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A tale of three countries: How did Covid-19 lockdown impact happiness?

Talita Greyling¹, Stephanie Rossouw², Tamanna Adhikari³

Abstract Since the start of the Covid-19 pandemic, many governments have implemented lockdown regulations to curb the spread of the virus. Though lockdowns do minimise the physical damage of the virus, there may be substantial damage to population well-being. Using a pooled dataset, this paper analyses the causal effect of mandatory lockdown on happiness in three very diverse countries (South Africa, New Zealand, and Australia), regarding population size, economic development and well-being levels. Additionally, each country differs in terms of lockdown regulations and duration. The main idea is to determine, notwithstanding the characteristics of a country or the lockdown regulations, whether a lockdown negatively affects happiness. Secondly, we compare the effect size of the lockdown on happiness between these countries. We make use of Difference-in-Difference estimations to determine the causal effect of the lockdown and Least Squares Dummy Variable estimations to study the heterogeneity in the effect size of the lockdown regulations; a lockdown causes a decline in happiness. Furthermore, the negative effect differs between countries, seeming that the more stringent the stay-at-home regulations are, the greater the negative effect.

Keywords: Happiness; Covid-19; Big data; Difference-in-Difference

JEL classification codes: C55, I12, I31, J18

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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 during the pandemic peoples' happiness decreases (Greyling et al. 2020), the number of reported negative emotions increase (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 spread of the virus were not controlled, the loss of life would be overwhelming. To this end, lockdown regulations were implemented around the globe, albeit at differing levels 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, the main cost of this confinement has been in terms of the economy. However, while the cost of lockdown on the gross domestic product (GDP) is considerable, there may be additional substantial damage to population well-being. Joblessness, social isolation and the lack of freedom, which are some of the by-products of lockdown, are all well-known risk factors for mental health and happiness (Leigh-Hunt et al. 2017, Verne 2009, Clark & Oswald 1994). However, as argued by Algan et al. (2019), GDP in itself, which is the measure mostly used to determine welfare, cannot measure these non-market factors such as social interactions with friends and family, nor the level of people's happiness or sense of purpose in life.

In saying the above, apart from a study conducted by Brodeur et al. (2020) and Fang et al. (2020), none of the other studies investigating the effect of Covid-19 or the consequent lockdown focused on determining causality (see discussion in section 2.3). Without establishing the causal relationship between lockdown regulations and well-being, we cannot extend precise policy advice.

Therefore, the primary aim in this study is to use the Gross National Happiness Index (GNH), a real-time measure of well-being (happiness), derived from Twitter, to investigate the causal 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 and implemented lockdown regulations, as well as the duration of their respective lockdowns. The main idea is, notwithstanding the characteristics of a country or the lockdown regulations, to determine whether a lockdown negatively affects happiness. We test for the causal relationship using Difference-in-Difference (DiD) estimations.

Additionally, we compare the well-being costs of the different degrees of strictness of the lockdown regulations implemented by these countries by using the Least Squares Dummy Variable estimation technique. This is the first study of its kind investigating the causal effect of lockdown in diverse countries and comparing the happiness costs of the stringency of lockdowns. The current paper adds to the limited literature on utilising Big Data in analysing happiness by being one of a handful of studies that have access to real-time data covering

both pre- and post-Covid-19 lockdowns.

Our main results that come from the DiD model indicate that 'lockdown', the treatment variable causes a negative effect on happiness, notwithstanding the different characteristics of the countries included in our sample, the duration and the type of lockdown regulations. Comparing the effect size of the lockdown regulations, we find that the more stringent the lockdown, the greater the happiness costs.

The rest of the paper is structured as follows. The next section contains a short background on the three countries in this study and briefly discusses literature about happiness and the impact of pandemics and lockdown. Section 3 describes the data and the 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

In this study, we focus on South Africa, New Zealand and Australia because it presents us with a unique case study to investigate the effects of different lockdowns regulations within diverse countries in terms of 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 for 2020 of 7.14⁴ (Greyling et al. 2019) and the economic outlook was positive. The annual GDP growth rate in the year to December 2019 was 2.3 per cent, debt as a percentage of GDP was 25 per cent and the unemployment rate was relatively low at 4.2 per cent (Statistics New Zealand 2020). Australia, with a significantly larger population of 25.5 million, had an average happiness score of 7.09 (Greyling et al. 2019). Their annual GDP growth rate in the year to December 2019 was 1.9 per cent, debt as a percentage of GDP was 41.73 per cent, and the unemployment rate was 6.2 per cent (Australia Bureau of Statistics 2020). South Africa, on the other hand, with the largest population out of the three countries, with 57.7 million people had a lower average happiness score of 6.32 (Greyling et al. 2019). The economy grew at only 0.15 per cent in 2019, debt as a percentage of GDP was 62.2 per cent, and the unemployment rate was significantly higher than in the other countries at 29 per cent (Statistics South Africa 2019). 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 on political stability, the level of 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.

⁴ The happiness scores cited here reflect the average for the period in 2020 before the first Covid-19 case was announced.

Under New Zealand's level 4 lockdown people were allowed to leave their homes only for an essential reason and were instructed to work from home. There was no travel 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 Index⁵ (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, which are comparable to the Philippines and Jordan. During South Africa's level 5 lockdown people were subjected to the same regulations as New Zealanders; however, with the additional stringency measures of a ban on the sale of alcohol and tobacco and no exercise was permitted outside their homes. Additionally, 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, which follows a Federal system of government, never went into complete lockdown, such as that implemented by both New Zealand and South Africa. The first confirmed case on Australian soil was reported on 25 January 2020, but it wasn't 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 cannot 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 this time period for Australia was 40, thus lower than that of either New Zealand or South Africa.

2.2 Why happiness?

As stated in section 1, Algan et al. (2019) argue that GDP cannot measure non-market social interactions, such as friendship, family, happiness, moral values or the sense of purpose in life. Additionally, Bryson et al. (2016) and Piekalkiewicz (2017) states 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

⁵Consisting 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.

maximising happiness is at the fore of their policymaking and individual revealed preferences and domain priority as measured through happiness, rather than GDP, could help them achieve this goal. As argued by Layard (2011), this can be achieved by directing economic, social, political and environmental policy to maximise well-being, while acknowledging that people's norms, aspirations, feelings and emotions are of the utmost importance. This underscores that understanding and measuring happiness should be an integral part of the efforts to maximise the quality of life of people.

As pointed out by Anik et al. (2009) and Lyubomirsky et al. (2005), happiness also has consequences for the social and health sectors of a country. Happy people display more altruistic behaviour in the long run. They are also more active, more creative, better problem solvers, more social, and display 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.

2.3 Pandemics, lockdowns and well-being

Studies that investigated *subjective well-being* during previous pandemics found that communityconnectedness and not isolation was a mitigating factor 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 & Salathe 2009).

More recently, studies investigating the effect of the pandemic and consequent lockdown on well-being using Big Data can be distinguished from those using survey data. With regard to Big Data, Brodeur et al. (2020) and Hamermesh (2020) used *Google Trends* to study the effect of government-imposed lockdown 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. While Hamermesh (2020), in running simulations, determined single people were less satisfied with life than married people. Greyling et al. (2020) relied on the social media platform *Twitter* and used the *GNH* to investigate the *determinants of happiness* before and after Covid-19 in South Africa. They found that the lack of mobility, of access to alcohol and school closures negatively affected happiness. Thus, they were linking regulations to control the spread of the virus to happiness levels. Additionally, they substantiated findings from Jones and Salathe (2009) that the threat of Covid-19 dissipated over time and did not seem to impact happiness as such. Rossouw et al. (2020) determined the stages of *GNH* in New Zealand, using a Markov switching model, and found that the factors important for New Zealand's happiness post-Covid-19 were related to 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. On the other hand, they also 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 the *intentions* of Italian residents to comply with the self-isolation restrictions responded to the length of their possible extension. They found, after collecting *survey data*, that respondents were more likely to reduce rather than to 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 the city of Wuhan 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 infection cases outside of Wuhan, even with the social distancing measures imposed later by other cities.

However, none of the above studies investigated the *causal effect of lockdown on happiness*, taking into consideration 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 the strictness of 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 lockdown.

3. Data and methodology

3.1 Data

In our analyses we use a pooled dataset including the three countries, as explained in section 2.1, to estimate the effects of lockdown on well-being. In our initial analyses we use a Difference-in-Difference (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 lockdown) to a counterfactual time period in the year before. For the control period, we select the same time period, with the same number of days in 2019, corresponding to the number of days in 2020, thus 150 days in each year (1 January 2020 to 30 May 2020, excluding 29 February 2020). Our results should thus be interpreted as the average impact of the lockdown on happiness (well-being), comparing pre- and post-lockdown in 2020 to the same time period in 2019, assumed to have normal levels of Gross National Happiness. In this manner, we also account for seasonal trends in happiness in the different countries and prevent them from influencing our results.

For our second objective, we employ the Least Squares Dummy Variable (LSDV) estimator to analyse the heterogeneity on the impact of the lockdown on the three countries, respectively (see section 3.2.2). For this specification, we focus exclusively on data from the year of the treatment, 2020. Our data is 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 for South Africa 6 March 2020. The end date of this sample was 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. After applying sentiment analysis, every tweet is labelled as having either a positive, neutral or negative sentiment. This sentiment classification is then applied to a sentiment-balance algorithm to derive a happiness score. The happiness scores range between 0 and 10, with five 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 day 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 (Kelly 2018, Helliwell & Wang 2011). 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.

Country	Average number of	Active Twitter	Percentage of
	tweets extracted for	users	population
	2020		
South Africa	68524	11 million	18%
New Zealand	5112	0.567 million	10.31%
Australia	26104	4.6 million	18%

 Table 1: Twitter statistics per country

Source: Omnicore (2020)

From table 1 it can be seen that the number of tweets is extensive and represents more than 10 per cent of the population across all three countries. In saying this, we do not claim that the tweets are representative. However, we do 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 the mood of a nation. As GNH is constructed at the country-level, one possible shortcoming in using it is that we cannot look at heterogeneity in the effects of the lockdown by different groups. Our results should thus 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 measure the robustness of the index by making use of 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.

3.1.1.2 Selection of the covariates

To select the covariates included in the models, we are led by the literature (see section 2.2 and 2.3). We are limited in our choice of variables, as i) the time period is relatively short (the number of observations is limited), thus it restricts 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), as following the trend in the happiness index we observed that the biggest effect is experienced on the date of the announcement rather than the date of implementation. Thus, the anticipation of lockdown 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, implemented, and duration of lockdown under investigation.

Country	Date of Announcement	Date of Lockdown	Duration of lockdown on 30 May 2020**
Australia*	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

Table 2: Dates for country lockdown announcements and implementation.

* As Australia never officially went into a full lockdown such as that seen in NZ and SA, we are using the day when the closure of international borders 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.

Furthermore, to account for the impact of the disease itself, we include new Covid-19 related deaths per million of the population (see Brodeur et al. 2020). This data is sourced from the Oxford Stringency Index (Roser et al.

2020) (see table 3). Before lockdown, there were no deaths, as deaths only occurred in the time period after the lockdown, with a mean number of 0.07 new deaths per million per day, in the three countries under analysis.

Variable	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	54.5	18.806	20.00	99.00

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

Source: Authors' calculations.

In the LSDV estimation, which we restrict to the treatment year 2020, we add the variable *job searches*, as we find 'jobs' a high trending topic in 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 & Zimmermann 2017).

Google search trends data is 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 make use of 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 & Fradkin 2017), it has certain limitations. One of these is that we cannot observe heterogeneity in searches by the characteristics of the respondents 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 per cent saturation, respectively, and 62 per cent 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 causal effect of the lockdown on happiness, we use a Difference-in-Difference estimation (DiD) which compares the 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:

$$GNH_{i,t} = \alpha_0 + \alpha_1 lockdown_i * Year + \alpha_2 New Daily Deaths_{i,t-1} + \alpha_3 New Daily Deaths_{i,t-1}^2 + lockdown_{i,t} + \mu_i + \sigma_i + \epsilon_{i,t}$$
(1)

Where GNH_{it} is the daily happiness for country *i* at time *t* (where *i* = Australia, New Zealand, South Africa). Our treatment variable *lockdown* varies by country and takes the value of 0 pre-announcement day and one post-announcement of lockdown in both the year of the actual lockdown (2020) and the year before the lockdown (2019). We do acknowledge that there could be variation in the intensity of the lockdown between the countries. Our results in section 4.3 account for these differences. *Year* is a dummy variable where 1 is the year 2020. We control for new deaths per million with a one-day lag. Further, we account for the quadratic effect of new deaths per million on GNH. The model includes country and week fixed effects (μ and σ). We report standard errors clustered around the date of the observation.

The identification strategy relies on the fact that the dates of the lockdown differ between countries. There is also a difference in the level of GNH pre- and post-lockdown in 2020, which is the Difference-in-Difference estimation mimicked in 2019. Thus, our interaction term *Lockdown*Year* will convey the causal impact of the lockdown on happiness.

3.2.2 Least Squares Dummy Variable Estimator

To answer our second research question to compare the effect size of the lockdown of each of the three countries, with different levels of lockdown strictness, we make use of the Least Squares Dummy Variable estimator. We estimate an additional specification similar to equation (1), but restricting our observations to 2020 after the first Covid-19 case was announced. However, in addition, we introduce an interaction term between our treatment variable and countries, thus a country-level fixed effect (μ) to convey the heterogeneous effects of the lockdown on each of the three countries. Furthermore, we control for the country and weekly fixed-effects (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 v and the equation is as follows:

$$GNH_{i,t} = \beta_0 + \alpha_1 lockdown_i * \mu + \beta_2 New Daily Deaths_{i,t-1} + \beta_3 New Daily Deaths_{i,t-1}^2 + \beta_3 New Daily Deaths_{i,t-1$$

$$+Year + lockdown_{i,t} + \mu_i + \sigma_i + \nu_{i,t}$$
(2)

It is possible that 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). To account for this, we cluster the standard errors at the level of the date in all these estimations.

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- the same day (the assumed lockdown day in 2019).

Figure 1 shows the graphs for the three countries included in the analysis: New Zealand, South Africa and Australia. Each graph depicts the 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 on a scale that varies between 0 and 10. The horizontal axis reflects the days before (negative values) and the days after (positive values) the announcement of lockdown in each country. The lockdown day is set equal to zero in 2020 and corresponds to the same day in 2019



Source: Authors' calculations using the GNH dataset, Greyling et al, 2019.

Figure 1: GNH pre- and post- lockdown in 2019 and 2020

In each country (see figure 1) we notice from the onset of the pandemic in 2020, that the GNH was lower than in 2019. A sharp decrease in the GNH started a few days before the announcement of the total lockdown (in Australia's case the severe lockdown restrictions). Approximately on the announcement day of the lockdown (day 0) it reached a low. The pattern is 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.

What we also see in the GNH is the resilience of people when facing adversity. In all three countries, happiness levels increased again, albeit not to before the lockdown levels, and continue 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 also felt 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 figure 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 this was, in fact, the 'lockdown' orders that caused the negative effect.

4.2 Results from DiD

To gauge the causal effect of lockdown on happiness, we examine the DiD estimation results in table 4, panel 1. Firstly, we find that the lockdown variable is significant and negative; indicating significant decreases in the happiness levels of all three countries after the lockdown was announced. Secondly, we notice that the 'year' variable (fixed effect) is significant and negative; thus, GNH was significantly lower in 2020 than in 2019, as was already revealed in the descriptive statistics (table 3) and figure 1.

	(1) Lockdown Announcement date		(2) Lockdown Implementation date	
	GNH	SE	GNH	SE
Lockdown Announcement* Year	-0.161***	(0.0397)		
Lockdown Implementation*Year			-0.126***	(0.0339)
Week FE	Yes		Yes	
Year FE	Yes		Yes	
Lagged new deaths and squared new deaths per million	Yes		Yes	
Country FE	Yes		Yes	

Table 4: Lockdown effect on happiness – DiD estimates

Standard errors are clustered at the level of observation.

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

Source: Authors' calculations.

To determine if the decrease in GNH was due to the lockdown (the treatment) specifically and not just due to 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 per cent level) and negative, indicating that 'lockdown' caused a mean decrease in GNH of 0.161 points when compared to its mean values for 2019, even when controlling for the general trend in the two years. Therefore, we can conclude that the lockdown regulations (although at different stringency levels), caused a significant decline in happiness of almost 6 per cent across all three countries under investigation. This implies that, notwithstanding the characteristics of a country or the severity and duration of the lockdown, *a lockdown has a negative effect on happiness*.

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 announcement of the lockdown, 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, due to the implementation of the lockdown orders.

4.2 Results from Least Squares Dummy Variable Estimator

Next, we compare the effect size of lockdown on happiness levels between the three countries (see table 5). 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, we find our treatment variable 'lockdown' being negatively and significantly associated with happiness for our sample. However, upon analysing the interactions between the country and lockdown, we see that the effect size is in increasing 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 Australia. This further confirms that, the more stringent the level of the lockdown, 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 a decrease in the mean GNH levels. This finding highlights the economic concerns brought about by the lockdown and stay-at-home orders. The lockdown orders restricted the movement of people and caused the shutdown of large sections of the economy, thus contributing to severe economic downturns in these countries. In Australia, approximately 87500 jobs were lost (Australia Bureau of Statistics 2020). For New Zealand, approximately 30000 more people were relying on the government's job seekers benefit than before the lockdown (Infometrics 2020) and in South Africa it is estimated that nearly 1.6 million jobs will be lost in 2020 (Weimar & 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.

	All Countries	SE
Lockdown	-0.165***	(0.042)
Country (South-Africa is the reference category)	-	-
Country: Australia	0.859***	(0.040)
Country: New-Zealand	0.641***	(0.039)
Lockdown*Country (Lockdown*South-Africa is the reference category)	-	-
Lockdown*Australia	0.171***	(0.044)
Lockdown *New-Zealand	0.112**	(0.048)
Job Searches	-0.004***	(0.001)
Constant	6.562***	(0.083)
N	318	318
Lagged Deaths	Yes	Yes
Adjusted R^2	0.82	0.79

 Table 5: Results from the LSDV estimation related to the effect size of lockdown on happiness

Standard errors are clustered at the level of observation. Base is SA in column 1. * p < 0.10, ** p < 0.05, *** p < 0.01

Source: Authors' calculations.

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. These could be, for example, increased family-time, lower fuel costs and higher levels of safety (South Africa). However, even with a margin of error, we report a significantly negative causal impact of the lockdown on happiness, with the effect size increasing with the level of strictness of the lockdown.

5. Conclusions

In this paper, we used the Gross National Happiness Index (GNH), a real-time measure of well-being, derived from Twitter, to investigate the causal relationship between lockdown and happiness. We focused on three diverse countries in our analyses, namely South Africa, New Zealand and Australia. These countries differ concerning 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 negatively affects happiness. We tested for a causal relationship using Difference-in-Difference (DiD) estimations. Additionally, we compared the well-being costs of the different strictness of lockdown regulations implemented by the countries, using the Least Squares Dummy Variable

estimation technique. This is the first paper of its kind to estimate the causal and the effect size of a lockdown during a pandemic on happiness, 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 causal effect of lockdown regulations on happiness, notwithstanding the countries included in our sample's diversity in characteristics and lockdown regulations. Further, considering the effect size of the lockdown, this negative impact is in increasing order of 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 causal effect of a lockdown on happiness, varying with the strictness of the lockdown, has important policy implications. Despite the clear message from the government 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 effect of lockdown on happiness levels, and considering the easing of lockdown measures, will increase prolonged lower happiness levels, which can have negative spill-over effects in various domains such as economic, social and political. However, any measures taken must be cognisant of not increasing 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

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