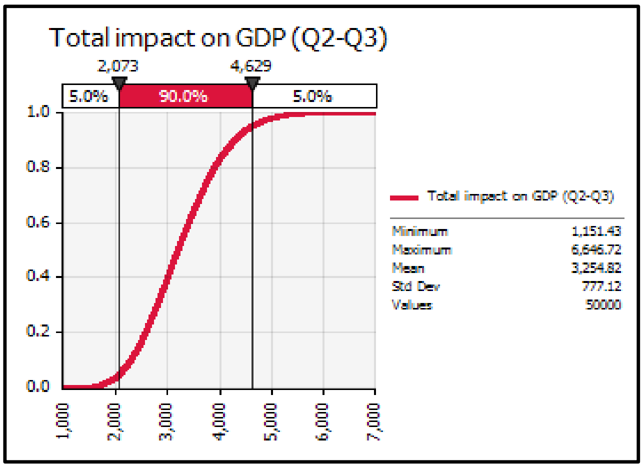
In order to reflect the uncertainty around the coefficients applied in the model, Monte Carlo simulations have also been used to identify a likely range for the indirect effect of misinformation.

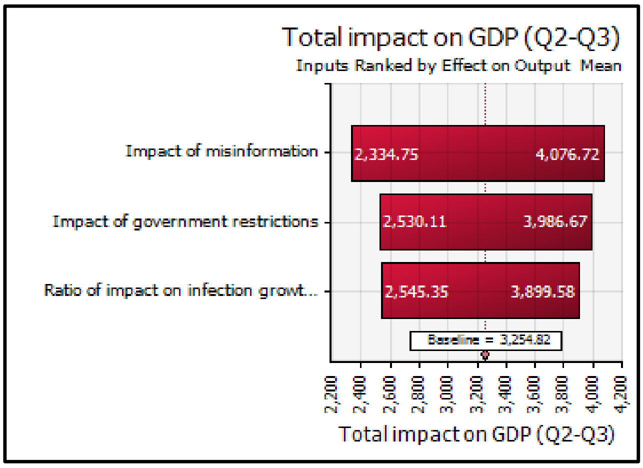
The ranges for the input values are based on the survey results, the different country panel regression estimates from the Goldman Sachs (2020) study and the analysis of the impact of government restrictions on GDP.

Figure 7 shows that the results of 90% of the simulations for the indirect impact in quarter 2 and quarter 3 lie within a **range from £2.073 billion to £4.629 billion**. The impact of the different input values on the simulated range is similar across all three variables.

Figure 7 Monte Carlo simulation of the indirect economic costs







Simulation Summary Information	
Number of Simulations	1
Number of Iterations	50000
Number of Inputs	3
Number of Outputs	1
Sampling Type	Latin Hypercube
Random # Generator	Mersenne Twister
Random Seed	1116568040

Summary Statistics for Total impact on GDP (Q2-Q3			
Statistics		**Percentile**	
Minimum	1,151	**5%**	2,073
Maximum	6,647	**10%**	2,290
Mean	3,255	**15%**	2,445
Std Dev	777	**20%**	2,573
Variance	603908.6156	**25%**	2,690
Skewness	0.379240756	**30%**	2,796
Kurtosis	2.942412865	**35%**	2,898
Median	3,197	**40%**	2,998
Mode	3,069	**45%**	3,099
Left X	2,073	**50%**	3,197
Left P	5%	**55%**	3,300
Right X	4,629	**60%**	3,409
Right P	95%	**65%**	3,520
Diff X	2,556	**70%**	3,635
Diff P	90%	**75%**	3,765
#Errors	0	**80%**	3,906
Filter Min	Off	**85%**	4,076
Filter Max	Off	**90%**	4,296
#Filtered	0	**95%**	4,629

Change in Output Statistic for Total impact on GDP			
Rank	**Name**	**Lower**	**Upper**
1	Impact of misinform	2,335	4,077
2	Impact of governme	2,530	3,987
3	Ratio of impact on i	2,545	3,900

Source: London Economics' analysis

4.5 Caveats

It is important to consider that the modelling approach is subject to a couple of caveats and limitations.

The **change in the government restrictions** that is required to offset the impact of misinformation is **relatively small** compared to the overall amount of restrictions imposed by the UK government. For this reason, it is difficult to say whether the change in face mask wearing due to misinformation by itself is big enough to initiate a noticeable change in the government restrictions. Similarly, the impact of a **small change in the government restrictions** might have a different effect on GDP compared to the one that can be measured in the data. The study provides an attribution analysis, which means that the estimated effect represents a proportional change in the variables. The attribution analysis assumes a linear relationship between the variables. This, for example, means that a change of ten points in the government restriction index causes an economic impact that is twice as big as a change of five points in the government restriction index.

Due to the fact that the parameters for the different steps originate from different sources, it is impossible to ensure that the variables used in each step are perfectly identical. However, the share of face mask wearers as well as the government restriction index used in step 1 and step 4 have been aligned as much as possible with the variables used in the Goldman Sachs study (2020) (see Annex 1 and Annex 4).

While the impact of misinformation on face mask wearing and the impact of government restrictions on GDP have been analysed on UK specific data, the coefficients for step 2 and step 3 are drawn from an international dataset. Furthermore, these two coefficients are based on data from the first half of 2020, while the survey in step 1 analyses self-reported data over the last 4 months. These issues arise due to the limited availability of data.

The caveats surrounding the survey analysis that have been outlined for the direct health costs in Chapter 0 also apply for the indirect costs.

5 Conclusion

The analysis has identified that **misinformation is widespread and consumed by a large share of the UK population, namely 70.2%.** The survey has also shown that a substantial proportion of the population (4.6%) is impacted by misinformation consumed online. This reflects in the self-reported mask wearing behaviour (and likelihood of self-isolating in case of a positive COVID-19 test, as outlined in Annex 1). As a result, the **share of the population wearing face masks could be 1.3 percentage points higher in the absence of misinformation**.

The modelling of the direct economic costs has shown that **21,947 COVID-19 cases, 2,187 hospitalisations and 509 deaths can be attributed to the effect of misinformation** in relation to face masks and the coronavirus from 01 April until 10 November. This had a direct impact on the NHS by creating **additional health costs of £9.58 million in quarter 2, £2.59 million in quarter 3 and £9.90 million in quarter 4** (until 10 November 2020). The impact over the **entire modelling period equals £22.1 million**. These figures reflect a conservative estimate for the incremental costs from misinformation. They do not include cost estimates for long-term health impacts, structural changes within the NHS or any side effects that occurred due to the wider response of the pandemic, such as the provision of additional equipment and the impact on mental health.

In addition to the direct costs, misinformation also has an indirect cost for the overall economy. These cost reflect the economic impact of the equivalent amount of government restrictions that would offset the negative effect of people not wearing face masks. The model suggests that the **indirect costs of misinformation was 0.426% (£2.379 billion) in quarter 2 and 0.212% (£1.185 billion) in quarter 3**. The impact over the **half-year period was 0.319% (£3,564)**.

These results highlight that misinformation can have a **significant effect on people's health, which results in additional financial stress on the NHS, and on the overall economy**. This study focusses on the misinformation relating to coronavirus and face masks. But, misinformation in relation to other related topics, such as vaccination, is likely to have a similar if not larger effect.

Annex 1 Survey analysis

Table 5 shows the number of individuals who report having seen one or more statements with misinformation on social media or other websites (other than traditional news websites). The most widely seen piece of misinformation is that COVID-19 is no more dangerous than the flu, followed by the statement which claims that masks do not help to reduce the transmission of COVID-19. Just over 70.2% of people report that they have come across at least one of these statements online. This proportion represents 37.0 million adults in the UK.

Table 5 Individuals who report to have seen the statement on social media or otherwise

	Number of resp.	%	UK adults (million)
Masks don't help to reduce the transmission of COVID-19	1,200	56.6%	29.8
Masks can be dangerous to wearers, even healthy adults	777	36.7%	19.3
COVID-19 is no more dangerous than the flu	1,301	61.4%	32.3
Any of the above	1,488	70.2%	37.0

Table 6 shows the distribution of the reported frequency of wearing face masks in different situations. It shows that the majority of people always wear face masks in public indoor spaces, such as shops, public transport and in pubs and restaurants.

Table 6 Proportion of adults who wear face masks in different situations[32]

	Shops	Public transport	In pubs and restaurants[33]	At my place of work or study	Walking on a busy street	When mixing households inside a home
Always	87.4%	88.2%	61.7%	33.6%	6.4%	4.8%
Most of the time	8.9%	5.9%	21.1%	20.5%	15.4%	6.5%
Sometimes	2.1%	1.9%	9.4%	17.5%	24.6%	11.9%
Rarely	1.1%	1.1%	3.7%	7.5%	24.2%	17.3%
Never	0.6%	2.9%	4.1%	20.9%	29.4%	59.4%

Table 7 presents the same information but focusses on the sub-sample of people who report having changed their behaviour due to misinformation (this sub-sample is based on the results presented in Table 9). As can be seen in the table, individuals who are impacted by false statements online, are less likely wear masks across all situations. The only outlier is the category 'Walking on a busy street'.[34]

[32] This analysis is based on the sub-sample that excludes respondents who are exempt from wearing face masks, who prefer not to say, or report that the question is not applicable to them. It also excludes respondents who report wearing face masks 'always' in every situation. This makes the sample more comparable to the sub-sample of people impacted by misinformation.

[33] The question asked specifically about moving around inside restaurants (i.e. not sitting down in restaurant or pubs)

[34] In order to compare Table 6 and Table 7, it was necessary to remove people who answered that they 'always' wore face masks in all situations from Table 6. This is because, people were only asked the reasons for not wearing face masks if they reported that they did not 'always' wear a mask in at least one of the situations listed. As a result, the two tables have the same basis. That is, people who report that do not always wear a mask in at least one of the situations.

Table 7 Proportion of adults wearing face masks in different situation who reported that misinformation was one of the reasons for their mask wearing behaviour[35]

	Shops	Public transport	In pubs and restaurants[36]	At my place of work or study	Walking on a busy street	When mixing households inside a home
Always	55.4%	59.6%	39.2%	19.7%	1.0%	0.0%
Most of the time	19.4%	20.6%	13.6%	7.5%	72.9%	0.0%
Sometimes	14.0%	10.1%	16.9%	24.6%	9.3%	5.9%
Rarely	4.7%	0.0%	15.0%	11.0%	16.8%	9.7%
Never	6.6%	9.6%	15.3%	37.2%	0.0%	84.4%

Table 8 presents the difference in the percentages between Table 6 and Table 7 for the answer options ‘always’ and ‘never’. There is a marked decrease in the proportion of people reporting they always wear a mask in shops among those who are impacted by misinformation, compared to those who are not. Individuals who are influenced by misinformation are also more likely to respond that they ‘never’ wear a mask. The average decrease in the proportion of individuals who always wear masks inside shops, public transport and in pubs and restaurants is 27.7%.

This figure is relevant, as the share of people reporting that they always wear face masks aligns with the YouGov survey results used in the Goldman Sachs study (2020), which feeds into the indirect model in Chapter 4. A change in the ‘always; category is, therefore, comparable to a change in variable used by Goldman Sachs. The average value for the categories ‘inside shops’, ‘public transport’ and ‘in pubs and restaurants’ is considered, as they most resemble the situations, which are commonly asked for in other surveys.

Table 8 Change in the proportion of adults who report they “always” and “never” wear face masks between those who report being influenced by misinformation and those who do not[37]

	Shops	Public transport	In pubs and restaurants	At my place of work or study	Walking on a busy street	When mixing households inside a home
Reduction in 'always' responses (pp)	-31.9%	-28.6%	-22.5%	-13.9%	-5.5%	-4.8%
Increase in 'never' responses (pp)	6.0%	6.8%	11.2%	16.3%	-29.4%	25.0%

[35] This analysis is based on the sub-sample that excludes respondents who are exempt from wearing face masks, who prefer not to say, or report that the question is not applicable to them. This question has not been asked to respondents who ‘always’ wear face masks in every situation.

[36] The question asked specifically about moving around inside restaurants (i.e. not sitting down in restaurant or pubs)

[37] This analysis is based on the sub-sample that excludes respondents who are exempt from wearing face masks, who prefer not to say or report that the question is not applicable to them.

The respondents who did not select 'always' option for every situation, were then asked the reason for not wearing a face mask. The reasons were the following[38]:

1) I don't believe they help to reduce transmission of COVID-19
2) I believe they can be dangerous to wearers, even healthy adults
3) I forgot/did not have one with me
4) It was too much effort
5) I believe COVID-19 is no more dangerous than the flu
6) I always keep a 2-metre distance from other people
7) It wasn't mandatory to wear one in that location
8) I find them uncomfortable
9) I don't like the way they look
10) None of the above/Other (please specify): __________ [OPEN ANSWER]

Options (1), (2) and (5) are reasons based on misinformation. Table 9 presents the proportion of people who report they do not wear a mask due to misinformation.

Table 9 Individuals who report having seen misinformation online and it is a reason for not wearing a mask

	Number of resp.	%	UK adults (million)
Masks don't help to reduce the transmission of COVID-19	65	3.1%	1.6
Masks can be dangerous to wearers, even healthy adults	27	1.3%	0.7
COVID-19 is no more dangerous than the flu	49	2.3%	1.2
Any of the above	97	4.6%	2.4

The survey also asked respondents if they would self-isolate under different situations. Table 10 presents these results for the full sample and for those people who report that they do not always wear a face mask and the reason for this is due misinformation. For each situation asked in the survey people who are impacted by misinformation are less likely to self-isolate. Particularly interesting is that 13% of the whole sample and 30% of those impacted by misinformation would not self-isolate if they test positive for the coronavirus.

Table 10 Self-isolation behaviour across different situations

Situation	Full sample	Sub-sample of people impacted by misinformation[39]
I would self-isolate if I had mild coronavirus-like symptoms (e.g. mild cough, loss of taste or smell etc.)	70%	41%
I would self-isolate if Track and Trace contacted me and told me to quarantine	74%	36%

[38] The order in which the response options were presented were randomised across respondents.

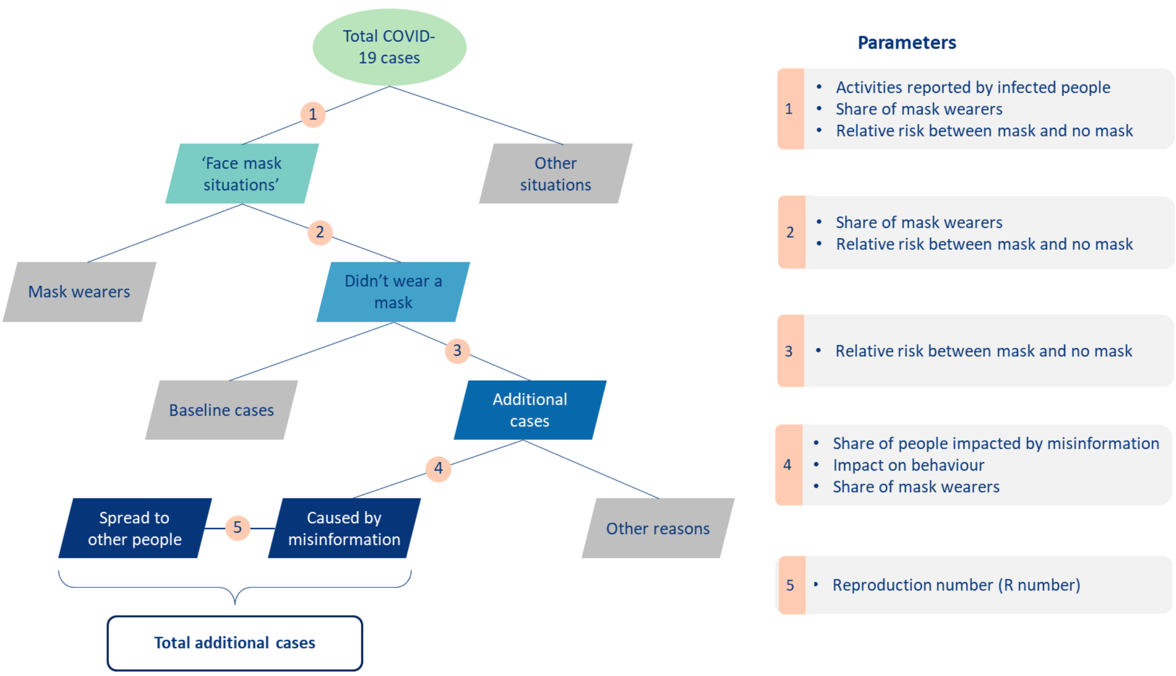
[39] This sub-sample includes people who have seen a false statement regarding face mask coverings online and have identified this particular piece of misinformation as a reason for not wearing a face mask.

I would self-isolate if a member of my household was told to quarantine or had coronavirus-like symptoms	74%	48%
I would self-isolate if a friend who I have been in contact during the last 14 days tested positive for COVID-19	68%	28%
I would self-isolate if I tested positive for COVID-19	87%	70%
If I was asked to self-isolate, I don't think I would be able to	3%	12%
Don't know	3%	5%

Annex 2 Estimating the number of cases attributable to misinformation

Figure 8 illustrates the modelling structure for estimating the number of COVID-19 cases that can be attributed to misinformation. Various parameters from official government sources, the academic literature and representative surveys are used to split the official government figure of COVID-19 cases in the UK into sub-groups. The final result is the number of additional cases due to misinformation.

Figure 8 Approach for estimating the COVID-19 cases attributable to misinformation



Source: London Economics

1. The first step considers that misinformation can only have an impact on those situations, in which people generally wear face masks. For this reason, it is important to understand how many cases originate from 'face mask situations' – those in which face masks should be worn – and how many originate from other situations.
   There is no data in the UK, which clearly identifies the source of infections. However, NHS Test and Trace collects data on the 'Events and activities reported by people testing positive, prior to symptom onset' as well as on 'Common locations reported by people testing

positive'. These statistics can help to understand the situations, in which people are likely to have caught the virus, and the frequency that each situation has been recorded.

For the purpose of this modelling, each category in the Test and Trace statistics has been classified as a face mask or other situation. For example, 'shopping' and 'travel and commuting' are considered to be 'face mask situations', whereas 'exercising' and 'events within a shared household' are classified as 'other situations', in which face masks are generally not worn and misinformation would, thus, not have an effect.

Each category has been weighted by the number of recorded mentions in the Test and Trace data. For example, activity A will count more towards the average than activity B if more people have mentioned activity A compared to activity B. The average share of observations in 'face mask situations' feeds into the model.

In addition to applying the share of 'face mask situations', the share of people wearing face masks and the relative risk of getting coronavirus is considered. This reflects that people are more likely to catch a virus when not wearing face masks. It applies the same logic as outlined in the next step.

2. The number of cases that occurred in 'Face mask situations' have to be divided into cases that involve people not wearing a face mask and cases of people that do wear face masks. In order to do so, it has to be taken into account how many people do not wear face masks and how much more likely they are to contract COVID-19. It should be noted that this approach does not model the protection that wearing a face mask has for others. This means that it is likely to be an underestimate.
3. It is important to consider that infections can occur even if everybody were to wear a face mask. For this reason, only the incremental number of cases (the difference between the number of expected cases without a face mask and with a face mask) can be attributed to not wearing face masks. By applying the relative risk between wearing a mask and not wearing a mask, the additional cases can be isolated.
4. Up until this point, the additional number of cases due to people not wearing face masks has been identified. The next step identifies the sub-sample of these cases that can be attributed to misinformation. In order to do so, the share of impacted people as a percentage of the total share of people not wearing face masks is applied as taken from the survey.
5. Individuals that have the coronavirus are likely to pass it on to other people. This is expressed in the R number. In order to produce conservative estimates, only the people that get the virus directly from those impacted by misinformation are included in the direct impact estimates. This means that the R number has been applied once only. It has also not been accounted for the fact that people without face masks are more likely to spread the virus to more people than the R number, which is an average for the entire population.

The number of COVID-19 cases attributable to misinformation is subsequently used to estimate the number of COVID-19 treatments and services which are due to misinformation. These treatments and services are:

- 111 calls;
- 999 calls;
- Hospital admissions;
- Days spent in Hospital;
- Days spent in ICU;
- Deaths;
- Cases and contacts reached and not reached by Test and Trace.

For example, the number of attributable 111 calls is based on the number of attributable COVID-19 cases and the ratio between the total number of COVID-19 cases and the total number of 111 calls. In some cases, the ratio has been calculated for a particular day (for example 111 calls), while a lagged average has been considered between the number of COVID-19 cases and some other variables, such as the number of hospital admissions and deaths. All case variables are based on official government data.

The number of attributable cases, as listed above, are calculated separately for each day in the modelling period. This approach takes changes in the model parameters over time into account. For example, the share of people wearing face masks has increased and the share of hospitalisations has decreased significantly over time. The model does not rely on average figures over the entire model period but provides a more realistic picture by drawing on the day-specific value for each parameter[40].

Table 11 provides an overview of the official government data underlying the estimation of attributable cases.

Table 11 Official data on COVID-19 Cases

Parameter	Source
Daily confirmed COVID-19 cases	Public Health England, (2020), 'Cases by specimen date in United Kingdom', GOV.UK.[41]
Daily hospital admissions	Public Health England, (2020), 'Patients admitted to hospital in United Kingdom', GOV.UK.[42]
Hospital beds and ICU beds occupied	Public Health England, (2020), 'Patients in hospital to United Kingdom', GOV.UK.[43]
Daily deaths	Public Health England, (2020), 'Deaths within 28 days of positive test by date of death in United Kingdom', GOV.UK.[44]
Daily 111 calls	NHS Digital, (2020), 'NHS Pathways Potential COVID-19 Open Data', NHS Digital.[45]
Daily 999 calls	NHS Digital, (2020), 'NHS Pathways Potential COVID-19 Open Data', NHS Digital.[46]

[40] A few parameters, such as those from the survey results, are not available over time. These exceptions have been treated as constant over time.

[41] https://coronavirus.data.gov.uk/

[42] https://coronavirus.data.gov.uk/

[43] https://coronavirus.data.gov.uk/

[44] https://coronavirus.data.gov.uk/

[45] https://digital.nhs.uk/data-and-information/publications/statistical/mi-potential-covid-19-symptoms-reported-through-nhs-pathways-and-111-online/latest

[46] https://digital.nhs.uk/data-and-information/publications/statistical/mi-potential-covid-19-symptoms-reported-through-nhs-pathways-and-111-online/latest

Weekly Test and Trace cases and contacts	Department of Health and Social Care, (2020), 'Weekly statistics for NHS Test and Trace in England and coronavirus testing in UK', GOV.UK.[47]

In addition, the model includes variables for the number of days spent in ICU, the number of ICU fatalities and the share of cases that develop into long COVID (Table 12).

Table 12 Sources to estimate further COVID-19 categories

Parameter	Source
Number of days in ICU per patient	ICNARC, (2020), 'ICNARC report on COVID-19 in critical care: England, Wales and Northern Ireland', ICNARC Report on COVID-19[48]
	Rees, E.M., Nightingale, E.S., Jafari, Y. et al, (2020), 'COVID-19 length of hospital stay: a systematic review and data synthesis', BMC Med 18, 270.[49]
Fatality rate of ICU patients	ICNARC, (2020), 'ICNARC report on COVID-19 in critical care: England, Wales and Northern Ireland', ICNARC Report on COVID-19.[50]
	Scottish Intensive Care Society Audit Group, (May 2020), 'Report on COVID-19', quoted on BBC.[51]
Share of cases that develop long COVID-19	Public Health England, (Sept 2020), ' COVID-19: long-term health effects', GOV.UK.[52]
	Covid Symptom Study (Oct 2020), 'One in 20 likely to suffer from 'Long Covid' but who are they?'[53]

Table 13 presents the sources, on which the parameters in Figure 8 are based on.

Table 13 Sources for the attribution of cases to misinformation

Parameter	Frequency of data	Source
% of people who say they wear a face mask in public places	Approximately every 2 weeks	YouGov, (2020), 'YouGov COVID-19 behaviour changes tracker', YouGov.[54]
	Weekly	Statista, (2020), 'How often have you worn a face mask outside your home to protect yourself or others from COVID-19?', Statista.[55]

[47] https://www.gov.uk/government/collections/nhs-test-and-trace-statistics-england-weekly-reports

[48] https://www.icnarc.org/Our-Audit/Audits/Cmp/Reports

[49] https://bmcmedicine.biomedcentral.com/articles/10.1186/s12916-020-01726-3

[50] https://www.icnarc.org/Our-Audit/Audits/Cmp/Reports

[51] https://www.bbc.co.uk/news/uk-scotland-52922818

[52] https://www.gov.uk/government/publications/covid-19-long-term-health-effects/covid-19-long-term-health-effects

[53] https://covid.joinzoe.com/post/long-covid

[54] https://yougov.co.uk/topics/international/articles-reports/2020/03/17/personal-measures-taken-avoid-covid-19

[55] https://www.statista.com/statistics/1114248/wearing-a-face-mask-outside-in-the-uk/

	12-13 November 2020	London Economics Citizens Survey
% of situations which can be classified as 'face mask situations'	Weekly from 21/09/2020 - 19/10/2020	Public Health England. (2020). 'National COVID-19 surveillance reports', GOV.UK.[56]
Risk ratio of becoming infected with COVID-19 if not wearing a mask		Chu D, Duda S, Solo, K, Yaacoub S, and Schunemann H, (2020), 'Physical Distancing, Face Masks and Eye Protection to Prevent Person-to-Person Transmission of SAS-COV-2 and COVID-19', *Journal of Vascular Surgery*, 72(4), 1500.[57]
		Wang, Y., Tian, H., Zhang, L., Zhang, M., Guo, D., Wu, W., Zhang, X., Kan, G. L., Jia, L., Huo, D., Liu, B., Wang, X., Sun, Y., Wang, Q., Yang, P., & MacIntyre, C. R. (2020). Reduction of secondary transmission of SARS-CoV-2 in households by face mask use, disinfection and social distancing: a cohort study in Beijing, China. *BMJ global health*, 5(5), e002794. [58]
Share of people impacted by misinformation	12-13 November 2020	London Economics Citizens Survey
Impact of misinformation on behaviour	12-13 November 2020	London Economics Citizens Survey
Reproduction-rate (R-number)	Daily	Government Office for Science, (2020), 'The R number and growth rate in the UK', GOV.UK.[59]
	Daily	Gallagher, J. (2020). 'Coronavirus: What is the R-number and how is it calculated?'. BBC.co.uk[60]

[56] https://www.gov.uk/government/publications/national-covid-19-surveillance-reports

[57] https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(20)31142-9/fulltext

[58] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7264640/pdf/bmjgh-2020-002794.pdf

[59] https://www.gov.uk/guidance/the-r-number-in-the-uk

[60] https://www.bbc.co.uk/news/health-52473523

Annex 3 Estimating the costs associated with COVID-19 cases

The unit cost estimates applied in this study are often based on figures from previous diseases and, thus, are of a rather conservative nature. Bartsch et al. (2020) find that "even when only the costs during the acute infection and not those of follow-up care after infection are considered, the direct medical costs of a symptomatic COVID-19 case tend to be substantially higher than costs for other common infectious diseases."

Table 14 presents the parameters used to estimate the number of treatments/services, whereas Table 15 presents the data used for the unit costs.

Table 14 Sources use to estimate the number of treatments/services

Parameter	Source
Number of COVID-19 tests per case	Department of Health and Social Care (2020), 'Coronavirus (COVID-19): getting tested', GOV.UK.[61]
Number of COVID-19 tests per hospitalised case	Public Health England, (2020), 'Guidance for stepdown of infection control precautions and discharging COVID-19 patients', GOV.UK. [62]
Number of GP appointments for cases of long COVID	London Economics estimate
Number of cases in system handled by human tracers	London Economics estimate
Time per case and contact	London Economics estimate

Table 15 Sources for unit cost elements

Parameter	Source
Cost per 111 call	Curtis, L, and Burns, A, (2019), 'Unit Costs of Health and Social Care 2019', Personal Social Service Research Unit, University of Kent.[63]
Cost per 999 call	Curtis, L, and Burns, A, (2019), 'Unit Costs of Health and Social Care 2019', Personal Social Service Research Unit, University of Kent[64]

[61] https://www.gov.uk/guidance/coronavirus-covid-19-getting-tested#who-can-be-tested

[62] https://www.gov.uk/government/publications/covid-19-guidance-for-stepdown-of-infection-control-precautions-within-hospitals-and-discharging-covid-19-patients-from-hospital-to-home-settings/guidance-for-stepdown-of-infection-control-precautions-and-discharging-covid-19-patients#:~:text=People%20who%20are%20discharged%20from,adult%20social%20care%20plan.

[63] https://www.pssru.ac.uk/publications/pub-5833/https://www.pssru.ac.uk/publications/pub-5833/

[64] https://www.pssru.ac.uk/publications/pub-5833/

Cost per COVID-19 test	Janes, L., (2020), 'Private COVID-19 tests: where you can get one, costs & how they work', lovemoney.com. [65][66]
Hourly cost for tracer	Perraudin, F. (2020). 'No one had any idea: Contact tracers lack knowledge about COVID-19 job'. The Guardian.[67]
	NHS Scotland (2020). 'Job details for Contact Tracing Practitioner'.[68]
Hourly cost for HPT	NHS Professionals (2020). 'Job details for clinical contact caseworkers'.[69]
	NHS Scotland (2020). 'Job details for Contact Tracing Practitioner'.[70]
Cost of hospital bed per day - general	Department for Health and Social Services, (2016), 'Together for Health – A Delivery Plan for the Critical Ill', Welsh Government.[71]
	Marti, J., Hall, P., Hamilton, P., Lamb, S., McCabe, C., Lall, R., Darbyshire, J., Young, D., & Hulme, C. (2016). One-year resource utilisation, costs, and quality of life in patients with acute respiratory distress syndrome (ARDS): secondary analysis of a randomised controlled trial. Journal of Intensive Care, 4(1), 1.[72]
Cost of hospital bed per day – ICU	Hex, N, Retzer, J, Bartlett, C, and Arber, N, (2017), 'The Cost of Sepsis Care in the UK', York Health Economics Consortium.[73]
	Marti, J., Hall, P., Hamilton, P., Lamb, S., McCabe, C., Lall, R., Darbyshire, J., Young, D., & Hulme, C. (2016). One-year resource utilisation, costs, and quality of life in patients with acute respiratory distress syndrome (ARDS): secondary analysis of a randomised controlled trial. Journal of Intensive Care, 4(1), 1.[74]
	Department for Health and Social Services, (2016), 'Together for Health – A Delivery Plan for the Critical Ill', Welsh Government.[75]
Cost of rehabilitation after ICU	Marti, J., Hall, P., Hamilton, P., Lamb, S., McCabe, C., Lall, R., Darbyshire, J., Young, D., & Hulme, C. (2016). One-year resource utilisation, costs, and quality of life in patients with acute respiratory distress syndrome (ARDS): secondary analysis of a randomised controlled trial. Journal of Intensive Care, 4(1), 1.[76]
Cost per GP appointment	Curtis, L, and Burns, A, (2019), 'Unit Costs of Health and Social Care 2019', Personal Social Service Research Unit, University of Kent.[77]

[65] https://www.lovemoney.com/news/101151/private-covid19-tests-where-you-can-get-one-costs-how-they-work-antigen-antibody-uk

[66] These figures have been adjusted to account for a profit margin in the private cost of a COVID-19 test.

[67] https://www.theguardian.com/world/2020/may/20/no-one-had-any-idea-contact-tracers-lack-knowledge-about-covid-19-job

[68] https://apply.jobs.scot.nhs.uk/displayjob.aspx?jobid=36112&source=JobtrainIndeed&utm_source=Indeed&utm_medium=organic&utm_campaign=Indeed

[69] https://www.nhsprofessionals.nhs.uk/en/contact-tracer/Clinical-Contact-Caseworker/Job-Description

[70] https://apply.jobs.scot.nhs.uk/displayjob.aspx?jobid=36112&source=JobtrainIndeed&utm_source=Indeed&utm_medium=organic&utm_campaign=Indeed

[71] http://www.wales.nhs.uk/documents/delivery-plan-for-the-critically-ill.pdf

[72] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4982209/

[73] http://allcatsrgrey.org.uk/wp/download/health_economics/YHEC-Sepsis-Report-17.02.17-FINAL.pdf

[74] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4982209/

[75] http://www.wales.nhs.uk/documents/delivery-plan-for-the-critically-ill.pdf

[76] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4982209/

[77] https://www.pssru.ac.uk/publications/pub-5833/

Annex 4 Estimating the impact of government restrictions on GDP

In order to calculate the impact of the government restrictions necessary to achieve the same effect on the infection growth rate as face masks, it is important to understand the relationship between government restrictions and the percentage change in GDP.

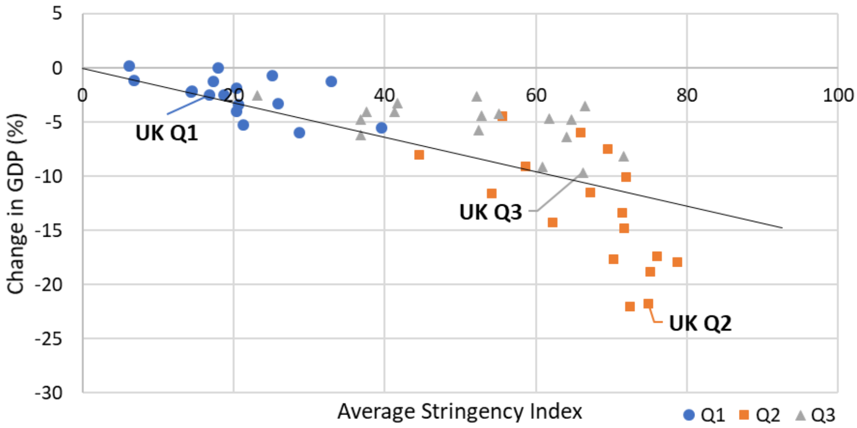
The University of Oxford has published a government stringency index, which has been used as a measure of government restrictions in this study. This index has been chosen because it most closely resembles the effective lockdown index (ELI) that has been used in the regressions the Goldman Sachs (2020) study. Goldman Sachs created the ELI, which has not been published, and based it on Oxford's stringency index and Google mobility data[78].

Figure 9 provides insights on the relationship between the stringency index and the percentage change in GDP by plotting 17 countries over three quarters. The y-axis indicates the change in GDP[79] and the x-axis shows the Average Stringency Index for each country. The observations appear to lie on a downward-sloping line, which would indicate a linear, negative relationship: As the Average Stringency Index increases, the change in GDP becomes more negative.

The figure also shows that the UK experienced one of the largest changes in GDP in the second quarter (orange observations). This even holds in the comparison with countries that have a similar level of government restrictions, which indicates that the relationship is particularly strong in the UK.

The line in the figure is a trendline, which shows the best fit through the origin and the individual observations. The slope of the line reflects the strength of the association between the two variables.

Figure 9 Impact of government restrictions on GDP – international quarterly data



Source: London Economics' analysis based on OECD (2020)

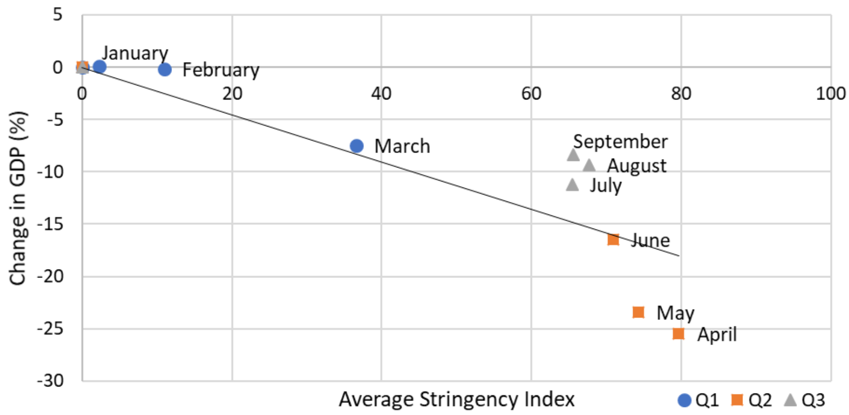
[78] https://www.gspublishing.com/content/research/en/reports/2020/04/27/3a0089c7-c1d1-4243-8dbd-da6141a501be.html

[79] The change in GDP is expressed relative to the level of GDP in Q4 2019 for the international quarterly data.

Figure 10 shows another scatter plot but instead of quarterly data from a range of international countries, the observations represent monthly data for the UK only[80]. The UK specific data suggests a similar relationship between the two variables compared to the previous figure.

The colours, which group the observations by the separate quarters of 2020, also indicate the same, distinct pattern over time. Observations in quarter 2 have the highest values in terms of the change in GDP and the Average Stringency Index. These observations tend to lie below the trendline, while observations in quarter 3 are consistently above the line for the UK data. This indicates that the strength of the association varies over time and provides support for analysing the relationship on a quarterly basis.

Figure 10 Impact of government restrictions on GDP – UK monthly data



Source: London Economics' analysis based on ONS (2020)

Figure 11 presents scatter plots for the UK specific and for the international data - for each quarter separately. Table 16 summarises the slope of the trendlines for the different plots. The coefficients show the percentage change in GDP in response to a one-point change in the Average Stringency Index.

The UK experienced a stronger decline in GDP in response to government restrictions across all quarters compared to the international sample. Furthermore, government restrictions had the strongest impact on the UK and the international community in quarter 2 and the least strong impact in quarter 3.

The difference across quarters could be explained by the first nation-wide lockdown that occurred in the second quarter. The lockdown might have had a disproportionally strong impact compared to some of the other restrictions imposed over the summer and autumn period.

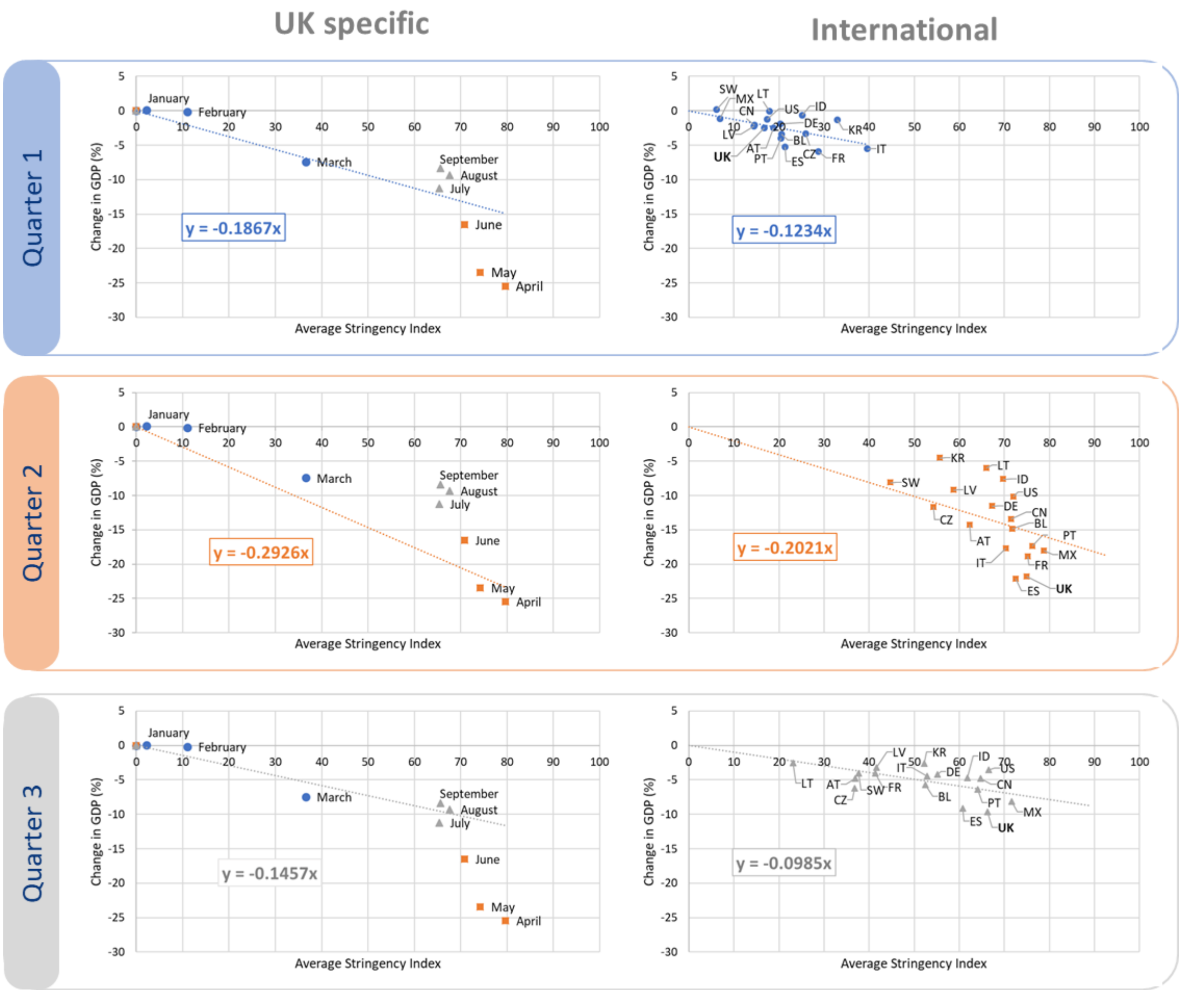
[80] The change in GDP is expressed relative to the level of GDP in December 2019 for the UK monthly data.

Table 16 Impact of government restrictions on GDP – overview

	UK (monthly data)	International (quarterly data)
Q1	0.1867	0.1234
Q2	0.2926	0.2021
Q3	0.1457	0.0985

Source: London Economics' analysis based on ONS (2020), OECD (2020)

Figure 11 Impact of government restrictions on GDP – by quarter



Source: London Economics' analysis based on ONS (2020), OECD (2020)

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