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COVID-19 and Subjective Well-Being

Separating the Effects of Lockdowns from the Pandemic



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COVID-19 and Subjective Well-Being: Separating the Effects of Lockdowns from the Pandemic

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Scholars, journalists, and policymakers have raised concerns that lockdown policies implemented in response to the COVID-19 pandemic may be damaging to mental health. However, existing evidence for this claim is confounded by an inability to separate the mental health effects of lockdowns from those of the pandemic. We address this issue using one year of weekly mood surveys from Great Britain, together with weekly cross-country data from Google Trends. While we find a clear negative impact on mental health from the pandemic, lockdown measures are mostly associated with improvements in subjective well-being. Multilevel models, which estimate the changing effects among demographics by survey week, suggest the largest relative gains occurred among lower socioeconomic status groups.

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The YouGov-Cambridge Centre for Public Opinion Research is a joint research centre run by YouGov and the Cambridge University Department of Politics and International Studies, which promotes in-depth collaboration between survey practitioners and academic experts.

Suggested citation: Foa, R.S., Gilbert, S. and M. Fabian. (2020). “COVID-19 and Subjective Well-Being: Separating the Effects of Lockdowns from the Pandemic”. Cambridge, United Kingdom: Bennett Institute for Public Policy.

^aThe authors would like to thank YouGov for sharing the Great Britain tracking poll survey data, and in particular Joel Rogers de Waal for his timely data updates and commitment to the project, and Stephan Shakespeare for the consistent support provided to the YouGov-Cambridge Centre for Public Opinion Research. We would also like to thank Diane Coyle, Michael Kenny, Jonathan Wilmot, Pieter van Houten and other colleagues from the Bennett Institute for Public Policy for their feedback and comments on this manuscript.

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1 Introduction

The dramatic and widespread impacts of the COVID-19 pandemic make it imperative that we understand the efficacy of policy responses to it. Among the most prominent policies are “lockdowns” – mandated or voluntary stay-at-home and shelter-in-place orders that promote social distancing and reduce the spread of the virus. The evidence to date supports the view that lockdowns were good for *physical* health in that they reduced excess mortality associated with the virus (Hsieng et al. 2020, Flaxman 2020). However, the effects of lockdowns on *mental* health remains unclear. Most empirical studies to date are confounded by an inability to distinguish the effects of lockdown policies from those of the pandemic. In this study, we use one year of weekly survey data from YouGov’s Great Britain mood tracker together with global search data from Google Trends to overcome this issue. We find that while the *pandemic* had a large, negative impact on mental health, this occurred before lockdowns were introduced. Once lockdowns were in place, most countries experienced a large increase in subjective well-being (SWB). This effect remains robust to controls for mean reversion and progress in containing the virus outbreak. While the effects of lockdowns are mixed across aspects of mental health and heterogenous by demographic, we conclude that, overall, lockdowns appear to have been positive for mental health.

1.1 Literature Review

Studies published around the time lockdowns were implemented in the West raised concerns about the possibility of negative mental health effects, including loneliness, depression, and suicide (Brooks et al. 2020, Courtet et al. 2020). Some empirical studies of the effects of lockdown appear to bear out these concerns. Banks and Xu (2020), for example, find that mental health in the United Kingdom (UK), measured using the Good Health Questionnaire (GHQ-12), worsened by about 10% during the pandemic. Sibley et al. (2020) find similar effects for New Zealand. Zhang et al. (2020) found modest declines in SWB and worsening psychological distress in a Chinese sample. Gao et. al. (2020) and

Cao et al. (2020) found similarly mild effects in China using different measures.

However, other empirical studies have found mixed effects varying by aspect of mental health, and heterogenous effects by demographic. In the UK, using data collected after lockdown began, Fancourt et al. (2020) found that anxiety and depression did not worsen during lockdown. Bu et al. (2020), using the same dataset, found that lockdowns exacerbated loneliness among the already lonely but reduced it among the least lonely. Similar, though milder effects on loneliness were observed in a sample in the United States (US) by Luchetti et al. (2020). Returning to the UK, Brodeur et al. (2020) found increases in Google searches associated with loneliness, boredom, worry, and sadness during lockdown, but decreases in searches associated with stress, suicide, and divorce. In France, Recchi et al. (2020) found that SWB, operationalised using questions about whether respondents felt nervous, low, relaxed, sad, or happy, improved during lockdown. The exception was Parisians, perhaps because their lifestyles are defined by small apartments and a reliance on city life for entertainment.

A shortcoming of nearly all of these studies is an inability to distinguish empirically the effects of the pandemic from the effects of lockdown policies. They typically rely on measures of mental health taken well before the onset of the pandemic, and then follow-up surveys administered after lockdowns were introduced. For example, the studies using Chinese samples discussed above (Zhang et al. 2020, Gao et al. 2020, and Cao et al. 2020) all rely on data collected after the pandemic began. They have no reasonable counterfactual against which to measure changes in mental health, and must rely instead on people's own assessments. In studies utilising a counterfactual, such as Banks and Xu (2020) and Sibley et al. (2020), measures were taken before the pandemic and after lockdowns were announced, but not between the advent of the pandemic and the introduction of lockdowns. This confounds the effects of the two events. This is problematic for evaluating the impact of lockdowns as a policy response because the pandemic itself could reasonably be expected to have negative mental health impacts. Some commentators have wisely noted that mental and not just physical health should be taken into consideration when deciding when to lift lockdowns (Layard et al. 2020). In this con-

text, it is important that we assess whether lockdowns are in fact bad for mental health, otherwise we risk exacerbating the negative mental health effects of the pandemic by prematurely ending our main policy response to it.

We overcome the conflation of the effects of the pandemic with the effect of lockdowns by utilising weekly data from YouGov's Great Britain Mood Tracker poll and weekly reports from Google Trends. Our sample covers the year before the pandemic, the outbreak of the virus, and both the introduction and the relaxation of lockdowns. This allows us to differentiate, at least to some extent, the separate impacts of the pandemic and lockdowns on mental health and well-being. We find that the pandemic had a large, negative impact on mental health. However, this effect occurs before lockdowns were implemented and reverses once they are in place. While levels of boredom, frustration, and loneliness continued worsening after lockdowns came into effect, sadness, stress, and fear declined and happiness, optimism, and contentment increased. A comparison of countries with different approaches to lockdowns provides further support for our thesis. Notably, in cases where income support measures were implemented as part of lockdown policies (including the UK and US), suicide-related Google searches declined. On the other hand, where lockdowns were not accompanied by comprehensive income support, suicide searches increased.

Digging deeper, we find clear winners and losers from lockdown, in line with other studies that find heterogeneous effects by demographic (Webb-Hooper et al. 2020, Millet et al. 2020, Yancy 2020). The mental health of the elderly, professionals, and women living alone seems to have deteriorated during lockdown, even relative to the societal baseline. In contrast, the relative mental health of low socioeconomic status (SES) groups has improved, especially for low SES men. As low SES and being male are both major risk factors for successful suicide attempts (Nock et al. 2008, Pirkis 2017, Pittman et al. 2012), this improvement provides a partial explanation for reported falls in suicide rates in Japan, New Zealand, and several US states so far reporting data.

2 Data and Methods

2.1 The Great Britain Weekly Mood Tracker Survey

From June 2019 to June 2020, the polling company YouGov has surveyed the feelings and well-being of 1,890 to 2,071 respondents weekly across England, Scotland and Wales. Respondents are drawn from a panel of over one million British adults recruited since 2000, and selected so as to be representative by age, gender, social class and education (YouGov 2020).¹ A total of 99,719 respondents had completed this survey by the middle of June 2020, with additional surveys continuing to be conducted on a weekly basis. Individuals were asked to complete a shortened variant of the Profile of Mood States (POMS) battery initially developed by McNair et al. (1971) and subsequently refined by other scholars (e.g. Curran et al. 1995). This asked whether participants had experienced any from a list of positive and negative mood states during the past week: happiness, sadness, apathy, energy, inspiration, stress, optimism, boredom, contentment, loneliness, and fear (Watson et. al 1988, Heinrich and Gullone 2006, Westgate 2020). In addition, a total of 13,954 respondents from within these surveys also completed a variant of the 11-point Cantril Scale, to report their life satisfaction on a 0 to 10 scale with 0 being the worst possible level, and 10 the best possible (World Happiness Report 2019, Bjørnskov 2010, Cantril 1965).

2.2 Google Trends

To validate the YouGov Great Britain weekly mood tracker results and facilitate cross-country comparisons, data was collected from Google Trends, which enabled the relative popularity of Google searches to be analysed. Google Trends allows for a comparison of both search queries and ‘topics’ (clusters of related queries), and has previously been

¹In order to overcome the sample biases introduced by conventional sampling methods, such as random phone or doorstep polling, YouGov has built a unique mass panel from which it has steadily improved sampling accuracy over time. Of 453 survey projects rated by FiveThirtyEight in its latest assessment for quality and accuracy (Silver et al. 2020), YouGov is ranked level with Gallup in the top quintile (86th percentile rank).

applied to research questions in the fields of public health (Cho et al. 2013, Bragazzi et al. 2017, Husnayain et al. 2019), economics (Vosen and Schmidt 2011, Choi and Varian 2012, Preis et al. 2013) and political science (Mellon 2013). Data for Google Trends topics was acquired for eight English-speaking countries during the period from 30 June 2019 to 21 June 2020, corresponding to matching affective states in the YouGov weekly mood tracker: stress (‘psychological stress’), boredom, frustration, sadness, loneliness, feeling scared (‘fear’), apathy, happiness, contentment, energy, inspiration (‘artistic inspiration’), and optimism.

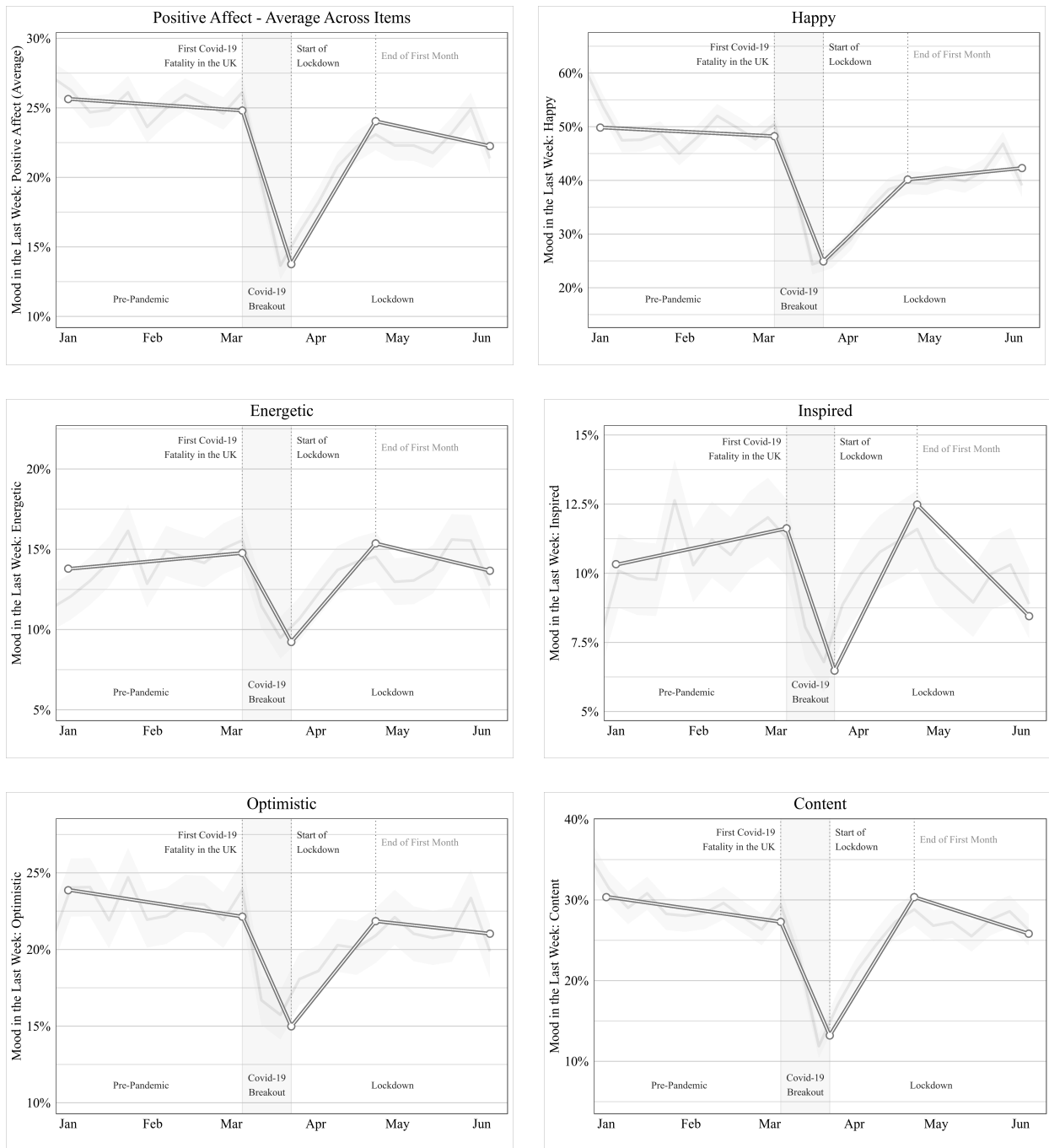
3 Descriptive Statistics and Trends

3.1 Survey Measures of Subjective Well-Being

Before constructing aggregative affect indexes for the purpose of statistical analysis, it is useful to begin by taking a brief overview of how the prevalence of specific mood states changed in the UK during different stages of 2020 COVID-19 pandemic. Positive affect states – happiness, energy, inspiration, optimism and contentment – show a very similar pattern (Figure 1). Levels were broadly stable before the crisis, fell sharply during the virus breakout in March, then reverted higher following the stay-at-home order. During the first month under lockdown, positive mood states returned to their pre-pandemic baselines, with feelings of inspiration, energy, and contentment seeing the greatest recoveries, then remained stable thereafter, with the exception of happiness levels which continued to recover.

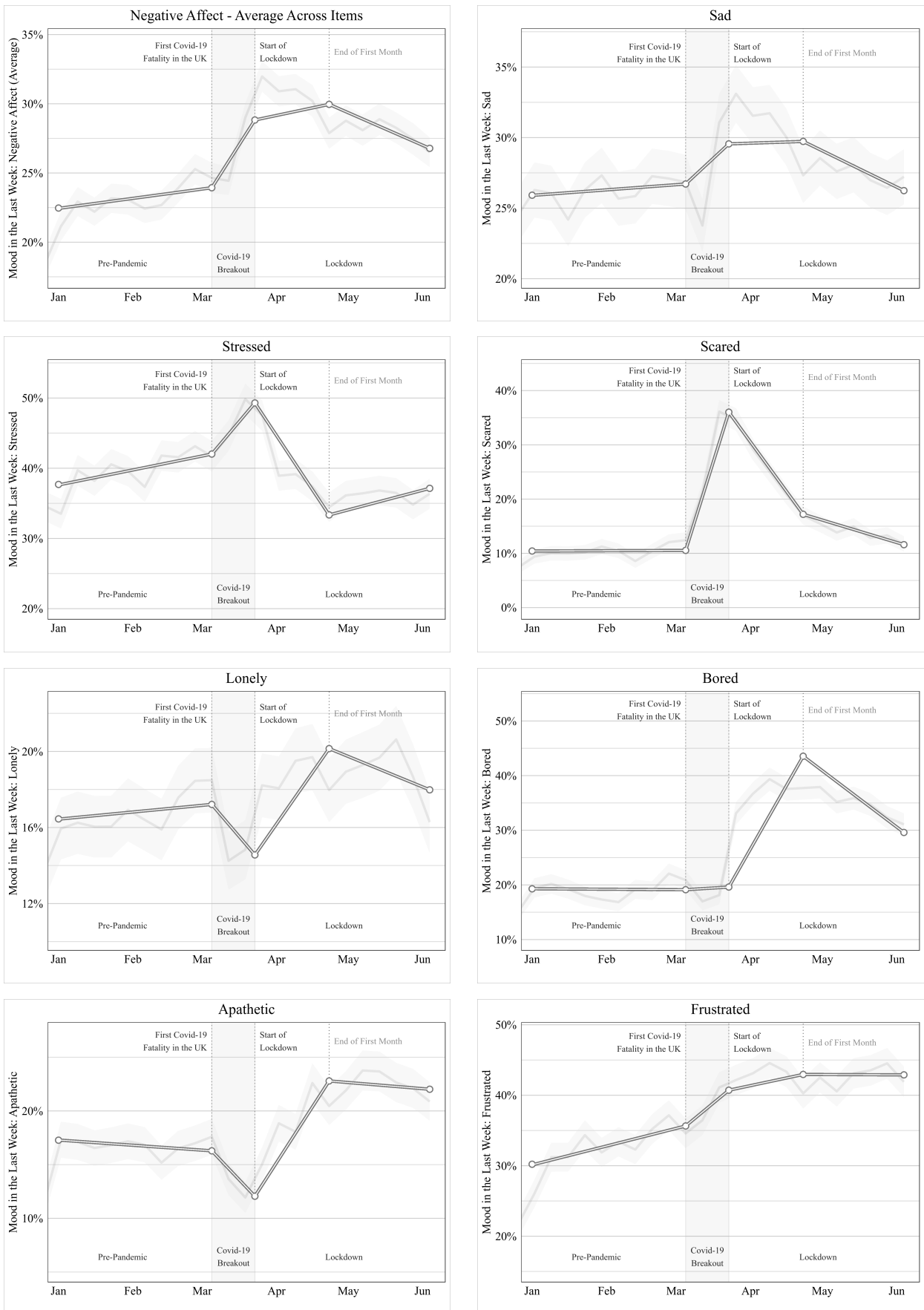
Negative mood states, by contrast, show more divergent trends. In the period of the pandemic breakout from 5 March to 26 March 2020, feelings of fear, stress, sadness, and frustration all rose, as individuals became attuned to the risks facing their health and livelihoods. However, there were also statistically significant falls in apathy and loneliness, consistent perhaps with the galvanising and solidarity effects of a major societal crisis.

Figure 1: Positive Affect Survey Items, January–June 2020.



Notes: Positive Affect Measures during 2020 surveys. Regression discontinuity slopes calculated by period using Ordinary Least Squares (OLS), using the previous period final estimate as intercept for the successive period. Also shown in the background are raw weekly averages and their 90% confidence intervals. Positive affect was generally stable in the period before the pandemic, fell markedly during the month of the epidemic breakout, and then recovered once lockdown began. Period of epidemic breakout from the first UK fatality (5 March 2020) to the announcement of the national lockdown (23 March 2020) highlighted.

Figure 2: Negative Affect Survey Items, January–June 2020.



Notes: Negative Affect Measures during 2020 surveys; see notes to Positive Affect charts.

The first month of lockdown brought substantial falls in anxiety and stress; indeed, stress levels after one month of lockdown reached their lowest levels of the year. In addition, sadness also fell, after reaching a peak during the first week of lockdown. However, feelings of loneliness, apathy, frustration and boredom spiked higher, and while boredom, sadness, and loneliness fell back again in the second month, frustration continued upwards.

3.2 Constructing Affect Indexes

Following Diener et al.'s (1985) suggestion that there are three separable components of SWB – positive affect (PA), negative affect (NA), and life satisfaction – we construct three corresponding indexes. Using the Positive and Negative Affect Scale (PANAS) as a guide (Watson et al. 1988), the first measure that we develop is a simple ‘positive affect index’, which takes mean average values for survey respondents’ reported positive mood states – happiness, energy, inspiration, optimism, and contentment. The second is a corresponding ‘negative affect index’ which takes average mentions from the list of possible negative states – sadness, apathy, frustration, stress, boredom, loneliness, and fear. Both indexes are calculated for the entire 50-week period for which data are presently available. At the individual-level these measures exhibit a strong correlation with Cantril scale life satisfaction ($R = 0.39$ and $R = -0.40$, respectively).²

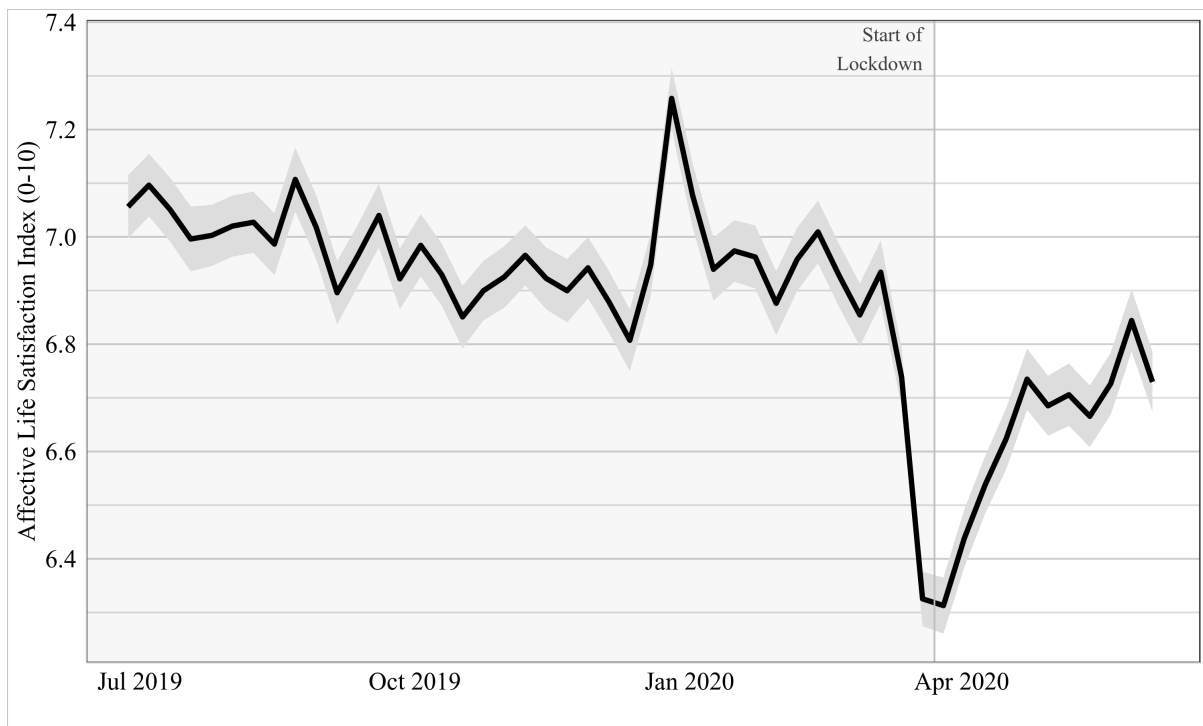
In order to produce an improved measure of respondent life satisfaction for the full series, we then further develop an Affective Life Satisfaction metric (ALS) using the individual mood states reported in the modified POMS question battery to estimate individual life satisfaction scores relative to the 11-point Cantril scale item. All independent effects had the expected polarities, and coefficients for imputation models are shown in Appendix Table A.1.³ The purpose of the ALS measure is to estimate that portion of life satisfac-

²This is despite a very large number of shared observations (13,954 respondents), which tends to compress estimates of Pearson’s R. For comparison, sociodemographic variables in the dataset correlate with life satisfaction at between ± 0.00 to ± 0.10 .

³The largest effect magnitude for predicting life satisfaction was the mood state response for feeling ‘happy’, which accounted for 24% of the total variance in Cantril scale life satisfaction that could be explained by the mood state indicators. Feelings of loneliness accounted for a further 13% of explained variation, followed by sadness (13%), contentment (11%), stress (9%), optimism (8%), apathy (7%), fear (4%), frustration (4%), energy (4%), boredom (3%), and inspiration (2%).

tion that is due to respondents' positive and negative affective states. As Cropanzano and Wright (2001) argue, SWB consists of both 'experienced' well-being – captured by affective states – and a cognitive component, typically referred to as 'evaluative' well-being, which the ALS does not directly measure. Nonetheless, the ALS provides a reasonably close empirical approximation of life satisfaction: individual mood states could be used reliably to predict Cantril Scale life satisfaction at the individual respondent level (13,954 observations; $R = 0.57$), by sociodemographic group (48 observations, $R = 0.88$; see Appendix Figure A.2), and almost perfectly in ALS-response clustered comparisons (63 observations, $R = 0.99$; see Appendix Figure A.1).⁴

Figure 3: Raw Series Trend: Affective Life Satisfaction, June 2019 to June 2020.



Notes: Mean scores by week, with 90% confidence intervals.

Using the ALS measure as a benchmark, how was the SWB of British residents affected by the COVID-19 pandemic of 2020 and the subsequent lockdown measures? Figure 3

⁴13,954 individuals that had answered both the profile of mood states battery and the Cantril scale (0-10) life satisfaction question were clustered into 63 groups, using their scores on the affective life satisfaction measure rounded to one decimal place. Values ranged from 2.4 (the lowest group cluster) to 8.6 (the highest cluster). The mean average surveyed Cantril scale life satisfaction response for each group correlated almost perfectly ($R = 0.99$) with their mean affective life satisfaction scores (R^2 of 0.97).

shows the change in affective life satisfaction in the UK from June 2019 to June 2020. A large and statistically significant drop in life satisfaction occurred before the implementation of lockdown measures, during the period from Thursday 5 March, when the first diagnosed COVID-19 death in the United Kingdom occurred, to Thursday 26 March, when lockdown measures began. In contrast to the view that lockdown measures contributed to a crisis of mental health, the low point for SWB was recorded only three days after the announcement of the ‘stay-at-home’ order, and on the exact day that police enforcement measures came into effect.

4 Cross-Country Comparisons with Search Data

The geographic scope of the YouGov weekly mood tracker is limited to a single country. But are its findings unique to the British context, or do they reflect a broader global trend? To enable cross-country comparisons, we supplemented British survey data from YouGov with Google Trends data on search-based equivalents of the affect measures for a wider range of cases. Starting from the United Kingdom, Pearson’s R correlations were calculated for each mood state and corresponding Google Trends topic during the 50-week period under observation, to determine how effectively the changes in surveyed affect were proxied by Google Trends topics. These results are shown in Table 1. With the exception of ‘loneliness’, Google Trends topics were found to be a good proxy for negative moods; yet a poor proxy for positive moods.

In order to confirm the validity of the data, ‘Related Queries’ were also qualitatively reviewed to check for the extent of false positives, i.e. search queries which are lexically related, but do not imply the corresponding mood state.⁵ False positives partially explained the weakness of Google Trends topics as a proxy for positive mood states.⁶ Of the negative moods, only the topic ‘apathy’ contained obvious false positives, though not

⁵Google Trends describes the concept of Related Queries as follows: ‘Users searching for your term also searched for these queries’.

⁶For example, the topic ‘energy’ contained queries relating to gas and electricity suppliers, while the topic ‘happiness’ included queries relating to ‘happy birthday’, presumably reflecting a UK government public health campaign encouraging citizens to wash their hands for as long as it takes to sing ‘Happy Birthday’ twice.

Table 1: Mapping of YouGov Mood States to Google Trends Topics

YouGov Mood State	Corresponding Google Trends Topic	R Value	Accepted as Proxy?
<i>Negative Affect</i>			
Stressed	Psychological Stress	0.46	Yes
Bored	Boredom	0.85	Yes
Frustrated	Frustration	0.65	Yes
Sad	Sadness	0.55	Yes
Lonely	Loneliness	0.01	No
Scared	Fear	0.49	Yes
Apathetic	Apathy	0.44	Yes
<i>Positive Affect</i>			
Happy	Happiness	-0.05	No
Content	Contentment	-0.41	No
Energetic	Energy	0.19	No
Inspired	Artistic Inspiration	-0.08	No
Optimistic	Optimism	-0.32	No

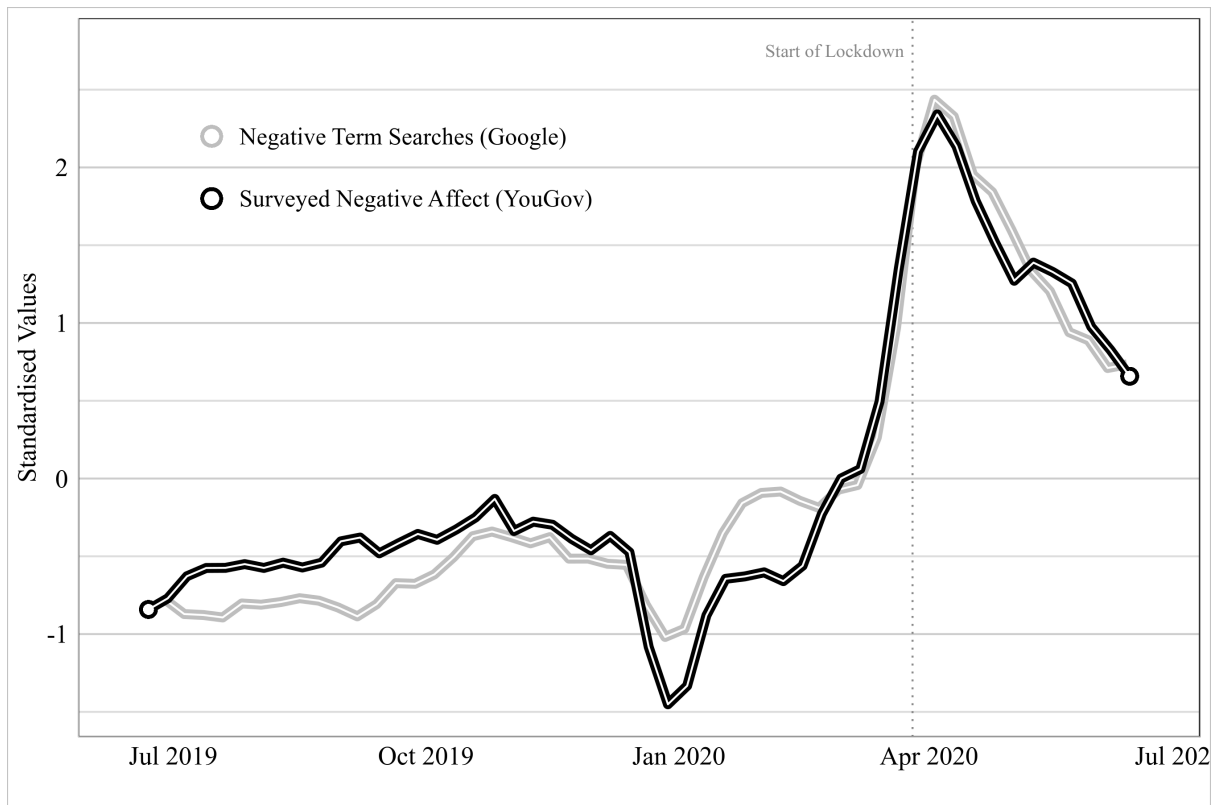
Notes: R-values calculated for the 50 shared weekly affective state observations in both the YouGov Mood Tracker survey and weekly Google search data.

sufficient to eliminate covariance between weekly apathy-related searches and surveyed apathy levels in the YouGov data.⁷

As Google Trends topics were a poor proxy for positive mood states, we base our cross-country comparisons on the ‘negative affect search index’, compiled from the standardized averages of the Google Trends topics for psychological stress, boredom, frustration, sadness, fear, and apathy. Weighting the Google Trends topics by their R^2 correlation coefficient with their matching YouGov survey mood state, a search-based negative affect index correlates highly ($R = 0.92$, $R^2 = 0.84$) with the sum of negative mood states reported in the weekly polling data series (Figure 4).

⁷Related Queries for apathy included esoteric searches such as ‘indifferent crossword clue’, yet substantive queries largely related to mental self-help and diagnosis.

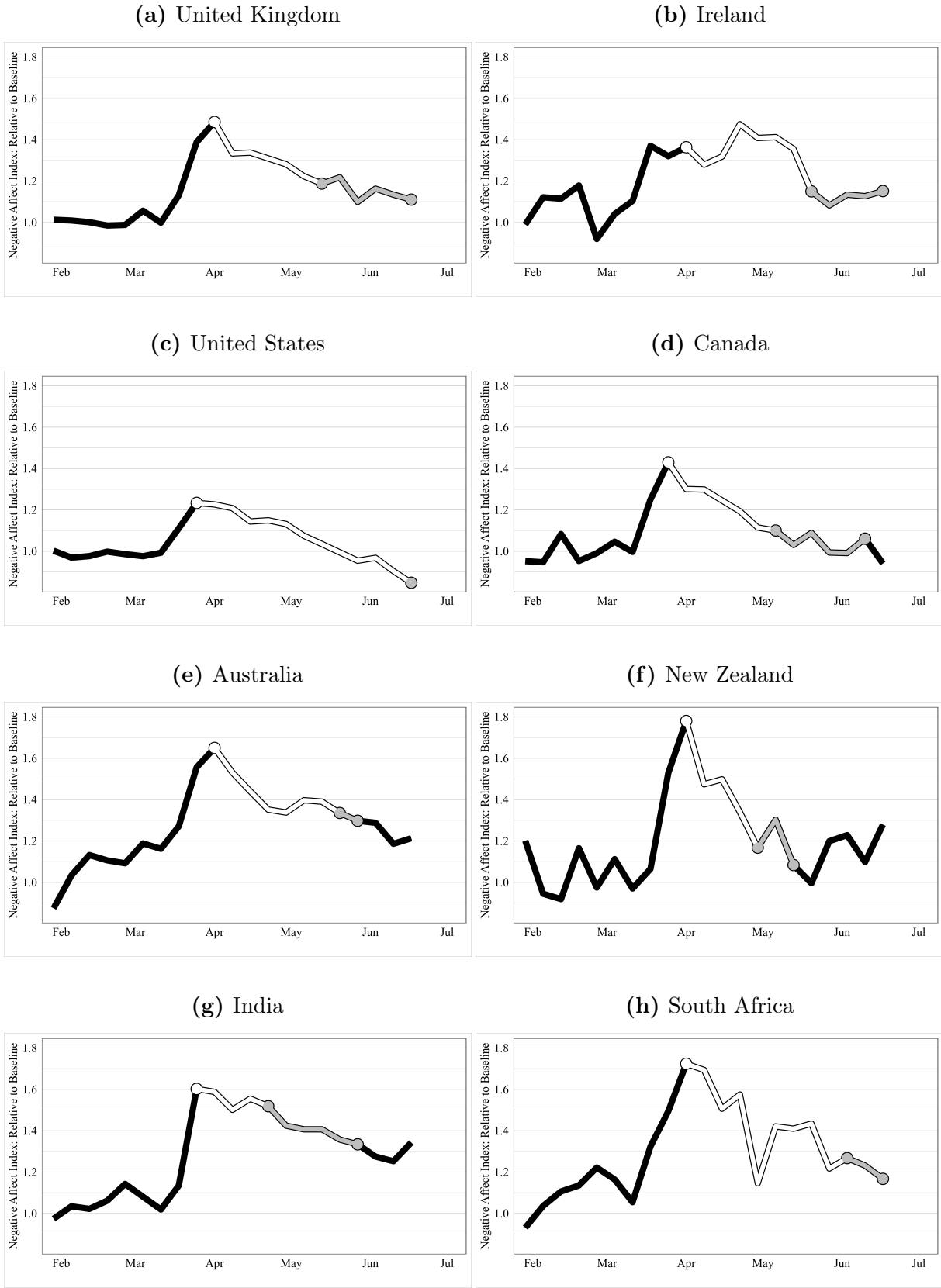
Figure 4: Comparison of Survey and Google Trend Series, June 2019 to June 2020.



Notes: Negative Affect Index is based on YouGov weekly polling data, for a representative sample of circa 2,000 respondents across England, Scotland and Wales (99,719 total). It comprises the sum of all negative affect states reported by respondents. The Negative Affect Search Index is based on Google Trends data for the United Kingdom, and includes corresponding matches for stress ('psychological stress'), boredom, sadness, feeling scared ('fear') and apathy, weighted by their R^2 correlation with their individual matching terms. A two-week smoothing function has been applied to the weekly data for both measures. Indexes standardised (mean 0, standard deviation 1) for comparison purposes.

Having constructed and validated a negative affect search index for the UK, we are then able to compare UK trends with those in other parts of the world. These comparisons are shown in Figure 5, which displays trends in the negative affect index in the UK together with a broader range of English-speaking countries: Ireland, Canada, Australia, the United States, New Zealand, India and South Africa.

Figure 5: Negative Affect Search Index and Lockdowns: Cross-Country Comparisons.



Notes: Cross-country comparisons on the negative affect Google Trends index. All countries set relative to their pre-pandemic baseline period (15 January to 15 February). Full lockdown indicated by white lines; partial lockdown indicated by grey lines. Dates of lockdown, partial easing, and return to work listed in Appendix Table A.2.

The observation found in the British weekly survey data – of a sharp decline in SWB before the lockdown as the COVID-19 pandemic accelerated, followed by a steady recovery after lockdown measures were put in place – is confirmed across a wide variety of English-speaking countries across the world. All cases experienced a spike in negative affect as the pandemic spread locally, and this appears synchronous with the country-specific timing of the outbreak. In Ireland, for example, the pandemic arrived much later than in other parts of the world, such that the peak in negative affect was reached only in mid-April; whereas in Australia, negative affect began rising already in February, as the country registered cases during Asia’s initial exposure to the virus. In India, a slow recovery of SWB during the lockdown period is consistent with the fact that new virus infections continued to spike higher in May and June. The implementation of lockdown measures coincides with a fall in negative affect across all country cases during April. As lockdown measures were gradually eased, SWB continued to improve, though with the return to ordinary economic activity further reductions ceased, and may even have partly reversed.

5 Estimating the Independent Effect of Lockdown Measures

5.1 Time-Series Cross-Sectional Models

While the descriptive trends outlined in the previous sections suggest a common pattern, additional tests are required to serve as a basis for reliable causal inference. First, further evidence is required that the timing of the negative affect spike (and its subsequent decline) across countries is associated with the country-specific timing of coronavirus outbreaks. Relatedly, the recovery of SWB during lockdown might be wholly explained by the pandemic subsidence, to which lockdown was only one contributor alongside behavioural change and rising population immunity (Pollán et al. 2020). Third, even if pandemic outbreaks are found to produce large increases in negative affect, we need to show that the return to baseline during lockdown was more than a simple ‘mean reversion’

to set-point levels of happiness, as this too would imply that SWB recovery was possible in the absence of emergency measures (Lykken and Tellegen 1996, Easterlin 2005).

To identify the independent effect of lockdown restrictions upon SWB, therefore, we estimate time-series models that control for the severity of the pandemic over time among countries for which comparative negative affect estimates can be calculated, as well as automatic mean reversion effects. Data on the severity of the COVID-19 pandemic is taken from the Johns Hopkins University Covid-19 Tracking Project (Dong et al. 2020). As there is wide variation between countries and over time in the quality and effectiveness of COVID-19 testing, we use a logged term for the rate of new daily COVID-19 infections per million. This functional transformation also helps to capture the most theoretically important aspect of pandemic outbreak, namely the transition from the pre-pandemic to the breakout phase.⁸

Models are then estimated in the form:

$$NA_{c,t} = \alpha + \beta_1 NA_{c,t-2} + \beta_2 NA_{c,t-4} + \beta_3 C_{c,t} + \beta_4 LD_{c,(t-l)} + \beta_5 E_{c,(t-e)}$$

Where $NA_{c,t}$ refers to the negative affect index in time t and country c , $NA_{c,t-2}$ to the two week lagged negative affect index in time t and country c , $NA_{c,t-4}$ to the four week lagged negative affect index in time t and country c , $C_{c,t}$ to the log daily new case diagnosis per million in time t and country c , $LD_{c,t-l}$ to the cumulative number of days $(t-l)$ since the onset of hard lockdown restrictions in country c , and $E_{c,t-e}$ to the cumulative number of days $(t-e)$ since the easing of lockdown restrictions upon small businesses and retail, by country. All models are estimated using robust standard errors clustered by country, so as to account for serial autocorrelation.

Our hypothetical priors in specifying these models are as follows. First, a substantial body of psychological research has debated whether following negative life shocks, individuals and societies revert naturally over time towards a psychological ‘set point’ (Sheldon and

⁸Because the log of zero cannot be estimated, we take the $\log(x + 0.1)$ rate of new daily infections per million population.

Lucas 2014, Inglehart et al. 2008, Foa et al. 2018). If so, reductions of negative affect during national lockdowns may not be due to the effect of such measures, but rather, due to a natural reversion process. We therefore design the models with a distributed lag structure including the four-week lagged dependent variable, so as to capture mean reversion effects. A positive coefficient for short term lagged affect together with a negative coefficient for longer term lagged affect would imply that, when longer-term negative affect is above the set-point level, this is naturally followed by a subsequent decline.

Second, lockdown measures imposed by governments are likely to have a range of differentiated effects upon SWB. Negative effects could include increased social isolation; loneliness; boredom; alcohol and drug abuse; economic insecurities related to small business closures and staff furloughs; a rise in relationship conflicts, divorces, and spousal domestic violence; and the burden placed upon parents by home schooling (Brooks et al. 2020, Craig and Churchill 2020, Wright et al. 2020). On the other hand, lockdown orders may have mental health benefits including greater work-life balance; a reduction in workplace and commuter stress; increases in remote worker autonomy; paid rest and recovery time for those on government support schemes; a broader sense of social solidarity (as demonstrated by Britain’s weekly ‘clap for the NHS’ or Italy’s ‘balcony concerts’); time for life perspective and mindful reflection; a reduction in social media consumptive status competition or ‘fear of missing out’; and an increase in long-distance reconnection between family and lifelong friends (Helliwell et al. 2014, Greenhaus et al. 2003, Mirchandani 2000). We therefore include two variables relating to lockdown measures in order to estimate their SWB effects. First, we count the cumulative number of days since the imposition of lockdown restrictions, including stay at home orders, home working protocols, and limitations upon gathering sizes and public events. This variable is scaled to increase cumulatively by the number of days since lockdowns were imposed, with the pre-lockdown period set to zero, and the post-lockdown period fixed at the cumulative number of days spent under lockdown as of its last effective day. Second, we count the number of cumulative days since the easing of lockdown impositions, considered as the point at which small businesses and retail employees could return to work (See Appendix

Table A.2).

Finally, our observation of descriptive time-series trends suggests that the severity of the pandemic itself is likely to play a role in reducing SWB, due to fears regarding family infection and illness, together with voluntary behavioural changes such as self-isolation by vulnerable populations, and changes in social activities and life plans among the broader population. A variable for log daily new cases per million of population is included, together with its interaction term with lockdown duration in some model specifications. Results across a range of specifications are shown in Table 2.

Table 2: Negative Affect Under Lockdown: Time-Series Models

Dependent variable: Negative Affect						
	<i>Sample frame:</i>					
	Since January 2020	Since Lockdown Onset	Since July 2019			
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Affect Index, Lagged 2 Weeks	0.57*** (0.068)	0.488*** (0.06)	0.264* (0.07)	0.251* (0.082)	0.563*** (0.056)	0.485*** (0.041)
Negative Affect Index, Lagged 4 Weeks	0.153* (0.044)	0.051 (0.05)	0.004 (0.061)	0.031 (0.066)	0.18** (0.061)	0.11** (0.027)
Days Under Lockdown, Cumulative	-0.003*** (0.000)	0.000 (0.001)	-0.005*** (0.001)	-0.006* (0.002)	-0.003*** (0.001)	-0.001 (0.001)
Days Since Easing, Cumulative	0.007† (0.002)	-0.001 (0.002)	-0.002 (0.001)	0.000 (0.002)	0.008*** (0.002)	0.000 (0.002)
Log Daily New Cases, Per Million	0.026* (0.008)	0.045** (0.01)	-0.021 (0.012)	-0.043* (0.015)	0.033*** (0.006)	0.05** (0.008)
Days Under Lockdown × Log New Cases (p.m.)	- -	-0.001*** (0.000)	- -	0.001 (0.001)	- -	-0.001*** (0.000)
Constant	0.392* (0.11)	0.594** (0.115)	1.172*** (0.147)	1.212** (0.19)	0.346*** (0.049)	0.519*** (0.078)
Observations	200	200	100	100	376	376
Adjusted R ²	0.577	0.619	0.59	0.603	0.634	0.666

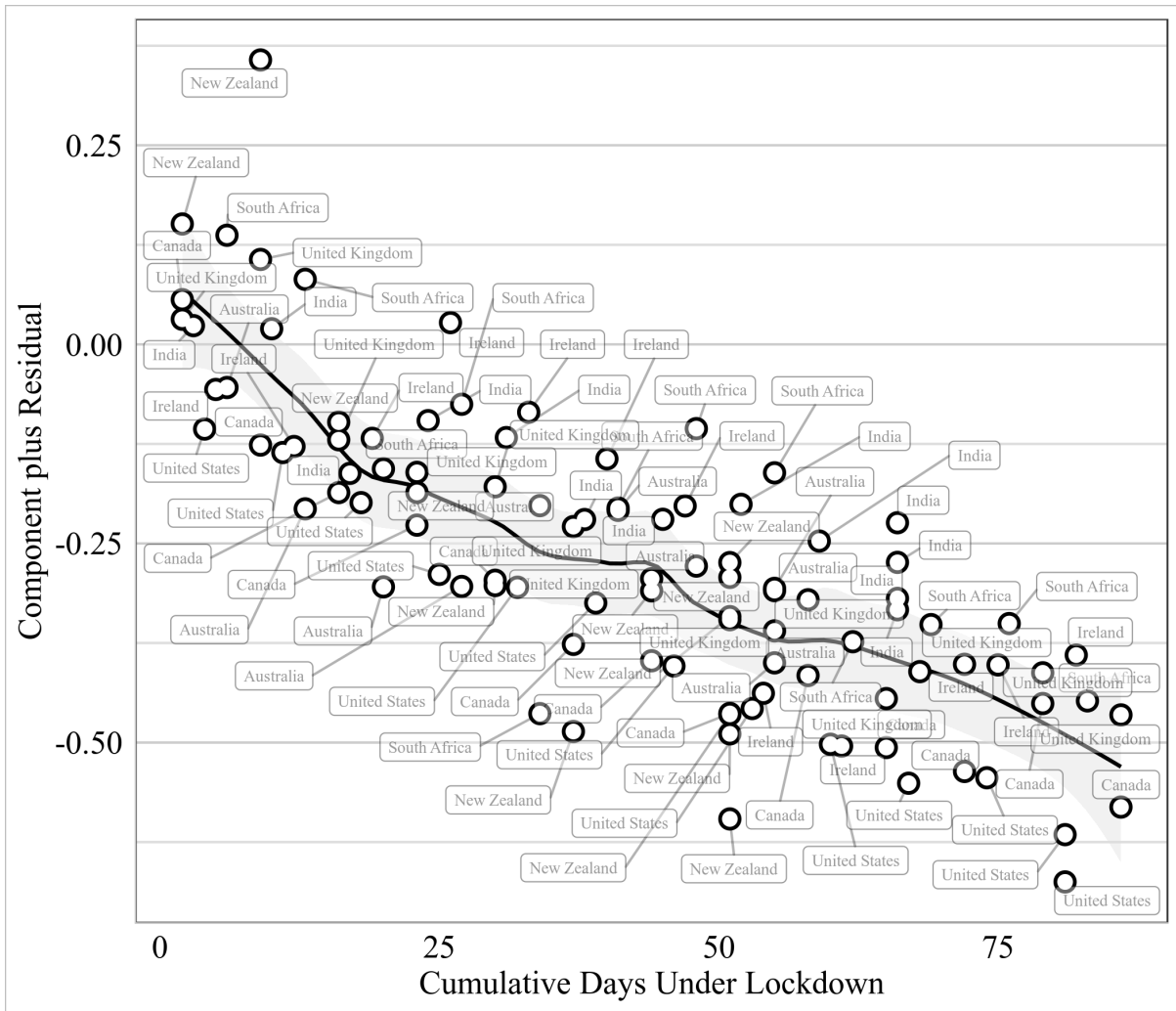
Notes: All models use robust standard errors, clustered by country. Country-fixed effects exist by default: negative affect indexes were standardised by country prior to use. Models are shown using three different sample frames: a) all observations in the dataset (since July 2019), b) all observations since the start of the lockdown period by country, and c) all observations since the diagnosis of initial cases in China (the start of 2020). †p<0.1; *p<0.05; **p<0.01; ***p<0.001.

The model coefficients suggest the following inferences. First, even controlling for pandemic severity, there is a strong positive independent association between time spent in lockdown and improvements in SWB, as measured by declines in the negative affect index. This effect is large, significant, and robust in most models. The exception is when time spent in lockdown is included with the interaction term for pandemic severity (log new cases per million population), in which case, their joint effect replicates that of the individual coefficient. The model coefficients suggest that a one-month period in lockdown reduces negative affect by around -9% relative to the baseline index level of 1 (Models 1 and 5), rising to -17% in models where the sample space is restricted to the period following lockdown onset (Models 3-4). This effect is further illustrated in Figure 6, which shows the independent association between lockdown duration and negative affect via a component-plus-residual plot.

Second, the results support the hypothesis that country-specific pandemic severity was the major contributor to increases in negative affect. The coefficient for log new cases per million is large and significant, such that an initial increase in pandemic severity from 0 daily cases per million to 10 daily cases per million (as occurred in New Zealand or Australia) raises estimated negative affect by 13.8% on average, relative to baseline, and by 20.7% in the case of an increase to 100 daily cases per million (as occurred in the United Kingdom; Models 1 and 5). Given the risks to public health and concerns regarding individual vulnerability, this result is not surprising. It also suggests that one of the most effective policy interventions for governments seeking to reduce the negative mental health consequences of the pandemic is to address the actual pandemic itself, before *secondarily* considering aspects of lockdown policy that may alleviate specific inconveniences to citizens' quality of life.

Third, the results offer tentative evidence that the effectiveness of lockdowns in improving SWB was conditional upon pandemic severity. Periods spent in lockdown with a higher rate of disease outbreak were associated with larger declines in negative affect than those concurrent with lesser outbreaks. This result is also intuitive in that one of the main mechanisms by which lockdown measures improved SWB was by giving citizens'

Figure 6: Component-plus-Residual Plot: Fall in Negative Affect During Lockdowns.



Notes: Controlling for natural mean reversion effects and the severity of the COVID-19 pandemic, negative affect is found to decline significantly during lockdown periods. Locally-estimated (loess) line of fit between points, with 95% confidence interval bound displayed. Regression coefficients used to estimate the component-plus-residual derived from Model 3.

confidence that the pandemic would be brought under control. The interaction term for lockdown duration and log new cases per million implies that a one-month period in lockdown is effective in reducing the rate of new infections from 71 to 51 per million (as occurred in the UK during the second lockdown month) reduces negative affect by an additional -13.2% relative to baseline, on top of the -5.5% effect that is produced from the change in the case severity coefficient alone (Models 2 and 6). By contrast periods in lockdown at very low levels of pandemic outbreak have limited, if any, estimated effect upon SWB.

Fourth, the results offer tentative evidence that the period of lockdown easing and economic normalisation is associated with a minor rise in negative affect. The estimated coefficients in Models 1 and 5 imply that two weeks following the return to work for small business and retail, negative affect rises by +0.1% relative to baseline. This effect is relatively minor, and most countries are still at an early stage of lockdown easing. Hence we do not yet know whether this effect will persist into the future, or eventually reverse as the initial backlog of economic activity clears.

Finally, we find little evidence to support the view that improvements in SWB during the lockdown phase were simply an automatic mean reversion effect, with citizens psychologically adapting to the “new normal” of increased health risk and mortality concerns. Even taking the most favourable results for this hypothesis, based upon the models that exclude pre-lockdown data (Models 3 and 4), the coefficient for four-week lagged affect remains positive. That is, there is no mean reversion evident here on a one-month rolling basis.

5.2 Multilevel Models on the Great Britain Mood Tracker

The models in the preceding section can assist in identifying how changes in SWB at a cross-country level independently covary with the pandemic outbreak and the ensuing lockdowns. However, while the models suggest a large negative effect during pandemic breakouts, and a counterbalancing positive effect under lockdown, they provide a limited basis for inferring the mechanism of action linking these with SWB. In this section, therefore, we use the YouGov weekly mood tracker to estimate multilevel models with random slopes and intercepts by week of observation for key demographic groups by age, gender, ethnicity, socioeconomic status, and other life circumstances. This allows us to parse out changes in SWB by group within Britain from July 2019 to June 2020.

Multilevel models are commonly used in longitudinal analyses where period-specific events or processes may alter the relationships between individual attributes and outcomes of interest (Skrondal and Rabe-Hesketh 2004, Singer and Willett 2003, Steele 2008, Wright

and London, 2009).⁹ With respect to causal inference, this approach has two merits. First, it allows us to adjudicate between competing hypotheses regarding how lockdowns affected society. For example, if the positive effects of lockdown were concentrated among home-workers while its negative effects were concentrated among those on furlough, this would be supportive of the hypothesis that work-life balance and the elimination of workplace commuting delivered mental health benefits, but also suggest that economic insecurity among manual workers had deleterious effects. Second, it allows us to separate the *sociotropic* effect of the pandemic upon subjective well-being, i.e. that effect (if any) which impacts upon all groups in society, from those which are *specific* to certain social and demographic categories alone.

We therefore estimate multilevel models according to the standard specification:

$$SWB_{ij} = (\beta_{0j} + X_{0j}) + \beta_1 A_{ij}$$

Where SWB_{ij} represents the score of subject i on the subjective well-being measure in period j , X_{0j} denotes the random effects design matrix consisting of ones in the first column (corresponding to the estimation of random slope intercepts) and second-level variables in the other columns, β_{0j} to the set of random slope coefficients for each time period j , A_{ij} to a matrix of first-level independent variables including a constant term, for which time-invariant coefficients are provided by the vector β_1 .

A full description of variables included in the fixed and random effects categories is provided in the descriptive statistics table (Appendix Table A.3).¹⁰ As noted, the second-

⁹In addition, the structure of our data is highly appropriate for advanced multilevel modelling, as with circa 2,000 observations drawn on a nationally representative sample within each of 50 observation weeks, this grants sufficient variation within and between weeks to enable relatively complex model specification among combinations of fixed and random effects.

¹⁰For reasons of model parsimony and computational efficiency, several variables were omitted from random slope estimation, following careful consideration of their necessity. First, investigation of regional trends over time found no significant differences among regions. These were therefore estimated only at the first level. Second, variables for (i) newspaper readership and (ii) 2016 EU referendum vote were found to have high covariance with variables for party political affiliation, thus only the latter were retained at level two. Finally random effects for household income were excluded, due to (i) high covariance with social grade AB ($R = 0.55$ among 99,719 observations), and (ii) the large number of non-responses to the household income question, which within smaller samples, may bias estimates for social grade – insofar as the differentiating factor between the two becomes willingness to report income, rather than its objective level.

level analysis groups variables by time for each of the 50 weeks of observation. Multilevel model fixed effect estimates are shown in Appendix Table-A.4, while model results for random slopes, estimated by week of survey, are shown in Figure 8 (for significant effects) and Appendix Figure A.3 (for other variables).

5.3 Specific Demographic Subjective Well-Being Effects

5.3.1 Sociotropic Effects

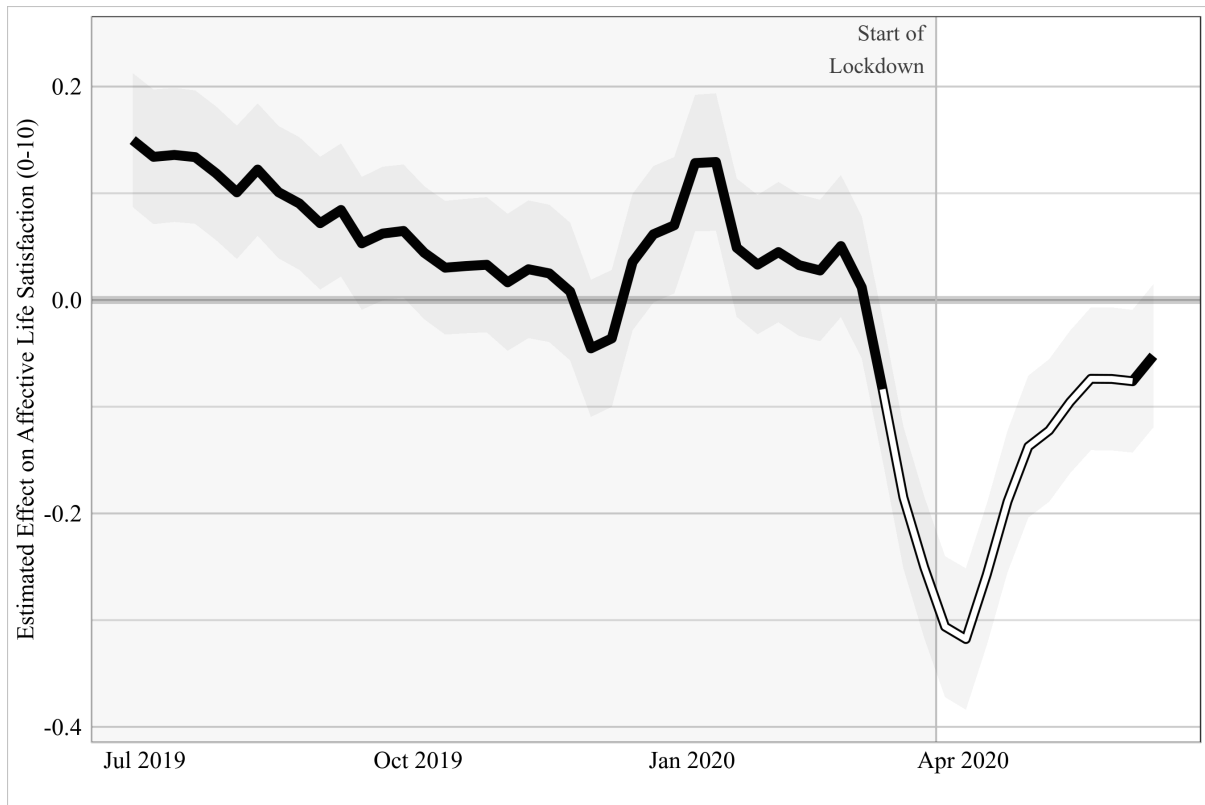
One of the salient research questions raised by the cross-country analysis is whether there is a sociotropic effect of lockdowns upon SWB, or whether instead the observed changes at the aggregate level are concentrated among key demographic groups, such as the elderly or infirm. To find answers, we examine the change over time in the random effects constant term, which tells us the proportion of SWB (if any) by period that cannot be specifically attributed to either the global constant (the fixed effect for all periods) or the effect associated with sociodemographic groups included as second-level terms. This is shown in Figure 7.

We find that the random slope intercept coefficient by week broadly follows the raw descriptive change reported in Figure 3. It exhibits a sharp drop in the initial phase of the pandemic outbreak in February and March. This is followed by a substantial rebound in affective life satisfaction during the April and May lockdown. The effect magnitude is somewhat lower than the shift in raw averages, with the random slope falling by over -0.4 from peak to trough, around half of the drop in the raw average trend shown in Figure 3. This implies that around half of the drop in SWB during the pandemic outbreak can be considered a sociotropic effect, with the rest concentrated among identified groups or the stochastic term.

5.3.2 Group-Specific Random Effects

Much of the literature on the mental health consequences of the pandemic has highlighted its differential impact across society. For example, increases in social isolation, loneliness,

Figure 7: Independent Period Effect, Controlling for All Demographics.



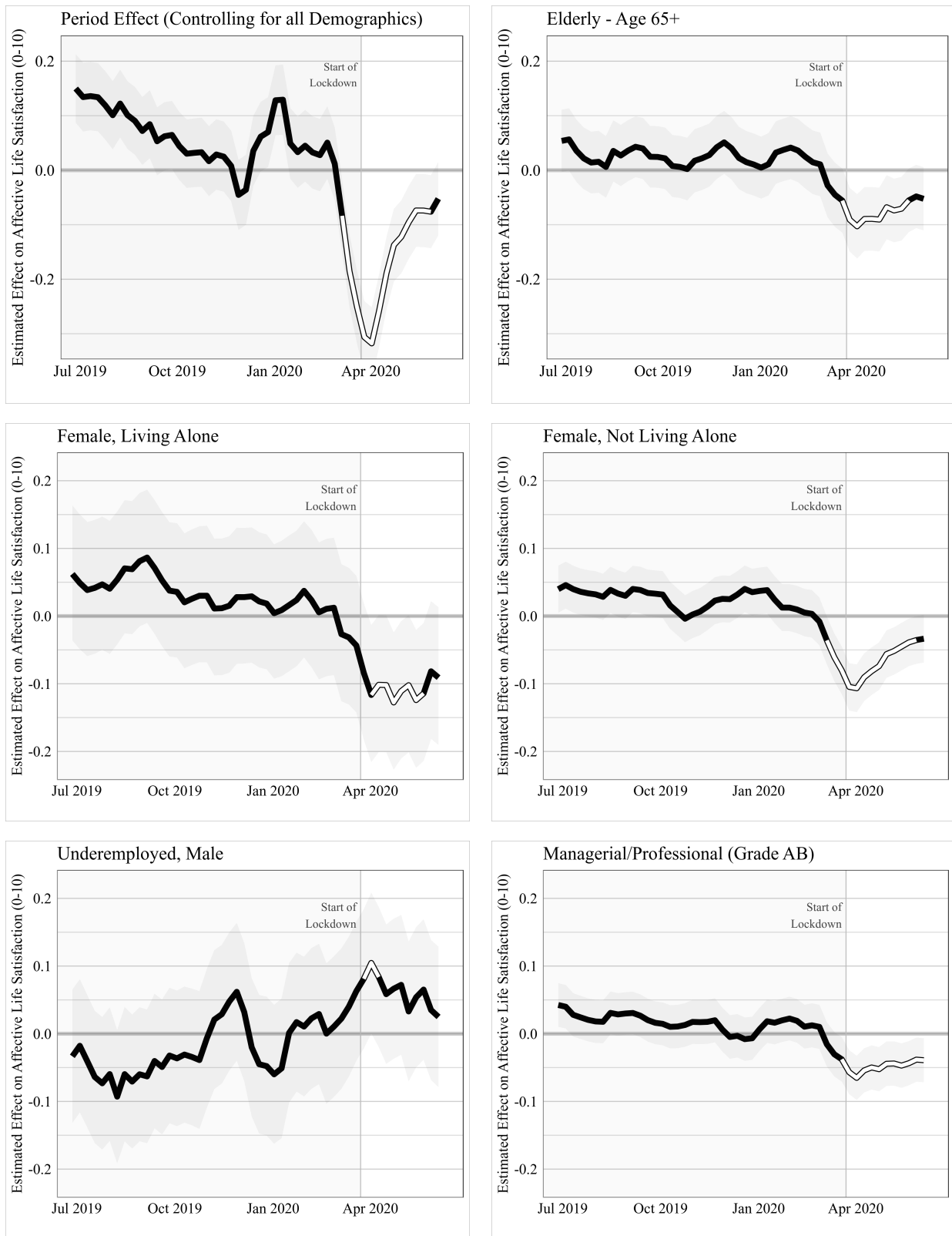
Notes: Multilevel model random slope intercept term for each time period. Rolling average slope over the two prior and succeeding weeks. 90% bootstrap estimated confidence intervals.

and boredom may especially affect the elderly and those living alone, while economic insecurities related to retail closures and employee furloughs disproportionately affect upon small business owners and staff. Meanwhile, lockdowns may have entailed particular hardship for women, due to the greater potential for domestic violence, and the unfair partition of responsibilities for childcare and home schooling (Lob et al. 2020, Collins et al. 2020). On the other hand, there may have been diffuse benefits for professionals seeking greater work-life balance, long-distance commuters, those able to benefit from government support schemes, and those previously suffering high levels of workplace stress (Recchi et al. 2020).

Sociodemographic group effects with statistically significant results during the COVID-19 pandemic are shown in Figure 8, and suggest the following inferences. First, elderly individuals (those aged 65 years and over) experienced a steady fall in life satisfaction as

COVID-19 transformed into a global pandemic during February and March 2020, and it became clear that older age-groups were especially susceptible to becoming symptomatic or dying. During the initial months of the lockdown (April and May), elderly citizens remained significantly below baseline well-being, before staging a partial recovery in late May and June. While it is possible that lockdowns may have disproportionately affected the lives of elderly individuals by cutting off contact with younger family members, the age-specific infection fatality rate of the novel coronavirus is a more likely contributor to this effect, which had already reached its peak before lockdown measures began.

Figure 8: Multilevel Model Random Effects for Key Demographics, by Survey Week:
Variables with Significant COVID-19 Period Effects.



Notes: Random effect slopes for socio-demographic variables, clustered by week of survey. Includes rolling average slope over the two prior and succeeding weeks. 90% bootstrap estimated confidence intervals. Periods with statistically significant positive or negative effects highlighted.

Second, underemployed individuals - that is, those of working age who are either unemployed, out of work but not in education or seeking employment, or working fewer than eight hours a week – showed a significantly positive relative effect in comparison to other groups. This effect was statistically significant for underemployed males during the start of lockdown, and remained positive throughout the period. Meanwhile, for underemployed females the effect is also large and positive throughout the lockdown period, even if it falls short of statistical significance (See Appendix Figure A.3). There are several possible interpretations of this finding. The first is that this constitutes a relative effect: as underemployed individuals were not subject to the same fears concerning employment security as those in work, SWB was resilient relative to the societal baseline. A second interpretation is that underemployed individuals have relatively lower income and consumption levels, such that the onset of lockdown measures entailed fewer changes to consumer spending or travel, and consequently, a reduced effect upon hedonic well-being. A third interpretation, however, is that the exceptional support measures enacted during the crisis – including delays to rental payments, temporary debt forbearances, and welfare reforms, including adjustments to the British government’s Universal Credit scheme – may have especially alleviated stress factors for groups living in precarity. A February 2020 study in *The Lancet*, for example, linked earlier changes in the Universal Credit scheme to a 6.6% increase in psychological distress among the unemployed from 2013 to 2018 (Wickham et al. 2020). During the pandemic, the Universal Credit scheme was expanded, its Minimum Income Floor requirements relaxed, rules regarding proof of an active work search removed, and a £500m Hardship Fund for low-income individuals established. The result of these changes very likely brought mental health benefits for welfare recipients. They also coincide with the timing of relative affective outperformance of underemployed Britons, in that exceptional income support measures were announced in March, the month before the start of the lockdown, and this is the point from which relative well-being improvements began.

Third, we find a corresponding significant negative effect among high social status groups (professionals and managers, classified as social grades A and B), whose relative affective

decline preceded the onset of lockdown measures, then remained stable and significant throughout. While the effect magnitude is relatively low (a circa -0.05 drop on a 0-10 point scale) the low standard error implies a fairly uniform decline. This may imply widespread boredom or stress as a result of having to uphold workplace duties from the domestic environment; or instead, be linked to a disproportionate decline in consumption of goods and services among higher socioeconomic status groups, a thesis to which we return in the next section.

Fourth, we find that the lockdown period negatively affected individuals living alone, though the effect is larger and only statistically significant for women. These effects persisted through the lockdown period, suggesting that limitation of social contact was a major contributor to the lockdown's negative mental health consequences. This is also confirmed by observation of the individual mood state trends, which show that while feelings of sadness, stress, and anxiety (fear) fell during the lockdown, loneliness increased sharply – at least, during its first month (See Appendix Figure 2).

Building on this observation, women in general (either with partners, family, or cohabiting) were more negatively affected by the COVID-19 pandemic than men. However, SWB declined during the month before lockdown, reaching its low point only as lockdown measures were introduced in late March. This again suggests that the pandemic outbreak rather than the lockdown was the main driver of increased negative affect. In the case of co-habiting females, affective life satisfaction recovered immediately from the start of the lockdown, and by the second month was no longer significantly below the societal baseline. The latter observation lends support to the hypothesis that deprivation of social contact as a result of lockdown measures had especially negative effects upon women's well-being during the pandemic.

6 Discussion

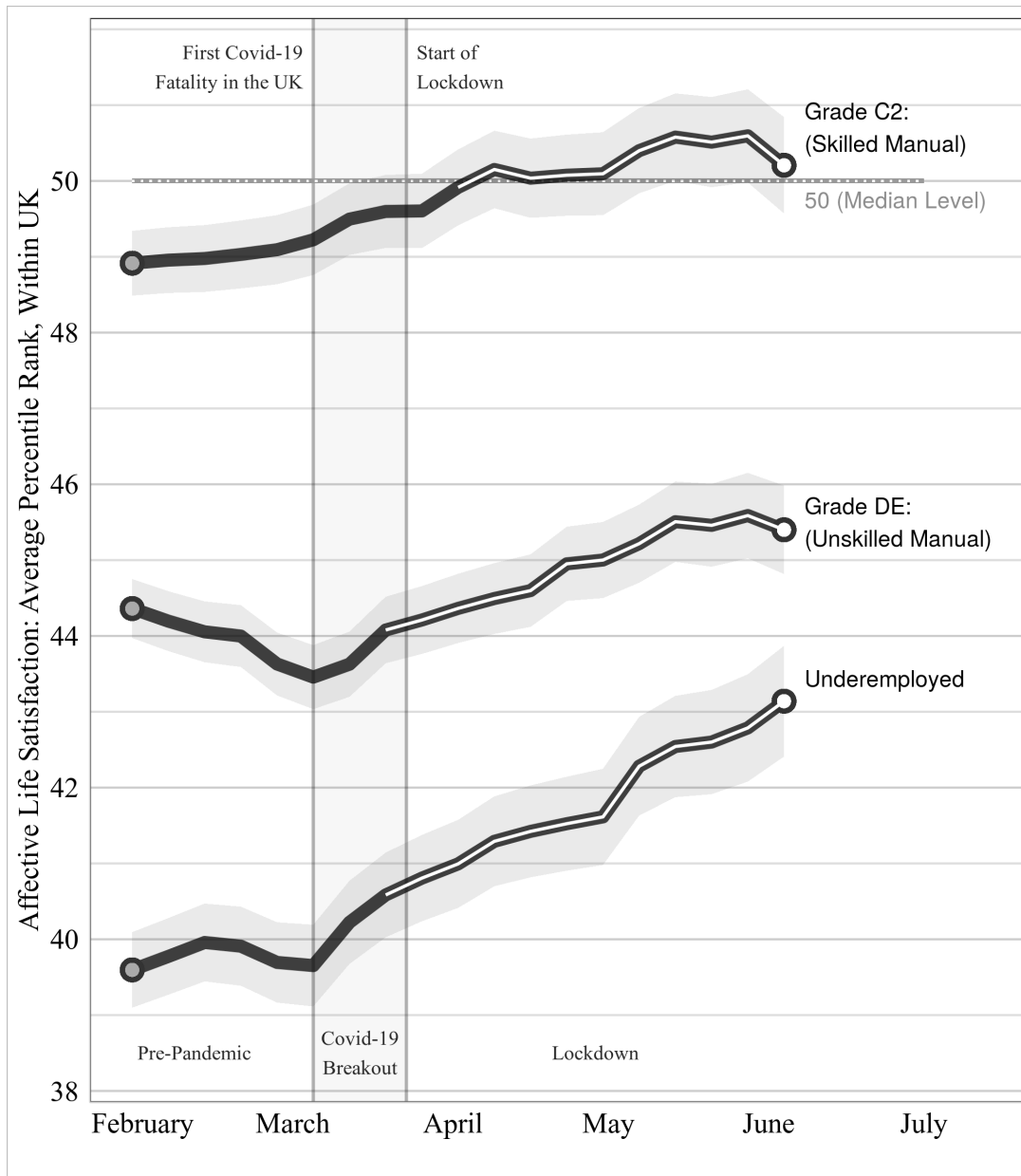
One of the most striking findings from the disaggregated analysis is that SWB inequality declined during the pandemic, as the relative well-being of high socioeconomic status

groups (social grades A and B) fell, while that of low socioeconomic status groups (in particular, the underemployed) rose. Given the differential impacts of COVID-19 upon lower income families and the obvious difference in household living circumstances between upper and lower income groups in society (Wright et al. 2020), this might appear surprising. However, on further reflection the result may not be so counterintuitive: after all, a wealth of literature has shown that relative income and socioeconomic status are strongly related to overall life satisfaction (Frank 2007). Indeed, this may be one of the most consistent and robust findings from 40 years of SWB research (Frijters and Mujcic 2012). It has also been found true in the United Kingdom (Boyce et al. 2010), including in the YouGov weekly tracking survey, which shows that before the pandemic those in the highest household income bracket scored a median of 7.44 on the affective life satisfaction measure (63rd percentile of the sample), compared to a median of 6.43 among those in the lowest income bracket (35th percentile).

The literature suggests two main mechanisms by which income affects SWB. First, a ‘hedonic’ explanation that focuses upon the translation of economic resources into utility through consumer spending (Stevenson and Wolfers 2013); and second, a ‘relative status’ explanation that emphasises the importance of income *position* in producing self-esteem, sense of accomplishment, and valuation by peers (Boyce et al. 2010, Frijters and Mujcic 2013). During the lockdown period, there has been a substantial increase in household savings rates, with an especially acute rise among high-income households due to constraints in the ability to consume services (such as travel, domestic care and cleaning, and recreational activities). One hypothesis is that the combination of limited consumption – and the limited conspicuousness of consumption – may have depressed well-being among high SES groups, while reducing feelings of relative deprivation among those unable to participate in similar consumption habits and lifestyles. In addition, relative inequality itself may have fallen, due to loss of income for landlords and business owners, combined with government welfare and income-support measures for the poor.

Our findings regarding socioeconomic status and relative well-being may also shed light upon another recent paradox, which is the apparent decline in suicide rates during the

Figure 9: Compression of Affective Well-Being Inequality: Low SES Groups.



Notes: Affective well-being is the affective life satisfaction measure. Highlighted portions of lines indicate a statistically significant difference since 5 March, the date of the first diagnosed COVID-19 fatality. Percentile ranks are calculated by respondent for each survey week. Shown are the average percentile ranks for individuals in each category, with a 10-week rolling smooth. 90% confidence intervals shown in gray.

2020 COVID-19 pandemic. A feature of public discourse about the well-being impact of lockdown policies has been concern about potential increases in suicide rates, supported by reported actual increases in demand for suicide prevention training courses, and significantly higher call volumes to mental health helplines (Guardian 2020, BBC 2020,

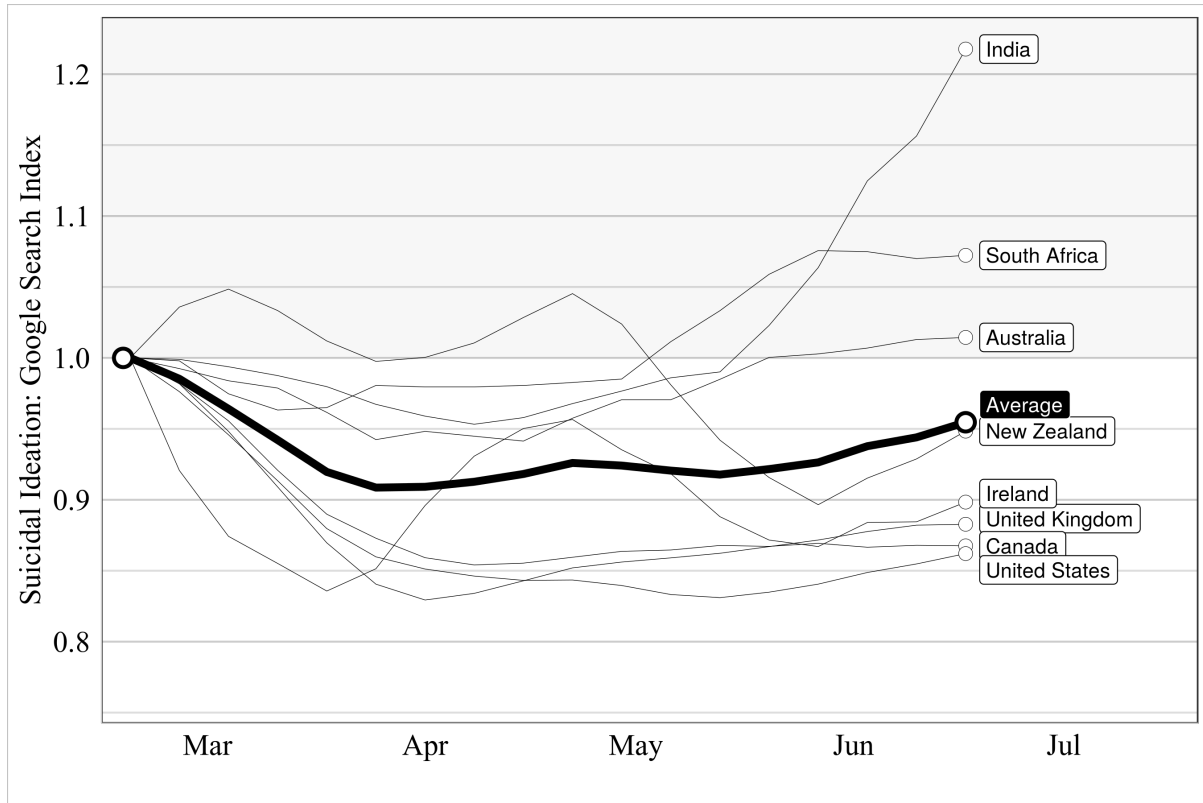
New York Times 2020). Furthermore, a previous study of suicide behaviour in the US in the period 1910-1920 attributed an increase in suicides to the Great Influenza Epidemic (Wasserman 1992).

However, while official statistics for suicides year to date in the United Kingdom are not yet available, early reports from other countries are ambiguous. In New Zealand, reports of a spike in suicides under lockdown were directly contradicted by the Ministry of Health, which reported that there was ‘absolutely no truth’ to the claim, without providing further information. In the United States, while New Hampshire reported year-to-date suicides to be flat on the previous year, Vermont and Idaho reported year-on-year declines, while Colorado reported a 40% suicide rate drop in March and April (Denver Post 2020). In Japan, suicides in April 2020 were down 20% on 2019, reaching their lowest level in five years. These observations are further supported by Google Trends data, which show a decline in interest in the topic ‘Suicidal Ideation’ in the majority of our country cases (Figure 10)¹¹. Such results are especially noteworthy as for northern hemisphere countries (Ireland, the United Kingdom, Canada and the United States) this decline runs counter to an established seasonal pattern whereby suicide rates rise in April and May (Maes et al. 1993).

Yet our analysis may assist in interpreting this paradox. While the majority of calls made to suicide helplines are by women (Gould et al. 2007), in Europe and the United States the vast majority (80%) of successful suicide attempts are made by men, especially men in lower SES groups (Nock et al. 2008, Pirkis 2017, Pitman et al. 2012). If the position of those in high SES positions worsened while that of low SES males improved, it could explain why suicide rates fell, despite a reduction of overall societal SWB. And this may carry important implications for reducing such ‘deaths of despair’ in future. In 2019, the UK reached its highest suicide rate in 17 years. This year, the exceptional welfare and income support measures introduced during the crisis – including supplementary benefits,

¹¹A qualitative review of Related Queries led us to reject the Google Trends topic for ‘suicide’, as it contained clear false-positives, such as ‘Suicide Squad’ (a film), ‘YNW Melly, Suicidal’ (a song), and ‘Suicidal Tendencies’ (a band). We found the topic for ‘suicidal ideation’ better reflected the search queries identified as predictive of actual suicides by Barros et al. (2019).

Figure 10: Trends in Searches Relating to Suicidal Ideation.



Notes: Rebased relative to mid-February. Two observations are especially notable: i) a decline in springtime suicidal ideation across the northern hemisphere, in contravention of established seasonal patterns; and ii) a steady rise in suicidal ideation in India and South Africa, which are countries with limited income support measures.

universal transfers, and debt forbearance – may have helped, thus far, to reduce status and income pressures on low SES individuals. The link from social support to mental health is supported by the outlier position of India and South Africa in Figure 10, where lockdowns were implemented with limited and patchwork social support mechanisms, and instead produced a steady rise in economic distress and suicidal ideation (Indian Psychiatric Society 2020).

7 Conclusion

We are still at an early stage of understanding the mental health impacts of the coronavirus pandemic, and the lockdown policies it entails. This paper does not provide definitive answers: rather, it serves as a preliminary contribution to a debate that will

continue in the months and years to come.

For now, we see four immediate avenues for further research. Firstly, there is a need for additional country-level survey panel data. While we have shown indices based on search data are a reliable proxy for negative affect, it is not possible to analyse changes in positive affect over time using Google Trends topics. Secondly, Google Trends-based analysis of negative affect should be extended to non English-speaking countries. This will require qualitative validation by native speakers of the robustness of Google Trends topics corresponding to negative mood states. Thirdly, as more comprehensive suicide data are released, both time series and disaggregated analysis will be required. Finally, as new data sources are synthesised, work will be needed to examine the subjective well-being effects not only of lockdowns, but of policies aimed at restoring normality to economic and social life.

However, the severity and urgency of the pandemic are such that even preliminary answers are of great importance to policymakers. At the time of writing, many governments are planning how lockdown easing should be phased. Meanwhile, in parts of the United States, southeastern Europe, Australia, and sub-Saharan Africa, other governments are re-imposing or tightening lockdowns to address renewed local outbreaks. Mental health implications are a significant consideration for policymakers as they weigh up both the costs and the social sustainability of further lockdowns. Concerns about adverse mental health consequences have been cited as reasons to delay or avoid these interventions; and yet, until now, few studies have systematically tested the hypothesis that lockdowns are bad for mental health.

This systematic testing has been the main contribution of this study. We have advanced on prior work by empirically distinguishing the effects of lockdown policies from those of the pandemic. By using survey data from Great Britain, combined with internet search data for a larger set of countries, we examined subjective well-being in the period before, during, and after both COVID-19 outbreaks and the imposition of lockdowns. While the pandemic had a large, negative impact on mental health, we find that lockdowns have

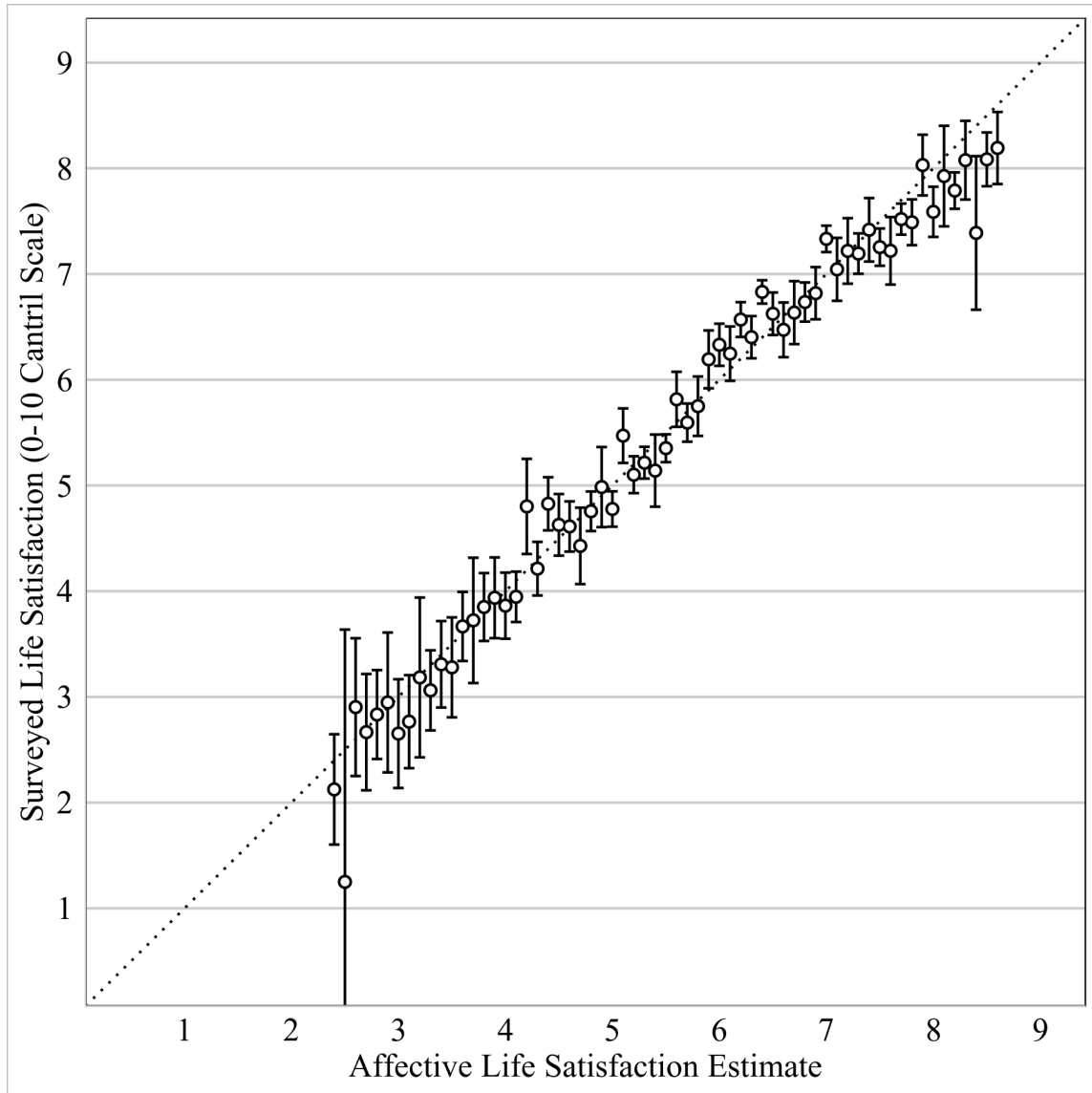
been associated with a large, positive effect on subjective well-being.

Our results suggest that in the context of COVID-19, the most effective measure governments can take to improve the subjective well-being of their citizens is to reduce the severity of the pandemic. Lockdown policies deliver this outcome. However, our cross-country results also suggest that subjective well-being improvements under lockdown are conditional on welfare and income-support measures, which alleviate distress among low socioeconomic status groups in particular. Winding down furlough schemes and other income support policies prematurely could be expected to reverse favourable trends in subjective well-being, potentially leading to an increase in suicide rates. At the same time, our demographic results show that the mental health benefits of lockdowns are unevenly distributed. When lockdown tightening is required in future, policies such as ‘support bubbles’ which reduce the rigidity of social distancing rules may help improve subjective well-being among the elderly and those living alone.

Finally, our results suggest a critical caveat and warning. If the exceptional support measures implemented under lockdown have been associated with a significant reduction in stress, anxiety, and negative affect among low SES groups, maintaining these improvements will depend upon the economic sustainability of government support and the capacity to return workers to stable and secure employment. Otherwise, lockdown easings may bring declines in mental health, and a renewed widening of well-being inequality. With the initial shock of the pandemic fading, it may only be after lockdowns end that the real mental health challenges begin.

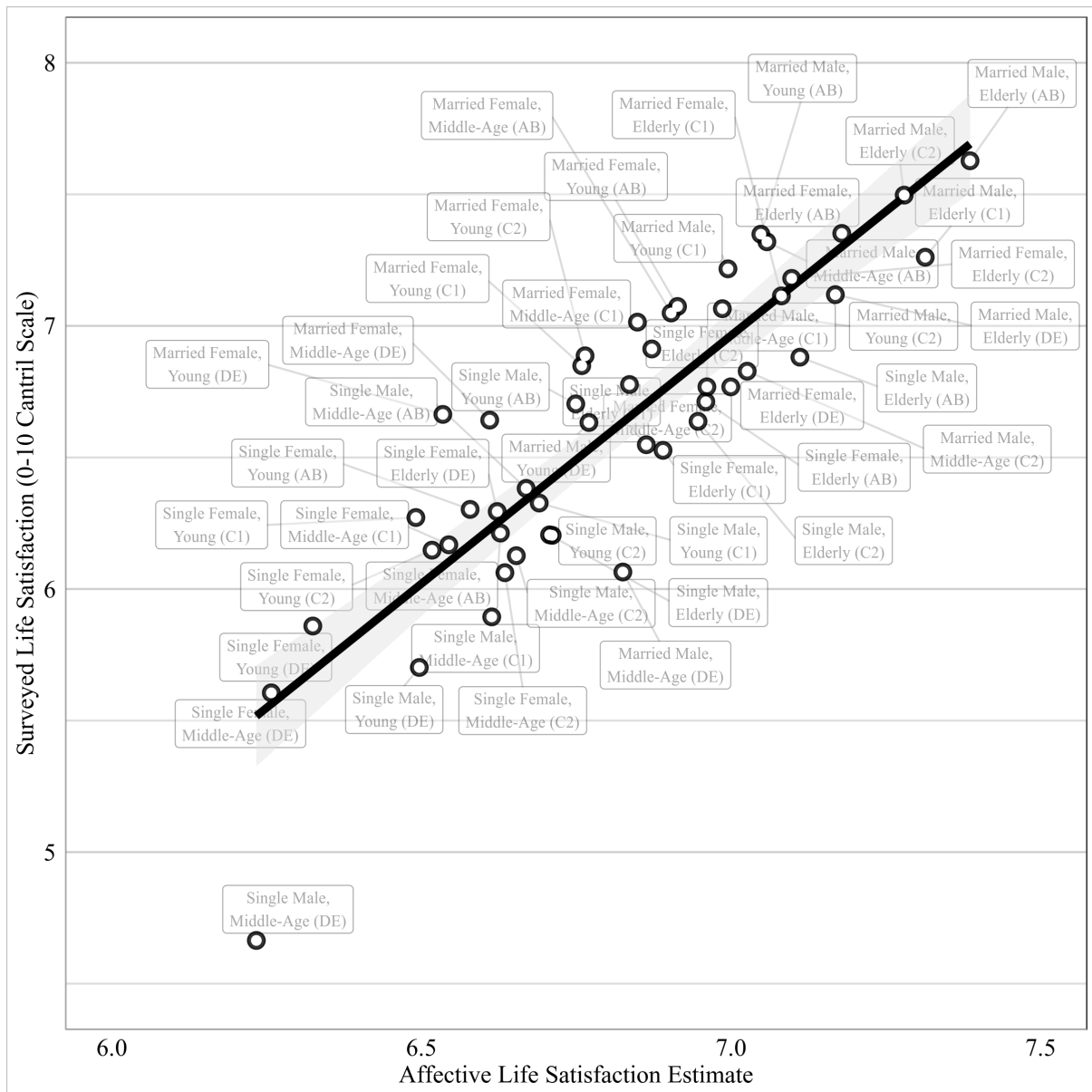
Appendix

Figure A.1: Validation of the Affective Life Satisfaction measure (ALS) and Cantril Scale Life Satisfaction Survey Responses.



Notes: 45-degree line on the chart indicates perfect equivalence. Mean scores shown by points, and the 95% confidence intervals for clustered observations on the Life Satisfaction Index measure.

Figure A.2: Validation of the Affective Life Satisfaction (ALS) measure and Cantril Scale Life Satisfaction Survey Responses, Using Sociodemographic Clusters.



Notes: Mean scores shown by points, with linear OLS line of fit and 95% confidence interval. $R = 0.88$. Clusters are defined based on aggregates for age, gender, socioeconomic status (social grades A-E), and relationship status (marriage or equivalent relationship vs. single).

Table A.1: Imputation of the Affective Component of Life Satisfaction

<i>Dependent variable:</i>	
Life Satisfaction: Cantril Ladder (0-10)	
<i>Positive Affect States</i>	
Happy	0.637*** (0.018)
Content	0.305*** (0.017)
Optimistic	0.207*** (0.018)
Energetic	0.095*** (0.018)
Inspired	0.042** (0.018)
<i>Negative Affect States</i>	
Lonely	-0.347*** (0.017)
Sad	-0.336*** (0.019)
Stressed	-0.240*** (0.019)
Apathetic	-0.175*** (0.015)
Scared	-0.105*** (0.017)
Frustrated	-0.096*** (0.017)
Bored	-0.091*** (0.015)
Constant	6.878*** (0.017)
Observations	13,954
R ²	0.320

Notes: Standardised coefficients. *p<0.05; **p<0.01; ***p<0.001.

Table A.2: Coding of Lockdown, Easing, and Return to Work Policies.

Country	Lockdown	Initial Easing	Normalisation Phase
United Kingdom	26 March. Prime Minister announces stay at home order evening of 23 March, and on 26 March police enforcement powers come into effect.	13 May. Stay at home order is relaxed, allowing small groups to meet, followed by further easing on 15 June, as non-essential shops are allowed to reopen.	4 July. Reopening of bars, restaurants, hotels, theatres, museums, leisure centres, outdoor gyms, places of worship (for congregations), and hairdressers.
United States	21 March. Date of maximal restrictions, according to OxCGRT dataset. However stay at home orders are issued on a state by state basis between March and April 2020.	15 June. Date of eased workplace restrictions in OxCGRT dataset, allowing retail activity to resume. However there is variation state by state, as in many cases stay at home orders expire one month after proclamation.	6 July. Many states (e.g. New York, Massachusetts) begin business re-opening, including bars and restaurants. Some states reopen in late June, while others delay reopening due to second wave concerns.
Australia	30 March. On 23rd, closure of pubs, cafes and restaurants. 29th – gatherings limited to two persons. 30th – states announce new public health orders to enforce stay at home rules.	15 May. New South Wales, Queensland allow bars and restaurants to reopen; Tasmania and South Australia already on 11th, but Victoria only June 1st.	1 June. Further wave of easing begins, with reopening of hairdressers, cinemas, and retail in Western Australia, Queensland, New South Wales. Staggered later in the month in Victoria and Tasmania.
New Zealand	26 March. On the 24th, government announces stay at home order, to commence midnight 25th.	28 Apr. Easing begins by allowing greater work travel, visitation of partners, takeaway deliveries and limited retail reopening.	14 May. Stay at home order ends, and hairdressers, retail, office work, restaurants, cinemas and gyms reopen. Bars reopen 21 May.
Ireland	27 March. Taoiseach announces stay at home order.	18 May. Stay at home order eased, outdoor workers and shops allowed to resume.	29 June. Bars and restaurants, churches, and retail reopen.
South Africa	26 March. ‘State of disaster’ declared 15 March, but lockdown only announced 23 March, to begin 26 March.	1 June. Stay at home order eased, reopening of mining, manufacturing, construction, and retail.	-
Canada	23 March. Ontario, British Columbia, and Alberta begin initial restrictions on 17th (Quebec on 13th), increasing over time. Enforcement powers begin 26 March - 2 April.	4 May. Quebec and Ontario begin retail reopening on 4 May, with Maritime Provinces doing so prior week and British Columbia later in May.	12 June. Ontario begins reopening bars and hairdressers, Quebec 25 June, while British Columbia began in mid-May.
India	22 March. Initial stay at home order announced for 14 hours, subsequently extended to (initial) 21 days on 24 March.	20 April. Self-employed professions, some retail, farming and transport allowed to reopen. Stay at home directive relaxed 4 May.	8 June. Workplace restrictions begin to ease 1 June, with further easing and resumption of public services on 8 June, when Prime Minister declares lockdown “over”.

Notes: Lockdown orders in Australia, Canada and the United States are implemented on a state-by-state basis, with varying degrees of central government coordination. Oxford COVID-19 Government Response Tracker used to assist in determining date of lockdown phases in U.S., Canada and Australia.

Table A.3: Descriptive Statistics for Multilevel Model Variables.

Variable	Sample Percent	Percent Missing
<u>Included as Both Fixed and Random Effect:</u>		
Married, Live as Married, or in Civil Partnership	59.4%	-
Young (18-24)	9.2%	-
Elderly (65+)	25.6%	-
Live Alone	18.8%	4.7%
Black, Asian or Minority Ethnic	5.1%	13.6%
Voted Conservative in Previous Election	32.3%	17.8%
Voted Labour in Previous Election	28.5%	17.8%
Female	53.2%	-
Underemployed: Not in Employment (>8 hrs/week), Education, or Retirement	13.4%	3.2%
Social Grade – Professional (AB)	29.6%	-
Alone × Female	10.1%	4.7%
Underemployed × Female	8.4%	3.2%
<u>Included as Fixed Effect Only:</u>		
Household Income Above £50,000	31.1%	24.4%
Voted Remain in 2016 EU Referendum	46.8%	1.4%
Newspaper: Centre-Left (Guardian or Independent)	17.5%	-
Newspaper: Right Broadsheet	10.2%	-
Newspaper: Tabloid	22.3%	-
London	12.2%	-
Southern England (Ex-London)	32.9%	-
Midlands	16.8%	-
Northern England	24.3%	-
Scotland	8.8%	-
Wales	5.0%	-

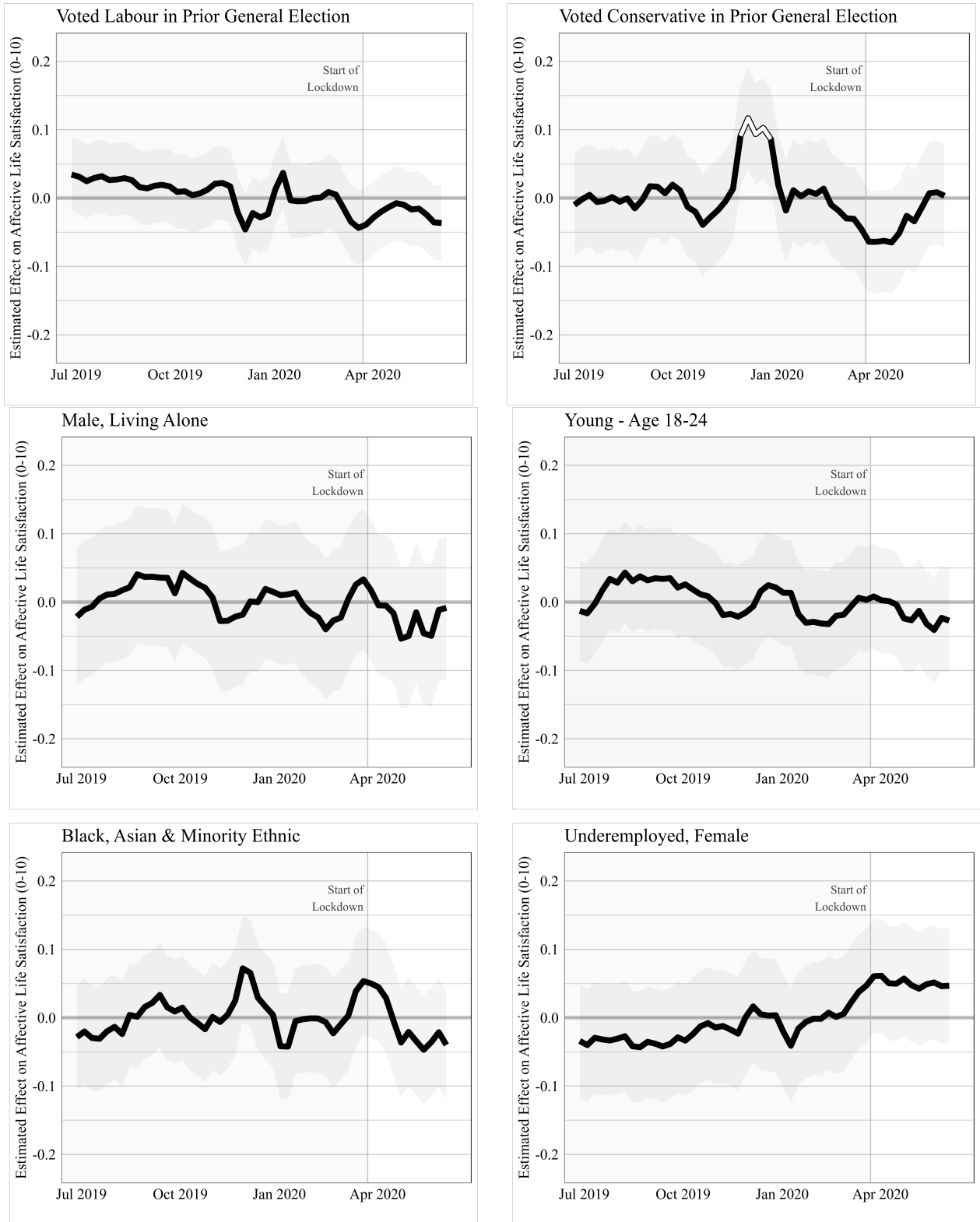
Notes: There are no missing observations for age, gender, region, marriage or socioeconomic status, as these are already included by virtue of YouGov’s panel sampling methodology. In order to preserve sample size, non-respondents for party affiliation (past vote) and household income were coded as 0 rather than as missing: these variables therefore capture self-identified party support, and self-identified household income over £50,000, respectively.

Table A.4: Multilevel Models: Fixed Effects

	<i>Dependent variable:</i>		
	Affective Life Satisfaction	Positive Affect	Negative Affect
	(1)	(2)	(3)
Partnership Status: Married, Live as Married, or in Civil Partnership (=1) or Single (=0)	0.307*** (0.013)	0.022*** (0.003)	-0.045*** (0.002)
Young (Age 18-24) (=1)	0.059** (0.021)	0.063*** (0.004)	0.050*** (0.004)
Elderly (Age 65+) (=1)	0.279*** (0.014)	0.011*** (0.002)	-0.071*** (0.002)
Household Income Above £50,000 (=1)	0.109*** (0.012)	0.022*** (0.002)	-0.003 (0.002)
Live Alone (=1)	-0.045* (0.022)	-0.005 (0.004)	-0.001 (0.004)
Female (=1)	-0.161*** (0.013)	-0.002 (0.002)	0.043*** (0.003)
Ethnicity: Black, Asian or Minority Ethnic (=1) or White (=0)	0.044* (0.024)	0.011** (0.004)	-0.020*** (0.005)
Voted Conservative in Prior Election (=1)	0.201*** (0.016)	0.025*** (0.003)	-0.026*** (0.002)
Voted Labour in Prior Election (=1)	-0.079*** (0.014)	-0.0003 (0.003)	0.026*** (0.003)
Underemployed: Unemployed, Out of Work, or Working Less than 8 Hours a Week (=1)	-0.414*** (0.026)	-0.049*** (0.005)	0.055*** (0.004)
Professional (Social Grades A & B)	0.105*** (0.012)	0.020*** (0.003)	-0.013*** (0.002)
Voted "Remain" in 2016 EU Referendum	0.016 (0.010)	0.012*** (0.002)	0.011*** (0.002)
Newspaper: Centre-Left (Guardian or Independent)	-0.056*** (0.013)	0.024*** (0.003)	0.033*** (0.002)
Newspaper: Centre-Right (Times, FT, or Telegraph)	0.147*** (0.016)	0.041*** (0.003)	-0.009** (0.003)
Newspaper: Tabloid	0.034*** (0.012)	-0.004* (0.002)	-0.013*** (0.002)
Live Alone × Female, Interaction Term	0.055** (0.026)	0.010* (0.005)	-0.009† (0.005)
Underemployed × Female, Interaction Term	0.147*** (0.032)	0.020*** (0.006)	-0.016*** (0.005)
Constant	6.644*** (0.028)	0.189*** (0.005)	0.252*** (0.005)
Observations	82,890	82,890	82,890
Model R ²	0.09	0.04	0.10
Log Likelihood	-137,590	-4,137	4,510

Notes: Also included in the model (not reported) are fixed effects by nation of residence: England, Scotland, Wales and Northern Ireland. Random effects by period are shown separately. †p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Figure A.3: Multilevel Model Random Effects for Key Demographics, by Survey Week. Variables Without Significant COVID-19 Period Effects.



Notes: Random effect slopes for socio-demographic variables, clustered by week of survey. Includes rolling average slope over the two prior and succeeding weeks. 90% bootstrap estimated confidence intervals. Lack of a significant effect among minority ethnic respondents cannot be considered definitive: the survey sample includes only self-identifying minority group members (5.1% of sample) while 13.6% of respondents refused to provide a response and may disproportionately include minority individuals.

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