Guest Editorial: Costing Covid-19 a year later: retrospective thoughts on an early economic evaluation of UK government policy

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Introduction

In the first quarter of 2020, over 150 countries introduced some variation of nonpharmaceutical interventions (NPI) in response to the COVID-19 pandemic (Zhu et al, 2020). These unprecedented public health strategies involved measures designed to isolate infectious cases and limit transmission through social mixing. In February 2020, the UK government introduced voluntary mitigation restrictions such as self-isolation for those with symptoms and social distancing advice for those most at risk (BFPG, 2020). By the fourth week of March, official UK government policy could be described as a strategy of suppression, defined as case isolation and home quarantine, general social distancing (including a social venue ban), and school and university closure.

The Imperial College COVID-19 Response Team report (Ferguson et al, 2020) and its projections published on March 16 (2020) are widely believed to have influenced the introduction of suppression policies by the UK government. The exploratory economic evaluation "*Costing the COVID-19 Pandemic: An Exploratory Economic Evaluation of Hypothetical Suppression Policy in the United Kingdom*" (Zala et al, 2020) was an attempt to cost and evaluate the menu of NPIs in the Imperial College report from a health economics perspective. Although it was published online in August 2020, the analysis and corresponding results were only finalised in mid-April and so less than a month after the formal introduction of suppression policy (i.e. the first "lockdown") in the UK.

This article will critically reflect on the methods and results of that early exploratory economic evaluation in the light of the events and findings of the last year. It will also compare Zala et al. (2020) with more recently published economic evaluations of UK government policy.

Imperial College COVID-19 Response Team report projections

The methodology in Zala et al. (2020) involved measuring the accrual of costs and QALYs associated with (non-ICU and ICU) hospitalisation and death predictions (up to late 2021) from the Imperial College report for the following NPIs: unmitigated pandemic, mitigated pandemic and 2 versions of suppression policy (i.e. with different ICU bed occupancy on/off triggers).

In some sense, the predictions of the Imperial College report were not especially surprising in that with an infection mortality ratio (IFR) of just under 1% applied to the UK adult population we would expect around half a million deaths – the prediction for an unmitigated pandemic (i.e. the counterfactual scenario of no change in behaviour whatsoever). A simulation model of this nature can never be perfectly accurate, in that it is an average across many model realisations based on plausible (but unknowable) starting conditions (e.g. time and location(s) of infection seeding). A full exploration is beyond the scope of this paper, but some comment can be made on the possible reasons for differences between model predictions and the observed trajectory of the pandemic. In general, there are 3 reasons why predictions could differ systematically from reality:

- Structural model features that do not reflect reality
- Disease and population-level input parameters that do not capture the true epidemiology of COVID-19
- Modelled NPIs that do not reflect government policy as undertaken in practice

It is important to note that the different independent modelling group predictions that help produce SPI-M (Scientific Pandemic Influenza Group on Modelling) advice have tended to give similar results (particularly at shorter time intervals) for similar inputs and assumptions (SPI-M, Oct and Dec 2020, Jan 2021). There were also alternative modelling approaches in early 2020 that produced results with broadly comparable features (Edward, 2020). Another study reproduced the model associated with Ferguson et al (2020) with alternative "code" but with the same inputs and produced almost identical results (Rice et al, 2020).

Disease relevant variables can relate to the following, many of which are still uncertain: incubation period, period of infectiousness and symptoms onset, infectiousness of asymptomatic cases, length of immunity, proportion of cases hospitalised, lengths of hospitalisation and so on. General epidemiological inputs are easier to assess. Zala et al. (2020) uses the base-case Ferguson et al. (2020) predictions consistent with a basic UK reproduction rate (i.e. under unmitigated pandemic) of R0 = 2.2-2.4. This is almost certainly an underestimate, with recent estimates as high as 3.3 and a more recent published simulation model applying an 11-study consensus value of R0 = 2.7 (Davies et al, 2020; Sandmann et al, 2021). These may well be underestimates given the emergence of new variants (Davies et al, 2021). This explanation is supported by Rice et al. (2020), which notes that their "replica" of the Ferguson et al. (2020) model reproduced observed cumulative deaths reported in the first wave most convincingly with inputted values of R0 = 3.0.

The age stratified infection fatality ratios (IFRs) applied in Ferguson et al. (2020) are consistent with an overall UK specific IFR of around 0.9%, which is broadly consistent with other simulation studies from last year (Davies et al, 2020). However, again these may be minor underestimates with recently published estimates at slightly above 1% (Brazeau et al, 2020).

Contrary to media perception, the Imperial College report did not outline the eventual suppression strategy followed by the UK government. These modelled NPIs can be considered "exogenous" (i.e. policy variables that are pre-set) and were completely hypothetical and so differences will inevitably lead to divergences between predictions and observed data. For example, the timing and length of lockdowns (i.e. suppression) in the UK were not based on any explicit ICU triggers. Modelled NPIs also required assumptions about reductions in contact rates in various settings (and so adherence to rules) and could not have predicted the start of vaccination as early as December 2020. Unsurprisingly, evidence suggests that the model is particularly sensitive to inputs related to NPI effectiveness. A multivariate sensitivity analysis of the model found that 2 of the 3 most important inputs were "Relative spatial contact rate given social distancing" and "Delay to start case isolation" – variables closely related to the effectiveness of social distancing (Edeling et al. 2020).

At face value, the predictions of the Imperial College report used in Zala et al. (2020) are a significant underestimate. For example, deaths up to late 2021 under suppression 1 and suppression 2 were estimated as 15k and 46k, respectively. By Feb 2021, UK deaths were around 100k using any measure (GOV.UK, 2021; Kings Fund, 2021). In summary, much of the explanation for this may be early underestimation of COVID-19 fatality and rate of transmission, but also divergences between modelled NPIs and actual policy (i.e. timing, length, adherence and effectiveness). Predicted deaths under a mitigated pandemic were 255k, which supports the hypothesis that government policy (and public compliance) reduced transmission by somewhere between the modelled mitigation and suppression strategies.

Cost and QALY inputs

As discussed in Zala et al. (2020), it is not always clear what cost and QALY inputs should be included in an economic evaluation of this nature. For example, if the analysis had assumed an NHS perspective, the incremental analysis would have shown suppression strategy to be dominant (lower QALY loss and costs); but this would ignore the significant burden of costs that fall outside of the NHS budget that are required to achieve a reduction in deaths and hospitalisations (i.e. national income loss).

Table 1 presents the cost and QALY inputs that could be included in an economic evaluation, with those in bold excluded from Zala et al. (2020). Intangible Costs and QALYs include but are not limited to the following:

- Changes in healthcare costs and QALY loss due to displacement or delay of other treatments (or prophylactic avoidance of healthcare)
- Costs and QALY loss (or gain) related to other sector effects such as changes in criminal behaviour (burglary, domestic abuse etc)
- QALY loss (or gains) due to social distancing and financial issues (including mental health issues and unemployment)

Intangible costs and QALYs were not included in a systematic way in Zala et al. (2020) but scenario analyses explored QALY loss due to unemployment and savings in long-run NHS and social care costs due to a COVID-19 death, both of which made little difference to results. Virtually all QALY loss (≈ 99%) for any of the four strategies in Zala et al. (2020) was due to COVID-19 deaths and so QALY loss and costs associated with treatment of symptomatic (but not hospitalised) patients is not expected to make much difference to results.

Zala et al. (2020) assumed the costs of any fiscal schemes (e.g. furlough) were replacements for lost income and so included in lost national income (i.e. GDP loss). It is not clear if any other direct costs of government action should have been included. For example, the costs of test and trace are not directly related to mitigation and suppression and were intended to remove the need for the latter. Nevertheless, reported costs of test and trace are relatively small compared to GDP loss for any of the strategies - £20 billion is less than 1% of national income (Full Fact, 2021) – and so inclusion would not make much difference to results.

Table 1. Direct and indirect cost and QALY loss inputs

	Costs incurred	QALY loss
Direct	**Treatment of non-hospitalised**	**COVID-19 illness (symptomatic)**
	Treatment of hospitalised (non-ICU)	Hospitalised (non-ICU)
	Treatment of hospitalised ICU	Hospitalised (ICU)
	Costs of government action (e.g. test and trace)	COVID-19 deaths
	End of life cost (COVID-19 death)	
Indirect	GDP (national income) loss	**Intangible QALY effects**
	Intangible cost effects	

Abbreviations: ICU, intensive care unit; QALY, quality-adjusted life year

Notes: in bold are those costs and QALYs excluded from analysis in Zala et al. (2020)

Zala et al. (2020) estimated that the average QALY loss due to a COVID-19 death is 8.8 and this included age adjustment based on age-variant IFRs and UK lifetables. However, it did not adjust for the higher prevalence of comorbidities in individuals most likely to die from COVID-19. Subsequent estimates suggest fully adjusted losses may be closer to 5 QALYs (Briggs et al, 2021), which would reduce all incremental QALYs in Zala et al. (2020) by around half and double reported ICERs (Suppression vs. mitigated and unmitigated pandemics).

Results in Zala et al. (2020) were sensitive to differences in GDP loss between strategies. Based on Keogh-Brown et al. (2010), base-case 2020-21 GDP loss estimates were assumed to be 1.85% (unmitigated), 2.75% (mitigated) and 6.05% (suppression). These were considered "guesstimates" and so results in Zala et al. (2020) were framed as conditional on different possible GDP loss levels. Current estimates of GDP loss are around 11% for the 2020-21 period and so these appear as underestimates (OBR, 2020). A macro-economic assessment of the strategies in Ferguson et al. (2020) conducted in early 2020 projected 1.7%, 11.4% and 27.7% in lost GDP respectively for 2020 (Keogh-Brown et al, 2020). These predictions seem like substantial overestimates in retrospect. More recent summaries of the evidence that reflect cross-country data from 2020, suggest that GDP loss would have been high even without lockdowns (e.g. up to 60% of the loss) for various reasons: substantial voluntary prophylactic behaviour, high spill-over effects in a globalised economy (i.e. tourism and exports are a large component of GDP) and in particular because of the experience of countries like Sweden (Ilzetzki et al, 2020). This suggests that incremental differences may not be too dissimilar from the original base-case assumptions; however, GDP loss estimates were and continue to be highly uncertain inputs.

Comparison with other economic evaluations

In order of publication, Table 2 presents Zala et al. (2020) against more recent economic evaluations. Two papers are retrospective in nature, attempting to compare actual government policy outcomes against possible counterfactual policies. Miles et al. (2020) compares reported QALY weighted outcomes and costs (including GDP loss) against a policy of no "lockdown" up to 24th May 2020. No explicit modelling is undertaken, and the counterfactual policy is never defined and so it can be argued the analysis is not truly incremental. There is also some confusion about time periods – in one scenario they use the headline death figures for unmitigated pandemic from Ferguson et al. (2020), but these are projections up to the end of 2021 and so are not relevant to the chosen horizon. The comparison in Thom et al. (2021) is better defined and compares the observed policy outcomes under the first wave (up to 20th July) with a “no mitigation” strategy; projections for the counterfactual are estimated using the LSHTM group CMMID simulation model and GDP loss based on the Swedish experience.

Both provide useful insights, but such relatively short time horizons are unlikely to capture the full cost and benefit trade-offs involved in policy making. For example, disease dynamics and the impact of policy on the economy in subsequent waves will be partly determined by the effect of restrictions in the first wave (i.e. there can be trade-offs between waves).

Rowthorn et al. (2020) and Sandmann et al. (2021) present predictive de novo models that attempt to integrate economic outcomes directly as a function of policy. The former was published early in the pandemic and does not present health economics outcomes (e.g. QALYs), but is framed as a more traditional optimisation problem in economics: a variety of government policies are optimised while maintaining an assumed value of life constraint. There is little justification given for assumed epidemiological parameters such as R0 and death rates.

Sandmann et al. (2021) is the most recent publication and provided analyses most relevant to policy making in the future. An updated CMMID model is used to project benefits and costs over a 10-year horizon for different vaccination scenarios overlaid with different social distancing policies. An explicit attempt to capture input parameter uncertainty via probabilistic sensitivity analysis is included, in contrast to all other studies. The study results provide a powerful insight that needs more acknowledgment: all policy options available give net negative health benefits (i.e. QALYs valued in monetary terms net of all costs) and so the optimal policy is the one that is least “bad”.

In line with Zala et al. (2020), none of the papers attempt to integrate intangible costs and QALYs in a systematic way. Rowthorn et al. (2020) and Sandmann et al. (2021) calculate GDP loss as a function of days under restrictions, but estimates vary widely (Table 2) which is an acknowledgement of the remaining uncertainty in this parameter. All studies that use QALYs assume a threshold consistent with NICE (£20k or £30k per QALY) in the base-case, but as discussed in Zala et al. (2020) it is unclear that this value reflects the true opportunity costs associated with GDP loss.

Conclusions

It is likely that Zala et al. (2020) overestimated incremental death QALYs because it did not adjust for comorbidities. GDP loss is a major driver of results in all economic evaluations and remains highly uncertain for all counterfactual policy scenarios; however incremental GDP loss may be lower than earlier estimates suggested and not dissimilar to base-case assumptions in Zala et al. (2020). There is no clear consensus in the literature as to what QALY threshold is the relevant one for the decision problem.

Table 2. Summary of Zala et al. (2020) and more recent evaluations of UK government policy

	Decision problem	Strategies compared	Modelling methodology	Evaluation length	Retrospective or predictive	Health economics outcomes	GDP loss estimates and source	QALY, Costs excluded	Threshold applied	Conclusion
Zala et al. 2020	Calculates the relative cost-effectiveness of the hypothetical suppression policies found in the Imperial College COVID-19 Response Team model	Hypothetical strategies including Unmitigated (do nothing), mitigated and 2 alternative suppression strategies	Use of published Imperial College COVID-19 Response Team model projections (March report Ferguson et al. 2020)	Same as Ferguson et al (2020) model (seeding in Jan 2020 until late 2021 assuming no vaccines)	Predictive	QALYs, ICERs conditional on GDP loss	For counterfactual unmitigated/mitigated from earlier macroeconomic study (Keogh-Brown et al, 2010). For suppression based on published estimates.	Intangible QALY/costs of lockdown	No explicit threshold, but range explored.	Difficult to claim that the hypothetical Imperial model–projected suppression policies are obviously cost-ineffective. Uncertain and sensitive to GDP loss estimates.
Miles et al. 2020	Valuing excess deaths and comparing to excess GDP loss, up to the end of May 2020	Government policy up to 24th May vs. undefined policy with no "lockdown"	No modelling undertaken. Compare a range of estimated deaths saved because of government policy up to 24th May against GDP loss estimate ranges.	Up to week ending 24th May 2020 (some of wave 1)	Retrospective	HRNB with 5 or 10 QALYs lost per Covid death (assuming £30k per QALY) but not explicitly incremental	Range of GDP loss due to lockdown estimates (9%, 15%, 20%, 25%), based on various sources including OBR.	Most intangible costs/QALYs (but attempt to account for some indirect health savings from lockdown)	£30k per QALY	The costs of continuing severe restrictions are great relative to likely benefits in lives saved (i.e. net cost)
Rowthorn et al. 2020	Cost–benefit analysis to find optimal policy mix, given a fixed value of life objective set by the government	All hypothetical strategies that determine pandemic paths such as do nothing, tight lockdown of 5.3 weeks, earlier and shorter lockdown, vaccine available at 1 and 2 years etc	De novo mathematical SIR model of disease propagation with government policy framed in context of (traditional) economic optimisation problem with assumed value of life constraint (e.g. £2 million per life)	1st April for 52 weeks	Purely predictive - estimates of death rate and R0 are not based on any data or referenced	No QALYs (value of life analysis). No incremental analysis presented (i.e. just optimal options given value of life constraint).	The per capita weekly cost of full lockdown is £200 which is in line with OBR predictions at the time	QALY loss of illness, intangible QALY/costs of lockdown	N/A	A 10-week lockdown is only optimal if the value of life for COVID-19 victims exceed £10m. Results sensitive to timing of intervention.

Thom et al. 2021	Compare health economics outcomes of observed country "mitigation" strategies vs counterfactual (modelled) "no mitigation" strategy	Observed "mitigation" strategy that occurred in real life (varies by country) vs. counterfactual "no mitigation"	For no mitigation outcomes open-source age-structured deterministic mathematical model of SARS-CoV-2 transmission (CMMID model) used to predict outcomes. Different no mitigation comparators tested, each with different inputted R0.	Wave 1 (Jan 1st to 20th July)	Retrospective	Per capita QALYs, HRNB (assuming £20k per QALY)	Retrospective estimates from various sources for mitigation. Attempt to account for non-NPI reductions in GDP (trade, prophylactic behaviour), with no mitigation base-case as Swedish GDP loss.	Direct government policy costs (e.g. test and trace costs), intangible QALY/costs of lockdown	£20k per QALY	Benefit of government Covid-19 responses may outweigh their economic costs. The extent that HRNB offset economic losses varies widely by country and assumed R0 under no mitigation.
Sandmann et al. 2021	Compares net monetary value of different combinations of social distancing measures with introduction of vaccination scenarios	Compare different vaccination/revaccination scenarios assuming different vaccine efficacy and duration of protection to no vaccination scenario. In addition to different lockdown and social distancing measures (some counterfactual such as no lockdowns in 2020).	De novo age-structured dynamic transmission model with fully integrated economic model (CovidM CMMID model)	10 years from Jan 1st 2020	Largely predictive but starting Jan 2020 to allow for counterfactual scenarios (some attempt at alignment with observed 2020 data like hospitalisations)	QALYs, HRNB with assumed QALY values, scenario analysis with GDP loss included	Under voluntary distancing GDP loss accrues at a rate of 2% of daily GDP (≈ £115 million) for days with new reported cases over 1000. Under stricter distancing and lockdowns daily GDP loss can be 2% to 15% (scenario analyses).	No intangible costs/QALYs but includes wider range of direct QALY loss including symptomatic cases (no hospitalisation) and vaccine adverse events. Includes costs such as setting up a vaccine programme and govt research subsidies.	£20k per QALY, but scenarios up to £60k per QALY	At virtually all assumed QALY values (but particularly £60k per QALY) vaccination scenarios are superior to no vaccination in HRNB, with or without including GDP loss. In all distancing and lockdown scenarios, vaccination has a higher HRNB than no vaccination.

Abbreviations: ICER, incremental cost-effectiveness ratio; QALY, quality-adjusted life year; GDP, gross domestic product; HRNB, health-related net benefit; OBR, Office of Budget Responsibility; CMMID, LSHTM Centre for the Mathematical Modelling of Infectious Diseases Covid-19 model

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