A TALE OF THREE COUNTRIES: WHAT IS THE RELATIONSHIP BETWEEN COVID-19, LOCKDOWN AND HAPPINESS?

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Abstract

The COVID-19 pandemic led many governments to implement lockdown regulations to curb the spread of the virus. Though lockdowns do minimise the physical damage caused by the virus, there may also be substantial damage to population well-being. Using a pooled data set, we analyse the relationship between a mandatory lockdown and happiness in three diverse countries: South Africa, New Zealand and Australia. These countries differ amongst others in terms of lockdown regulations and duration. The primary aim is to determine, whether a lockdown is negatively associated with happiness, notwithstanding the characteristics of a country or the strictness of the lockdown regulations. Second, we compare the effect size of the lockdown on happiness between these countries. We use Difference-in-Difference estimations to determine the association between lockdown and happiness and a Least Squares Dummy Variable estimation to study the heterogeneity in the effect size of the lockdown by country. Our results show that a lockdown is associated with a decline in happiness, regardless of the characteristics of the country or the type and duration of its lockdown regulations. Furthermore, the effect size differs between countries in the sense that the more stringent the stay-at-home regulations are, the greater it seems to be.

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1. INTRODUCTION

According to Johns Hopkins University (2020) the global health pandemic, brought on by the outbreak of the Coronavirus (COVID-19), has claimed over 460,000 lives worldwide (as of June 2020). At the time of writing this paper, more than 8.9 million people worldwide have tested positive for the virus. Research related to well-being and COVID-19 has shown that peoples' happiness decreased during the pandemic (Greyling *et al.*, 2020), the number of reported negative emotions increased (Sibley *et al.*, 2020) and there has been a significant increase in Google searches on boredom, loneliness, worry and sadness (Brodeur *et al.*, 2020).

Most governments worldwide reacted in unison against COVID-19, recognising that if the virus's spread were not controlled, the loss of life would be overwhelming. To this end, lockdown regulations were implemented around the globe, albeit at differing levels

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of stringency. This meant that for a significant period of time between March and June 2020, approximately one-third of the world's population was living in some form of mandatory government-imposed lockdown. In much of the discourse, this confinement's main cost has been in terms of the economy. However, while the cost of lockdown on the gross domestic product (GDP) is considerable, there may be substantial damage to population well-being. Joblessness, social isolation and a lack of freedom, which are some of the by-products of lockdowns, are all well-known risk factors for mental health and happiness (Clark and Oswald, 1994; Verne, 2009; Leigh-Hunt *et al.*, 2017).

Algan *et al.* (2019) argues that GDP in itself, which is the measure most often used to determine welfare and well-being is flawed, as it cannot measure all dimenions of well-being, including non-market factors such as social interactions with friends and family, people's happiness and sense of purpose in life. Bryson *et al.* (2016) and Piekalkiewicz (2017) state that happiness may act as a determinant of economic outcomes: it increases productivity, predicts one's future income and affects labour market performance. Many constitutions state that maximising happiness is at the core of their policymaking. The revealed individual preferences and domain priorities, as measured in terms of the happiness they bring about, rather than the GDP, could help them to achieve this goal. As argued by Layard (2011), this can be achieved by directing economic, social, political and environmental policy towards maximising well-being, while acknowledging that people's norms, aspirations, feelings and emotions are of the utmost importance. This underscores understanding and measuring happiness to be an integral part of the efforts to maximise people's quality of life.

As pointed out by Anik *et al.* (2009) and Lyubomirsky *et al.* (2005), happiness also has consequences for a country's social and health sectors. Happy people display more altruistic behaviour in the long run. They are also more active, more creative, better problem solvers and more social, while displaying less anti-social behaviour. In terms of health, happy individuals are physically healthier, live longer and engage less in risky behaviour, such as smoking and drinking.

This study's primary aim is to use the Gross National Happiness Index (GNH), a real-time measure of well-being (happiness) derived from Twitter, to investigate the relationship between lockdown and happiness. We include three diverse countries in our analyses, namely South Africa, New Zealand and Australia. These countries differ concerning their characteristics, strictness and the duration of their respective implemented lockdown regulations. Notwithstanding the aforementioned differences, the main idea is to determine whether a lockdown is negatively associated with happiness. We test this association using Difference-in-Difference (DiD) estimations and testing the robustness of these findings we use an event study. Additionally, we compare the well-being costs of the different degrees of strictness of the lockdown regulations implemented by these countries using the Least Squares Dummy Variable estimation technique.

This is the first study of its kind, since it: i) investigates the relationship between a nationwide lockdown and happiness, ii) conducts a cross-country analysis using diverse countries and iii) compares the happiness costs of the stringency of lockdown regulations. Furthermore, the current paper adds to the limited literature on utilising Big Data in analysing happiness by being one of a handful of studies with access to real-time data covering both pre-and post-COVID-19 lockdowns.

Our main results from the DiD model indicate that "lockdown," the treatment variable, is negatively related to happiness, notwithstanding the different characteristics of the countries included in our sample and the duration and type of lockdown regulations. The event study supports these findings. Comparing the effect size of the lockdown regulations, we find the more stringent the lockdown, the greater the happiness costs.

The rest of the paper is structured as follows. The next section contains a brief background to the three countries in this study and briefly discusses literature on the impact of pandemics and lockdowns. Section 3 describes the data and selected variables and outlines the methodology used. The results follow in Section 4, while the paper concludes in Section 5.

2. BACKGROUND AND LITERATURE REVIEW

2.1. Country Background

This study focuses on South Africa, New Zealand and Australia because this presents us with a unique case study to investigate the effects of different lockdown regulations within diverse countries on their economies, social and human capital.

When COVID-19 hit, New Zealand, an island economy with a relatively small population of 5.5 million people, had an average happiness level of 7.14[1] for 2020 (Greyling *et al.*, 2019) and the economic outlook was positive. The annual GDP growth rate in the year to December 2019 was 2.3%, debt as a percentage of GDP was 25% and the unemployment rate was relatively low at 4.2% (Statistics New Zealand, 2020). With a significantly larger population of 25.5 million, Australia had an average happiness score of 7.09 for 2020 (Greyling *et al.*, 2019). Their annual GDP growth rate in the year to December 2019 was 1.9%, debt as a percentage of GDP was 41.73% and the unemployment rate was 6.2% (Australia Bureau of Statistics, 2020). Moreover, South Africa, with the largest population of the three countries, namely 57.7 million people, had a lower average happiness score of 6.32 for 2020 (Greyling *et al.*, 2019). The economy grew at only 0.15% in 2019, debt as a percentage of GDP was 62.2% and the unemployment rate was significantly higher than those of the other countries at 29% (Statistics South Africa, 2020). In light of the bleak economic outlook, the country's sovereign credit rating was downgraded by Moody's to junk status in March 2020, which impacted political stability, the national debt and debt interest payments.

In addition to the above, all three countries had a different response to curbing the spread of COVID-19. New Zealand and South Africa both decided to *"go fast and go hard,"* although there were still significant differences in what constitutes *"fast and hard."* The first confirmed case for New Zealand was reported on 28 February 2020, and 27 days later on 26 March, the country went into alert level 4, which brought about a complete lockdown. Under New Zealand's level 4 lockdown people were allowed to leave their homes only for essential reasons and were instructed to work from home. No travelling was allowed and the schools were closed. However, they were allowed to purchase alcohol and tobacco and to exercise outside their homes at any given time. There was very rarely a need to enforce compliance. According to the Stringency Index[2] (Roser *et al.*, 2020), the mean stringency for the period (1 January to 30 May), was 41.35 (the stringency index ranges from 0 to 100 with 100 being the most stringent).

For South Africa, the first confirmed case was on 6 March 2020 and 21 days later on 27 March; the country implemented strict lockdown regulations comparable to those of the Philippines and Jordan. During South Africa's level 5 lockdown, people were subjected to the same regulations as the New Zealanders; however, with the additional stringency measures of a ban on the sale of alcohol and tobacco and no exercise being permitted outside their homes. In addition, the South African government called in the help of the defence force to ensure compliance with the restrictions. The mean Stringency Index (Roser *et al.*, 2020) for this time period for South Africa was 44.90, thus somewhat higher than that of New Zealand.

At the other end of the spectrum, Australia that follows a federal government system never went into complete lockdown, such as that implemented by New Zealand and South Africa. The first confirmed case on Australian soil was reported on 25 January 2020, but it was not until 15 March (50 days later) that the Australian government banned gatherings of more than 500 people. On 18 March, the Australian government banned indoor gatherings of more than 100 people, but the border was only closed to non-residents on 21 March. From 23 March onwards, different states implemented different lockdown regulations related to bars, clubs, cinemas, places of worship, casinos and gyms, and in some states schools were closed. On 29 March, the government urged (not mandated) that Australians should stay at home other than for food shopping, medical care needs, exercise or work/education that could not be done from home.

Additionally, there was a ban placed on congregating in public of more than two people. But this was the most stringent lockdown regulation mandated by the Australian government. The mean Stringency index (Roser *et al.*, 2020) for Australia's time period was 40, thus lower than that of either New Zealand or South Africa.

2.2. *Pandemics, Lockdowns and Well-Being*

Studies that investigated *subjective well-being* during previous pandemics found that community-connectedness and isolation were mitigating factors on subjective well-being during the SARS outbreak (Lau *et al.*, 2008). Additionally, anxiety levels waned along with the perception of the H1N1 virus being less of an immediate threat (Jones and Salathe, 2009).

More recently, studies investigating the pandemic and consequent lockdown effect on well-being using Big Data can be distinguished from those using survey data. Concerning Big Data, Brodeur *et al.* (2020) and Hamermesh (2020) used *Google Trends* to study the effects of government-imposed lockdowns on *well-being and mental health,* and *life satisfaction*, respectively. Brodeur *et al.* (2020) found a negative effect on *well-being and mental health* as measured by the increase in searches for sadness, worry and loneliness. Hamermesh (2020) determined that single people were less satisfied with life in running simulations than married people.

Greyling *et al.* (2020) relied on the social media platform *Twitter* and used the *GNH index* to investigate the *determinants of happiness in an extreme country case,* namely South Africa. Stringent lockdown regulations were enforced against the background of a weak economy and already low levels of well-being. First, they estimated the determinates of GNH for the period from 1 January 2020 to 8 May 2020, and then for subsamples before and after the announcement of the lockdown, using OLS estimations. When comparing GNH determinants before and after the lockdown, they found that after the lockdown

other factors connected to the lockdown regulations became significantly related to South Africans' happiness. Factors found to be significant and negatively related to GNH after the lockdown were the lack of mobility and access to alcohol and school closures. Furthermore, they estimated the likelihood that happiness levels would reach the same levels of happiness experienced in 2019, using ordered probit estimations. The results showed that the likelihood had decreased by 7% during this time.

Rossouw *et al.* (2020) sought to determine whether *different stages of happiness* (GNH) existed during the time period from 1 January 2020 to 25 May 2020 in New Zealand, using a Markov switching model. They found evidence of two stages: the unhappy and the happy state, and discovered that the pandemic had been the cause. Additionally, they calculated the probabilities of transitioning between the two states. For New Zealanders, their happier state is quite persistent. However, the probability of moving from an unhappy state to a happy state is only 22%, while the probability of staying in an unhappy state is relatively high, at 78%. Thus, they concluded that, once New Zealanders achieve an unhappy state (their state of happiness during the pandemic), the likelihood of becoming happy is relatively small, while the likelihood to remain unhappy is relatively big. Therefore, they argued that policy intervention was a priority to ease the unhappy state. Lastly, they found that the factors important for New Zealand's happiness post-COVID-19 were international travel, employment and mobility.

Using *survey data* collected at two points in time (December 2019 and April 2020) for 1003 individuals, Sibley *et al.* (2020) found that lockdown regulations slightly increased people's sense of community and trust in institutions. However, moreover, they cautioned that there would be longer-term challenges to mental health, since anxiety and depression levels were up post-lockdown. Briscese *et al.* (2020) studied how Italian residents' intentions to comply with the self-isolation restrictions responded to the length of their possible extension. After collecting survey data, they found that respondents were more likely to reduce rather than increase their self-isolation efforts if an extension was longer than they had expected. Fang *et al.* (2020) quantified the causal impact of human mobility restrictions, particularly the lockdown of Wuhan's city on the containment and delay of the spread of COVID-19. They found that the lockdown of the city of Wuhan contributed significantly to reducing the total number of infection cases outside of Wuhan, along with the social distancing measures imposed later by other cities.

However, none of the above studies investigated the *relationship between lockdowns and happiness*, considering the wide spectrum of differing degrees of lockdown in diverse countries. Also, not one of the studies compared the *effect sizes of countries with different levels of strictness of their lockdown regulations* on happiness. Furthermore, very few considered Big Data as a data source to access real-time high-frequency data for both the periods preceding and following the worldwide pandemic and consequent lockdowns. Therefore, in the current study we address these gaps in the literature.

3. DATA AND METHODOLOGY

3.1. *Data*
Our analyses use a pooled dataset, covering the three countries, as explained in Section 2.1, to estimate the relationship between lockdown and well-being. In our initial analysis, we use a DiD estimation technique (see Section 3.2.1). The technique compares the variable

under consideration, in this instance happiness, before and after the treatment (the lock-down) to a counterfactual time period in the year before. We select the same time period as the control period, with the same number of days in 2019 as the corresponding number of days in 2020, being 150 days in each year (1 January 2020 to 30 May 2020, excluding 29 February 2020). We recognise that the trends in the years 2019 and 2020 are not always in perfect unison, and therefore the strict assumption of parallel trends is not fully fulfilled. Consequently, we are hesitant to draw strict causal conclusions; however, we do perform an event study to substantiate and test the robustness of our results. The results may be interpreted as the average impact of lockdown on happiness (well-being), comparing pre- and post-lockdown periods in 2020 to the same time periods in 2019 that were assumed to have relatively normal Gross National Happiness levels.

For our second objective, we employ the Least Squares Dummy Variable (LSDV) estimator to analyse the heterogeneity of the lockdown's impact on the three countries, respectively (see Section 3.2.3). For this specification we focus exclusively on data from the year of the treatment, 2020. Our data are an unbalanced panel, starting from when the first case of COVID-19 was confirmed in each country. For Australia this was on 25 January 2020, for New Zealand 28 February 2020 and South Africa 6 March 2020. This sample's end date were dictated by data availability and is the same for all three countries, namely 30 May 2020. It is imperative to note that, at the time of writing "lockdown" was still ongoing in each of the three countries, albeit with varying degrees of easing of the strictness of the lockdown regulations.

3.1.1. Selection of Variables.
3.1.1.1. The Outcome Variable: Gross National Happiness Index We use the Gross National Happiness (GNH) index to measure happiness (the outcome variable). To construct the GNH index, we extract a live feed of tweets from the voluntary information-sharing social media platform Twitter (please see Rossouw and Greyling (2020) for a detailed discussion). Sentiment analysis is subsequently applied to every tweet. Sentiment analysis, using Natural Language Processing, is the process of determining whether a piece of writing (product/movie review, tweet, etc.) is positive, negative or neutral. It can be used to identify the follower's attitude towards an event using variables such as context, tone and so on. 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. After applying sentiment analysis, every tweet is labelled as having either a positive, neutral or negative sentiment.

After each tweet has been classified, we apply a sentiment balance algorithm to derive a happiness score per hour. The happiness scores scale is between 0 and 10, with 5 being neutral, thus neither happy nor unhappy. The index is available live on the GNH website (Greyling *et al.*, 2019). As happiness varies over the days of the week, with a Monday low and a Saturday high, we adjust the time series to remove the average day of the week effect (Helliwell and Wang, 2011; Kelly, 2018). We notice that the mean level of GNH for the period under consideration is 7.02 in 2019, considerably higher than the 6.81 in 2020 (see Table 2 for descriptive statistics).

The question can be asked whether this index is a robust measure of a country's happiness. To answer this question, we first turn to the Twitter statistics per country in Table 1.

Table 1. Twitter statistics per country

Country	Average number of tweets extracted for 2020	Active Twitter users	Percentage of population
South Africa	68,524	11 million	18%
New Zealand	5,112	0.567 million	10.31%
Australia	26,104	4.6 million	18%

Source: Omnicore (2020).

Table 2. Dates for country lockdown announcements and implementation

Country	Date of announcement	Date of lockdown	Duration of lockdown on 30 May 2020
Australia[1]	16 March 2020	17 March 2020	75 days
New Zealand	23 March 2020	25 March 2020	67 days
South Africa	23 March 2020	27 March 2020	65 days

[1]As Australia never officially went into a full lockdown such as that seen in NZ and SA, we are using the day when international borders' closure was announced as a proxy for "lockdown." At the time of writing the paper, the lockdown was still ongoing in all countries; thus, we report the number of days for which the countries were observed to be under lockdown in this paper.

Source: Authors' calculations.

Table 1 shows that the number of tweets is extensive and represents more than 10% of the population across all three countries. In saying this, we do not claim that the tweets are representative. However, we maintain that Twitter accommodates individuals, groups of individuals, media outlets and organisations representing a kind of disaggregated sample, thus giving access to the moods of a vast blend of Twitter users not found in survey data. Additionally, after analysing GNH and the tweets underpinning the index, since 2019, it seems that the GNH index gives an extraordinarily robust reflection of a nation's mood. As GNH is constructed at country level, one possible shortcoming in using it is that we cannot look at heterogeneity in the effects of the lockdown by different groups. Therefore, our results should be interpreted as the mean impact on happiness. This limits the conclusions we can draw on within-country samples.

As there are no other measures of its kind, we opted to test the index's robustness by correlating it to time series data, reflecting emotions related to well-being. The data are derived from survey data, Twitter and Google Trends. First, using survey data, we correlate the GNH index of each country with the "depression" and "anxiety" variables of that country included in the *"Global behaviours and perceptions at the onset of the COVID-19 Pandemic data"* survey for the period from 1 March 2020 (OSF, 2020). We find a negative and significant relationship, mostly greater than 0.5 ($r > 0.5$). Therefore, it seems that the GNH index derived from Big Data and the "depression" and "anxiety" variables derived from survey data give similar trends, though in opposite directions.

Second, we correlate GNH with the emotions, "fear" and "joy" derived from Twitter data. To derive these emotions, we use Natural Language Processing methods that capture the specific emotion in each word of a tweet (this method differs from sentiment analysis). We find that the Pearson Correlation Coefficient is $r = -0.59$ if "fear" and GNH are considered, and $r = 0.63$ if "joy" and the GNH are considered. Both relationships are significant at the 99% level ($p = 0.000$).

Third, we correlate the GNH index with Google Trends search data for the topics "well-being" and "happiness." These topics were previously used in Brodeur *et al.* (2020) (see Section 2.2). We find the Pearson correlation coefficient to be $r = 0.5$ and $r = 0.4$, respectively. Based on these results, we believe that the GNH index is a valid measure of the evaluative mood (sentiment) of a nation.

3.1.1.1. Selection of the Covariates To select the covariates included in the models, we are led by the literature (see Section 2.2). We are limited in our choice of variables, as i) the time period is relatively short (the number of observations is limited), thus restricting the number of covariates that can be included in the estimation to avoid overfitting the models and ii) we can only include data that is available on a daily frequency. Therefore, in the DiD estimation, we restrict our selection of covariates (similar to Fang *et al.*, 2020 and Brodeur *et al.*, 2020) to the lockdown variable (the treatment), the number of new COVID-19 deaths as a control for the pandemic, and weekly and country fixed effects.

The lockdown date in our analysis is the date on which the lockdown was announced, not the implementation date (see Brodeur *et al.*, 2020) since, following the trend in the happiness index, we observed that the biggest effect is experienced on the date of announcement rather than the date of implementation. Thus, lockdown anticipation is reflected in the decrease in the happiness scores before lockdown is implemented. As a robustness test, we also run all estimations on the date of implementation of the lockdown. The lockdown variable takes the value of 1 after the lockdown is announced or implemented, depending on the model estimated. See Table 2 for the dates on which the lockdown was announced and implemented, as well as the duration of the lockdown under investigation.

As mentioned above, to account for the disease's impact, we include new COVID-19-related deaths per million of the population (see Brodeur *et al.*, 2020). This data are sourced from the Oxford Stringency Index (Roser *et al.*, 2020) (see Table 3). There were no deaths before lockdown, as deaths only occurred in the time period after the lockdown, with a mean number of 1.38 new deaths per million per day in the three countries under analysis.

In the Least Squares Dummy Variable (LSDV) estimator, which we restrict to the treatment year 2020, we add the variable *job searches*, as we find "jobs" a high trending topic in the tweets of all three countries after lockdown. We include this variable since the economic cost of the lockdown cannot be ignored. We use the methodology as set out by Nuti *et al.* (2014) and Brodeur *et al.* (2020), and the daily searches on Google Trends for jobs, as a proxy for job uncertainty in the future (see also Simionescu and Zimmermann, 2017).

Table 3. Descriptive statistics of the variables included in the estimations of happiness

Variables	2019				2020			
	Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max
GNH	7.02	0.507	5.29	7.90	6.81	0.467	5.35	8.00
New daily deaths per million	0.00	0.000	0.00	0.00	1.38	0.158	0.00	13.35
Jobs Searches	69.46	14.49	39	99	54.50	18.806	20.00	99.00

Source: Authors' calculations.

Google search trends data are comparable across countries within a year (as it is rebased to 100), but not across years. In this study, as we restrict the LSDV model to only the treatment year (2020), we do not use any scaling procedures to make the data comparable across years. Using the index for job searches, which is derived by the number of daily searches for "jobs" divided by the maximum number of daily searches for the time period, we find the mean number of job searches for the period to be 54.50, varying from 20 to 99 per day (see Table 3).

It should be noted that although Google Trends has the benefit of showing aggregated measures of search activity per country and, therefore, is less vulnerable to small-sample bias (Baker and Fradkin, 2017), it has certain limitations. One of these is that we cannot observe heterogeneity in searches by the respondents' characteristics within the country. Another limitation is that Google Searches are more likely to be popular with the younger cohort of the population. However, internet use is widespread in New Zealand and Australia with 93% and 88% saturation, respectively, and 62% in South Africa (Statista, 2020). This implies that there are a vast number of users. These users are primarily between the ages of 15 and 65, which is the age group of the economically active population and often also the age group included in survey analyses.

3.2. Methodology

3.2.1. Difference-in-Difference To investigate the relationship between lockdown and happiness, we use a Difference-in-Difference estimation (DiD)[3] which compares GNH for pre-and post-lockdown periods in 2020 to the same time periods in 2019, assumed to have normal happiness levels.

Specifically, we estimate the following equation:

$$GNH_{c,t} = \alpha_0 + \alpha_1 lockdown * Year_t + \alpha_2 lockdown + \alpha_3 New\ Daily\ Deaths_{c,t-1} \\ + \alpha_4 New\ Daily\ Deaths^2_{c,t-1} + \mu_c + \sigma_t + \in_{c,t}$$

(1)

where $GNH_{c,t}$ is happiness for country c (where c = Australia, New Zealand and South Africa) *on day t*. α_1 (the treatment effect) reflects the relationship of a lockdown in year 2020 on GNH. The variable *lockdown* is a dummy variable, assuming a value of zero if country c is not in lockdown and one if country c is in lockdown. $Year_t$ is the year at time t of the lockdown; thus either 2019 or 2020. We do acknowledge that there could be variation in the intensity of lockdown between the countries. Our results in Section 4.3 account for these differences. The variable *New Daily Deaths*$_{c,t-1}$ controls for new deaths per million with a 1-day lag in country c. Furthermore, we account for the quadratic effect of new deaths per million on GNH. We do this because it could possibly be that in the earlier stages of the pandemic, with very few new COVID-19 deaths, people were more positive and optimistic as the fatality rates were very low and the recovery rates very high. However, as time progressed the higher fatality rates could have turned the relationship around so that the number of new COVID-19 deaths became negatively related to happiness. Furthermore, a lagged effect on happiness is likely due to COVID-19 deaths being reported in the media only the following day. The model includes country and week fixed effects (μ_c and σ_t). We report standard errors clustered around the observation date. Some common daily factors might influence happiness in all three countries, generating the possibility of intra-cluster correlation. Regular standard errors or even White's

standard errors might lead to an overstatement of precision, as shown in Bertrand *et al.* (2004). We cluster the standard errors at the date's level in all these estimations to account for this. There are 150 clusters, the number of clusters being the same as the number of dates (days) we have in our data.

Our interaction term *lockdown* ∗ *Year*$_t$ conveys the association between lockdown and happiness. However, there are some caveats to this interpretation. It is possible that the DiD estimator could conflate the true effect of the lockdown with the broader economic scenario in 2020, particularly since our results later show that a significant proportion of the negative effects of the lockdown on well-being is economic in nature. For the interaction between *lockdown* ∗ *Year*$_t$ to truly convey the causal impact of the lockdown, we assume that the year before the lockdown (2019) provides a true counterfactual for the 2020 levels. Thus, the GNH followed the same trend as the year before. This implies maintaining the common-trend assumption. This might not strictly be the case as the happiness levels in 2019 could have been affected by events that did not happen in 2020. Given this limitation, we restrict our interpretation to indicate a significant association rather than to make causal claims. Furthermore, some sensitivity tests might gauge the robustness of this negative impact of the lockdown. To this end, we employ an event study analysis explained in Section 3.2.2 below.

3.2.2. Event Study We estimate an event study model outlined in Brodeur *et al.* (2020) as a sensitivity test to gauge the robustness of the negative association between lockdown and happiness. The event study model can be written as follows:

$$GNH_{c,t} = \sum_{m=-3}^{m=4} \delta_m W_{c,m} * Year_t + \sum_{m=-3}^{m=4} \rho_m W_{c,m} + \gamma \, New \, Daily \, Deaths_{c,t-1} + \mu_c + \rho_t + \in_{c,t}$$

$$(2)$$

where $W_{c,m}$ are dummy variables for the 3 weeks before the lockdown announcement and the 4 weeks after the lockdown was announced (interacted with the dummy variable *Year*$_t$). Country fixed effects are referred to with μ_c, yearly fixed effects with ρ_t, and $\in_{c,t}$ is the error term. We use the fourth week before the lockdown as the reference period. Therefore, we interpret the estimated coefficients of *the* $W_{c,m}$ dummy variables as the effect of being in, for example, the third week after the lockdown was announced ($W_{c,m}$) as compared to 4 weeks before this date.

3.2.3. Least Squares Dummy Variable Estimator We use the Least Squares Dummy Variable estimation technique to answer our second research question. Here, we compare the well-being costs (the effect size) of the different degrees of strictness of the lockdown regulations implemented by each of the three countries under investigation.

We estimate an additional specification similar to equation (1) but restrict our observations to 2020 after the first COVID-19 case was announced. However, we introduce an interaction term between our treatment variable and the different countries (South Africa is the reference group), to convey the heterogeneous effects of the lockdown on each of the three countries. Furthermore, we control for the country (μ_c) and weekly fixed effects (σ_t) (similar to equation 1). We also control for daily job searches to account for the economic effects of the lockdown on GNH. The error term is represented by $\in_{c,t}$ and the equation is as follows:

$$GNH_{c,t} = \beta_0 + \beta_1 lockdown * c + \beta_2 NewDailyDeaths_{c,t-1} + \beta_3 NewDailyDeaths^2_{c,t-1} + \beta_4 Year_t$$
$$+ \beta_5 lockdown + \beta_6 jobsearches_{c,t} + \mu_c + \sigma_t + \in_{c,t}$$

(3)

4. RESULTS AND ANALYSIS

4.1. Descriptive Analysis

In our initial analysis, we compare the GNH levels in 2020, pre-and post-lockdown day (the date the lockdown was announced), to the GNH levels (assumed to be normal) in 2019, pre-and post-lockdown the same day (the assumed lockdown day in 2019). However, we note that South Africa, an extreme country case where relatively low levels of well-being are especially sensitive to political, social and economic changes, also have a high level of well-being volatility. Therefore, although the GNH index was smoothed, we preferred to retain some volatility, as it can be assumed to be the norm. For example, during February 2019 South Africa suffered from newly introduced load shedding (that is when the electricity supplier ESCOM shuts down the electricity supply for predetermined periods), which had a negative effect on GNH. Other incidents that had a significant negative effect on GNH in 2019 include (i) the death of school children, due to a bridge collapsing at a school, (ii) the announcement of funds earmarked for drought relief vanishing without explanation (corruption), (iii) xenophobic attacks in Durban and (iv) the political unrest preceding the national elections in May 2019. Therefore, high volatility in well-being is the norm, as shown in Fig. 1, showing that South Africans respond accordingly when a negative event happens. However, known for their resilience, South Africans seem to recover relatively quickly from these events.

Fig. 1 shows the three countries' graphs included in the analysis: New Zealand, South Africa and Australia. Each graph depicts GNH adjusted for day of the week variations, thus Monday lows and Saturday highs, for the year 2019 (the dotted line) and 2020 (the solid line). The vertical axis shows the GNH scores. The GNH scores vary on a scale between 0 and 10. The horizontal axis reflects the days before (negative values) and the days after (positive values) the country's lockdown announcement. The lockdown day is set equal to zero in 2020 and corresponds to the same day in 2019. We added vertical lines (see Fig. 1) to indicate the days on which the lockdowns (solid line) or the easing of lockdowns (dashed line) were announced. The reader will note that lockdown was not eased in South Africa for the time period analysed.

In each country (see Fig. 1) we notice from the onset of the pandemic in 2020 that the GNH was lower than in 2019. A sharp decrease in GNH started a few days before the full lockdown announcement (in Australia's case, severe lockdown restrictions). Approximately on the announcement day of the lockdown (day 0), it reached a low. The pattern was only seen in 2020; there are no sharp decreases in any country, or in the aggregated happiness scores, in 2019 around the same date.

Interesting to note that the levels of happiness started decreasing before the announcements of strict or total lockdown were made. This is likely because, in the days before these announcements, there were already regulations that enforced social distancing. Furthermore, there were expectations that strict or total lockdown regulations would follow.
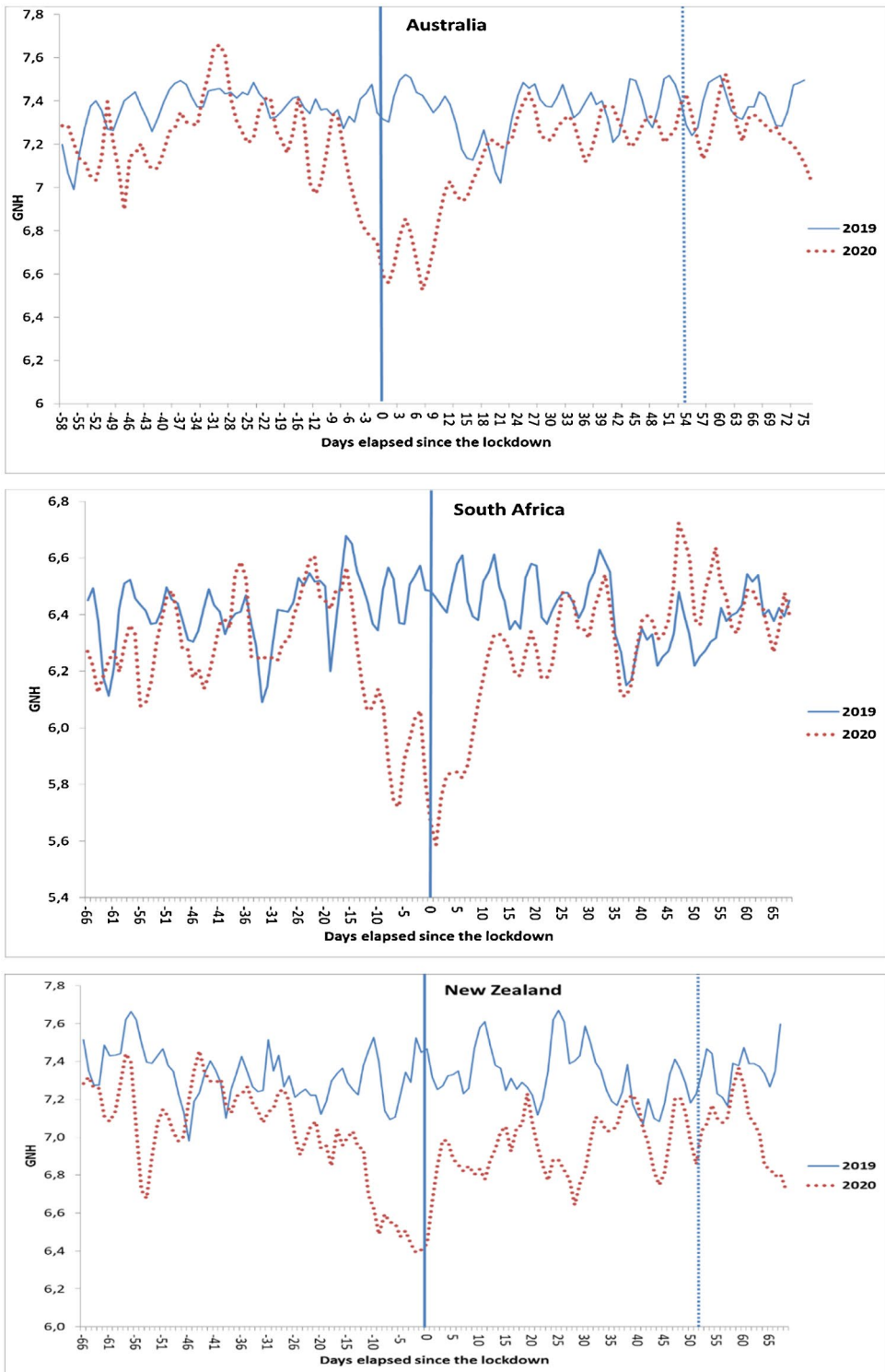
Figure 1. GNH pre- and post-lockdown in 2019 and 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

What we also see in the GNH is the resilience of people when facing adversity. In all three countries, the happiness levels increased again (albeit not to the levels before the lockdown and continuing to be at lower levels than in other time periods). This is not surprising, seeing that there are positive links between well-being and close social relationships. Having entire populations under lockdown meant that families could spend time together and reconnect, save on travel time and expenses and feel safer. For example, in New Zealand people were asked to form "bubbles." These "bubbles" could include your loved ones or individuals integral to your family. In South Africa crime rates decreased remarkably, enhancing the feeling of safety.

Thus, based on the descriptive statistics (Table 3) and Fig. 1, it seems that the pandemic as a whole and the anticipation of going into lockdown (the announcement), as well as the day on which the stay-at-home orders themselves were announced (see the robustness test in Table 4 panel 2), negatively affected happiness. The same pattern was not observed around the same date in 2019. In the next section, we will determine whether it was, in fact, the "lockdown" orders that contributed to the negative effect.

4.2. Results from DiD

To gauge the relationship between lockdown and happiness, we examine the DiD estimation results in Table 4, panel 1. First, we find that the lockdown variable is significant and negative; indicating significant decreases in all three countries' happiness levels after the lockdown was announced. Second, we notice that the "year" variable (fixed effect) is significant and negative. The GNH is significantly lower in 2020 than in 2019, as revealed in the descriptive statistics (Table 3) and Fig. 1.

To determine whether the decrease in GNH was associated with the lockdown (the treatment) specifically and not only the trend (we also control for the number of new deaths per million as a proxy for the pandemic), we consider the estimated coefficient of the interaction variable "lockdown and year," *i.e.* the DiD estimator. We find it to be statistically significant (at the 1% level) and negative, indicating that "lockdown"

Table 4. Lockdown effect on happiness – DiD estimates

	(1) Lockdown announcement date	(2) Lockdown implementation date
	GNH	GNH
Lockdown announcement × year	–0.161***	
	(0.0397)	
Lockdown implementation × year		–0.126***
		(0.0339)
2020	–0.225***	–0.235***
	(0.022)	(0.033)
Lagged new deaths per million	0.089***	0.079***
	(0.016)	(0.014)
Lagged new deaths squared	–0.006***	–0.005***
	(0.001)	(0.001)
Country FE	Yes	Yes
Week FE	Yes	Yes
R^2	0.86	0.84
N	868	868

Note: Standard errors are clustered at the level of observation. There are 150 clusters.

*p < 0.10, **p < 0.05, ***p < 0.01.

Source: Authors' calculations.

contributed to a mean decrease in GNH of 0.161 points compared to its mean values for 2019. Thus, the year in which the treatment (lockdown) was applied, people were unhappier after the lockdown than before. This result holds true even if we control for trends (although the trends in 2019 and 2020 may not be strictly parallel) in the time series, using 2019 as the counterfactual. Therefore, we can conclude that the lockdown regulations (although at different stringency levels) were associated with a significant decline in happiness of almost 6% across all three countries under investigation. This implies that *a lockdown is associated with a decline in happiness levels,* notwithstanding the characteristics of a country or the severity and duration of the lockdown.

To test the robustness of these findings we repeat the DiD estimation (see Table 4, panel 2), but instead of using the date of the lockdown announcement, we use the date on which the lockdown orders of various strictness, were implemented. We find similar results, with the DiD estimator being statistically significant and negative, showing a decrease in GNH of 0.126 points, which can likely be explained by the lockdown orders.

In order to verify the sensitivity of the results from the DiD estimator, we employ an event study framework (see Section 3.2.2). As can be seen, the estimated coefficients in Table 5 and in Fig. 2 show that the happiness levels continued to be lower throughout the lockdown period compared to 4 weeks before the announcement of the lockdown.

However, as can be inferred from the coefficients in Table 5, happiness levels started declining 1 week before the lockdown with significantly greater reductions seen during the week of the lockdown announcement (which would also include the day of the lockdown implementation) and 1 week after the lockdown announcement. As seen in Table 5, the GNH levels are significantly lower up to 3 weeks after the lockdown announcement, but there is no significant difference in average weekly GNH levels up to 2 weeks before the announcement. Therefore, we are quite confident that the lockdown was the main factor behind the fall in happiness levels.

Table 5. Lockdown effect on happiness – Event study

	Dependent variable: GNH
3 Weeks before lockdown	0.050
	(0.032)
2 Weeks before lockdown	−0.008
	(0.035)
1 Week before lockdown	−0.316***
	(0.059)
Week of the lockdown	−0.514***
	(0.029)
1 Week after lockdown	−0.433***
	(0.035)
2 Weeks after lockdown	−0.233***
	(0.049)
3 Weeks after lockdown	−0.063**
	(0.025)
Lagged new deaths per million	0.0035
	(0.010)
Lagged new deaths per million squared	0.00003
	(0.0009)
Year FE	Yes
Country FE	Yes
2	0.89

Note: Standard errors are clustered at the level of observation. There are 150 clusters. The fourth week before lockdown is the reference week.
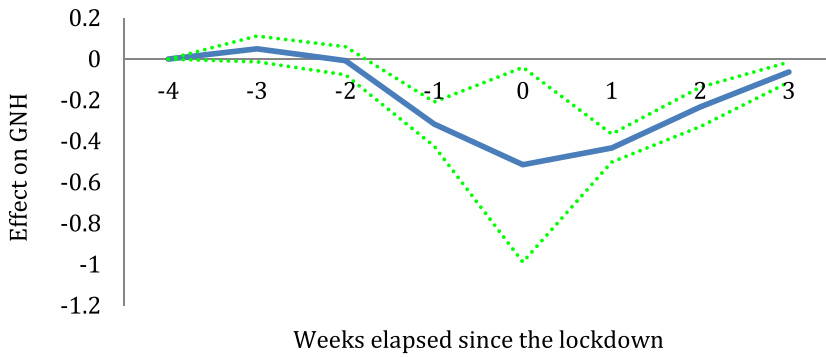
*p < 0.10, **p < 0.05, ***p < 0.01.

Figure 2. Effect on GNH up to 3 weeks before and after the lockdown announcement. Note: *Dotted lines represent the 95% confidence interval. The X-axis is in terms of weeks [Colour figure can be viewed at wileyonlinelibrary.com]*

Fig. 2 plots the event study estimates, using 2019 figures as the counterfactual for the weeks before and after the lockdown. The solid line plots the coefficient while the dotted lines around them represent the 95% confidence interval. The fourth week before the stay-at-home-order (in 2019 or 2020) is the reference period. The estimation results are given in Table 5. We can see that for periods up to 1 week before the lockdown announcement, the GNH is not statistically different from its value 4 weeks before the announcement, on average. However, starting from 1 week before the lockdown announcement, the negative effect is sustained and statistically significant until 3 weeks after the announcement. The DiD estimation results in Table 4 and the event study results in Table 5 reinforce each other. Therefore, we are satisfied with the robustness of the findings from the DiD estimation.

4.3. Results from Least Squares Dummy Variable Estimator

Next, we compare the well-being costs (the effect size) of the different degrees of strictness of the lockdown regulations implemented by each of the three countries under investigation (see Table 6). As we control for COVID-19-related deaths, we restrict the time period to when the first COVID-19 case was confirmed in 2020.

Overall, our treatment variable "lockdown" is negatively and significantly associated with happiness for our sample. However, upon analysing the country's interactions and lockdown, we see that the effect size is increasing in order to the severity of the lockdown (see Section 2.1 for additional information on the Stringency Index). Thus, South Africa has the largest negative association, followed by New Zealand and, interestingly, the overall effect of the lockdown on the happiness of Australia is almost negligible (−0.165 + 0.171). This is consistent with the lack of severity of the lockdown in Australia. This further confirms that, the more stringent the lockdown level, the greater the negative impact on happiness levels.

Furthermore, we find that the Google Searches for "jobs" during this period are negatively and significantly related to GNH; thus, an increase in the searches for "jobs" is related to decrease mean GNH levels. This finding highlights the economic concerns brought about by the lockdown and stay-at-home orders. The lockdown orders restricted

Table 6. Results from the LSDV estimation related to the effect size of lockdown on happiness

Variables	All countries
Lockdown	−0.165***
	(0.042)
Country: Australia (South Africa is the reference category)	0.859***
	(0.040)
Country: New Zealand	0.641***
	(0.039)
Lockdown × Australia (Lockdown × South Africa is the reference category)	0.171***
	(0.044)
Lockdown × New Zealand	0.112**
	(0.048)
Job searches	−0.004***
	(0.001)
Lagged new deaths per million	−0.004
	(0.021)
Lagged new deaths per million squared	0.002
	(0.001)
Constant	6.562***
	(0.083)
N	318
Adjusted ^{2}	0.82

Note: Standard errors clustered at the level of observation base in SA in column 1. There are 150 clusters.

*p < 0.10, **p < 0.05, ***p < 0.01.

people's movement and caused the shutdown of large sections of the economy, thus contributing to severe economic downturns in these countries. In Australia, approximately 87,500 jobs were lost (Australia Bureau of Statistics, 2020). For New Zealand, approximately 30,000 more people relied on the government's job seekers benefit than before the lockdown (Infometrics 2020). In South Africa, it is estimated that nearly 1.6 million jobs will be lost in 2020 (Weimar and Radebe, 2020). Additionally, this finding is in line with the work done by Greyling *et al.* (2020) and Rossouw *et al.* (2020) who found a similar negative effect on happiness levels.

It must be noted that, due to restrictions on the number of covariates, there are several "positives" that may positively impact happiness during this period; thus, there might be certain positive influences captured in the error term. For example, these could be increased family time, lower fuel costs and higher safety levels (South Africa). However, even with a margin of error, we report a significantly negative relationship between lockdown and happiness, with the effect size increasing with the level of strictness of the lockdown.

5. CONCLUSIONS

In this paper, we used the GNH, a real-time measure of well-being derived from Twitter, to investigate the relationship between lockdown and happiness. We focused on three diverse countries in our analyses, namely South Africa, New Zealand and Australia. These countries differ in their characteristics and implemented lockdown regulations, as well as the duration of their respective lockdowns. Therefore, notwithstanding the country characteristics or the lockdown regulations, we could determine whether a lockdown is negatively related to happiness. We tested for the relationship using DiD estimations and an event study.

Additionally, we compared the well-being costs of the different levels of strictness of the countries' lockdown regulations, using the Least Squares Dummy Variable estimation technique. This is the first paper of its kind to estimate the association between happiness and lockdown. Additionally, we estimate the effect size of this relationship during a pandemic, considering countries with very diverse characteristics and different lockdown stringencies, thus controlling for the heterogeneity of countries. This is also one of the very few papers that consider Big Data to derive a happiness index and includes Google Trend data to derive high frequency real-time daily data.

Our results show robust evidence of a negative relationship between the lockdown regulations and happiness, notwithstanding the diversity in characteristics and lockdown regulations of the countries included in our sample. Furthermore, considering the lockdown's effect size, the negative association is in increasing order of the stringency of the restrictions. Thus, South Africa suffers the largest negative effect compared to the other two countries, New Zealand and Australia.

Our results on the negative relationship between a lockdown and happiness, varying with the levels of strictness of the lockdown, have important policy implications. Despite the government's clear message that we should all stay at home to save lives, the evidence of a substantial decrease in happiness cannot be denied. Failure to introduce policy measures to alleviate the negative consequences of lockdown on happiness levels will increase prolonged lower happiness levels, which can have negative spill-over effects in various domains, which may be economic, social or political. However, any measures taken must be cognisant of preventing an increase in the spread of the COVID-19 virus.

One shortcoming of this study is the inability to draw heterogeneous within-country conclusions, seeing that we employ country-level representative indicators for happiness. Thus, it is important to interpret our results as the mean effect on happiness.

CONFLICT OF INTEREST

There is no potential conflict of interest.

NOTES

[1] The happiness scores cited here reflect the average for the period in 2020 before the first COVID-19 case was announced.

[2] Consisting of the following indicators: school closing, workplace closing, cancelling of public events, restrictions on gatherings, stay at home requirements, restrictions on internal movement, restrictions on international travel and restrictions on public information campaigns.

[3] For other studies that use DiD, please see for example Kollamparambil and Etinzock (2019), D'Addio *et al.* (2014) and Dolan and Metcalf (2008).

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