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Does a health crisis change how we value health?

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Conflict of interest

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Abstract

Background General population health state values are used in healthcare resource allocation, including health technology assessment.

Aim Examine whether UK general population health valuations changed during the COVID-19 pandemic.

Methods Ratings of EQ-5D-5L health states 11111 (no problems), 55555 (extreme problems), and dead were collected in a UK general population survey during the pandemic (April-May 2020) using the 0=worst imaginable health, 100=best imaginable health visual analogue scale (EQ-VAS). Ratings for 55555 were transformed to a full health=1, dead=0 scale. Responses were compared to similar data collected pre-pandemic (2018). After propensity score matching to minimise sample differences, EQ-VAS responses were analysed using Tobit regressions.

Results On the 0-100 scale 11111 was rated on average 8.67 points lower, 55555 rated 9.56 points higher, and dead rated 7.45 points lower post-pandemic onset compared to pre-pandemic. On the full health=1, dead=0 scale, 55555 values were 0.09 higher post-pandemic onset. There was evidence of differential impacts of COVID-19 by gender, age and ethnicity, although only age impacted values on the 1-0 scale.

Conclusion COVID-19 may have affected how people value health. It is unknown whether the effect is large enough to have policy relevance, but caution should be taken in assuming pre-COVID-19 values are unchanged.

Keywords: COVID-19; valuation; EQ-5D; EQ-VAS; visual analogue scale; health-related quality of life

1. Introduction

The COVID-19 pandemic has had severe health consequences (Williamson et al., 2020), including 1.2 million deaths worldwide as of November 2020 (World Health Organization, 2020). Those who survive experience a variety of sequelae which are not yet well understood (Greenhalgh, Knight, Buxton, & Husain, 2020; Xiong et al., 2020), including neurological (Troyer, Kohn, & Hong, 2020) and cardiac problems (Demertzis et al., 2020). The general population is also impacted, including through increased anxiety and depression (Davillas & Jones, 2020). The economic fallout of the pandemic and its long-term health consequences, including a backlog of demand due to cancelled operations, will result in continued pressure on healthcare resources in the future (Leahy et al., 2020). As a consequence, the processes for making decisions about how to allocate scarce healthcare resources will likely become more heavily scrutinised by all stakeholders, including patients and the public at large.

Evidence of the cost-effectiveness of healthcare interventions generally incorporates generic measures of health-related quality of life such as EQ-5D (Dolan, 1997), HUI (Horsman, Furlong, Feeny, & Torrance, 2003), SF-6D (Brazier, Roberts, & Deverill, 2002) or AQoL (Richardson, Iezzi, Khan, & Maxwell, 2014). Each of these measures has a finite number of health states defined by a descriptive classification. For EQ-5D, these health states are formed by combining different levels of problem on each of five separate dimensions (mobility, self-care, usual activities, pain/discomfort and anxiety/depression). Its latest form, EQ-5D-5L defines five levels of problem from none to extreme, thereby creating 3,125 (5^5) unique health states (Herdman et al., 2011).

When used in economic evaluation, EQ-5D health states are assigned a value on a scale where full health (defined as no problem on all 5 EQ-5D dimensions) and dead are respectively given the values 1 and 0. Regulatory agencies such as NICE stipulate that the values applied to EQ-

5D should represent the preferences of the general population (National Institute for Health and Care Excellence (NICE), 2013).

There are reasons to believe that COVID-19 may have impacted on how people value health. Firstly, the pandemic and the responses to it have negatively affected individuals' mental and physical health, and there is evidence that one's own health influences how one values health in general (Badia, Herdman, & Kind, 1998; Dolan & Kahneman, 2008; Dolan & Roberts, 2002; Kind & Dolan, 1995). Second, living through a pandemic, with the risk of contracting a serious and potentially life-threatening disease prominent in people's minds may have led to a reassessment of, for example, the relative priorities given to length and quality of life. The societal upheaval caused by the response to COVID-19, including lockdown, could also have led to people reconsidering how they value health vis a vis other aspects of their lives that they also see as having importance, for example the need for social contact. It is crucial to know if and how general population preferences for health have been impacted by COVID-19 since this can ultimately affect decisions about healthcare resource allocation.

This study is the first empirical comparison of health state valuations before and during the COVID-19 pandemic. Any finding that general population values may have changed is important, since this would indicate that caution is needed when using general population health valuations collected in previous years to inform future resource allocation decisions.

2. Methods

This study is based on visual analogue scale (VAS) data. EQ-5D value sets have previously been estimated using EQ-VAS (Claes, Greiner, Uber, & Graf von der Schulenburg, 1999; Greiner et al., 2003; Gudex, Dolan, Kind, & Williams, 1996). A variation in the standard form of EQ-VAS previously proposed (Kind, Hennessy, & Macran, 2004) has also been employed in a UK survey of the general population to anchor discrete choice experiment (DCE) values for EQ-5D-3L to a full health=1, dead=0 scale (Webb, O'Dwyer, Meads, Kind, & Wright, 2020). The revised form of EQ-VAS provides for the capture of ratings for the logically best (11111) and worst (55555) health states. It also allows respondents to provide an explicit rating for the state "dead", unlike alternative methods such as time-trade off (TTO) or standard gamble (SG). So as to distinguish it from the standard EQ-VAS format, the revised format is referred to here as VAS.

2.1 Data collection

Cross-sectional data were collected using two online surveys of the UK general population. The first survey was conducted during Q3 2018 as part of the project Life After Prostate Cancer Diagnosis (Downing et al., 2016; Wright et al., 2019). A market research company was used to recruit a sample from their respondent pool which was representative of the UK population in terms of age and gender. The second survey was conducted during the first UK COVID-19 wave (Q2 2020). A market research company was again used for recruitment, with the sample being representative of the UK population in terms of age, gender and location as defined by first level Nomenclature for Territorial Units for Statistics (NUTS) regions. In both surveys, respondents answered questions about their own sociodemographic characteristics and health (including EQ-5D-5L). Participants rated two EQ-5D health states (11111, 55555) and dead on the revised EQ-VAS (Kind et al., 2004).

In the 2018 survey, prior to the VAS rating tasks respondents were asked to complete ten discrete choice experiment tasks in which they ranked two EQ-5D-5L states, the analysis of which is not presented here.

2.2 Data preparation

VAS responses with 55555 and/or dead rated better than 11111 were considered illogical and not included in the main analysis of VAS responses. A scale ranging from 0 (dead) to 1 (full health) was generated by transforming VAS responses for 55555 using the formula

$$VAS_{55555}^{rescaled} = (VAS_{55555} - VAS_{dead})/(VAS_{11111} - VAS_{dead}).$$

Rescaling VAS scores in this way can result in a small number of extremely low valuations for 55555, possibly as low as -500, which can skew results (Webb et al., 2020). To avoid this, rescaled values were censored at -1. This was chosen to make the minimum value of -1 symmetric with the maximum value of 1, and also to match the censoring point of the EQ-VT protocol (Oppe, Rand-Hendriksen, Shah, Ramos-Goñi, & Luo, 2016). As a robustness test, the analysis was repeated using -2, -1.5 and -0.5 as alternative censoring points.

2.3 Analysis

Data from the two surveys were pooled for analysis. Propensity score matching, as implemented in the MatchIt package for R, was used to match respondents with logical VAS responses in each survey using the following variables: sex, ethnicity (five groups), employment status (seven categories), school leaving age (below or above minimum age), degree or equivalent status (binary), EQ-5D-5L state, and number of long-term conditions (0 to 10). The nearest-neighbour algorithm was used to match individuals (Rosenbaum & Rubin, 1983). Individuals were excluded if their propensity scores were outside the common support, i.e. the range where the propensity scores from each sample overlapped (Garrido et al., 2014). We make the assumption that, after matching, differences in VAS responses between the 2018 and 2020 samples are largely caused by the COVID-19 pandemic. We return to this assumption and discuss its validity in section 4.1.

Differences in VAS responses for each of 11111, 55555 and dead between survey years were assessed using Mann-Whitney U tests. VAS ratings were also analysed using Tobit regressions, to account for responses being bounded at 0 and 100. Separate Tobit regression models were run with the VAS scores for each of 11111, 55555 (raw and rescaled) and dead as the dependent variables and respondent characteristics as independent variables along with survey year. To assess the level of multicollinearity between the dependent variables, the variance inflation factor (VIF) was calculated for each regressor. This is a measure of how much multicollinearity inflates a regression coefficient (Greene, 2012),. Tobit models were also estimated with interactions between respondent characteristics and survey year.

2.4 Robustness tests

We ran several robustness tests to examine the dependence of our results on various assumptions and analytical choices.

To ensure that discarding illogical VAS responses did not bias results, we repeated the analysis by instead treating illogical responses as missing values. These missing values were then replaced using multiple imputation, as implemented in the missForrest package for R (Stekhoven & Bühlmann, 2012), which generates replacements for missing values based on the distributions of observed data.

To test the dependence of results for rescaled values of 55555 on censoring values at -1, analysis of that dependent variable was repeated using -2, -1.5 and -0.5 as alternative censoring points.

To test the results' dependence on using the nearest neighbour algorithm in propensity score matching, an alternative algorithm was used to generate alternative matched samples, and the analysis repeated. Specifically, we used the genetic matching algorithm (Diamond & Sekhon, 2013), which may sometimes perform better than nearest neighbour depending on the data (Colson et al., 2016).

3. Results

3400 people responded to the survey in 2018 and 2328 in 2020. Table 1 summarises respondents' characteristics and Table 2 summarises measures of their health. A higher proportion of respondents in 2020 gave illogical VAS responses (14.5%) than in 2018 (6.7%), and both figures are higher than a similar exercise using EQ-5D-3L in which 5.3% of respondents gave illogical responses (Webb et al., 2020). In both 2018 and 2020, the samples including and excluding illogical VAS responses were similar, although individuals in worse EQ-5D-5L states and with more long-term conditions were more likely to be excluded. Relatively few respondents gave rescaled values for 55555 which were below -1, and were therefore censored, although similar to illogical VAS responses, there were more censored values in 2020 than in 2018. Respondents from 2018 were more likely to have a long-term condition and report being in a worse EQ-5D-5L state. They were also less likely to be employed or have a degree, and more likely to have left school at the minimum age.

Table 1 and Table 2 also summarise the samples after propensity score matching. The propensity scores of 10 respondents from the 2020 sample were outside the common support (i.e. the overlap of propensity scores from each sample) and were excluded, leaving 1,980 respondents from the 2020 survey matched with the same number from the 2018 survey. Standardised differences between the samples were small, with the largest being 0.061 for the proportion of respondents who left school after the minimum age.

Error! Reference source not found. compares histograms of VAS responses from the matched 2018 and 2020 samples, as well as giving the means, medians, standard deviations and interquartile ranges for each distribution. VAS ratings for full health were lower in 2020 than in 2018 (mean 89.9 vs. 94.0, $p<.001$), with fewer respondents scoring it between 95 and 100. Scores for dead were also lower in 2020 compared to 2018 (mean 10.4 vs. 11.3, $p<.001$). The pattern was reversed for 55555, with higher scores in 2020 compared to 2018 (mean 17.9 vs. 12.4, $p<.001$) and a reduction in the number of people scoring it between 0 and 5. For rescaled 55555 responses, the mean value was 0.050 in 2020 compared to -0.034 in 2018 (p<.001), with more respondents in 2020 scoring 55555 as higher than 0 (i.e. better than dead) compared to 2018 (68.2% vs. 47.9%, p<0.001).

Table 3 gives the results of Tobit regressions. For all models there is an effect of survey year, with 11111 being rated 9 points lower, 55555 being rated 10 points higher and dead being rated 7 points lower in 2020 compared to 2018. The rescaled values for 55555 were 0.09 points higher on average in 2020 compared to 2018 on a scale with full health=1 and dead=0.

Table 3 also gives the variance inflation factor (VIF) for each dependent variable. A VIF above 10 is commonly used as a rule-of-thumb to indicate serious problems with multicollinearity (Hair, Anderson, Thatham, & Black, 1995; Marquaridt, 1970; Neter, Wasserman, & Kutner, 1989; O'Brien, 2007). The only variables which exceeded this threshold were age and age^2, which were collinear by construction, with all other variables having a VIF below four.Table 4 contains the results of models with interactions between survey year and respondent characteristics. For the three raw VAS scores, the main effects of survey year are no longer significant, although note the coefficient for dead is relatively large at 17.4 and is significant at the 10% level. For full health, female respondents rated the state around 6 point higher in 2020, even though the overall mean score was lower compared to 2018. Participants in levels 2-5 for usual activities and anxiety/depression rated full health around 5 and 3 points lower in 2020 compared to 2018. Age significantly influenced differences in scoring of 55555 with older participants giving higher scores in 2020, although the rate of increase slows with age. For dead, several significant interactions with survey year were seen, with lower ratings in 2020 from female and white participants, and higher ratings from participants with a degree and in levels 2-5 for usual activities and anxiety/depression. With the rescaled responses for 55555, there was a significant main effect of survey year of -0.3 on the 0-1 scale. There was also a significant positive interaction of survey year with age, and significant negative interactions with age^2 and being in levels 2-5 for anxiety/depression.

The robustness tests of using multiple imputation to replace illogical VAS responses, using a genetic matching algorithm rather than nearest neighbour matching, and using alternative censoring points for rescaled 55555 responses are given in the appendix. Results are qualitatively unchanged.

4. Discussion

This article has presented evidence that how individuals value hypothetical health states may have changed during the Covid-19 pandemic. In 2020, individuals' VAS ratings for 11111 and dead were lower, and their ratings for 55555 higher compared to 2018. Ratings for 55555 were also higher after being transformed to a 0-1 scale. Only around 20 months separates the two surveys, and participants were matched on their demographics and self-reported health states. Thus it is plausible that COVID-19, a hugely significant health crisis which has impacted everyone's lives, has led people to re-examine how they value health, and what aspects of health are important to them.

There is evidence that COVID-19 may have influenced different groups' valuations in different ways. For example, although the overall rating of 11111 decreased by four points on average, female participants' ratings increased by six points. There is also an indication that the impact of COVID-19 on valuation may differ according to socioeconomic group, as proxied by educational attainment: Participants with a degree rated dead almost seven points higher in 2020 compared to 2018. It could be argued that differential effects are of most relevance for rescaled values of 55555, since if the effects on 11111 and dead cancel out, there would be limited implications for valuation. With rescaled 55555, the only demographic variable to have a significant interaction with survey year was age. Yet examining the confidence intervals in

Table 4 shows that meaningful effect sizes cannot be ruled out for several demographic variables. For example, on the full health=1, dead=0 scale, differential effects of survey year of -0.07 for female and -0.09 for having a degree cannot be ruled out.

The extra-welfarist framework of using general population value sets to guide healthcare resource allocation rests on the premise that values are reflective of the general public (Brazier, Ratcliffe, Saloman, & Tsuchiya, 2017). A differential impact of a health crisis across different social groups may bias valuations to an even greater extent than if the impact were uniform. Some social groups may see resource allocation decisions diverge from their values just as resources are most scarce, causing inequalities with those social groups whose values are less affected.

There was an influence of individuals' own EQ-5D-5L health status on their valuations of hypothetical states, for example, the downward shift in rescaled values for 55555 was even lower for people in anxiety/depression levels 2-5 compared to those in level 1. The two samples in this paper were matched using participants' responses to EQ-5D-5L, and this process is likely to have attenuated the effect of self-assessed health status on hypothetical health state valuations. Thus the results reported here are likely to be an underestimate of the impact of COVID-19 on the general population, since they do not take account of any additional shift in valuations due to their health state changing.

We are not aware of any previous research that has explored the impact of the pandemic on health valuation. In fact, other than short-term repeated measurement to test psychometric properties, there appears to be very little existing research that has explored the reliability or stability of health values for the general population over longer periods of time. The most obvious case in point is that of the UK EQ-5D-3L value set that is based on social preferences collected more than 25 years ago. There is a convincing argument for updating valuation sets periodically since health, population characteristics and expectations can change over time even in the absence of major health or economic shocks (Pickard, 2015). Research to date has been limited to a few studies of the stability of patient preferences (Auriemma et al., 2014) and of evaluations of health status over time (Cha, Law, Shaw, & Pickard, 2019), neither of which provide useful context for the current study.

Understanding how COVID-19 and other health crises affect how people value health is of great importance for health policy. Healthcare resources, always scarce, are even scarcer due to the pandemic, with tensions between COVID-19 care and caring for people with other conditions (Maringe et al., 2020). The financial fallout of the pandemic may also mean reduced health budgets in the longer term. Optimal allocation of resources is thus vital, yet it requires that the measurement of health benefits is established using values that represent the long-term average devoid of any short-run perturbation.

It is not possible to tell from the results presented here what aspects of COVID-19 are driving changes in hypothetical health state valuations. COVID-19 has affected everyone, but in different ways. Valuation differences may be affected by personal experience of the disease, by seeing a loved-one become ill, by the mental health impact of social isolation and worry, or by the knock-on effects of lockdown, for example reduced opportunities to exercise. Although we have controlled for current health status, we were not able to control for recent health changes. It is likely that the pandemic has affected health status and hence, although current health status of respondents is matched, it is possible that those in the COVID survey would have experienced a recent decrease in health status which may affect their values. It is conceivable also that alterations to hypothetical health state values are related to future health expectations given the pandemic.

If the shift in health valuation is a real effect of the pandemic, there are a number of significant implications, dependent upon whether those effects are transient or more permanent. The change may be short-lived, caused by the shock of the initial impact of the pandemic. It could also be medium term, lasting for the duration of the pandemic, or it could be a permanent shift. There are a substantial number of valuation studies planned and on-going, including national questionnaire valuation studies (both generic and condition specific measures) and other health preference studies (e.g. stand-alone TTO studies). If the impact of the pandemic on health values is transient, the values elicited from these studies may have a short shelf-life and, should they be used in HTA decision-making, lead to mis-allocation of resources. If the impact on values is more permanent, then existing value sets may need updating to reflect this.

The principal strength of this study is that data were gathered at an ideal time to assess the impact of COVID-19 on health valuation. It also used an elicitation method which allowed direct comparison with existing, available dataset collected using almost identical online survey methods.

VAS is not reflective of the methods most commonly used to construct general population value sets, and this study does not provide evidence that values elicited using alternative methods such as TTO or SG would be influenced by COVID-19. Nevertheless, both VAS and alternative methods such as TTO elicit individuals' underlying preferences, in which case the changes in VAS responses associated with COVID-19 documented here should also be expected to be observed in other exercises, regardless of the elicitation method used. Further investigation is required to examine what impact COVID-19 has had on health state valuation using methods such as TTO, SG and DCE. We believe that in the light of our findings, any claims that preferences elicited by an alternative method than VAS have not been influenced by COVID-19 should be treated with caution without supporting evidence.

4.1 Limitations

The importance of our results relies on the assumption that differences in VAS responses are caused by the COVID-19 pandemic. This assumption is supported by evidence that the 2018 and 2020 samples were similar even prior to matching, as evidenced by the small number of respondents outside the common support, and the matching procedure maximised the possibility of drawing causal inference. However, the matching procedure could only compensate for differences between respondents' observed, measurable characteristics, meaning that there are several other possible drivers of the results which it could not account for. The two surveys were not identical, as different recruitment strategies were used, responses were gathered at different times of year, and participants were told they had different purposes.

In 2018, participants completed a DCE prior to the VAS tasks, so they had more exposure to hypothetical EQ-5D-5L states than 2020 participants, and more experience interrogating their preferences for them (Campbell, Boeri, Doherty, & Hutchinson, 2015; Carlsson, Mørkbak, & Olsen, 2012). Participants being less familiar with EQ-5D-5L states in 2020 may have led to different VAS responses. The greater number of illogical responses in 2020 compared to 2018 could indicate that greater familiarity with EQ-5D-5L states led to less noisy data, rather than a change in participants' mean ratings. If this is the case, it would still be possible to measure the causal inference of COVID-19. On the other hand, Augustovski et al. (2020) demonstrate that performing a valuation task using one method can alter the valuations elicited by a subsequent valuation task using another method. In their case, a composite TTO task was performed prior to a DCE, and it is not certain whether a similar effect would be seen for individuals performing a DCE prior to a VAS task. Nevertheless it is a limitation of our results that we cannot rule out the prior DCE task significantly changing the ratings of 2018 participants.

It is possible that health preferences have changed in the two intervening years between valuation surveys independently of the pandemic. If this is the case, our results would still be of some importance, as they would raise major questions about the use of health state valuations in resource allocation, as value sets are assumed to have a shelf-life much longer than two years, for example the UK still uses values from over 25 years ago (National Institute for Health and Care Excellence (NICE), 2013)).

Even if the change in VAS ratings was related to COVID-19, the EQ-5D value sets used to guide resource allocation are usually constructed using TTO and/or DCE (Oppe et al., 2016). Individuals' VAS ratings of hypothetical health states do not necessarily imply a similar change to how individuals respond to TTO and DCE tasks, meaning the immediate policy implications are limited.

In addition, we present results for only two out of 3,125 EQ-5D-5L states, and for only one of those, 55555, do we have results on the full health=1, dead=0 scale. While 55555 plays an important theoretical role as the worst state in the EQ-5D-5L descriptive system, very few people self-report being in the 55555 health state.[3] It is not clear whether valuations of more common, milder health states have also been impacted by COVID-19. However, the VAS ratings of 11111 was lower in 2020 than in 2018, which may indicate that a similar decrease may have been seen for nearby states such as 12111 or 11211.

We do not claim that the results presented here constitute definitive evidence that individuals' valuation of hypothetical health states has changed due to COVID-19. However, given the observed results and importance of health state value sets, the burden of proof is on those using

[3] For example, none of the approximately 10,000 respondents to the 2017 Health Survey for England reported being in 55555 (University College London Department of Epidemiology and Public Health & National Centre for Social Research (NatCen), 2019).

recently generated value sets and those currently conducting valuation surveys to provide evidence regarding the potential impact of COVID-19.

4.2 Further research

Future research on whether and how values have changed due to COVID-19 is required, which will provide guidance for future crises. In general, changes in how health valuations change over time, both on an individual and population level, is a neglected topic, and is worthy of future investigation. Follow-up valuation surveys are needed to determine whether the impact of the current pandemic on health valuation is transient or is a more permanent effect.

Another future avenue of research is investigating whether there was a "dose-response", with greater changes in responses from individuals in more affected regions, or more at-risk from the disease. There is some suggestion of such effects in our results, given the significant age interaction terms, and that COVID-19 poses greater risks for older people. We do not explore such effects further here in order to emphasise changes to the values of the average population, which are most commonly used in health technology assessment (National Institute for Health and Care Excellence (NICE), 2013).

Further work is also required to explore the mechanisms through which health "shocks" or indeed other significant non-health factors such as Brexit, can affect the measurement of social preferences for health; qualitative research may help elucidate the driver of such changes. This in turn may ultimately help to design surveys to protect against transient shocks or allow for value adjustment.

5. Conclusion

This paper has presented the first evidence that the COVID-19 pandemic may not just have affected people's self-assessed health status, but also how they value health in general. The results do not provide conclusive evidence, and it is unknown whether any effect would be large enough to have meaningful relevance for policy or to influence economic evaluation in practice. However, this study raises serious questions as to the legitimacy of assuming that pre-COVID-19 health values are unchanged, and evidence should be required for making such a claim.

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Table 1: Respondent characteristics

		2018	2020	2018 - logical VAS	2020 - logical VAS	2018 - matched	2020 - matched	Standardised difference in matched data
Age	Mean (years)	47.7	46.8	47.8	47.5	48	47.5	-0.03
	18-24	9.41	12.2	9.46	11.3	7.93	11.4	
	25-34	17.6	17.2	17.6	16.7	18.9	16.6	
	35-44	15.2	15	14.7	15.1	16.1	15.1	
	45-54	21.7	20.1	21.5	19.5	20.9	19.5	
	55-64	17.2	13.1	17.6	13.2	15.5	13.1	
	65-74	15.1	18.6	15.4	20.1	17.1	20.2	
	75+	3.79	3.91	3.75	4.12	3.64	4.14	
Female		46	48.5	45.4	49.1	48.6	48.9	0.007
Ethnicity	White	91.3	88.1	91.4	88.6	90.6	89.1	-0.046
	Asian	3.59	4.6	3.59	4.57	4.24	4.6	0.017
	Mixed	2.15	1.85	2.11	1.66	1.31	1.62	0.024
	Black	1.68	3.44	1.64	3.47	2.27	3.03	0.041
	Other	1.26	2.02	1.26	1.66	1.62	1.67	0.004
Occupation	Employed	48.4	58.9	48.3	59.2	58.6	59.1	0.01
	Retired	22	21.3	22.2	22.7	23.8	22.8	-0.024
	Housework	8.97	6.49	8.95	6.18	6.31	6.21	-0.004
	Student	5.65	4.21	5.8	4.27	4.19	4.29	0.005
	Unemployed	6.79	4.08	6.72	3.82	3.69	3.84	0.008
	Missing	1.38	2.1	1.42	1.61	1.57	1.62	0.004
	Other	6.79	2.88	6.65	2.21	1.87	2.17	0.021
Education	Left school after minimum age	70.9	77.2	71.5	77.8	75.5	77.8	0.056
	Degree or equivalent	41.9	52.4	41.8	52.4	49.1	52.2	0.061
Gave logical VAS responses		93.3	85.5	100	100	100	100	
Censored rescaled 55555 value		4.06	5.41	4.35	6.33	4.14	6.31	
N		3400	2328	3172	1990	1980	1980	

Note. Figures are percentages unless otherwise specified. Standardised differences refer to differences in means between matched datasets divided by the standard deviation of 2018 data.

Table 2: Respondent health status

		2018	2020	2018 - logical VAS	2020 - logical VAS	2018 - matched	2020 - matched	Standardised difference in matched data
Mobility	Level 1	68.2	77.1	69.3	79.8	79.2	79.8	0.025
	Level 2	18.9	12	18.9	11.2	12.7	11.2	
	Level 3	8.85	6.53	8.26	5.78	5.35	5.81	
	Level 4	3.56	2.96	3.18	2.11	2.47	2.12	
	Level 5	0.471	1.33	0.378	1.11	0.202	1.11	
Self-care	Level 1	86.3	86.9	87.4	89.8	89.7	89.7	0.023
	Level 2	8.21	6.83	7.76	5.98	6.77	6.01	
	Level 3	4.29	4.55	3.85	3.12	2.78	3.13	
	Level 4	0.941	1.37	0.851	0.905	0.556	0.909	
	Level 5	0.265	0.387	0.126	0.201	0.152	0.202	
Usual activities	Level 1	66.7	76.5	67.6	79.9	79.6	79.8	0.03
	Level 2	19.7	11.8	19.7	11	12.6	11	
	Level 3	9.5	7.3	9.02	5.88	5.45	5.91	
	Level 4	3.29	3.22	3.12	2.46	1.82	2.47	
	Level 5	0.824	1.16	0.631	0.754	0.505	0.758	
Pain/discomfort	Level 1	41.4	55.9	41.9	57.6	55.8	57.4	0.001
	Level 2	35.6	26.5	36.2	26.8	29.7	27	
	Level 3	16	11.7	15.5	10.9	10.2	10.9	
	Level 4	5.38	3.99	5.14	3.32	3.28	3.33	
	Level 5	1.59	1.98	1.26	1.36	1.06	1.36	
Anxiety/depression	Level 1	48.6	53	49	55.4	56	55.5	0.047
	Level 2	26	22.8	26.3	22.8	25.3	22.7	
	Level 3	15.7	15.7	15.4	14.9	12.4	14.9	
	Level 4	6.26	4.98	6.12	4.12	4.24	4.09	
	Level 5	3.5	3.61	3.25	2.76	2.07	2.78	
In 11111		24.1	34.5	24.4	36.2	34.3	36.2	0.039
EQ-5D-5L utility		0.821	0.847	0.827	0.867	0.872	0.867	-0.028
Has long-term condition(s)		40.8	32.7	40.1	30.4	31.6	30.5	-0.024
Mean number of long-term conditions		0.796	0.625	0.777	0.574	0.577	0.576	-0.001
Own health rating (1=excellent,5=poor)		2.9	2.67	2.88	2.62	2.66	2.62	-0.039
N		3400	2328	3172	1990	1980	1980	

Note. Figures are percentages unless otherwise specified. Standardised differences refer to differences in means between matched datasets divided by the standard deviation of 2018 data. EQ-5D-5L utility values taken from Devlin, Shah, Feng, Mulhern, and Hout (2018).

Table 3: Results of Tobit regressions

	Full health	55555	Dead	55555 rescaled	Variance inflation factor
Constant	108*	12.8*	23.4*	-0.182*	
	(102 - 114)	(5.58 - 19.9)	(13.6 - 33.2)	(-0.301 - -0.0633)	
Age	-0.00658	-0.105	-0.338	0.00256	46.5
	(-0.263 - 0.250)	(-0.414 - 0.204)	(-0.764 - 0.0879)	(-0.00254 - 0.00767)	
Age^2	-4.73×10^{-4}	2.92×10^{-4}	0.00197	-1.97×10^{-5}	52.3
	(-0.00327 - 0.00232)	(-0.00310 - 0.00368)	(-0.00272 - 0.00665)	(-7.57×10^{-5} - 3.62×10^{-5})	
Female	-0.24	-1.27	0.322	-0.0107	1.01
	(-1.51 - 1.03)	(-2.80 - 0.268)	(-1.80 - 2.44)	(-0.0360 - 0.0146)	
White	4.03*	-3.77*	-9.86*	0.0535*	1.13
	(1.84 - 6.22)	(-6.41 - -1.12)	(-13.4 - -6.30)	(0.00938 - 0.0977)	
Employed	-2.93*	1.93	2.01	-0.00168	2.08
	(-4.77 - -1.09)	(-0.278 - 4.13)	(-1.01 - 5.03)	(-0.0380 - 0.0347)	
Retired	-1.98	1.76	1.48	-0.013	3.43
	(-4.72 - 0.766)	(-1.57 - 5.08)	(-3.11 - 6.07)	(-0.0677 - 0.0418)	
Left school after minimum age	1.77	-1.7	-4.09*	0.0127	1.5
	(-0.0512 - 3.59)	(-3.91 - 0.502)	(-7.13 - -1.05)	(-0.0236 - 0.0490)	
Degree	-0.402	1.11	1.25	0.00726	1.52
	(-1.96 - 1.16)	(-0.766 - 2.99)	(-1.35 - 3.85)	(-0.0236 - 0.0382)	
Mobility levels 2-5	-2.62*	3.49*	1.32	0.0368	2.04
	(-4.84 - -0.397)	(0.796 - 6.18)	(-2.40 - 5.04)	(-0.00783 - 0.0815)	
Self-care levels 2-5	-0.213	3.04	7.18*	-0.0369	1.75
	(-2.93 - 2.50)	(-0.245 - 6.33)	(2.70 - 11.7)	(-0.0918 - 0.0181)	
Usual activities levels 2-5	-0.181	2.61	1.76	0.0127	2.21
	(-2.50 - 2.14)	(-0.195 - 5.41)	(-2.10 - 5.62)	(-0.0338 - 0.0592)	
Pain/discomfort levels 2-5	2.36*	0.569	1.23	-0.0179	1.47
	(0.810 - 3.92)	(-1.31 - 2.44)	(-1.36 - 3.81)	(-0.0488 - 0.0129)	
Anxiety/depression levels 2-5	-0.472	0.223	0.318	0.00585	1.28
	(-1.91 - 0.965)	(-1.51 - 1.96)	(-2.08 - 2.71)	(-0.0228 - 0.0345)	
Number of long-term conditions	0.496	-0.522	0.738	-0.0121	1.58
	(-0.224 - 1.22)	(-1.40 - 0.354)	(-0.463 - 1.94)	(-0.0266 - 0.00243)	
Description of own health (1=excellent, 5=poor)	-2.56*	-0.298	-1.14	0.00885	1.57
	(-3.36 - -1.76)	(-1.26 - 0.665)	(-2.47 - 0.183)	(-0.00707 - 0.0248)	
Covid-19 survey	-8.57*	9.22*	-7.48*	0.0832*	1.02
	(-9.84 - -7.30)	(7.69 - 10.8)	(-9.60 - -5.36)	(0.0579 - 0.108)	

Note. 95% confidence intervals in parentheses; *=significant at 5% level

Table 4: Results of Tobit regressions including interactions

	11111	55555	Dead	55555 rescaled
Constant	100*	22.1*	8.07	0.0249
	(91.0 - 109)	(11.3 - 32.9)	(-6.27 - 22.4)	(-0.152 - 0.202)
Age	0.167	-0.547*	0.0362	-0.0052
	(-0.219 - 0.553)	(-1.00 - -0.0892)	(-0.572 - 0.645)	(-0.0127 - 0.00229)
Age^2	-0.00187	0.00589*	$-1.9\text{x}10^{-4}$	$5.06\text{x}10^{-5}$
	(-0.00603 - 0.00229)	($9.49\text{x}10^{-3}$ - 0.0108)	(-0.00677 - 0.00639)	($-3.04\text{x}10^{-5}$ - $1.32\text{x}10^{-4}$)
Female	-3.46*	-0.256	1.12	0.00904
	(-5.36 - -1.55)	(-2.53 - 2.01)	(-1.88 - 4.12)	(-0.0279 - 0.0460)
White	5.17*	-3.4	-5.76*	0.0233
	(1.92 - 8.43)	(-7.31 - 0.515)	(-10.9 - -0.612)	(-0.0411 - 0.0876)
Employed	-3.11*	1.93	0.959	0.000603
	(-5.83 - -0.390)	(-1.26 - 5.13)	(-3.24 - 5.16)	(-0.0512 - 0.0524)
Retired	-2.4	0.809	-1.96	0.0198
	(-6.46 - 1.65)	(-4.00 - 5.62)	(-8.31 - 4.39)	(-0.0585 - 0.0981)
Left school after minimum age	1.95	-3.23*	-1.68	0.00452
	(-0.659 - 4.57)	(-6.35 - -0.109)	(-5.78 - 2.42)	(-0.0463 - 0.0554)
Degree	-0.111	1.45	-1.78	0.0237
	(-2.37 - 2.15)	(-1.23 - 4.13)	(-5.31 - 1.75)	(-0.0197 - 0.0672)
Mobility levels 2-5	-3.47*	3.49	2.23	0.0208
	(-6.70 - -0.237)	(-0.345 - 7.33)	(-2.88 - 7.33)	(-0.0421 - 0.0837)
Self-care levels 2-5	-0.263	-0.103	5.69	-0.0414
	(-4.36 - 3.83)	(-4.95 - 4.74)	(-0.722 - 12.1)	(-0.121 - 0.0380)
Usual activities levels 2-5	2.33	1.31	-3	0.0352
	(-1.13 - 5.79)	(-2.75 - 5.38)	(-8.43 - 2.43)	(-0.0312 - 0.102)
Pain/discomfort levels 2-5	3.72*	0.352	-0.762	0.00256
	(1.47 - 5.97)	(-2.30 - 3.01)	(-4.28 - 2.75)	(-0.0406 - 0.0458)
Anxiety/ depression levels 2-5	0.838	-0.405	-1.69	0.032
	(-1.28 - 2.96)	(-2.92 - 2.11)	(-5.02 - 1.64)	(-0.00898 - 0.0730)
Number of long-term conditions	0.0572	-0.667	0.448	-0.00627
	(-1.08 - 1.19)	(-2.03 - 0.691)	(-1.34 - 2.24)	(-0.0284 - 0.0158)
Description of own health (1=excellent, 5=poor)	-1.76*	-0.694	-0.0617	-0.00374
	(-2.98 - -0.537)	(-2.15 - 0.762)	(-1.98 - 1.86)	(-0.0274 - 0.0200)
2020	3.46	-9.23	17.4	-0.272*
	(-8.50 - 15.4)	(-23.6 - 5.11)	(-2.06 - 36.9)	(-0.510 - -0.0347)
2020 x Age	-0.303	0.867*	-0.613	0.0140*
	(-0.818 - 0.211)	(0.247 - 1.49)	(-1.46 - 0.237)	(0.00370 - 0.0242)
2020 x Age^2	0.00282	-0.0111*	0.00313	$-1.30\text{x}10^{-4}$*
	(-0.00278 - 0.00841)	(-0.0179 - -0.00436)	(-0.00620 - 0.0125)	($-2.42\text{x}10^{-4}$ - $-1.83\text{x}10^{-5}$)
2020 x Female	6.36*	-3.06	-4.61*	-0.0214
	(3.76 - 8.96)	(-6.20 - 0.0819)	(-8.93 - -0.280)	(-0.0733 - 0.0306)
2020 x White	-1.38	-1.08	-8.39*	0.061
	(-5.76 - 2.99)	(-6.37 - 4.21)	(-15.5 - -1.32)	(-0.0274 - 0.149)
2020 x Employed	1.04	-0.264	1.39	-0.00268
	(-2.66 - 4.73)	(-4.67 - 4.15)	(-4.63 - 7.40)	(-0.0756 - 0.0702)
2020 x Retired	1.04	1.83	6.06	-0.0606
	(-4.44 - 6.52)	(-4.79 - 8.46)	(-3.07 - 15.2)	(-0.170 - 0.0487)
2020 x Left school after minimum age	-0.388	3.42	-3.92	0.00695
	(-4.01 - 3.24)	(-0.975 - 7.82)	(-10.0 - 2.15)	(-0.0657 - 0.0797)
2020 x Degree	-0.718	-0.746	6.85*	-0.0359
	(-3.82 - 2.38)	(-4.48 - 2.99)	(1.67 - 12.0)	(-0.0975 - 0.0258)
2020 x Mobility levels 2-5	1.91	-0.409	-3.2	0.0386
	(-2.52 - 6.34)	(-5.77 - 4.95)	(-10.6 - 4.18)	(-0.0506 - 0.128)
2020 x Self-care levels 2-5	0.561	5.43	0.888	0.0158

	(-4.92 - 6.04)	(-1.18 - 12.0)	(-8.05 - 9.83)	(-0.0945 - 0.126)
2020 x Usual activities	-5.04*	2.57	9.51*	-0.0417
levels 2-5	(-9.69 - -0.385)	(-3.02 - 8.15)	(1.85 - 17.2)	(-0.135 - 0.0512)
2020 x Pain/discomfort	-2.91	0.866	4.19	-0.0372
levels 2-5	(-6.01 - 0.193)	(-2.87 - 4.60)	(-0.953 - 9.33)	(-0.0989 - 0.0246)
2020 x Anxiety/depression	-2.90*	1.4	5.68*	-0.0583*
levels 2-5	(-5.78 - -0.0188)	(-2.08 - 4.87)	(0.900 - 10.5)	(-0.116 - -0.000774)
2020 x Number of long-term	0.74	0.12	0.439	-0.00972
conditions	(-0.725 - 2.21)	(-1.65 - 1.89)	(-1.96 - 2.84)	(-0.0390 - 0.0196)
2020 x Description of own	-1.54	1.3	-1.06	0.0203
health (1=excellent, 5=poor)	(-3.15 - 0.0690)	(-0.641 - 3.24)	(-3.71 - 1.60)	(-0.0119 - 0.0524)

Note. 95% confidence intervals in parentheses. *=significant at 5% level