Greyling, Talita; Rossouw, Stephanié

Working Paper

Re-examining adaptation theory using Big Data: Reactions to external shocks

GLO Discussion Paper, No. 1129

Provided in Cooperation with:
Global Labor Organization (GLO)

Suggested Citation: Greyling, Talita; Rossouw, Stephanié (2022) : Re-examining adaptation theory using Big Data: Reactions to external shocks, GLO Discussion Paper, No. 1129, Global Labor Organization (GLO), Essen

This Version is available at:
https://hdl.handle.net/10419/261320

Re-examining adaptation theory using Big Data: Reactions to external shocks

Talita Greyling[1¶], Stephanié Rossouw[2¶*]

[1] School of Economics, College of Business and Economics, University of Johannesburg, Gauteng, South Africa, Honorary Adjunct Academic, School of Social Science & Public Policy, Auckland University of Technology, New Zealand, ORCID: 0000-0002-3777-7003.

[2] School of Social Science & Public Policy, Faculty of Culture and Society, Auckland University of Technology, Auckland, New Zealand, Senior Research Associate, School of Economics, College of Business and Economics, University of Johannesburg, Johannesburg, South Africa, ORCID: 0000-0003-3538-9215.

* Corresponding author

Email: stephanie.rossouw@aut.ac.nz (SR)

¶ These authors contributed equally to this work.

Abstract

During the global response to COVID-19, the analogy of fighting a war was often used. In 2022, the world faced a different war altogether, an unprovoked Russian invasion of Ukraine. Since 2020 the world has faced these unprecedented shocks. Although we realise these events' health and economic effects, more can be known about the happiness effects on the people in a country and how it differs between a health and a war shock. Additionally, we need to investigate if these external shocks do affect wellbeing, how they differ from one another, and how long it takes happiness to adapt to these shocks. Therefore, this paper aims to compare these two external shocks for ten countries spanning the Northern and Southern hemispheres to investigate the effect on happiness. By investigating the aforementioned, we also re-examine the adaptation theory and see whether it holds at the country level. We use a unique dataset derived from tweets extracted in real-time per country. We derive each tweet's underlying sentiment by applying Natural Language Processing (machine learning). Using the sentiment score, we apply algorithms to construct daily time-series data to measure happiness (Gross National Happiness (GNH)). Our Twitter dataset is combined with data from Oxford's COVID-19 Government Response Tracker. We find that in both instances, the external shocks caused a decrease in GNH. Considering both types of shocks, the adaptation to previous happiness levels occurred within weeks. Understanding the effects of external shocks on happiness is essential for policymakers as effects on happiness have a spillover effect on other variables such as production, safety and trust. Furthermore, the additional macro-level results on the adaptation theory contribute to previously unexplored fields of study.

1. Introduction

During the global response to COVID-19, the analogy of fighting a war was often used. COVID-19 severely impacted world health (loss of life), damaged the world economy and negatively impacted wellbeing. In 2022, the world faced a different war altogether, an unprovoked Russian invasion of Ukraine. The invasion displaced over 14 million people (at the time of writing this paper), caused a significant loss of life and damaged world economies (severe effects on oil prices, sunflower oil, wheat etc., which led to higher inflation levels). Additionally, the world experienced the threat of nuclear war

and the possible outbreak of World War III. Although we realise the health and economic effects of these external shocks, more can be known about externals shocks' effect on people's happiness in countries and how it differs between health- and war-related shocks. Additionally, information is needed on how severe these effects are, compared to one another and how long it takes people to adapt to these shocks.

To this end, our primary aim is to compare these two external shocks (a health and war shock) for ten countries spanning the Northern and Southern hemispheres to determine how quickly countries' happiness levels adapt. We will determine (if) and how external shocks affect happiness to achieve the aforementioned. Additionally, we will use an event study to determine whether the adaptation theory holds at the macro-level (similar to studies conducted at the micro-level). Lastly, we also draw comparisons between countries in the Northern and Southern hemispheres.

We define an external shock as an unexpected event that changes emotions, happiness levels, and economic and other social factors. The shocks we are investigating are the COVID-19 pandemic and the Ukrainian war. However, these shocks have vast differences, including how they affect countries. In the panel under investigation, the shock of COVID-19 directly impacted the countries. In contrast, the Ukrainian war indirectly impacted these countries, as the war did not take place in these countries, though the negative effects affected all countries worldwide. These shocks create upheavals in emotions, for example, anger and fear. It increases instability in resources, food and other markets, leading to weaker economic growth, higher unemployment, higher inflation rates and increased poverty.

In our analysis, we take the first lockdown as the date of the COVID-19 shock and the invasion as the date of the Ukrainian war shock. We equate these negative shocks to negative life events used in micro-level studies and see these shocks as an ailment and analyse the intervention effect. In the instance of the COVID-19 health shock, the intervention is the first lockdown; in the case of the Ukrainian war, it is the invasion of Ukraine.

Previous studies explored adaptation patterns of individuals for one single event at the micro-level (Brickman et al. [1], Silver [2]) and did not necessarily inform us about adaptation patterns across

events. Studies such as Clarke et al. [3], Clarke and Georgellis [4], Frijters et al. [5], and Rudolf and Kang [6] went further than single events by providing standardised information on how individuals' wellbeing develops in the approach to and aftermath of major life events. Clarke et al. [3] investigated marriage, divorce, widowhood, the birth of a child, and layoff. Frijters et al. [5] used marriage, divorce, childbirth, injury/ illness, death of spouse or child, being a victim of crime, redundancy, change in financial situation, and change in residence. Rudolf and Kang [6] investigated marriage, divorce, widowhood, unemployment, first job entry, and the shift from the six- to five-day working week. However, all of these studies were conducted at the micro-level (individual level) using survey data such as the Korean Labor and Income Panel Study (KLIPS), Household Income and Labour Dynamics in Australia (HILDA), German Socio-Economic Panel (GSOEP) and British Household Panel Survey (BHPS).

Following the above, our study makes three main contributions to the existing literature. First, no other study has investigated two different types of external shocks, such as COVID-19 and the Ukrainian war, on happiness at a macro-level. Second, no other study has tested whether adaptation theory holds at the country level across events using a cross-country analysis. Third, this is the first study to use real-time information from Big Data instead of survey data to re-examine adaptation theory.

Our analyses use a unique dataset, which we construct from tweets extracted in real-time at a country level. Natural Language Processing (machine learning) is used to code (score) the tweets' underlying sentiment, and algorithms are applied to the sentiment scores to derive a happiness score per tweet. We derive the mean scores per day to develop our daily happiness time-series data per country, i.e., the Gross National Happiness index (GNH). Thus, we use sentiment analysis, analysed over time to derive time-series data. The GNH, our variable of interest, measures wellbeing/happiness and has been well-established in previous studies (see Greyling and Rossouw [7], Greyling et al. [8] and [9], Rossouw et al. [10] and [11], Morrison et al. [12] and Sarracino et al. [13] and [14]).

To achieve the study's aims, we first conducted a Difference-in-Difference (DiD) estimation for the whole panel to establish whether the two external shocks caused the observed effect on happiness (GNH). Subsequently, we also conducted a DiD estimation for both the Northern and Southern

hemispheres. Second, we perform an event study to determine the effect of the external shocks on the GNH from 3 weeks pre-event (lockdown for COVID-19 and the invasion of Ukraine) to 9 weeks post-event. Therefore, also measuring the adaptation of GNH levels compared to the reference week, three weeks before the shock.

Our results show that COVID-19 and the Ukrainian war caused a decrease in happiness. However, after 3 weeks post-event, adaptation to previous happiness levels (reference week is three weeks before the event) occurred. Four- and five weeks post-event, happiness was higher than 3 weeks pre-event. Therefore, we found strong evidence of adaptation and show that for both events, there is a rapid return to a baseline level of happiness.

Regarding the comparison between the hemispheres, we found similar results for the Northern hemisphere than for the entire panel. With both the COVID-19 and the Ukrainian war shock, adaptation is already evident in week 3 and week 2, respectively and gains statistical significance by weeks 4 and 5. In the Southern hemisphere, it seems that adaptation is somewhat slower. In the instance of lockdown only from week 7 after the event week, whereas with the invasion adaptation occurred in week 4 after the event.

The rest of the paper is structured as follows. The next section contains a brief discussion on studies related to adaptation theory. Section 3 describes the data and the selected variables and outlines the methodologies used. The results and discussion follow in section 4, while the paper concludes in section 5.

2. Literature review

2.1 Adaptation at micro-level

Since the primary aim of this study is to determine whether adaptation occurs at the macro-level, our literature review will focus on adaptation studies. The literature on adaptation theory is vast; however,

we limit our discussion to a few seminal and across-life events' studies at a micro-level that investigated adaptation.

Subjective wellbeing (SWB) research has been significantly affected by the hedonic treadmill theory (see, for example, Mancini et al. [15], Diener et al. [16], Kahneman et al. [17]). Lykken and Tellegen [18] used the hedonic treadmill theory to conclude that adaptation is quick, complete, and inevitable and that genetic predispositions and personality rather than life events accounted for nearly all of the long-term stable variance in SWB. According to this idea of a hedonic treadmill, people have happiness 'set-points' to which they inevitably return following major life events (Brickman & Campbell [19], Headey & Wearing [20], Larsen [21], Williams & Thompson [22]).

However, studies conducted by Diener et al. [16], Lucas [23] and [24], Lucas et al. [25] and Lucas et al. [26], although not refuting the happiness set-point model, concluded that even though happiness levels are relatively stable over time, this stability does not preclude large and lasting changes. "*Happiness levels do change, adaptation is not inevitable, and life events do matter*" (Lucas [27: p 78].

Most evidence for adaptation comes from single-life event cross-sectional studies. Brickman et al. [1] investigated the SWB of people with spinal cord injuries and lottery winners in one of the most cited studies. They found that individuals with spinal cord injuries were happier than expected, and lottery winners were less happy than expected. However, due to limitations such as the lottery winners being marginally happier than the control group (but not significantly happier), individuals with spinal cord injuries going against the adaptation theory expectations (by being significantly less happy than the comparison group, even if they were not quite as unhappy as they expected) and not using longitudinal data to compare pre-and post-events Brickman et al. [1] could not offer strong support for adaptation.

Subsequent studies provide stronger evidence that some form of hedonic adaptation does occur after improving on Brickman et al.'s [1] research design. Silver [2] also investigated people with spinal cord injuries; however, individuals were followed from one to eight weeks after the disability-causing accident. One week after the major life event, negative emotions were stronger than positive emotions. Over the subsequent 7 weeks, happiness increased while negative emotions steadily decreased. By the

8th week, there was some adaptation with positive emotions stronger than negative emotions. However, it is unclear whether these individuals returned to their pre-event baseline levels of SWB.

Studies such as Clarke et al. [3], Clarke and Georgellis [4], Frijters et al. [5], and Rudolf and Kang [6] went further than single-life event studies such as Brickman et al. [1] and Silver [2] by providing standardised information on how individuals' wellbeing develops in the approach to and aftermath of major life events. Clarke et al. [3] and Clarke and Georgellis [4] use unemployment, marriage, divorce, widowhood, the birth of a child, and layoff. Frijters et al. [5] use marriage, divorce, childbirth, injury/ illness, death of spouse or child, being a victim of crime, redundancy, change in financial situation, and change in residence. Rudolf and Kang [6] use marriage, divorce, widowhood, unemployment, first job entry, and the shift from the six- to the five-day working week. Using survey data collected at the micro-level from KLIPS, HILDA, GSOEP and BHPS, all the abovementioned studies suggest that the adaptation phenomenon may be general. These studies surmise that people initially react strongly to both positive and negative events, but then their emotional reactions diminish. People return to a positive rather than a neutral happiness baseline, and life circumstances are necessary to understand long-term SWB; happiness is not completely determined by personality.

2.2 Adaptation at macro-level

As far as the authors know, only two studies investigate *adaptation theory at the macro-level*. The first study focuses on countries involved in civil conflict, and the second investigates one external shock and does not involve a cross-country analysis. However, no studies investigate adaptation theory *across external shocks* involving a *cross-country analysis using Big Data*.

In a study of 44 countries actively involved in civil conflict and using average happiness by country from representative surveys (World Database of Happiness from Veenhoven [28]), Welsch [29] found that the current number of conflicts significantly reduced the wellbeing of people in civil wars. However, Welsch [29] concluded that the change in the number of victims (the number of victims per 1000 inhabitants), rather than their absolute number, reduces wellbeing in civil wars, suggesting that

there is some, but no complete, adaptation to the conditions of a war shock. Additionally, he calculated that, on average, the compensating variation for one fatality is about 108,000 US dollars. This means that income must increase by 108,000 US dollars to have happiness at constant levels when one additional person dies. The direct effects in terms of suffering, fear and agony are larger than the indirect effects due to the smaller income brought about by premature death.

The idea that some adaption occurs could be that people get used to the horrors of war to some extent. When one experiences that many persons die, then the fact that one's son, husband, father or other relative has died may be more bearable because the people affected are aware that they are no exception to the rule. That other persons have had to come to terms with similar grief. On the other hand, one can well argue that experiencing the death of many others has a cumulative negative effect on one's own happiness.

Morrison et al. [12] used the GNH and Plutchik's [30] wheel of emotions to investigate the response to the COVID-19 pandemic in New Zealand. The authors found distinct reactions to the pandemic using the period 14 February – 14 June 2020. There was an initial strong decrease in wellbeing in response to COVID-19, and this decrease was brought on by a decrease in the emotions' joy', 'anticipation' and 'trust'. However, this initial decrease in wellbeing was short-lived and recovered relatively quickly. Thereby finding evidence of hedonic adaptation.

3. Data

3.1 Data and countries

In the analyses, we use two external shocks, namely COVID-19 and the Ukrainian war and compare the days pre- and post-event. We use a panel dataset spanning the period 25 February – 23 May 2020 (COVID-19) and 1 February – 30 April 2022 (Ukrainian war). The following ten countries are included in our analyses; seven Northern hemisphere countries; Belgium, Germany, Great Britain, France, Italy, the Netherlands, and Spain and three Southern hemisphere countries; Australia, New Zealand and South Africa.

We have a total of 890 observations, thus 89 observations for ten countries for both the COVID-19 shock and the Ukrainian war shock time period. Primarily the choice of countries is determined by data availability. However, future studies can extend the dataset to include more countries. The current selection of countries from both hemispheres provides unique insights into the effect of two external shocks (external to the countries under investigation) on happiness and the time needed to adapt to these shocks. Table 1 summarises key statistics for each country used in the current study.

Table 1. Key summary facts of countries in this study.

Country	Total population	Average happiness levels** (2020)	Date of announcement	Date of first lockdown (2020)	Date of Ukraine invasion (2022)
Australia	25.5 million	7.09	15 March	17 March*	24 February
Belgium	11.6 million	6.98	17 March	18 March	24 February
France	66.99 million	6.66	16 March	17 March	24 February
Germany	83.02 million	7.08	22 March	22 March	24 February
Great Britain	66.65 million	7.17	23 March	23 March	24 February
Italy	60.36 million	6.39	8 March	9 March	24 February
Netherlands	17.28 million	7.73	14 March	15 March¶	24 February
New Zealand	5.5 million	7.14	23 March	26 March	24 February
South Africa	57.7 million	6.32	23 March	27 March	24 February
Spain	46.94 million	6.40	13 March	14 March	24 February

* Australia never officially went into a complete lockdown like that in other countries. We used the day when the closure of international borders was announced as a proxy for "lockdown."
¶ The Netherlands started a so-called 'intelligent lockdown' on this date.
** The happiness scores cited here reflect the average for the period in 2020 before the first COVID-19 case was announced.
Source: Greyling et al. [31], Hale et al. [32].

3.2 Twitter data: *GNH.today project*

The outcome variable, the Gross National Happiness index (GNH), which measures wellbeing, was sourced from the *GNH.today project*, launched in April 2019 (Greyling et al. [31]). This project measures the evaluative mood of a country's citizens over time. The GNH, as a measure of mood, captures the more volatile part of wellbeing, generally referred to as happiness (Diener et al. [16]).

However, the evaluative qualification indicates tweets reflect individuals' conscious decisions - they evaluate what they want to say. Since the GNH has been well-established and validated in previous studies, we will only provide a brief discussion here (see Greyling and Rossouw [7], Greyling et al. [8] and [9]), Rossouw et al. [10] and [11], Morrison et al. [12] and Sarracino et al. [13] and [14]).

To construct the GNH index, a live feed of tweets is extracted from the voluntary information-sharing social media platform Twitter (see Rossouw and Greyling [33] for a detailed discussion). Using Natural Language Processing, sentiment analysis, which is the process of determining whether a piece of writing (product/movie review, tweet, etc.) is positive, negative or neutral, is applied to every tweet. It can identify the follower's attitude towards an event through tone, context etc. Sentiment analysis is driven by an algorithm and is better than text analysis since it helps you understand an entire opinion and not merely a word from the text. For our sentiment analysis, we use the Sentiment140 lexicon; subsequently, every tweet is labelled as having either a positive, neutral or negative sentiment.

As a robustness check, we recalculate all indices using the sentiment scores from NRC (Turney and Mohammad [34]) and VADER (Hutto & Gilbert [35]). If the indices using different lexicons are highly correlated, we assume that the index is not sensitive to the type of lexicon used. The calculated GNH using Sentiment140, NRC and VADER are highly correlated. The Pearson correlation coefficient between GNH (Sentiment140) and GNH (NRC) is $r = 0.88$ ($p=0.000$) and between GNH (Sentiment140) and GNH (VADER) $r = 0.96$ ($p=0.000$). Therefore, we assume the GNH index is not sensitive to the type of lexicon used, and the results gained using the GNH index are robust.

After each tweet has been classified, a sentiment balance algorithm is applied to derive a happiness score per hour. The scale of the happiness scores is between 0 and 10, with 5 being neutral, thus neither happy nor unhappy. The index is available live on the *GNH.today project* website (Greyling et al. [31]). To derive time-series data, we calculate the mean GNH per day. We smooth the GNH data to adjust for trends using a 7-day moving average (Kelly [36], Helliwell & Wang [37]).

In our analysis, we compare the two external shocks of COVID-19 and the Ukrainian war. We take the first lockdown as the date of the COVID-19 shock and the invasion as the date of the Ukrainian war

shock. The lockdown was in 2020, and the invasion in 2022. As a counterfactual period, we use the year 2021, assumed to be the 'new normal' in which people have accepted that COVID-19 is a reality and part of their daily lives. However, we cannot directly compare the GNH from 2020 and 2021, and 2021 and 2022 as the mean levels of the GNH differ markedly across the years. Thus, we need to re-scale (standardise) the data to be comparable. To standardise the GNH data, we use the observation minus the mean per time period (either 2020 and 2021, or 2021 and 2022, respectively) divided by the standard deviation per time period. We report results using the standardised GNH time series in the Difference-in-Difference estimations.

The use of Twitter data presents several key advantages over survey data. First, the data are not self-reported by a subsample of respondents but rather capture the opinion of millions of Twitter users. Second, the data does not suffer from biases such as the observer-expectation effect or interviewer bias. Third, Twitter data are less vulnerable to small-sample bias. Nevertheless, Twitter data have limitations. One of these is that younger individuals are relatively more likely than older individuals to tweet; however, on Twitter accounts, the ages are spread from 19-65, similar to survey data. Another limitation is that we cannot look at heterogenous effects of COVID-19 and the Ukrainian war by demographic groups based on regions. Our results should thus be read as the average impact of COVID-19 (using the date of the first lockdown) or the Ukrainian war (date of invasion) on the happiness of Twitter users per geographical region. Although we cannot assume that Twitter users are representative of a country, we know that a vast number of the population do have Twitter accounts, and the number of tweets approximates millions per day. Therefore, biases are limited by the size of the sample.

3.3 Oxford data and covariates

To select the covariates included in the models, we are limited in our choice of variables, as we can only include high-frequency close to real-time data. Furthermore, the time periods we compare are relatively short. For example, the invasion in Ukraine was in February 2022 and even using real-time data, the number of observations is limited, seeing that the project commenced in April 2022, thus

allowing us to use data until the end of April. Given the relatively short period, we are restricted in the number of covariates that can be included in the estimations to avoid overfitting the models. Therefore, we limit our selection of covariates, similar to Fang et al. [38] and Brodeur et al. [39], to the following:

1. The lockdown or invasion variable is the assumed date of the external shock (intervention variable). We construct a dummy variable with 0 before the lockdown or invasion and 1 thereafter. For the external shock COVID-19, lockdown is the date specific to each country (see Table 1). For the Ukrainian war's external shock, the invasion date was 24 February 2022. However, in our analyses, we do not use the lockdown date or the day of the invasion itself, as we believe the effects on happiness may have started when policies were announced or the imminent threat of an invasion became apparent. Thus, our lockdown and invasion variables are constructed on the day each country announced their first lockdowns (see Table 1) and the day preceding the invasion, 23 February. In further support of our decision to use the dates of the lockdown announcements and the day preceding the invasion, literature has shown that wellbeing measures react to expectations rather than the event itself (see Greyling et al. [9] and Morrison [12]). In subsequent analyses, where we compare the Northern and Southern hemispheres, we construct the lockdown and invasion dummy variable following the same method explained above. As a robustness test, we also run all regressions using each country's lockdown date and the invasion's date.
2. The number of new COVID-19 cases. We use the lagged number of new COVID-19 cases per million to control for the evolution of the pandemic (Hale et al. [32]).
3. Country fixed effects. We use country-fixed effects to control for countries' observed and unobserved characteristics.
4. A day-of-the-week fixed effects. We control for any observed or unobserved day-of-the-week effects. For example, Mondays, the first workday of the week, often has lower levels of happiness than other days, whereas Friday and Saturdays, in expectation of more leisure time, have higher levels of happiness.

5. Event-week. We transformed the daily data into weekly data. Week 0 is equal to the event week. Our reference week is week -3, thus three weeks before the event. Similarly, three weeks after the event is referred to as week 3.

3.4 Methodology

3.4.1 Difference-in-Difference

We use a Difference-in-Difference (DiD) estimation to investigate the causal effect of the two external shocks (dates of first lockdowns and invasion) on happiness. The DiD estimation compared GNH for pre-and post-event in 2020 (lockdown) and 2022 (invasion) to the same time periods (counterfactual) in 2021, assumed to have normal happiness levels in the new "normal" era with COVID-19. Specifically, we estimate the following equation:

$$GNH_{i,c} = \alpha_0 + \alpha_1 \eta_{i,c} * Year_i + \alpha_2 X_{i-1,c} + \mu_c + \sigma_i + \epsilon_{i,c} \qquad (1)$$

Where $GNH_{i,c}$ is the daily happiness at time i for country c. Our intervention variable is $\eta_{i,c}$. It is a dummy variable denoting either $lockdown_{i,c}$or $invasion_{i,c}$ depending on the type of shock, COVID-19 (2020) or the Ukrainian War (2022). Our $lockdown_{i,c}$ and $invasion_{i,c}$variable take on the value of 0 pre-lockdown or invasion and one post-lockdown or invasion in both the year of the actual lockdown (2020) or war (2022) and the counterfactual year assumed to be normal (2021), thus a year in which COVID-19 has been accepted as the new normal with no lockdowns.

$Year_i$ is a dummy variable where 1 is the year 2020 or 2022, respectively. We control for new COVID-19 cases per million with a one-day lag ($X_{i-1,c}$). The model includes country and day-of-the-week fixed effects ($\mu_c \; and \; \sigma_i$). We report robust standard errors to address heteroscedasticity ($\epsilon_{i,c}$).

Our interaction term $\alpha_1 \eta_{i,c} * Year_i$ will convey the causal impact of the lockdown or invasion on happiness. We admit that it is possible that the DiD estimator could conflate the true effect of the lockdown and the Ukraine invasion with the broader negative economic spillover in 2020 and 2022. Therefore, we conduct an additional sensitivity test, namely an event study, to gauge the robustness of

the negative impact of the lockdown and the invasion on happiness. To this effect, we interpret the DiD results alongside the event study.

3.4.2 Event study

We also estimate an event study model to test for any adaptation of the GNH after the negative external shocks. Additionally, the event study results also serve as a sensitivity test to confirm the robustness of the DiD results. The analysis is for the time period 3 weeks pre-event (week -3, week -2, week-1), the event week (week 0) to 9 weeks post-event (week 1 to week 9). Thus, the reference week is week -3, and we test the adaptation of happiness to the GNH levels of the reference week.

To compare the data across events for 2020 and 2022, we recoded the dates as numbered days from 2 – 90. We start on day 2 to represent a Tuesday; thus, we assume Monday is the first day of the week. This is to compare the same day of the week between the two events since the day of the week also influences happiness– thus recognising the heterogeneity between different days of the week (normally a Monday low and a Saturday high) and addressing this heterogeneity by comparing the same day of the week across events.

Therefore, we estimate the following:

$$GNH_{i,c} = \sum_{k=-3}^{9} \alpha_k E_{k,c} + \gamma X_{i-1,c} + \mu_i + \rho_c + \epsilon_{i,c} \quad (3)$$

$GNH_{i,c}$ is the happiness measured at time i for country c. $E_{k,c}$ Where $k = -3, -2 \ldots, 9$, are dummy variables for the three-week pre-event week and nine-week post-event. The variable $X_{i-1,c}$ controls for the lagged number of new COVID-19 cases per day per million per country c. The model includes day-of-the-week fixed effects, μ_i, and country fixed effects, ρ_c. With $\epsilon_{i,c}$ the residual. The third-week pre-event week is the reference period. The estimated coefficients on the $E_{k,c}$ dummies should therefore be interpreted as the effect of being in (for example) the fourth-week post-event week compared to week three pre-event.

3.4.3 Robustness checks

To test the robustness of our results in the DiD analysis, we also use the lockdown date rather than the announcement date of the lockdown – and the day of the invasion rather than the day before the invasion. We find similar results.

Furthermore, we use the event study results as a robustness check for our DiD results. If we find similar results from the event study, thus happiness was negatively affected after the event, we can confirm our DiD results.

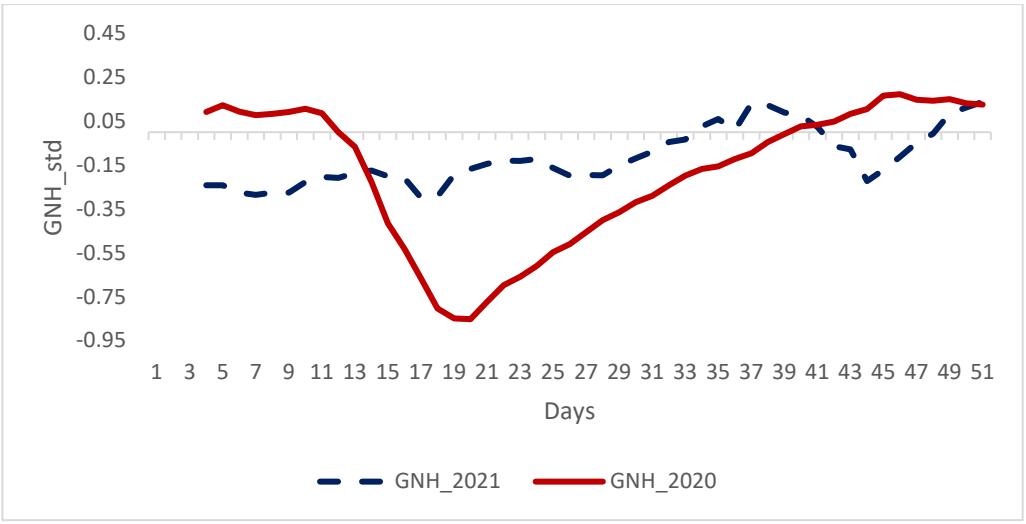
4. Results

4.1 Graphical analysis of the evolution of happiness across events

We start our analysis by comparing the GNH pre- and post-lockdown in 2020 to the same dates in 2021. We investigate the three weeks before, the event week and the three weeks after the event week. We follow the same method considering the invasion of Ukraine; however, comparing the years 2022 to 2021.

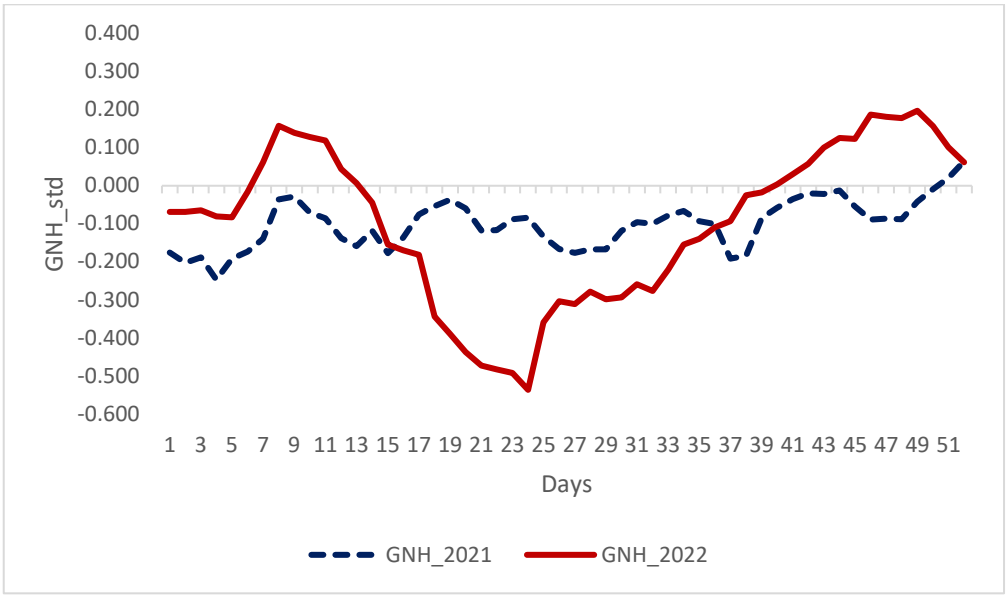
Fig 1 plots daily GNH for the period pre- and post-lockdown, and Fig 2 plots GNH for the time pre- and post-invasion. To make a comparison across the years, we number the days in all the years from 1 to 57 (see the X-axis), thus for a period of three weeks before the event, the week of the event and three weeks after the event week.

Fig 1 shows a sharp decline in GNH (solid red line) on the approximate date on which lockdowns were announced, this decrease in GNH is only seen in 2020, with no such changes in 2021. A similar pattern is seen in Fig 2, with GNH (solid red line) showing a sharp decrease on the day before the invasion in 2022. However, this is not reflected in the pattern in 2021.



Note: The blue dotted line indicates 2021 (counterfactual) and the solid red line, 2020, the year of the external shock.
Source: Greyling et al. [31]

Fig 1. Standardised GNH before and after lockdown.



Note: The blue dotted line indicates 2021 (counterfactual) and the solid red line 2022, the year of the external shock.
Source: Greyling et al. [31]

Fig 2. Standardised GNH before and after the invasion.

The graphical analysis of the GNH data shows a sharp decrease in the GNH brought on by external shocks. In the absence of lockdown or the invasion, we assume the GNH would have followed a similar pattern as in the counterfactual year, thus a common trend assumption. However, this assumption was violated by the external shocks. The DiD analysis should confirm this initial insight.

4.2 Difference-in-Difference

To answer our question regarding the causal effect of the two external shocks on happiness, we turn to our results from the DiD in Table 2, which compares GNH for three weeks pre-and post-event in 2020 (lockdown) and 2022 (invasion) to the same time periods (counterfactual) in 2021 for all ten countries, assumed to have new 'normal' happiness levels.

To determine whether the decrease in GNH was associated with the lockdown and the invasion (the intervention) specifically and not only the trend (we also control for new COVID-19 cases per million as a proxy for the evolution of the pandemic), we consider the estimated coefficient of the interaction variable "$lockdown_{i,c} * Year$ or $invasion_{i,c} * Year$," i.e., the DiD estimator. We find it statistically significant (at the 10 and 1% levels, respectively) and negative. Therefore, indicating that "lockdown or the invasion in the year of COVID-19 (2020) and the year of the Ukrainian war (2022)" had lower levels of GNH of 0.0803 and 0.249 points, respectively, compared to the counterfactual year with no lockdown or invasion. Thus, in the year when the intervention (lockdown and invasion) was applied, people were unhappier after the lockdown announcement and imminent invasion of Ukraine compared to the counterfactual year. This implies that *the lockdown and the invasion of Ukraine caused a decline in happiness levels,* controlling for COVID trends (COVID cases), observed and unobserved differences in the characteristics of countries and day-of-the-week effects.

Table 2. The effects of COVID-19 lockdown and the invasion of Ukraine - DiD estimates for all countries.

Variable	Lockdown		Invasion	
	GNH_std	SE	GNH_std	SE
Lockdown #year COVID	-0.0803*	(0.0460)		
Lagged new COVID-19 cases per million	Yes		Yes	
Country FE	Yes		Yes	
Day of the week FE	Yes		Yes	
Invasion # year War			-0.2490***	(0.0670)
_cons	-0.1651***	(0.0378)	-0.1033***	(0.0517)
N	972		972	
adj. R^2	0.046		0.026	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Lockdown = Day when lockdowns were announced in each country, and Ukraine =23 February 2022 (the day before the invasion)

Consequently, we split our sample between the Northern and Southern hemispheres. We see from Table 3 that our intervention variable 'lockdown' is significant and negatively related to happiness in both hemispheres. Regarding the intervention variable' invasion of Ukraine', we find a similar result: the GNH in the year of the war after the invasion is lower than in the counterfactual year with no invasion in the Northern and the Southern hemispheres.

These results show that even if we consider the Northern and Southern hemispheres separately, we find that the "lockdown" and the "invasion" caused lower happiness levels in both hemispheres. The fact that the countries in the Southern hemisphere are much further geographically removed from Ukraine makes no difference to the effect of the invasion on their happiness levels. The imminent threat of a nuclear or World War III, as well as all the other negative consequences of the war, affects people's happiness in general, no matter how far they are geographically separated.

Table 3. The effects of COVID-19 lockdown and the invasion of Ukraine – DiD estimates for the Northern and Southern hemispheres.

Variable	Lockdown Northern hemisphere		Lockdown Southern hemisphere		Invasion Northern hemisphere		Invasion Southern hemisphere	
	GNH_std_sd_cov	SE	GNH_std_sd_cov	SE	GNH_std_sd_ukr	SE	GNH_std_sd_ukr	SE
Lockdown #Year COVID	-0.1386**	(0.0550)	-0.2348***	(0.0888)				
Lagged new COVID cases per million	Yes		Yes		Yes		Yes	
Country FE	Yes		Yes		Yes		Yes	
Day of the week FE	Yes		Yes		Yes		Yes	
Invasion #Year War					-0.2828***	(0.0699)	-0.2281**	(0.0982)
_cons	-0.0453	(0.0456)	-0.4026***	(0.0704)	0.0298	(0.0537)	-0.3939***	(0.0732)
N	448		188		448		188	
adj. R^2	0.027		0.295		0.173		0.532	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Event study

Following the DiD results, we continue our analysis concerning the period it takes for happiness to adapt after the two different types of external shocks. We divide our time-series data into weeks. The event week is week 0, which includes the announcement of the lockdown dates (see Table 1) and the day before the invasion of Ukraine (23 February 2022). We extend our time period of analysis up to 9 weeks after the event to gain better insights into adaptation to happiness levels.

Table 4. Duration of the external shocks on happiness (GNH): lockdown and the invasion.

Reference week = -3 pre-event	Lockdown		Ukraine invasion	
	GNH_ma	SE	GNH_ma	SE
Week -2	-0.0010	(0.0266)	0.0237	(0.0386)
Week -1	-0.3346***	(0.0264)	0.0379	(0.0387)
Week 0	-0.3297***	(0.0265)	-0.1097***	(0.0387)
Week 1	-0.1672***	(0.0268)	-0.1154***	(0.0388)
Week 2	-0.0489*	(0.0268)	-0.0536	(0.0387)
Week 3	0.0431	(0.0268)	0.0290	(0.0386)
Week 4	0.0350	(0.0269)	0.0889**	(0.0386)
Week 5	0.1083***	(0.0265)	0.0447	(0.0386)
Week 6	0.1135***	(0.0265)	0.0569	(0.0387)
Week 7	0.1200***	(0.0264)	0.0959**	(0.0387)
Week 8	0.1321***	(0.0264)	0.0867**	(0.0388)
Week 9	0.1863***	(0.0314)	0.1580***	(0.0402)
Lagged new COVID-19 cases per million	Yes		Yes	
Country FE	Yes		Yes	
Day of the week FE	Yes		Yes	
_cons	7.1111***	(0.0237)	7.3409***	(0.0385)
N	818		830	
adj. R^2	0.686		0.316	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From Table 4, we see in terms of the lockdown shock that weeks - 1 to week 2 have lower GNH levels than the reference week (week -3). However, after that, the GNH recovers, and from week 5, it is significant and higher than in week -3, thus adaptation. For the external Ukrainian invasion shock, we see that weeks 0 and 1 have lower levels of GNH compared to week -3. Even though not statistically significant, the GNH remained lower until week three post-event. This might reflect the surprise of this

external shock; thus, people only realised the threat the week of the invasion, whereas, with the lockdown shock, people were aware of this earlier. However, in both instances, the effect of the shock on happiness only lasts two weeks post-event. Therefore, it indicates a quick recovery to levels of GNH compared to week -3 pre-event.

Continuing our investigation into the Northern and Southern hemisphere countries, we refer to the results in Table 5. Regarding the external lockdown shock on the Northern hemisphere, we see that weeks - 1 to 0 have lower GNH levels than the reference week (week -3). Even though not statistically significant, the GNH remained lower until week 3. By week 5, GNH levels were higher than what was experienced in week -3, gaining statistical significance. For the Southern hemisphere, we note that lower levels of GNH were experienced during weeks -2 to 0 and week 2 again.

In the Northern hemisphere, we find similar results as in the analysis for all the countries. With both the interventions lockdown and invasion, adaptation is already evident in week 3 and week 2, respectively, after the event week and gains statistical significance by weeks 5 and 4. In the Southern hemisphere, it seems that adaptation is somewhat slower. In the instance of lockdown only from week 7 after the event week, whereas with the invasion adaptation also occurred in week 4 after the event. Though these results are not statistically significant, the coefficients are positive, implying that GNH is at higher levels than the reference week.

From the event study, it seems that GNH levels adapt relatively quickly after a shock to previous levels of GNH. Therefore, we conclude that adaptation at the macro-level is quick and complete for the countries under investigation. This confirms that the adaptation theory holds at a macro-level for negative external shocks, similar to studies focusing on life events at a micro-level as argued by Larsen [21], Lykken and Tellegen [18], Williams and Thompson [22], Headey and Wearing [20] and Brickman and Campbell [19].

Table 5. Duration of the external shocks (lockdown and the invasion) on happiness (GNH): A comparison between the Northern and Southern hemispheres.

Reference week = -3 pre-event	Lockdown – Northern hemisphere		Lockdown – Southern hemisphere		Invasion – Northern hemisphere		Invasion – Southern hemisphere	
	GNH_ma	SE	GNH_ma	SE	GNH_ma	SE	GNH_ma	SE
Lockdown Week -2	0.0161	(0.0211)	-0.0954*	(0.0312)				
Lockdown Week -1	-0.3672***	(0.0731)	-0.3107**	(0.0693)				
Lockdown Week 0	-0.2688***	(0.0713)	-0.5219**	(0.0699)				
Lockdown Week 1	-0.0886	(0.0781)	-0.4024	(0.1452)				
Lockdown Week 2	-0.0204	(0.0868)	-0.1635*	(0.0394)				
Lockdown Week 3	0.0536	(0.0689)	-0.0293	(0.0392)				
Lockdown Week 4	0.0434	(0.0615)	-0.0258	(0.0141)				
Lockdown Week 5	0.1339*	(0.0594)	-0.0017	(0.0046)				
Lockdown Week 6	0.1494*	(0.0692)	-0.0241	(0.0383)				
Lockdown Week 7	0.1339	(0.0837)	0.0283	(0.0268)				
Lockdown Week 8	0.1382	(0.0833)	0.0519	(0.0194)				
Lockdown Week 9	0.2001*	(0.0909)	0.0813	(0.0355)				
Invasion Week -2					0.0621*	(0.0269)	-0.0678	(0.0401)
Invasion Week -1					0.0834*	(0.0420)	-0.0734	(0.0711)
Invasion Week 0					-0.0628	(0.0541)	-0.2132*	(0.0683)
Invasion Week 1					-0.0359	(0.0582)	-0.2728**	(0.0632)
Invasion Week 2					0.0212	(0.0581)	-0.1971*	(0.0536)
Invasion Week 3					0.0642	(0.0675)	-0.0027	(0.0450)
Invasion Week 4					0.1451**	(0.0583)	0.0183	(0.0415)
Invasion Week 5					0.0857	(0.0584)	0.0100	(0.0808)
Invasion Week 6					0.0639	(0.0547)	0.0998	(0.0428)
Invasion Week 7					0.1214	(0.0769)	0.0845	(0.1150)
Invasion Week 8					0.1343*	(0.0642)	0.0171	(0.0756)
Invasion Week 9					0.1804**	(0.0652)	0.1422	(0.0636)
Lagged new COVID-19 cases per million	Yes		Yes		Yes		Yes	
Country FE	Yes		Yes		Yes		Yes	
Day of the week FE	Yes		Yes		Yes		Yes	
cons	7.2025***	(0.0572)	6.9382***	(0.0321)	7.4448***	(0.0476)	7.1139***	(0.0297)
N	579		239		581		249	
adj. R^2	0.701		0.786		0.281		0.532	

5. Conclusions

In this study, we compared two negative external shocks (health shock – COVID-19 and a war shock – the Ukrainian war) for ten countries spanning the Northern and Southern hemispheres to determine how quickly countries' happiness adapt. By doing the aforementioned, we contributed to literature in three significant ways. First, no other study has compared two different types of external shocks on happiness at a macro-level. Second, no other study has tested whether adaptation theory holds at the country level across events using a cross-country analysis. Third, this is the first study to use real-time information from Big Data instead of survey data to re-examine adaptation theory. This allowed us to contribute to the debate on whether adaptation at a macro-level is quick and complete.

Our Difference-in-Difference model established that both COVID-19 and the Ukrainian war caused a significant decrease in happiness. This finding holds for both the Northern and Southern hemisphere countries. Similarly, the event study showed that the external shocks negatively affected the happiness levels before, during and after the week of the event. The happiness levels were lower in the week leading up to lockdown and stayed lower for two weeks after the event. For the invasion of Ukraine, we saw that happiness levels were lower during the event week and stayed lower for two weeks post-event. However, we saw that adaptation occurred three weeks post-event in both external shocks. We find similar results across the Northern hemisphere countries, although, in the case of the Southern hemisphere, adaptation to the COVID-19 shock seems slower.

Therefore, considering both external shocks, we can conclude that happiness levels adapted relatively quickly to pre-event levels. Our findings are the first to confirm adaptation theory at a macro-level *across events* using a cross-country analysis. Our study is also the first to confirm that the macro-level adaptations of countries to happiness shocks within our sample are similar to the micro-level findings, suggesting that people initially react strongly to negative events. Though, their happiness levels return to previous levels.

It would be negligent of us not to discuss our study's limitations. Our panel of countries under investigation does not include Ukraine, Russia or neighbouring countries. It is plausible that if they had

been included, we might not have seen a complete adaptation. Furthermore, as discussed in section 3.2, there are limitations when working with Twitter data. However, we believe that despite these limitations, the results contribute to understanding the adaptation to external shocks at a macro level.

In future studies, we would like to investigate the emotional effect of external shocks by analysing Plutchik's [30] wheel of emotions and the adaptation of these emotions over time. Furthermore, we would like to conduct narrative analysis and topic modelling of the tweets to understand better why we see the patterns in the emotions.

References

1. Brickman P, Coates D, & Janoff-Bulman R. Lottery winners and accident victims: Is happiness relative? Journal of Personality and Social Psychology. 1978; 36: 917–927.
2. Silver, RL. Coping with an undesirable life event: A study of early reactions to physical disability. Unpublished doctoral dissertation. 1982. Northwestern University.
3. Clarke AE, Diener E, Georgellis Y, & Lucas R. Lags and leads in life satisfaction: a test of the baseline hypothesis. Economic Journal. 2008; 118: F222–F243.
4. Clarke AE, & Georgellis Y. Back to Baseline in Britain: Adaptation in the British Household Panel Survey. Economica. 2013; 80: 496–512.
5. Frijters P, Johnson D, & Shields MA. Life satisfaction dynamics with quarterly life event data. Scandinavian Journal of Economics. 2011; 113: 190–211.
6. Rudolf R, & Kang SJ. The baseline hypothesis revisited. Evidence from a neo-confucianist society. 2011. University of Göttingen, mimeo.
7. Greyling T, & Rossouw S. Positive attitudes towards COVID-19 vaccines: A cross-country analysis. PLOS ONE. 2022; 17(3): 0264994.
8. Greyling T, Rossouw S, & Adhikari T. The good, the bad and the ugly of lockdowns during Covid-19. PLoS ONE. 2021; 16(1): e0245546.
9. Greyling T, Rossouw S, & Adhikari T. A tale of three countries: How did Covid-19 lockdown impact happiness? South African Journal of Economics. 2021; 89(1): 25-43.

533 **10.** Rossouw S, Greyling T, & Adhikari T. The implied volatility of happiness pre and peri-
534 COVID-19: a Markov Switching Dynamic Regression Model. PLOS ONE. 2021; 16(12):
535 e0259579.
536 **11.** Rossouw S, Greyling T, & Adhikari T. Happiness-lost: Did Governments make the right
537 decisions to combat Covid-19? South African Journal of Economic and Management Sciences.
538 2021; 24(1): a3795.
539 **12.** Morrison PS, Rossouw S, & Greyling T. The impact of exogenous shocks on wellbeing. New
540 Zealanders' reaction to Covid-19. Applied Research in Quality of Life Studies. 2022; 17: 1787–
541 1812.
542 **13.** Sarracino F, Greyling T, O'Connor K, Peroni C, & Rossouw S. A year of pandemic: levels,
543 changes and validity of wellbeing data from Twitter. Evidence from ten countries. IZA
544 Discussion Paper. 2021; 14903.
545 **14.** Sarracino F, Greyling T, O'Connor K, Peroni C, & Rossouw S. Trust predicts compliance with
546 COVID-19 containment policies: Evidence from ten countries using big data. Quaderni Del
547 Dipartimento Di Economia Politica E Statistica. 2021; 858 – Giugno 202.1.
548 **15.** Mancini AD, Bonanno GA, & Clark AE. Stepping off the hedonic treadmill: Individual
549 differences in response to major life events. Journal of Individual Differences. 2011; 32(3):
550 144–152.
551 **16.** Diener E, Lucas RE, & Scollon CN. Beyond the Hedonic Treadmill: Revising the Adaptation
552 Theory of Well-Being. In: Diener, E. (eds) The Science of Well-Being. Social Indicators
553 Research Series. 2009; 37. Springer, Dordrecht.
554 **17.** Kahneman D, Diener E, & Schwarz N. (Eds.). Well-Being: Foundations of Hedonic
555 Psychology. 1999. Russell Sage Foundation.
556 **18.** Lykken D, & Tellegen A. Happiness Is a Stochastic Phenomenon. Psychological Science. 1996;
557 7(3): 186–189.
558 **19.** Brickman P, & Campbell DT. Hedonic relativism and planning the good society. In M. H.
559 Appley (Ed.), Adaptation level theory: A symposium (pp. 287-302). 1971. New York:
560 Academic Press.

561 **20.** Headey B, & Wearing A. Personality, life events, and subjective well-being: Toward a dynamic
562 equilibrium model. Journal of Personality and Social Psychology. 1989; 57: 731–739.
563 **21.** Larsen RJ. Toward a science of mood regulation. Psychological Inquiry. 2000; 11: 129–141.
564 **22.** Williams DE, & Thompson JK. Biology and behavior: A set-point hypothesis of psychological
565 functioning. Behavior Modification. 1993; 17: 43–57.
566 **23.** Lucas RE. Time does not heal all wounds: A longitudinal study of reaction and adaptation to
567 divorce. Psychological Science. 2005; 16: 945–950.
568 **24.** Lucas RE. Long-term disability is associated with lasting changes in subjective well-being:
569 evidence from two nationally representative longitudinal studies. Journal of Personality and
570 Social Psychology. 2007; 92(4):717-30.
571 **25.** Lucas RE, Clark AE, Georgellis Y, & Diener E. Re-examining adaptation and the set point
572 model of happiness: Reactions to changes in marital status. Journal of Personality & Social
573 Psychology. 2003; 84: 527–539.
574 **26.** Lucas RE, Clark AE, Georgellis Y, & Diener E. Unemployment alters the set point for life
575 satisfaction. Psychological Science. 2004; 15: 8–13.
576 **27.** Lucas RE. Adaptation and the Set-Point Model of Subjective Well-Being: Does Happiness
577 Change After Major Life Events? Current Directions in Psychological Science. 2007; 16(2):75-
578 79.
579 **28.** Veenhoven R. World Database of Happiness. 2006. Available from
580 https://worlddatabaseofhappiness.eur.nl/
581 **29.** Welsch H. The Social Cost of Civil Conflict: Essays from Surveys of Happiness. Kyklos. 2008;
582 61: 320-340.
583 **30.** Plutchik R. A general psychoevolutionary theory of emotion. In: Robert P, Henry K, editors.
584 Theories of Emotion. Cambridge, MA: Academic Press. 1980: 3–33.
585 **31.** Greyling T, Rossouw S, & Afstereo. Gross National Happiness Index. 2019. Available at
586 http://gnh.today

587 **32.** Hale T, Angrist N, Cameron-Blake E, Hallas L, Kira B, Majumdar S, Petherick A, Phillips T,
588 Tatlow H, & Webster S. Oxford COVID-19 government response tracker. 2020. Available from
589 https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker
590 **33.** Rossouw S, & Greyling T. Big Data and Happiness. In: Zimmermann, K.F. (eds) Handbook of
591 Labor, Human Resources and Population Economics. 2020. Springer, Cham.
592 https://doi.org/10.1007/978-3-319-57365-6_183-1
593 **34.** Turney P, & Mohammad S. Emotions evoked by common words and phrases: using
594 Mechanical Turk to create an emotion lexicon. 2010. In: Proceedings of the NAACL HLT 2010
595 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. 2010.
596 Presented at: NAACL HLT 2010 Workshop on Computational Approaches to Analysis and
597 Generation of Emotion in Text; Los Angeles, CA p. 26-34 URL:
598 https://www.aclweb.org/anthology/W10-0204
599 **35.** Hutto CJ, & Gilbert EE. VADER: A Parsimonious Rule-based Model for Sentiment Analysis
600 of Social Media Text. 2014. Eighth International Conference on Weblogs and Social Media
601 (ICWSM-14). Ann Arbor, MI, June 2014.
602 **36.** Kelly T. The mid-week effect and why Thursdays are blue: the weekly rhythm of satisfaction
603 in Hungary. Czech Sociological Review. 2018; 54(3): 371-400.
604 **37.** Helliwell J, & Wang S. Weekends and subjective well-being. Social Indicators Research. 2011;
605 116: 389-407.
606 **38.** Fang H, Wang L, & Yang Y. Human Mobility Restrictions and the Spread of the Novel
607 Coronavirus (2019-nCoV) in China. NBER Working Paper. 2020; 26906.
608 **39.** Brodeur A, Clark AE, Fleche S, & Powdthavee N. COVID-19, lockdowns and well-being:
609 Evidence from Google Trends. Journal of Public Economics. 2021; 193.

610