Greyling, Talita; Rossouw, Stephanie; Adhikari, Tamanna

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Happiness-lost: Did Governments make the right decisions to combat Covid-19?

Talita Greyling[1]
School of Economics, University of Johannesburg,
E-mail: talitag@uj.ac.za

Stephanie Rossouw,
Faculty of Business, Economics and Law, Auckland University of Technology,
E-mail: stephanie.rossouw@aut.ac.nz

Tamanna Adhikari
School of Economics, University of Johannesburg,
E-mail: tamanna.adhikari@ucdconnect.ie

Abstract Amidst the rapid global spread of Covid-19, many governments enforced country-wide lockdowns, with likely severe well-being consequences. The actions by governments triggered a debate on whether the well-being and economic costs of a lockdown surpass the benefits perceived from a lower infection rate. In this regard, South Africa is an extreme case: enforcing very stringent lockdown regulations, while amid an economic crisis. We analyse the impact of both Covid-19 and the lockdown on happiness. We use the Gross National Happiness Index to compare the determinants of happiness before and after the Covid-19 lockdown regulations. Further, we estimate the likelihood of happiness levels in 2020, reaching the average levels in 2019 using two models; one predicting the likelihood after the lockdown was enforced and the other if no lockdown regulations were in place. The results shed light on happiness outcomes in a scenario of lockdown versus no lockdown.

Keywords: Happiness; Covid-19; Big data; Regulations; Probabilities; South Africa

JEL classification codes: C55, I12, I31, J18

1. Introduction

An ongoing outbreak of the Coronavirus (Covid-19) has caused over 4 million confirmed cases with an excess of 280 000 deaths worldwide (as of 8 May 2020) (John Hopkins University 2020). Work by Bonanno et al. (2010), Kessler (2006) and Norris et al. (2002) have left no doubt that as people see a country or worldwide disaster unfold, such as Covid-19, people's mental and physical health and social relationships are negatively impacted. Ultimately the negative effects experienced in these domains decrease people's happiness levels. Additionally, during these times, there is an increase in the number of negative emotions reported by people, such as feeling tense, agitated, sad, anxious or lonely (Sibley et al. 2020).

In an attempt to curb the spread of Covid-19 and minimise the loss of life, governments around the world have imposed their version of mandatory self-isolation through implementing lockdown

[1] Corresponding author

regulations. At the time of writing this paper, a third of the world's population was living in some form of mandatory government-imposed lockdown. Unfortunately, restricting people's mobility and depriving them of what matters most has had an intensifying negative effect on happiness levels.

To this end, our primary aim in this study is to use the Gross National Happiness Index (GNH), a real-time measure of well-being, derived from Big Data, to investigate the determinants of happiness before and after Covid-19. This allows us to compare results on determinants of happiness before and after implementation of lockdown regulations and to determine what matters most to happiness under these changed circumstances. Furthermore, we estimate the likelihood that happiness levels will reach the same levels of happiness experienced in 2019. We do this using two models; one predicts the likelihood before and after the lockdown was enforced and the other if there were no lockdown regulations in place. The results shed light on the happiness outcomes in a scenario of a lockdown versus no lockdown. Currently, there is limited, if any, information on the conjoint effects of the pandemic, government regulations and social isolation, on people's happiness.

Against this backdrop, the current study makes several contributions to the literature:

i. This is the first study that investigates the determinants of happiness during a pandemic, considering both periods before and after lockdown regulations were implemented. Previous studies (see section 2) have investigated the macroeconomic determinants of happiness, but it was conducted under 'normal' times.
ii. Certain studies have investigated well-being and related matters during the pandemic, but they did not explicitly consider happiness (see section 2).
iii. Apart from the Hamermesh (2020) and Brodeur et al. (2020) studies that used Google Trends (see section 2), none of the current studies investigating the effect of Covid-19 on well-being makes use of real-time, Big Data, in the same manner as we do.
iv. No other study, to the knowledge of the authors', has attempted to measure the likelihood that a country can adapt to previous levels of happiness after suffering the consequences brought on by a pandemic, government regulations and self-isolation. Still, we take this further by comparing the happiness outcomes of being in lockdown versus being in no lockdown.

The results of the study inform policymakers on that which matters most to happiness during a pandemic and have possible applications to other countries with similar lockdown regulations (comparative studies will be done in future research). Furthermore, it measures the likelihood of happiness costs due to lockdown regulations. These results give policymakers the necessary information to take action in increasing the happiness of the nation and set the scene for increased economic, social and political well-being. It also allows them to reflect on happiness outcomes due to their policy actions. An additional benefit of the current study is that policymakers do not need to wait for extended periods to see the consequences of their policies, as we are making use of real-time data, with immediate information. Usually, policymakers can only evaluate their own decision making, with significant time-lags, prolonging the implementation of corrective actions.

Our results indicate that what matters most for happiness under lockdown, for an *extreme country case*[2], is not the standard macroeconomic determinants of happiness, but rather the factors directly linked to the regulations that were implemented. These factors can be classified as (i) social capital issues; lack of access to alcohol (beer), lack of mobility and concerns about schooling, and (ii) economic issues; concerns over jobs, the threat of retrenchments and lower levels of consumption. As expected, the number of daily Covid-19 cases is negatively related to happiness. Surprisingly over time, it seems that there is a U-shaped relationship between the number of Covid-19 cases and happiness. Thus, initially, the number of cases decreased happiness (the negative relationship), but as the threat of the Covid-19 disease looked less imminent, due to high recovery – and low mortality rates, it seems as if the happiness levels started increasing. However, the effect size is very small, thus negligible.

Using simulations, we answer the question of whether the likelihood to be happy without lockdown and an increased number of Covid-19 cases surpasses the likelihood to be happy with lockdown and less Covid-19 cases. This is an important issue, particularly for economies in dire straits with already low levels of well-being. We find the probability to be happy with lockdown regulations implemented to be 23 per cent and without lockdown 30 per cent. Thus, lockdown had a likelihood cost to be happy of 7 per cent. It seems even considering a margin of error that people in South Africa would have been happier with an increased number of Covid-19 cases and no lockdown regulations, than with a lower number of Covid-19 cases and lockdown regulations.

The rest of the paper is structured as follows. The next section contains a short background on South Africa and briefly discusses literature about happiness, Big Data and studies conducted on the impacts of pandemics. Section 3 describes the data, 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

In this study, we focus on South Africa because it presents us with a unique case to investigate the wide-spread effects of Covid-19 amidst an economic crisis. South Africa implemented one of the most stringent lockdown regulations (comparable to the Philippines and Jordan) which brought about high economic costs while already faced with a severe economic downturn. Therefore, South Africa is an example of an *extreme country case* which unfortunately amplifies the effects of the difficult choices

[2] We define an extreme country case as a country under stringent lockdown regulations coupled with a failing economy.

made by policymakers. Therefore, we take advantage of this unique country case and determine how stringent lockdown regulations impact happiness during a one in 100-year event. In South Africa, there are five levels of differing lockdown regulations, with alert level 5 the most stringent and alert level 1 the most relaxed. The idea behind these levels is while South Africa curbs the spread of Covid-19, South Africans receive increasingly more of their previous liberties back. During level 5, which started on 27 March 2020, South Africans were only allowed to leave their homes to purchase or produce essential goods. All South Africans were instructed to work from home, there was no travel allowed, the sale of alcohol and tobacco were banned, people were not allowed to exercise outside their homes, and the police and defence force ensured compliance to the restrictions. South Africa moved to level 4 lockdown on 1 May 2020 and with this move they received back the ability to exercise outside from 6 am - 9 am, purchase more than just essential goods, including food deliveries as long as it was within curfew. Interestingly, the sale of alcohol and tobacco was still banned. At the time of writing this paper, South Africa was still under level 4 lockdown.

Whereas everybody understands that the Covid-19 infections curve needs to be flattened, there are grave concerns that these stringent lockdown regulations will also flatline South Africa's economy. Before the Covid-19 lockdown, South Africa had a 29 per cent unemployment rate, and the gross domestic product (GDP) has been estimated to shrink by 4.8 per cent (Bureau of Economic Analysis 2020). According to the South African Reserve Bank (2020), an additional 3 to 7 million people can potentially become unemployed as a direct consequence of the pandemic, thereby increasing unemployment rates to approximately 50 per cent. The country's sovereign credit rating was downgraded to junk status in March 2020, which impacted on political stability, the level of the national debt and debt interest payments. Add to this already grim situation, the fact that consumption of South Africans has been declining in 2020, with major declines seen after the lockdown, then one can very easily see how the cogs that keep the economy ticking can come to a complete stop.

Why should we care whether people's happiness is adversely impacted by not only a global pandemic but also by the response from the government? The studies of Helliwell (2015), Layard (2011), Stiglitz et al. (2009), Veenhoven (2009), Diener and Seligman (2004) and others, have shown beyond a shadow of a doubt that if policymakers want to maximise the quality of life of their citizens, they need to consider subjective measures of well-being, such as happiness, and not merely economic measures. 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. By measuring happiness, individuals themselves reveal their preference and assigned priority to various domains, which cannot be identified by a measure such as GDP. As was pointed out by Layard (2006), while economists use exactly the right framework for thinking about public policy, the accounts we use of what makes people happy are wrong. In layman's terms, we say that utility increases with the opportunities for voluntary exchange. However, Layard (2006) argues that this overlooks the significance of involuntary interactions between people. Policymakers should formulate policy to maximise happiness or well-being, as is the main aim of many constitutions. 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 important. Thereby underscoring that understanding and measuring happiness should be an integral part of the efforts to maximise the quality of life.

On the other hand, if the happiness of people is negatively affected, such as in the wake of Covid-19 and the implementation of lockdown regulations, there are far-reaching consequences.

These consequences are as follows:

i. Social capital: unhappier people display less altruistic behaviour in the long run (Dunn et al. 2014). They are also less active, less creative, poor problem solvers, less social, and display more anti-social behaviour (Lyubomirsky et al. 2005). If unhappier people display more anti-social behaviour, South Africa could see an increase in behaviour such as unrests, violent strikes and perhaps higher crime rates.
ii. Health care: unhappier people are less physically healthy and die sooner (Lyubomirsky et al. 2005). Additionally, unhappy people engage in riskier behaviour such as smoking and drinking, thereby placing unnecessary pressure on national health systems.
iii. Economic: unhappy workers are typically less productive, in particular in jobs that require sociability and problem solving (Bryson et al. 2016). If an economy can raise the rate of growth of productivity, by ensuring their workers are happier, then the trend growth of national output can pick up.

Having established that policy should strive to maximise the happiness of their people, it is necessary to know what determines happiness. Previous studies have investigated, at a macro-level, what influences happiness and found that economic growth, unemployment and inflation play a significant role (Stevenson and Wolfers 2008, Perović 2008, Sacks et al. 2010). However, all of these studies were conducted in 'normal' periods and not under such conditions that are currently plaguing the world. The current study will have the opportunity to investigate this exact question, namely what determines happiness during a pandemic.

When the studies mentioned above were conducted, it was reasonable to use annual data in their estimations. However, as recently witnessed, timely implementation of government decisions requires as close to real-time data as possible, and policymakers cannot wait for data plagued by significant time-lags to inform their decisions. Being able to access real-time data to inform policymakers on the effect of their decisions on happiness levels, allows them the opportunity to within a very short period rectify decisions, which is to the detriment of people's happiness. Policymakers never before had this benefit as the results of their policy decisions are normally only visible after a considerable time lag, depending on the environment affected (economic, social or political).

Big Data, such as the social media platform Twitter, provides the above-mentioned real-time information for policymakers to assist them when facing short-term deadlines with imperfect information. Big Data also allows governments to 'listen' and capture those variables which their citizens deem to be important for their well-being, rather than relying on pre-defined economic utility theories. Big Data offers governments the opportunity to observe people's behaviour and not just their opinions. This approach of revealed preferences unveils a reflexive picture of society because it allows the main concerns of citizens (and the priority ranking of those concerns) to emerge spontaneously, and it complements as such the information captured by gross domestic product. Lastly, Big Data does not suffer from non-response bias (Callegaro & Yang 2018). In the current study, we take advantage of the benefits of Big Data and real-time measures to derive variables in the estimate of happiness functions. This will allow policymakers the benefit of continuous, timely information on the effects of their policies on the well-being of their citizens. To the knowledge of the authors', this is the first study that incorporates Big Data to estimate happiness functions.

When it comes to using Big Data to calculate a happiness index, there are but two measures apart from the one used in this study. The Hedonometer, created by Dodds and Danforth (2010) and their team is the first measure of happiness started at the end of 2008. They use the Twitter Decahose Application Programming Interface (API) feed, which is a Streaming API feed that continuously sends a sample, of roughly 10 per cent of all tweets. This allows Dodds and the team to measure happiness levels continuously per day, thus resulting in a time series since the end of 2008 to present (read the foundational paper by Dodds et al. 2011). However, the Hedonometer cannot deal with the context in which words are used, as words in itself are evaluated and not the sentiment of the construct. For example, a phrase such as "I did not enjoy the holiday", will attract a score of 7.66 for 'enjoy' and 7.96 for 'holiday', thus reflecting an overwhelmingly positive sentiment, when actually the sentiment is negative. Furthermore, the Hedonometer calculates a happiness index on a scale of 1 (sad) to 9 (happy), but it cannot detect the emotions underpinning the words or the tweets. Thus, it cannot determine if the changes in the levels of happiness are due to negative emotions such as fear or anger or positive emotions such as joy and trust.

The second known measure was developed in 2012 by Ceron, Curini and Iacus (2016). They used an Integrated Sentiment Analysis (a human supervised machine learning method) on Big Data extracted from Twitter, for both Italy and Japan. This allows them to obtain a composite index of subjective and perceived well-being that captures various aspects and dimensions of individual and collective life

(Iacus et al. 2020). Up until 2017, the researchers extracted and classified 240 million tweets over 24 quarters. To analyse the sentiment, they applied a new human supervised sentiment analysis and did not rely on lexicons or special semantic rules. Iacus et al.'s (2020) subjective well-being have a limited-time series from January 2012 to December 2017; thus, it is not available for analyses of current events such as the global pandemic. Furthermore, it also does not analyse the *emotions* underpinning tweets and does not analyse tweets made in English.

In the current study, we make use of the Gross National Happiness Index, which addresses the limitations of the indices mentioned above. It makes use of sentiment analysis to analyse the sentiment of tweets rather than just recognising certain happy words, and it covers a continuous time period from April 2019 (see Greyling, Rossouw & Afstereo 2019). Furthermore, the index also delves deeper and analyses the underlying emotions of each of the tweets, not done before.

Naturally, the number of studies being conducted to examine the effect of Covid-19 is growing exponentially. This increasing interest in the effect of a global pandemic as well as the policies implemented by governments on peoples' well-being, come on the back of relatively few studies conducted during prior pandemics such as SARS and the H1N1. When SARS hit in 2002 and then again when H1N1 hit in 2009, scholars were only truly starting to understand that for governments to formulate policies to increase well-being, you needed to measure well-being. Of those studies conducted during these pandemics, none of them can make a significant contribution to our study. However, for completeness, the most closely related to our study include:

i. Chew and Eysenbach (2010), who used 2 million tweets containing keywords," swineflu," or "H1N1" to determine the potential of using social media, such as Twitter, to conduct "infodemiology" studies for public health. Through their study, they were able to validate Twitter as a real-time content, sentiment, and public attention trend-tracking tool.

ii. Lau et al. (2008) examined the impact of the SARS outbreak in Hong Kong in 2003, on the subjective well-being of older adults and a younger comparative sample. Survey data were collected through individual face-to-face interviews. They found that while older adults living in severely infected districts showed significantly lower levels of subjective well-being, these levels and those of the younger sample were found to remain within the normative range. Interestingly, they found a sense of community-connectedness and not isolation was a mitigating factor on subjective well-being.

iii. Jones and Salathe (2009) investigated the uncertainty brought about the possibility of contracting H1N1 in Mexico by using an online survey (6,249 people). They found that after an initially high level of concern, levels of anxiety waned along with the perception of the virus as an immediate threat. They were able to determine that a person's emotional status mediates their behavioural response.

Of the current studies being conducted on the effect of Covid-19 on all affected domains, not many studies are in a position to use real-time Big Data, such as we do. Additionally, none of them, to the knowledge of the authors' investigated the effect on Covid-19 lockdown on happiness relative to before lockdown. However, for completeness, the most closely related studies to this one (at the time of writing this paper) examined:

i. nationwide lockdown on institutional trust, attitudes to government, health and well-being, using survey data collected at two points in time (1003 respondents) (Sibley et al. 2020)
ii. the happiness of married and single people while in government-imposed lockdown by running simulations to formulate predictions, using Google Trends data (Hamermesh 2020)
iii. the timing of decision-making by politicians to release lockdown based on a comparison of economic benefits with the social and psychological benefits versus the cost, increase in deaths if policymakers released lockdown too early (Layard et al. 2020)
iv. the role of various socioeconomic factors in mediating the local and cross-city transmissions, using two weeks of data on Covid-19 infection rates and other quarterly macroeconomic data (Qiu et al. 2020)
v. the potential magnitude of employment losses due to social distancing (Koren and Peto 2020)
vi. the changes in well-being (and mental health) after a lockdown was implemented, using Google Trends data (Brodeur et al. 2020).

In summary, taking all of the above into consideration, this study is the first of its kind to investigate the determinants of happiness during a pandemic (as opposed to 'normal' times), considering both periods before and after lockdown regulations were implemented. Additionally, ours is the first study to focus on the effect of Covid-19 on happiness (as opposed to well-being and mental health). Furthermore, apart from Hamermesh (2020) and Brodeur et al. (2020), our study is one of the first to use real-time, Big Data in our analyses. Lastly, no other study has measured the likelihood that a country can adapt to previous levels of happiness after suffering the consequences brought on by a pandemic, government regulations and self-isolation.

3. Data and methodology

3.1 Data

In the analyses, we make use of daily data for the time period from 1 January to 8 May 2020, which is 128 days. We use daily data as Covid-19 became imminent at the end of December. The spread of the pandemic, as well as the policy response, has been rapid and continually evolving, thus leaving us no choice but to work with high-frequency data.

3.1.1 Selection of variables (covariates)

Our primary aim is to determine the effect of the pandemic on happiness before and after the implementation of regulations, to curb the spread of the virus. Therefore, we construct a treatment variable, named 'lockdown' which divides the sample into two distinct time periods; *before* the first regulations were implemented on 18 March 2020 and *after* the implementation. The first time period; *before* 18 March 2020, from 1 January 2020 to 17 March 2020 (77 days), is coded as 0 and includes a period where Covid-19 was imminent and the first positive cases reported in South Africa, but no regulations to curb the spread were implemented as yet. The second time period; *after* 18 March 2020, thus from 18 March 2020 to 8 May 2020 (51 days) is coded as 1. This period includes the initial two weeks in which there was not a total lockdown, but restrictions on social gatherings were implemented. Subsequently, South Africa moved into level 5 and on 1 May into level 4 lockdown regulations. These were stringent and very limiting (see section 2 for the full description).

To select the covariates included in the model, we were led by the literature and data availability. The limited-time period under observation brings about further limitations to the choice of variables, in that it restricts the number of covariates that can be included in the estimation to avoid overfitting the models.

Considering all the pre-mentioned challenges and that daily data is scarce, we are restricted in our choice of variables (see Table 1 for the selection of variables and the descriptive statistics). From the literature, it has been shown that GDP, inflation and unemployment influences happiness (Stevenson and Wolfers 2008, Perovic 2008, Sacks et al. 2010). As we are only working with four months of data, we assume the inflation rate to be relatively stable. Following the works done by Stiglitz et al. (2009), we choose to use consumption as our measure for material well-being since material living standards are more closely associated with consumption than GDP. Additionally, Sachs et al. (2018) argue that consumption is a more appropriate variable to measure economic activity from a developmental point of view than income. Thus, to estimate consumption, we make use of the daily data available related to credit – and debit card sales together with ATM transactions (BETI 2020). We realise that sales are not a perfect proxy for consumption; however, given our data limitations, we believe it provides a reasonable representation of the situation in South Africa. We have no daily measure of unemployment; therefore, we use the methodology as set out by Nuti et al. (2014) and Brodeur et al. (2020) and use daily searches on Google Trends for jobs as a proxy for future job uncertainty (see also Simionescu & Zimmermann 2017).

To select other variables included in the estimation of the happiness function, we relied on the analysis of the tweets. We found ourselves in uncharted territory, as happiness functions have not been estimated previously under a pandemic and lockdown scenario (previously lockdown situations were only seen in war times). The tweets directed us on what influences happiness *during a lockdown,* as well as the most tweeted subjects. It was evident from the tweets that the main topics of discussion related to the regulations that were implemented to curb the spread of the virus. These, among others, include the prohibition of the sale of alcohol and tobacco. To proxy, the sale of alcohol and tobacco we use, similar to the method followed to derive the 'jobs' variable, the number of searches for these products using Google Trends (Nuti et al. 2014, Brodeur et al. 2020). We choose to use the searches for beer, rather than for alcohol, as it has a higher frequency of searches and beer is a good proxy for alcohol, seeing as beer is the most consumed alcoholic beverage by South Africans (Statistics South Africa 2017). The searches for both beer and tobacco follow the same trend during the lockdown period and are highly correlated (r=0.83). We are restricted in the number of covariates to include in the model and decided to include only 'beer' in the regressions. However, assumptions drawn from the results on beer will most likely also apply to tobacco.

Other topics that are trending are related to concerns about the schooling of children and the lack of mobility. To proxy concerns about schooling, we once again make use of Google Trend searches for the word 'schools' and for the lack of mobility we use data derived from the Covid-19 Community Mobility Reports (Google 2020). The reports show the percentage change in visits to certain destinations, for example, grocery stores and pharmacies, retailers, parks and workplaces. The data, however, have limitations, as the data only covers the period from 15 February 2020. We did incorporate the variable retail as a proxy for mobility in the estimations after lockdown and found it to be significant in explaining happiness. However, we could not compare these models to models for the time period before lockdown, due to the lack of data points.

Furthermore, we include the number of tweets per day, as it forms part of the Twitter data extracted daily for South Africa (Greyling et al. 2019), which is a proxy for connectivity. It also gauges the opportunity cost of not being able to have face to face interactions, which seems to be negatively related to happiness (Chae 2018, Wilson et al. 2012). Interestingly the number of tweets increased markedly during the lockdown period, from an average of 60 708 tweets per day before the lockdown to almost 80 000 tweets per day during the lockdown.

From analysing the trends in the happiness index per day (see section 3.2), we found that on certain days of the week people are happier or unhappier than other days (see section 4.1); thus we control for the day of the week in our estimations. We do find it significant in the estimation for the whole time period, but not if we split the sample. Due to the limited number of variables that we can include in the model, especially after splitting the samples, we decided not to include the days of the week, especially seeing that it varied from a Friday to a Saturday before and after the lockdown.

The Covid-19 pandemic and consequent spread of the virus is the reason for the lockdown, and as such are included in the estimations. We add the number of Covid-19 cases as well as the squared number of Covid-19 cases, to control for the seemingly U-shaped relationship between the number of Covid-19 cases and happiness. The data for the number of cases is sourced from the European Centre for Disease Prevention and Control (ECDC). This data is updated each day nationally using a wide number of mainly official sources as well as a handful of social media outlets of the national health ministries of each country. Table 1 provides descriptive statistics for the variables included in the estimations.

Table 1: Descriptive statistics of the variables included in the estimations of happiness

Variable	Mean	Std Dev.	Min	Max	N
Lockdown (1 = period of lockdown and 0= no lockdown)	40.3%	0.49	0	1	128
Sales Volumes, Logged	15.03	0.464	14.011	16.36	128
Jobs[1]	51.00	21.77	19	100	128
Tweets, Logged	68 524.81	13 189.12	42 803	104 744	128
Alcohol[2]	11.11	0.18	10.66	11.56	128
Covid-19 Cases	71.9	126.05	0	663	128
Covid-19 Cases Squared	20938	57582	0	439569	128
Retail	75.59	32.99	18	120	128
Schools	24.65	14.12	11	100	128

Source: Authors' calculations using data as explained in section 3.1.1
Note: 1 Jobs and schools is standardised between 0 and 100 and is computed such that a higher number represents a higher number of searches for UIF.
2 Alcohol is standardised between 0 and 100 and is computed such that a higher number is indicative of a 'lack' of beer.
3 Retail refers to a lack of mobility for purposes of retail as is computed as changes from a baseline of 100.

3.1.2 Gross National Happiness Index – the dependent variable

To measure happiness (the dependent variable), we make use of the Gross National Happiness Index (GNH) which was launched in April 2019 for three Commonwealth member states: South Africa, New Zealand and Australia (Greyling, Rossouw & Afstereo 2019). This project measures the happiness (mood) of countries' citizens during different economic, social and political events.

Since February 2020, the researchers extended the project that initially analysed the sentiment of tweets, to incorporate the analysis of the emotions underpinning tweets. The team did this to determine which emotions are most prominent on specific days or events. These analyses are especially insightful in cases where there are shocks, such is the case with this paper in terms of Covid-19, to determine the emotions of a nation under challenging circumstances and in events where one expects changes in emotions.

To construct the GNH index for the different nations, the researchers use Big Data methods and extract tweets from the voluntary information-sharing social media platform Twitter. Whereafter, the team applies sentiment analysis to a live Twitter-feed and label every tweet 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.

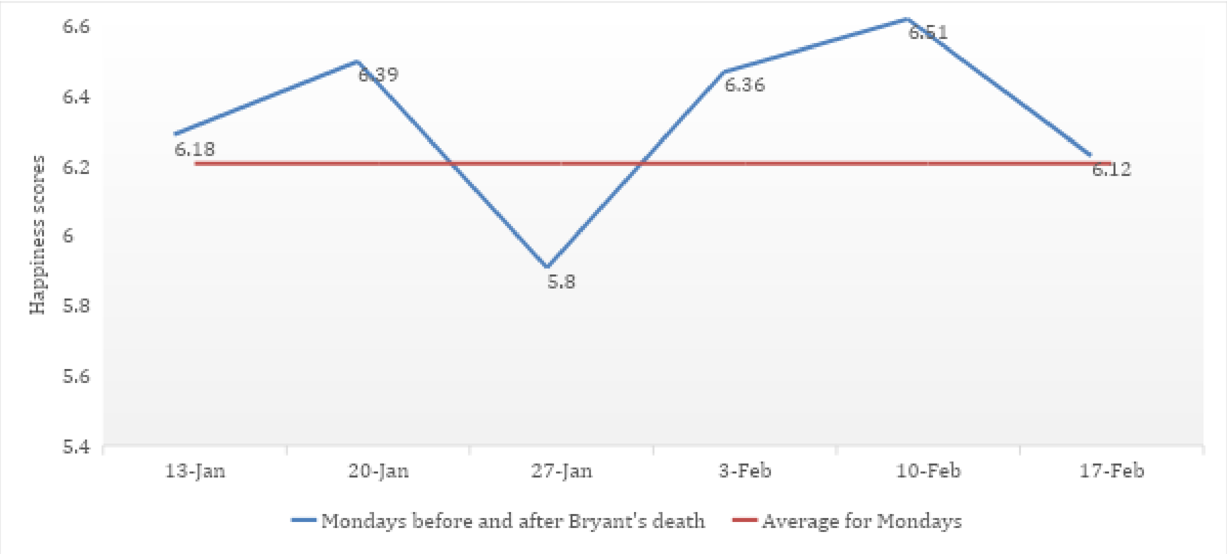
All tweets made in each of the three countries per day are extracted, and a happiness score per hour is calculated. The index is available live on the GNH website (Greyling et al. 2019). In South Africa, the average number of tweets extracted for 2020 is 68 524 per day. South Africa has approximately 11 million Twitter users, representing almost 18 per cent of the population (Omnicore 2020). Although the number of tweets is extensive and represents significant proportions of the populations of the countries, it is not representative. However, Twitter accommodates individuals, groups of individuals, organisations and media outlets, representing a kind of disaggregated sample, thus giving access to the moods of a vast blend of Twitter users, not found in survey data.

Furthermore, purely based on the vast numbers of the tweets, it seems that the GNH index gives a remarkably robust reflection of the mood of a nation. In addition, we correlate the GNH index with 'depression' and 'anxiety', derived from the *'Global behaviors and perceptions at the onset of the Covid-19 Pandemic data*' survey, for the period from 1 March 2020 (OSF 2020). We find it negative and statistically significant related, therefore, it seems that the GNH index derived from Big Data gives similar trends to survey data. (We would have appreciated the opportunity to correlate the GNH to a happiness measure – but a happiness measure, as such, was not included in the survey).

Considering the GNH index over time we found that the index accurately reflects a nation's emotions for example, when South Africa won the Rugby World Cup on 2 November 2019, the happiness index accurately depicted the joy experienced by South Africans (figure 1). The hourly happiness score was 7.9 at 13:00, the highest score ever measured, at the exact time that the final whistle was blown to announce the victory of the Springboks over England.

Source: Authors' calculations using GNH dataset (Greyling et al. 2019)
Fig. 1 Hourly happiness levels of South Africans during the Rugby World Cup final match.

Also, when the famous American basketball player, Kobe Bryant and his daughter Gigi, tragically passed away on 27 January 2020, the happiness index once again captured the negative mood of the nation, and the happiness score decreased to 5.8, significantly below the mean (see figure 2). The result of the GNH mirrors the one determined by the Hedonometer, that recorded an average happiness score of 5.89 on the day of Bryant's death. The top three words that made this day sadder than the previous seven were 'crash', 'died' and 'rip'.



Source: Authors' calculations using GNH dataset (Greyling et al. 2019)
Fig 2 Happiness level, Kobe Bryant's death.

To analyse the emotions rather than the sentiment of tweets, Greyling et al. (2019) analyse the words of a tweet to determine the emotion underpinning the specific word. The researchers differentiate between eight emotions, namely *joy, anticipation, trust, disgust, anger, surprise, fear and sadness*.

3.2 Methodology

3.2.1 OLS regression

We first estimate the following baseline model for the full sample from 1 January – 8 May 2020.

$$y_t = \alpha_0 + \alpha_1 lockdown_t + \alpha_2 X_t + \mu_t \tag{1}$$

Here, y_t refers to the Gross National Happiness Index (GNH) for each day, $lockdown_t$ is our treatment variable capturing the 'closure' of both economic and social activity as a response to Covid-19. It takes a value of 0 before 18 March 18 and one after that. Additionally, we use several relevant covariates to account for the changes in the economy as well as happiness overtime under consideration. This is encapsulated in X_t. (see section 3.1).

Due to the various factors that affect happiness, some of our independent variables may be correlated with the error term, leading to endogeneity concerns. Depending on the direction of the correlation between the error term and the X-variable, the coefficient could be biased upwards or downwards. For instance, the coefficient on the indicator for jobs is likely biased upwards as it, in all likelihood, shows the effect of concerns about jobs as well as some other negative economic shock on happiness. In the absence of panel data or an appropriate instrument, it is difficult to ascertain causality to equation (1). However, given the sudden and rapid spread of the pandemic and the likelihood of it having a knock-on effect on the economy, a study in terms of associations would also be relevant. A natural extension of the work, as better data becomes available with time, would be to address these concerns.

Next, we split our sample by our treatment variable to analyse the determinants of happiness before and after the lockdown. We cannot rule out the probability of autocorrelation and heterogeneity in our data, especially due to its time-series nature. We use robust standard errors to account for this. The choice of our controls, however, comes with a caveat. Seeing as we only have 128 observations using a larger battery of covariates would lead to problems arising due to overfitting of the model. This issue is considered in Green (1991), who suggests a minimum of 50 observations for any regressions as well as an additional eight observations per additional term. We conducted several diagnostics by including indicators for the average temperature (Connolly 2013), the value of the stock index and the daily exchange rates in our model (Bollen et al. 2011, Steyn et al. 2020). However, the model, as outlined in equation (1) seems to be most efficient without running into issues due to overfitting.

Finally, to estimate the full effect of the lockdown regulations on happiness, we add the mobility variable to the model, which we derived from the Covid-19 Community mobility reports. We remind the reader that this variable is only available from 15 February 2020; therefore, we only include it in the estimation for the period after lockdown.

3.2.2 Probabilistic Models

Our second objective is to consider the change in probability of being happy in the year 2020 because of the pandemic and lockdown. To this end, we first transform our dependent variable on happiness which is measured on a scale from 0 to 10, to a binary variable. We use the average happiness for the year 2019, which was a score of 6.35, as the cut-off point. We then estimate the following ordered probit model

$$Pr(Happy = 1|X) = \alpha + \beta_0(lockdown)_t + \beta_1 X_t + \varepsilon_t \quad (2)$$

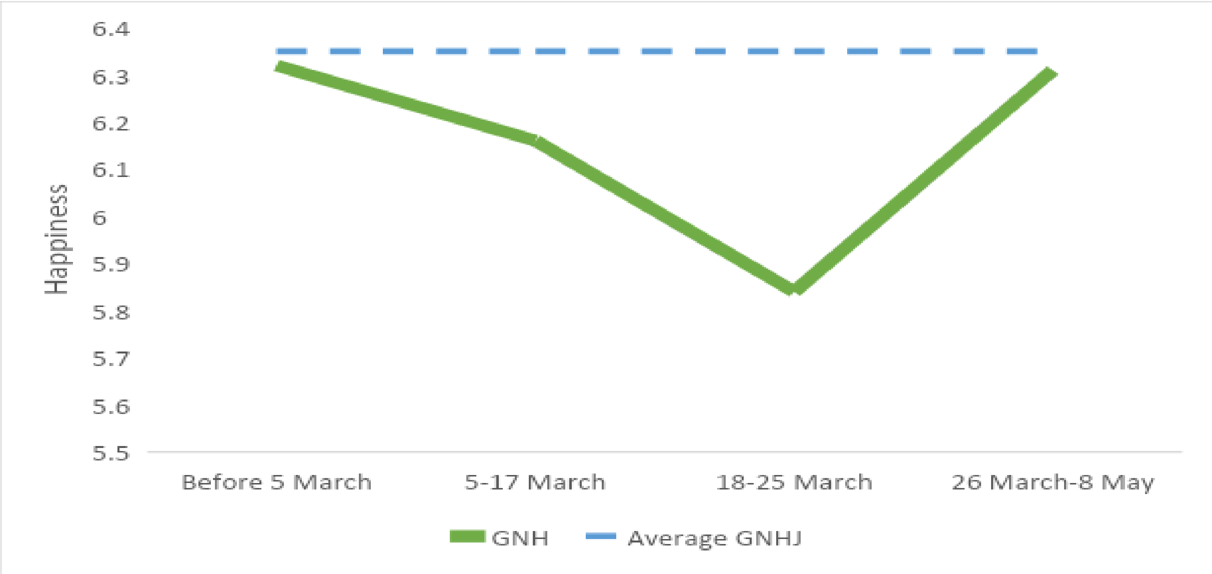
Where X_t is the vector of the controls as described in section 3.1. Using the probit regressions from equation (2), we compute the predicted probabilities of being happy first, over the entire sample and then, before and after the lockdown. Due to the method of constructing our binary dependent variable, we can interpret our computed probabilities as the likelihood of being happier than the average level achieved in 2019.

Lastly, we run a simulation model to estimate the probability of being happy in the event of no lockdown. To do this, we need to create several counterfactual scenarios for our variables. First, we make a reasonable assumption of an increase in the number of Covid-19 cases due to no lockdown. To simulate the number of cases, we use the example of Spain (a worst-case scenario). Spain is a likely choice due to its population size being similar to that of South Africa's and because of its somewhat delayed lockdown response to the pandemic, thus simulating a no lockdown period. Spain reported its first Covid-19 case on 31 January 2020 and only enforced a total lockdown on 14 March - 43 days later. This fits well with our timeline as the last date of our sample is 8 May - 43 days after the first reported case in South Africa. Admittedly, one could also use the example of Italy. Still, due to the similar trajectory in the two countries, we believe Spain is the better choice due to the matching number of days, 43, under investigation. We impute the number of Covid-19 cases for South Africa after its first case on 5 March. Next, to account for the lack of effect of the lockdown on our other covariates (jobs, schools, alcohol, sales and tweets) we use their 2019 values at the same time of that year - thereby accounting for seasonality. We then estimate equation (2) and report the resulting predicted probabilities. Thus, the predicted happiness levels against the backdrop of the Covid-19 pandemic with no lockdown regulations. Admittedly creating counterfactual situations in this way has its own concerns as it incorporates year-specific effects. Still, we believe that even with an error margin, the computed probability will shed light on the true effect of the lockdown on happiness levels.

4. Results and analysis

4.1 Descriptive results

Figure 3 shows the two periods for South Africa that we analyse; the period before the lockdown which covers 1 January to 17 March 2020, and then the period after the regulations were introduced and the lockdown was implemented, 18 March to 8 May 2020.



Source: Authors' calculations using GNH dataset (Greyling et al. 2019)
Fig. 3 Happiness levels before and after lockdown.

From figure 3, it is evident that declaring a state of emergency and informing the nation that they will go into a nationwide lockdown had a significant negative effect on the happiness level. While South Africans understood that measures had to be implemented to curb the spread of the virus, the complete loss of mobility, being forced to work from home, children not being allowed to attend schools, the restrictions on the sale of alcohol and tobacco as well as limitations on exercise, did not sit well with many.

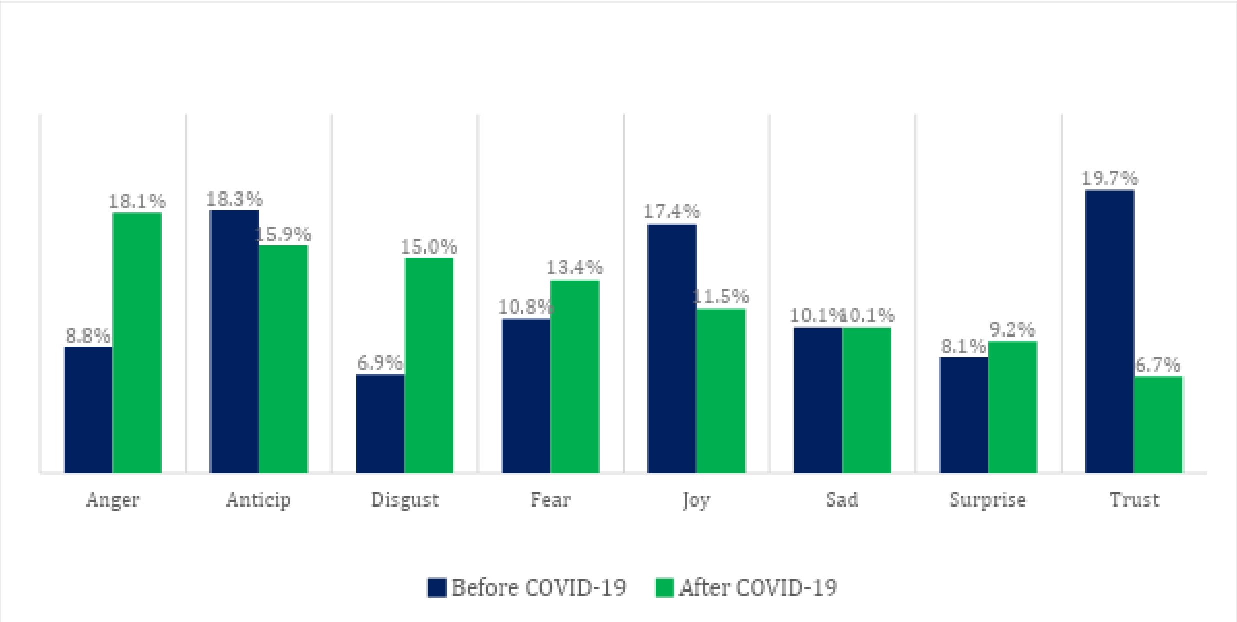
The happiness index also revealed that there were certain days of the week that people were happier. The happiest day before the lockdown was a Friday (happiness= 6.50), whereas after the lockdown it was a Saturday (happiness= 6.33). Before Covid-19 Fridays were associated with the end of the week and the promise of social gatherings, after Covid-19 it changed to a Saturday which had online concerts that positively affect people's happiness. The unhappiest day has not changed from before to after Covid-19. It seems people do not like Mondays regardless of global pandemics or not (happiness = 6.23 before lockdown and 6.03 after lockdown).

Analysing the happiness index, we found that certain events made people happy. In contrast, others had the opposite effect; we also found that the nature of these events changed from before to after lockdown.

Before lockdown, South Africans' happiness was the highest during celebrations, such as New Year's Day (7.13) and Valentine's Day (6.94). After the lockdown it changed to events such as online concerts, for example, Bang Bang Con on 17 April 2020 (6.5), the announcement that South Africa is moving from level 5 restrictions to level 4 restrictions on 23 April 2020 (6.57) and financial help to struggling individuals and businesses.

The lowest happiness before Covid-19 was recorded when there was negative news disseminated to the public. This included the death of celebrities, such as Kobe Bryant on 27 January (5.82), increase in load-shedding time (4 January 2020 – happiness = 5.98), retrenchments in big industries (10 March – happiness = 6.03) and the possibility that Covid-19 could devastate the country. The lowest happiness after Covid-19 was recorded with the announcements on lockdown (23 March – happiness = 5.35) and the death of a national celebrity (Maja passes away 9 April 2020, happiness = 6.02). Therefore, the main difference is that after Covid-19, public holidays and special celebrations are irrelevant for happiness and that Covid-19 announcements influence both the lower and higher level of happiness.

What about the emotions that underpin the sentiment expressed in the happiness index? From figure 4, it can be seen that South Africans experienced a change in their emotions from before to after Covid-19. South Africans were angrier after their first weekend spent in stringent lockdown. Additionally, the emotions expressed changed from being *joyful, anticipating good things to happen and showing trust*, to being *angry, anticipating the worst and showing disgust and fea*r. Over the period, the most significant gainers, among the emotions, were anger, up with almost 10 per cent, followed by disgust (+8 per cent). In contrast, the biggest losers were trust (-13 per cent) and joy (-6 per cent).



Source: Authors' calculations using GNH dataset (Greyling et al. 2019)
Fig. 4 Emotions of South Africans before and after Covid-19

4.2 *Regression analysis*

To address the first research question, namely, to determine the level of happiness after the lockdown was implemented, we consider the results of table 2. The coefficient on the treatment variable 'lockdown' is negative, indicative of lower happiness levels after the regulations were introduced as compared to before.

If we consider that the year 2020 was tainted by the Covid-19 virus from January 2020 onwards, even though the first case of Covid-19 was only announced on 5 March 2020, we can assume that happiness functions might look different in this pandemic year compared to other years.

Table 2: OLS estimation results of the relationship between different covariates and happiness

	(1)		(2)		(3)	
	Full Sample		**Before Lockdown**		**After Lockdown**	
Dependent Variable: GNH						
Lockdown	-0.2656**	(0.1066)				
Log Sales	0.1264**	(0.0499)	0.2115***	(0.0512)	0.0300	(0.0679)
Jobs	-0.0009*	(0.0014)	-0.0001	(0.0015)	-0.0004*	(0.0004)
Log Tweets	-0.3633*	(0.1956)	-0.1532	(0.3505)	-0.7012**	(0.3338)
Alcohol	-0.0104***	(0.0017)	-0.0085	(0.0060)	-0.0082***	(0.0014)
School	-0.0031***	(0.0010)	0.0432	(0.0800)	-0.0030**	(0.0012)
Covid-19	-0.0015**	(0.0007)	-0.0300**	(0.0141)	-0.0010*	(0.0009)
Covid-19	0.00001***	(0.0000)	0.0000	(0.0005)	0.0000*	(0.0000)
Retail					-0.0048**	(0.0019)
Constant	9.5322***	(2.2862)	6.9730**	(3.1482)	9.7575***	(2.8918)
N	128		77		51	
Adjusted R^2	0.368		0.330		0.667	

Robust Standard errors in parentheses
We exclude 'retail' from before lockdown estimations due to lack of variation observed.
* $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$

Table 2, panel 1, shows the statistically significant determinants of happiness, since the beginning of 2020 up to 8 May 2020. Sales, jobs and the square of daily Covid-19 cases are significant and positively related to happiness. Sales, in this instance, a proxy for consumption, is positively related to happiness, thus if sales increase happiness will likely also increase (Wang et al. 2019, Stanca and Veenhoven 2015). The positive relationship with the squared number of Covid-19 cases indicates a U-shaped relationship. We will discuss this in the next section.

The statistically significant determinants, which are negatively related to happiness, also showing the expected relationships are (see table 2, panel 1):

i. searches for jobs (a proxy for uncertainty about the future job market), as the number of searches, increases happiness decreases.
ii. the number of tweets, as mentioned in section 3, previous research has shown that increases in the use of social media are negatively related to happiness (Chae 2018, Wilson et al. 2012).
iii. searches for beer (a proxy for alcohol and tobacco), more searches for beer implies less happiness.
iv. searches for school (a proxy for the uncertainty of schooling during Covid-19), more searches regarding schooling is related to lower levels of happiness.
v. the daily number of Covid-19 cases and

If we consider the time periods before (1 January to 17 March 2020) (table 2, panel 2) and after the lockdown regulations were introduced on 18 March (up to 8 May 2020 the date of completing the research paper) (table 2, panel 3), we find the below differences in the factors that influence happiness.

Sales (a proxy for consumption) was a significant predictor of happiness before the lockdown period. After the lockdown was introduced, it seems that sales are no longer of importance to happiness, though it was still positively related to well-being. This might be explained as the *joy* derived from buying dissipated after the lockdown, due to the experience being negative. South Africans consumption experience was characterised by standing in cues before entering a store, only being allowed to purchase essential goods, enduring the discomfort of wearing masks and keeping to social distancing rules at all times.

Before the lockdown, searches for jobs was not significant. Still, after the lockdown, the concerns about jobs reflected in the increases in the searches for 'jobs' showed a statistically significant and negative relationship to happiness, emphasising the economic concerns of the lockdown.

The number of tweets is not significant before the lockdown, but after the lockdown, it is significant and negatively related to happiness. Interesting to note that the number of tweets during the lockdown period increased significantly. As mentioned previously, it has been shown that increased use of social media is often negatively related to happiness (Chae 2018, Wilson et al. 2012).

After the lockdown was introduced, the sales of all alcoholic beverages and tobacco were prohibited. Once the sales were prohibited, it became more apparent that the lack of these products is a significant contributor to the happiness of South Africans. Research done by Sommer et al. (2017) proved that because of the presence of hordenine in beer, it significantly contributes to mood-elevation. In South Africa, which is well-known for its high per capita beer and alcohol consumption (Statistics South Africa 2017), we notice that the lack of beer (alcohol) plays a significant role in the decrease in happiness. This could be related to the lack of 'socialising' which is a large part of the South African culture and synonymous for consuming alcoholic beverages. Analysing the tweets, we noticed that the lack of beer/alcohol was a major tweet topic.

Before the lockdown period searches for 'school', a proxy for people concerned about their children's schooling were not significant, but after the lockdown was introduced, it became significant. This is an indication of people's concern for their children's education and the uncertainty surrounding the schooling process for 2020. Furthermore, there is uncertainty on when schools will re-open and how teaching will take place without putting children at risk.

The number of daily Covid-19 cases is negatively related to happiness, before and after the lockdown. The significant relationship before lockdown is interesting, as the first Covid-19 case in South Africa was only confirmed on 5 March 2020. This is approximately two weeks before the lockdown regulations were implemented. However, the news about Covid-19 was available since the end of December, and the first tests for Covid-19 in South Africa were done in February 2020. Looking at the emotion 'fear', we see that it has increased since February and is likely linked to the negative relationship between the number of Covid-19 cases and the happiness levels before lockdown, but the fear emotion started to decline since April 2020. However, the coefficient on Covid-19 cases is much smaller after the lockdown than before. This reveals that the effect of the number of cases on happiness declined over time. Interesting is the U-shape significant relationship between the squared Covid-19 cases and happiness, after the lockdown that implies that initially the number of Covid-19 cases was negatively related to happiness, up to a certain point, whereafter it became positive, emphasising the results related to Covid-19 cases. Likely the positive relationship is an indication of fear dissipating due to the disease seemingly being less threatening and the mortality rates much lower than expected. However, we notice the effect size of the coefficient is very small, thus negligible.

If we only consider the period after lockdown and we introduce the lack of mobility (retail) (see column 3 of Table 2), we find that the lack of mobility, due to the 'stay at home' regulations plays a significant role. As the lack of mobility increase happiness decreases. (The reader is reminded that the mobility variable is only available for the period after lockdown and not before).

In summary, what changed when the lockdown regulations to curb the Covid-19 were implemented? Peoples' happiness levels decreased significantly, and new factors came to the fore, which were not previously relevant or known to affect happiness levels. These include the lack of alcohol, social events and gatherings, concerns about children's schooling and future employment, as shown by the increase in job searches. What is concerning is that sales, a well-established determinant of happiness are not significant after lockdown, implying that happiness levels are not increased by higher levels of consumption. This is against the standard utility theory of economics, which shows that as consumption increases, happiness (utility) increases as well. The main finding, however, is that the number of Covid-19 cases, although negatively related to happiness, became less of a threat to happiness after lockdown.

4.3 Results on the probability of reaching previous happiness levels

In this section, we address the question on the likelihood to reach the same levels of happiness in the year 2020 as experienced in the year 2019. We use the same models as estimated using OLS in section 3.3 with the difference that we collapse the happiness variable to a binary variable. Now, 1 indicates a level of happiness equal to or more than the mean happiness level of 6.35 in 2019, the average achieved in 2019 and 0 indicates the opposite. Furthermore, we make use of a probit model to determine the likelihood to be happy.

4.3.1 Likelihood to be happy for the period from 1 January to 8 May 2020 (real-life scenario)

Table 3 showing the results for the whole time period from 1 January 2020 to 8 May 2020 strengthens the OLS estimation results (see table 2 in section 4.2) and are very similar, with all signs having the same direction as in the OLS estimations. This indicates that the direction of the relationships did not change; the similarity of the results holds for the period before and after the lockdown. However, the number of tweets is no longer significant in the model. We find that if we increase the cut-off point, of the happiness variable to greater then 6.35, tweets become significant (negative relationship), but not at the current level. This implies that the likelihood to be *very happy* is negatively related to the number of tweets (re-emphasising the findings in the literature). Furthermore, the mobility (retail) variable, as mentioned earlier is only included in the after lockdown model, in which it is significant.

Thus, similar to the OLS results, sales increase the likelihood to be happy. In contrast, increased searches for beer, schooling and jobs decreases the likelihood to be happy. Additionally, as expected, the number of Covid-19 cases also decrease the probability to be happy (see table 3, panel I). Interestingly in the probability estimations, the squared Covid-19 cases are positive, but no longer significant.

Panel II of Table 3 shows the predicted probabilities of being happy. For the period 1 January to 8 May, thus a period with and without lockdown, we find that the likelihood to reach the same average happiness levels in 2020, as experienced in 2019 is *23 per cent*.

4.3.2 Likelihood to be happy for the period from 1 January to 26 March 2020 (real-life scenario, before lockdown) and from 27 March to 8 May 2020 (real-life scenario, after lockdown)

As mentioned, we find similar results in the probability estimations, as in the OLS estimations, for the period before and after the lockdown.

Before the lockdown period, we find that sales increase the likelihood to be happy, whereas the number of Covid-19 cases decreases the likelihood to be happy. If we consider the predicted probabilities of being happy before the lockdown, we find that the likelihood to reach the same average happiness levels in 2020, as experienced in 2019 is *26 per cent*.

After the lockdown, we find that searches for jobs, alcohol and school, Covid-19 cases as well as the lack of mobility decrease the likelihood to be happy. The likelihood to be as happy as in 2019 after the lockdown is only 17 per cent. Thus, South Africans have less than a one in four chance to be as happy as they were in 2019, with the lockdown regulations in place.

If we consider the real-life scenarios and compare the likelihoods to be happy before and after lockdown, it seems that after the lockdown the likelihood to be happy is much lower than before, *the difference between the likelihood of 26 per cent, to only 17 per cent to be happy.* These results reflect both i) the observed pattern of the spread of the disease post lockdown, although it seems as if peoples' fear of the disease is dissipating and ii) the negative effects of lockdown regulations.

Table 3: Probit estimations on the likelihood to be happy (Pr (happy =1)/(GNH=>6.35))

Panel I: Probit estimation results

	Pr(GNH>=6.35)	
	Coefficient	**SE**
Lockdown	-0.964*	(1.314)
Log sales	1.195***	(0.464)
Jobs	-0.013*	(0.011)
Log tweets	-1.597	(1.5259)
Alcohol	-0.055***	(0.0164)
School	-0.0126*	(0.0154)
Covid-19 cases	-0.0081*	(0.010)
Covid-19 cases squared	0.0000	(0.0000)
Retail		
Constant	-11.63*	(17.46)
N	128	
Panel II Probability to be happy		
Full Sample	0.23***	(0.031)
Before Lockdown	0.26***	(0.040)
After Lockdown	0.17***	(0.042)
No Lockdown	0.27***	(0.042)

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

4.3.3 Simulation of likelihood to be happy for the period from 1 January to 8 May 2020 if there was no lockdown

Panel III of Table 3 gives the predicted probabilities from our simulation exercise in the event of no lockdown for the entire time period under consideration (1 January – 8 May 2020). The details of the simulation can be found in the methodology section 3.3. We assume that the number of Covid-19 cases followed a similar trajectory to that in Spain, which did not impose a South African style lockdown, whereas we assume that the other covariates had similar levels (values) to that in 2019. We estimate the probability of being happy if no lockdown was imposed, but with the presence of Covid-19. Furthermore, we assume due to no lockdown regulations that the number of Covid-19 cases is significantly higher than in the real-life scenario. Considering these assumptions, we find that the likelihood to be as happy in 2020 as in 2019 is *30 per cent*. Thus if we compare the real-life probability to be happy to that found in the simulation model, it is 23 per cent compared to 30 per cent. Therefore, we have a loss in the likelihood to be happy of 7 per cent; we can ascribe this loss to the lockdown regulations. This indicates that even if we consider the threat of Covid-19, the stringent lockdown regulations further decreased happiness.

One caveat holds: the population of South Africa is approximately 9.5 million more than that of Spain (46 million in 2020) so it is plausible that the number of cases in South Africa could be higher, which would make the probability to be happy slightly lower than our estimations. But in general, even considering some margin of error, it seems that the lockdown regulations created a loss in the likelihood to be happy.

Conclusions

In this paper, we use the Gross National Happiness Index (GNH) to explore the determinants of happiness during the Covid-19 pandemic, before and after the lockdown regulations were introduced in South Africa. We estimate the relationship between GNH and our treatment variable *lockdown* as well as several relevant covariates to account for the changes in the economy as well as factors related to happiness over the time under consideration. By doing this, we were able to determine the significance of the relationship between different covariates and happiness levels before and after the lockdown.

We show a reduction in overall happiness after the lockdown. Furthermore, our results indicate that what matters most for happiness under lockdown, for an *extreme country case*, is not the standard macroeconomic determinants of happiness, but rather the factors directly linked to the regulations that were implemented. These factors can be classified as (i) social capital issues; lack of access to alcohol (beer), lack of mobility and concerns about schooling, and (ii) economic issues; concerns over jobs, the threat of retrenchments and lower levels of consumption (salary cuts).

As expected, the number of daily Covid-19 cases is negatively related to happiness. Surprisingly over time, it seems that there is a U-shaped relationship between the number of Covid-19 cases and happiness. Thus, initially, the number of cases decreased happiness (the negative relationship), but as the threat of the Covid-19 disease looked less imminent, due to high recovery – and low mortality rates, it seems as if the happiness levels started increasing. However, the effect size is very small, thus negligible.

Using simulations, we answered the question of whether the likelihood to be happy without lockdown and an increased number of Covid-19 cases surpassed the likelihood to be happy with lockdown and less Covid-19 cases. We found the probability to be happy with lockdown regulations implemented to be 23 per cent and without lockdown 30 per cent. Thus, lockdown had a likelihood cost to be happy of

7 per cent. It seems even considering a margin of error that people in South Africa would have been happier with an increased number of Covid-19 cases and no lockdown regulations, than with a lower number of Covid-19 cases and lockdown regulations.

Considering the results mentioned above, it ultimately means that if policymakers want to increase happiness levels and increase the probability to achieve the happiness levels of 2019, they must consider those factors that matter most to peoples' happiness. These factors include allowing creatures of habits some of their lost comforts by reinstating the sale of alcohol and tobacco. Additionally, consumers should be allowed to move around with fewer limitations. People should be allowed to return to work or the circumstances for working from home should be enhanced, for example, by providing reliable internet access and cheaper data. Furthermore, making it possible for children to be schooled (online teaching or schooling which allows for social distancing) and allowing people to restore a certain degree of their consumption patterns while being conscious to prevent the spread of Covid-19.

Additionally, policymakers should assure citizens that there is a credible plan to get the economy, which is currently in dire straits, back on track. Such an economic plan should stimulate growth, create job opportunities and increase employment rates, supply the necessary infrastructure and deal with curbing vast budget deficits and debt burdens. To achieve this, it is of utmost importance to open up the economy as soon as possible to allow businesses the opportunity to start-up production and hopefully fuel the dying embers of the economy, while making intelligent decisions to minimise the spread of Covid-19.

Conflict of Interest: The authors declare that we have no conflict of interest.

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