



# The impact of exogenous shocks on national wellbeing. New Zealanders' reaction to COVID-19

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## Abstract

In this paper, we explore the response of an aggregate measure of subjective wellbeing to the arrival and passage of the COVID-19 pandemic in a small, geographically separate economy in the South Pacific. Studies of national wellbeing and emotional responses to infection rates during a pandemic have been rare thus far. While several disciplines offer theoretical priors in the case of individuals, far less attention has been paid to the wellbeing and emotional response at a national level. Our paper contributes to the literature by applying a time-series approach to the relationship between wellbeing, emotions and the passage of a pandemic. As such we contribute to a wider literature on macro responses to exogenous shocks. Our analysis involves the use of a wellbeing index and emotional time-series derived from Big Data in the form of tweets originating within New Zealand. The index captures the daily evaluative mood of the country several weeks before the first domestic case of COVID-19 was recorded until several weeks of no new COVID-19 cases. We find distinct reactions to the pandemic: a initial fall in national wellbeing generated by a decrease in the emotions 'joy', 'anticipation' and 'trust'. Following a rapid and severe lockdown designed to limit domestic transmission of the virus national wellbeing recovered relatively quickly. Gaining insight into the wellbeing (happiness) response to pandemics at the national level is important because the average level of happiness within countries is known to be associated with a range of economic, social, health and political outcomes.

**Keywords** Wellbeing · Exogenous shocks · Epidemics · COVID-19 · New Zealand · Twitter

**JEL codes** J31 · I18

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## Introduction

“In only a few weeks, COVID-19 has profoundly changed our lives, causing tremendous human suffering and challenging the most basic foundations of societal well-being. Beyond the immediate impact on health, jobs and incomes, the epidemic is increasing people’s anxiety and worry, affecting their social relations, their trust in other people and in institutions, their personal security and sense of belonging” (Organisation for Economic Co-operation and Development (OECD), 2020, p. 2).

In their April 2020 report, the OECD recognised the profound challenge the COVID-19 pandemic was having on people’s wellbeing throughout the world. They also recognised that the economic consequences of the novel coronavirus could be long-lasting and could pose another set of indirect risks to people’s health and wellbeing that would play out over a longer period of time (OECD, 2020, p. 3–4).

The arrival of COVID-19 has increased the need for a wellbeing focus and the value of building an *epidemiology of happiness* (Helliwell et al., 2020). As these authors point out, “policy decisions being faced by governments dealing with the pandemic require an approach much broader than provided by more typical policy evaluations in all disciplines, including especially the social context and the distribution of costs and consequences” (Ibid, p.i).

There have been several recent attempts to address the wellbeing consequences of COVID-19. De Pedraza et al. (2020) drew on a cross-section of countries using web surveys which showed different responses to COVID-19. Brodeur et al. (2020a) apply a difference-in-difference approach in order to estimate the causal effect of a lockdown during a pandemic on wellbeing. Greyling et al. (2021a) have studied the causal effect of the stringency of lockdown measures on the wellbeing of a nation, comparing South Africa, New Zealand and Australia. All the aforementioned studies base their analysis on international comparisons and investigate the relationship between the enforcement of regulations and wellbeing.

Among the country-specific studies, Hamermesh (2020) studied the life satisfaction of married and single people while in government-imposed lockdown for the U.S. and U.K. using time diaries. Rossouw et al. (2021) investigated the determinants of happiness before and during the first few months of a lockdown in South Africa. However, neither of these studies follows a nation’s wellbeing dynamics on a day-to-day basis in order to document changes in national wellbeing and emotions over the course of a pandemic.

In this paper, we introduce the macro wellbeing response conceptually and then speculate on the way national wellbeing might fluctuate in response to passage of a pandemic through a country. This is followed by an introduction to the ‘epidemic curve’ and its manifestation as COVID-19 as it unfolded in New Zealand. We then raise two research questions. Firstly, did the fall/rise in national wellbeing precede or follow the rise/decline of the number of COVID-19 cases? Secondly, how did the relative ranking of emotions change as the national wellbeing index changed? (For

example did the emotions more closely associated with wellbeing, such as ‘joy’ and ‘trust’, differ in their dynamics from those emotions associated with illbeing, such as ‘anger’, ‘disgust’ and ‘sadness’.)

Our primary contribution has been to demonstrate the sensitivity of a national sentiment-based index of wellbeing to daily changes in the number of cases of COVID-19. By confining the study to a small geographically separated country of less than five million people, with tightly controlled borders, run by a highly popular government in a unicameral political system, we may have avoided many of the extraneous influences which complicate responses in larger more open countries with lower levels of social cohesion. The degree to which our results relating to the New Zealand experience foreshadow or depart from those in other countries will be apparent as studies of their experience emerge.

A characteristic feature of our study is our use of Big Data in the form of daily tweets sourced from Twitter.<sup>1</sup> There are marked variations in the way people experience pandemics. Reports from the front line, from those who present with symptoms, are considerably more grave than reports from samples that are representative of the population as a whole. The representative sample typically reports an “average” reaction to the pandemic, whereas studies of those who present in clinics or as media case studies constitute highly unrepresentative biased samples. Our study purports to capture the former perspective, that of the population. Although not a fully representative sample the wide coverage of the popular emotional response offered by daily Twitter feeds does allow us to track a more general or average response to the passage of the pandemic.<sup>2</sup>

Our analysis of a daily Twitter-based measure of national wellbeing, the Gross National Happiness index, suggests that New Zealand’s national wellbeing response to COVID-19 was dramatic but relatively short-lived. We also found a rather weak lead in the wellbeing curve that gradually changed to a much stronger lagged response in wellbeing as the pandemic took hold. The decline in national wellbeing following the arrival of the virus was accompanied by a decrease in the emotions ‘joy’, ‘anticipation’ and ‘trust’ which reversed as the government enacted policy measures to control the spread of the pandemic within the country.

The rest of the paper is structured as follows. The next section contains a brief background, discusses the relevant literature and summarises the COVID-19 experience in New Zealand. Section 3 describes the data used. The results follow in Section 4, limitations are noted in Section 5 and the paper concludes in Section 6.

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<sup>1</sup> For an introduction to the use of Big Data in the study of wellbeing see Bellett and Frijters (2019).

<sup>2</sup> Please note that we use the words ‘wellbeing’ and ‘happiness’ interchangeably.

## Background, literature review and the case of New Zealand

### Background

Measures of wellbeing fluctuate over time at both the individual and country level. Micro-level studies focus primarily on the characteristics of people experiencing fluctuations in wellbeing.<sup>3</sup> The changes themselves can result from planned events in the life course (Clark & Oswald, 2002) through to quite unanticipated events such as the sudden death of a partner, relative or friend (Ballas & Dorling, 2007).

The events which affect individuals vary in the degree to which they are arranged (marriage), anticipated and designed (the birth of a child) through to the unexpected (accidents). The events of interest in this paper differ in three respects: pandemics are exogenous shocks and, are largely unanticipated, as are earthquakes, floods and wars; they affect whole populations and require a collective, governmental response. In other words, they are macro rather than micro in nature.

At the same time, macro events have micro level consequences. A considerable body of work in psychology has already addressed the mental health consequences of pandemics, including COVID-19 (Li et al., 2020). For example, according to Behavioural Immune System (BIS) theory (John et al., 2013), people are likely to develop negative emotions such as aversion and anxiety (Mortensen et al., 2010; Schaller & Murray, 2020) and negative cognitive assessment for self-protection (Schaller, 2006). Faced with potential disease threat, people tend to develop avoidant behaviours and obey social norms strictly. According to stress theory (Norris et al., 2002) and perceived risk theory (Slovic, 2000), public health emergencies trigger more negative emotions and affect cognitive assessment.<sup>4</sup>

The literature on risk perception and public health shows that there is generally a very weak correlation between people's anxiety over a particular risk and the probability of death or disability arising from that risk (Frost et al., 1997; Young et al., 2008). At the same time, it is unclear whether anxiety over perceived risk will lead to efficacious protective behaviours. For example, the study by Jones and Salathe (2009) showed that anxiety levels over swine flue (H1N1) waned along with the perception of the virus as an immediate threat.

Li et al. (2020), among others, suggested that the uncertainty and low predictability of the COVID-19 pandemic threatened not only people's physical health but also affected their mental health, especially in terms of emotions and cognition. In another example, the case of hurricane Katrina, a doubling of mental illness was experienced by individuals who lacked established social relationships such as being married or being employed (Kessler, 2006). These examples remind us of the importance of monitoring psychological changes over time using a

<sup>3</sup> See for example Dambrun et al. (2012) and Powdthavee & Stutzer (2014).

<sup>4</sup> As summarised by Li et al. (2020).

representative sample of the population using measured responses to emotional and cognitive indicators (e.g., social risk judgment and life satisfaction) (Li et al., 2020, p. 1).<sup>5</sup>

The conventional approach to studying individual responses to disease, natural disasters and related events is to interview or administer questionnaires after the event. Given their unexpected occurrence questionnaires applied before the event are less common and usually not event specific. In both cases point-in-time surveys only offer snapshots of conditions prior to and/or after the event. Unless micro-level surveys are repeated regularly, they are unlikely to offer insight into the *dynamics* of the reactions which follow.

## Literature review

### Macro-level fluctuations in happiness

In his reflection over four decades of research into the economics of happiness, Andrew Clark argued, “There has not been enough work on the effect of exogenous movements in explanatory variables on well-being” (Clark, 2018, p. 262). Some events are exogenous by nature, such as natural disasters (Rehdanz et al., 2015).<sup>6</sup> Other such events are man-made, including terrorism and war (Clark et al., 2017; Frey et al., 2009; Metcalfe et al., 2011). Most who studied the 2011 Great East Japan Earthquake focused on depressive symptoms (Shiba et al., 2020).

However, not all exogenous shocks are negative. Several studies have examined the wellbeing impact of economic booms. For example, in Ireland, the economic upturn affected both the level and distribution of various domains of wellbeing. There was a substantial improvement in subjective wellbeing as well as a reduction in inequality and polarisation in virtually all domains of life satisfaction (Madden, 2011). By contrast, the diversity widened during the subsequent downturn (Weckroth et al., 2017).

The linkages between subjective wellbeing and national income have attracted a substantial research literature following Easterlin’s seminal paper (1974). In cross-section the relationship between gross domestic product per capita and subjective wellbeing is roughly log-linear across countries (Deaton,

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<sup>5</sup> For a recent review of the psychological impacts of quarantine see Brooks et al. (2020). Several similar studies are reviewed in Brodeur et al. (2020b).

<sup>6</sup> On 11 March 2011, following a major earthquake off the Pacific coast of Japan, a tsunami disabled the power supply and cooling systems of three reactors of the Fukushima Dai-ichi power plant, causing a major nuclear accident. The accident triggered substantial releases of radioactive material and resulted in one of the worst nuclear disasters ever, second only to the Chernobyl disaster in 1986. The earthquake and tsunami caused nearly 16,000 deaths, over 1.2 million destroyed or damaged buildings, and temporary evacuation from their homes for over 380,000 people. The combined event also disrupted water supply, power distribution, and train, highway, and air transport systems in extensive areas of eastern Japan. Rehdanz et al. (2015) used panel data set of 5979 individuals interviewed in Japan before and after the tsunami and nuclear accident at Fukushima to analyse the effects of the combined disaster on people’s subjective wellbeing.

2008; Helliwell et al., 2013; Stevenson & Wolfers, 2008a), but the time-series relationship remains the subject of an extended on-going debate. Some recent research identifies a positive relationship between the level of per capita GDP and subjective wellbeing over time (Sacks et al., 2010), while others fail to find a significant relationship (Easterlin et al., 2010; Layard, 2005). While subjective wellbeing tends to co-vary with macroeconomic variables (Di Tella et al., 2003), evidence of a long-run relationship between growth and happiness is mixed.

Other papers in the economics of happiness literature have documented the negative correlation between macroeconomic volatility and happiness over time (Di Tella et al., 2003; Wolfers, 2003) and its moderation in the 1980s (Stock & Watson, 2002) was associated with diminished wellbeing inequality (Stevenson & Wolfers, 2008b). A negative correlation between happiness inequality and income growth has also been documented (Clark et al., 2014). More recently, subjective wellbeing has been observed rising with the economic growth rate but falling at twice the rate when growth is negative (De Neve et al., 2018). Also see Welsch and Kuhling (2015).

The literature exploring the connections between economic growth and wellbeing and wellbeing inequality may contain valuable clues as to what might prevail when pandemics take hold although this connection has yet to receive sustained attention. Among associated responses of interest are those of anticipation and adaptation.

### The theory of anticipation and adaptation

Studies of wellbeing dynamics involve recognising that individuals (and by extension populations) anticipate events except when the shock is truly unexpected, in which case adaptation becomes the dominant response. The distinction between anticipation and adaptation is particularly important when considering the wellbeing effects of pandemics. Given it takes time for a virus to spread, most individuals will experience some lead time which, together with prior knowledge of the stereotypical ‘epidemic curve’, will result in many anticipating and planning their response accordingly.

An important corollary of anticipation and adaptation is the role of uncertainty. Evidence on the impact of uncertainty is limited because of the difficulties in stripping out cause and effect (Bloom, 2014, p. 167). At the same time, uncertainty introduces instability, which has been shown to reduce levels of happiness, as noted by Frijters et al., (2012, p. 159). For example, economic insecurity can increase angst and stress among employed individuals (Luechinger et al., 2010) because it introduces spill-over effects from the future. Similarly, individuals have been observed to be less happy one year *before* they experience job quits, layoffs and unemployment (Clark et al., 2008), a phenomenon also documented by Morrison (2017) in the New Zealand context.

Wellbeing can also be positively affected by expectations as evidenced by the tunnel effect (Senik, 2004) as articulated in the theory of erroneous income

expectations (Easterlin, 2001).<sup>7</sup> Regardless of expectations, people also adapt to changes in conditions, although the degree remains an empirical question. If people fully adapt, then, as Clark observed, “life is to some extent typified by a hedonic treadmill, in which conditions or circumstances may not matter, in the long run at least” (Clark et al., 2008 p. F222).

In summary, fluctuations and general volatility in aggregate measures of subjective wellbeing have received growing attention. Still, few systematic generalisations regarding their response to exogenous shocks, positive or negative, have gained widespread recognition. Anticipation, uncertainty and adaptation accompany the arrival and passage of pandemics and ascertaining how they alter levels of national wellbeing is the question motivating our study of COVID-19.

### COVID-19 in New Zealand

The stereotypical ‘epidemic curve’ shows the frequency of new cases over a time frame that begins with the date of onset of the disease and ends with its elimination.<sup>8</sup> The shape of an empirically constructed curve in relation to the incubation period for a particular disease can give clues about the source. Of the three types of curves, the “continuous common source epidemic” with its rapid increase and slower decrease seems to match the New Zealand COVID-19 experience.

The first case of COVID-19 in New Zealand was recorded on the 28<sup>th</sup> of February 2020.<sup>9</sup> By the 4<sup>th</sup> of March that year, the single case had doubled to two. It doubled again two days later and again nine days later. In three more days, the number had reached 20, and by the 20<sup>th</sup> of March, it had reached 39 confirmed cases. From the peak number of 89 newly infected people on the 2<sup>nd</sup> and 5<sup>th</sup> of April 2020, the numbers declined and had almost halved by the 10<sup>th</sup> of April (to 44). They halved again less than a week later, but it took over a month before the last (domestic) case in our series was recorded on the 22<sup>nd</sup> of May 2020.

Within a total of 84 days, COVID-19 appeared to have run its course in New Zealand. However, there was no official declaration of ‘elimination’. As the Director-General of Health, Dr Ashly Bloomfield, warned at the time: “We are successfully over the peak, but that is not the same thing as being out of the

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<sup>7</sup> Using waves 5–13 of the Russian Longitudinal Monitoring System (a database containing many attitudinal questions Senik (2004) followed the dynamics of expectations and satisfaction of the same individuals over nine consecutive waves.

<sup>8</sup> See [http://sphweb.bumc.bu.edu/otlt/MPH-Modules/EP/EP713\\_DescriptiveEpi/EP713\\_DescriptiveEpi3.html](http://sphweb.bumc.bu.edu/otlt/MPH-Modules/EP/EP713_DescriptiveEpi/EP713_DescriptiveEpi3.html)

<sup>9</sup> While suspected cases were under investigation from as early as January, the first person in New Zealand to test positive for the virus was announced on the 26<sup>th</sup> of February, 2020. Analysis of historic cases has since revealed that the first infections were in fact likely to have occurred several days earlier, but the patients did not meet criteria for testing at the time. News of New Zealand’s first death from COVID-19 broke at the end of March 2020.

woods” (Dom Post page 3, 16 April 2020). Following 100 days of no new domestic cases, there have been only minor periodic recordings mainly associated with people arriving in the country. By mid-November 2020, the death toll had been confined to 25.<sup>10</sup>

Several important policy decisions were made in New Zealand over the course of the COVID-19 period. A four-level alert level system was introduced on the 21<sup>st</sup> of March, 2020. Initially set at level 2 and two days later it was raised to level 3. It was raised to level 4 on the 26<sup>th</sup> of March placing the country into a nationwide lockdown where it stayed for over a month. People were instructed to stay home in their “bubble” (household) for all but essential personal movement including safe recreational activity. All gatherings were cancelled and public venues closed. All businesses were closed except for essential services, as were educational facilities. On the 27<sup>th</sup> of April the alert level was lowered to level 3, partially lifting some of the restrictions. It moved down to level 2 on the 13<sup>th</sup> of May, which permitted the lifting the rest of the lockdown restrictions while maintaining physical distancing and size limits on gathering. The country moved to level 1 on the 8<sup>th</sup> June when restrictions on work, school, sports, domestic travel and gathering size were lifted, but border controls remained in force.

Experts quickly recognised the challenges that life in lockdown could pose, from unemployment to family violence. However, positives were also recognised, such as lower emissions and, for some at least, greater freedom to work from home. While research revealed some of the negative impacts of isolation, including stress, heavier drinking and more anxiety, many enjoyed more time to spend with their families and not having to commute. Contrary to speculation, there was no increase in suicides at the start of the pandemic.<sup>11</sup> The variety of responses to the COVID-19 pandemic continues to receive attention from researchers both overseas (Jefferies et al., 2020) and domestically. Several journals set aside special issues to cover the story. Domestic examples include *New Zealand Economic Papers*<sup>12</sup>, *Policy Quarterly*<sup>13</sup> and *MAI Journal*. *A New Zealand Journal of Indigenous Scholarship*<sup>14</sup> and the *Journal of Open, Flexible and Distance Learning*.<sup>15</sup>

<sup>10</sup> Several web sites document the timeline. For examples include: [https://en.wikipedia.org/wiki/Timeline\\_of\\_the\\_COVID-19\\_pandemic\\_in\\_New\\_Zealand](https://en.wikipedia.org/wiki/Timeline_of_the_COVID-19_pandemic_in_New_Zealand) and <https://COVID19.govt.nz/alert-system/about-the-alert-system/#alert-level-4-%E2%80%94-lockdown> and <https://shorthand.radionz.co.nz/coronavirus-timeline/index.html>.

<sup>11</sup> Between the 1<sup>st</sup> of April 1 and 31<sup>st</sup> of July 2020, there were 190 suicides recorded in New Zealand – below the 241 expected based on previous years and contrary to at least one prediction, Gluckman and Bardsley (2020).

<sup>12</sup> The special issue of *New Zealand Economic Papers*, “COVID-19: Economic implications for New Zealand and the Pacific” edited by David Fielding, John Gibson and Ilan Noy is expected to be published by the end of 2020 or early 2021. Papers already on-line as of Nov 30, 2020 include (Gibson, 2020a and b).

<sup>13</sup> *Policy Quarterly*, Focus on COVID-19 vol 16, no 3, was published in August 2020 and is available on-line: <https://ojs.victoria.ac.nz/pq/article/view/6546> We have not cited these papers separately.

<sup>14</sup> <http://www.journal.mai.ac.nz/content/combined-call-papers-COVID-19-special-issues-2020>

<sup>15</sup> <http://www.jofdl.nz/index.php/JOFDL/article/view/399>

With the exception of papers by one or more authors of this study, all empirical enquiries into the wellbeing impacts of the pandemic in New Zealand to date have been cross-sectional: Sibley et al. (2020),<sup>16</sup> Every-Palmer et al. (2020)<sup>17</sup> and Prickett et al. (2020).<sup>18</sup> Each involves samples of individuals interviewed at one or two points in time within what we will refer to as the COVID-19 period—the 111-day period running from 14<sup>th</sup> February through the 14<sup>th</sup> of June 2020.

In contrast, our focus is on the national level and addresses the temporal relationship between changes in the number of COVID-19 cases, national wellbeing and emotional effects. It is also one of the first in New Zealand to draw on Big Data to monitor the impact of the pandemic.

## Big Data and the Gross National Happiness Index

This section will first discuss Twitter as a source of Big Data before turning to our variable of interest, the Gross National Happiness Index.

### Twitter as a source of Big Data

The literature in social psychology highlights a strong association between the wellbeing of individuals and their use of words. It is now possible to extract words from the messages posted on social networks such as Twitter to reconstruct the emotional content, infer psychological traits, and measure the subjective wellbeing of individuals (Quercia et al., 2012).

The user-defined dictionary approach is the most widely used method in Big Data assessments of wellbeing. For example, Bollen et al. (2009) counted the occurrence of words on Twitter from August to December 2008 and multiplied them with the valence and magnitude of each word. They identified tension, depression, anger, vigour, fatigue, and confusion, as defined by a text-based analytical tool called the Profile of Mood States, which generates a ‘mood score’ of Twitter for any given window of time within the period.

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<sup>16</sup> The Sibley et al. (2020) study investigated the effects of Alert Level 4 on wellbeing, business outlook, and institutional attitudes. They compared responses collected from the New Zealand Attitudes and Values Study between the 1<sup>st</sup> of October – 31<sup>st</sup> of December 2019 (N = 1,003) and compared them Post-Alert Level 4 using data collected between 26<sup>th</sup> of March – 12<sup>th</sup> of April 2020. They detected a substantial increase in trust in both science and public institutions as well as an increase in anxiety/depression post-lockdown despite general stability in subjective wellbeing.

<sup>17</sup> The Every-Palmer et al. (2020) project compared responses to three standardised measures of wellbeing reported by a demographically representative sample of 2010 adult New Zealanders drawn from the commercial survey platform Dynata whose members are incentivized by earning cash credits in online accounts. The 2018/19 New Zealand Health survey in April 2020 and the responses to the World Health Organisation wellbeing instrument (WHO-5) were compared to the distribution reported by the 2018/19 New Zealand General Social Survey.

<sup>18</sup> The study by the Roy McKenzie Centre for the Study of Families and Children and the Institute for Governance and Policy Studies was based on an on-line survey of 2002 people administered between the 15<sup>th</sup> and 18<sup>th</sup> of April during the third week of lockdown before any official announcement had been made on how long lockdown would continue. Their report suggests that close to half of all New Zealanders experienced an economic loss during Alert Level 4 lockdown and that wellbeing losses among those who experienced job or income loss were likely to have been substantial.

In another example, O'Connor et al. (2010) take a user-defined dictionary approach, using OpinionFinder to analyse the relationship between consumer confidence and political opinion. Their results were highly correlated with those from traditional surveys.

One of the first to demonstrate the use of Twitter feeds to measure wellbeing was Dodds and Danforth (2010) and Dodds et al. (2011).<sup>19</sup> Their approach, and the way it differs from the index we use below, has been described by Rossouw and Greyling (2020). In an early use of Twitter, Curini and Canova (2015) proposed an indicator of happiness, the iHappy Index, which drew on more than 43 million tweets to measure the average level of idiosyncratic happiness in all 110 provinces in Italy. In another application, Bollen et al. (2009) used a large-scale longitudinal study of happiness and popularity based on a network of nearly forty thousand Twitter users connected by 'friendship' relations to test the proposition that your friends are happier than you – the happiness paradox (Bollen et al., 2017).

When it comes to the use of Twitter, there has also been considerable interest in demonstrating a causal relationship between the presence of sentiments and the performance of stocks (You et al., 2017; Zhang et al., 2018). In another example, López-Cabarcos et al. (2019) construct investor sentiment proxies from social media to show that they all possess predictability for stock returns (see Steyn et al., 2020). Yet another team applied linear and nonlinear causality tests to investor sentiment proxies from Twitter (Zhang et al., 2018, p. 51).

By comparison, only a few studies outside the stock market arena have compared wellbeing series with other events. In one example, Abdullah et al (2015) compared their Smile Index with an economic index to demonstrate how well it captured predictive information about consumer economic confidence.

In summary, there is a range of applications to which Twitter data have been applied, many of them addressing mood, happiness, and other wellbeing indicators. As the sophistication of the sentiment algorithms improves, Big Data become more useful for monitoring national and subnational moods. Wellbeing indices gleaned from Big Data become particularly useful when pandemics disrupt the collection of survey data as well as serving as early warning indicators.

## Gross National Happiness Index

To measure national wellbeing, we use the Gross National Happiness Index (GNH) constructed by Greyling, Rossouw and Afstereo (2019), which was launched in May 2019 in New Zealand. The GNH measures the wellbeing (evaluative mood) of a country in response to different economic, social and political events, using a live feed of tweets extracted from Twitter. In order to derive the GNH index, sentiment analysis is applied to each tweet (Greyling et al., 2019).<sup>20</sup> The sentiment scores

<sup>19</sup> See <http://hedonometer.org/index.html>

<sup>20</sup> Sentiment analysis has an advantage over conventional text analysis by including an entire opinion expressed in the text and not merely the identified word. While text analysis works relatively well with straightforward negative or positive statements this is not the case with more complex cases. Consider the following text from a review of a restaurant: "everything tastes like garbage to me but we keep coming back because my wife loves the pasta." The reviewer clearly does not like this restaurant, despite the fact that his wife "loves" the pasta. Under text analysis, the words "like" and "love" are categorised as positive, and "garbage" would be neutral. Using text alone the Tweet would be rendered as a positive sentiment. Sentiment *analysis*, on the other hand, takes every word as well as the entire sentiment expressed in the Tweet into consideration and would therefore render this review as negative.

are subjected to a balance algorithm to derive the level of wellbeing, ranging from 0 (low levels of wellbeing) to 10, with five being neutral, thus neither happy nor unhappy.<sup>21</sup> The index and the data is publicly available on the GNH website (<https://gnh.today>). For a full description of the methodology see Rossouw and Greyling (2020).

The GNH index has only been used in a handful of studies addressing the effect of COVID-19 and government-mandated lockdowns on happiness. Greyling et al. (2021a) and Rossouw et al. (2021) conducted two studies that used the GNH index to investigate the determinants of happiness before and during the first months of the government-imposed lockdown in South Africa. In a third study, Greyling et al. (2021b) focused on using the GNH to investigate the relationship between the stringency of lockdowns and happiness in a cross-country study that focused on South Africa, New Zealand and Australia. None of these GNH studies followed the wellbeing dynamics of a nation on a day-to-day basis in order to understand the relationship between the number of daily COVID-19 cases, national wellbeing and emotions from before and during the passage of the pandemic or whether changes in the number of COVID-19 cases led or lagged national wellbeing.

The number of Twitter users in New Zealand exceeds 400,600, but they do not constitute a representative sample (Omnicores, 2020). Instead, they are dominated by young adults in the 18–29 age range and have a female skew.<sup>22</sup> At the same time, there is little evidence to suggest this age and gender bias changes over time, so the *temporal* variations in the sentiment series examined here may well reflect trends typical of a more representative population. The Twitter medium itself includes individuals, groups of individuals, organisations and media outlets. As such this heterogeneous sample reflects the moods of a wide range of Twitter users and we fully acknowledge the above demographic bias present in cross section the degree and nature of that bias remain quite uncertain. Far less clear is the presence of bias in the *dynamics*, that is in the consistency with which different members of the population experience change and express it in media such as Twitter. Whether an older population would have reacted very differently in emotional terms over the COVID-19 period compared to the younger population more likely to tweet is unclear.<sup>23</sup>

Although our analysis mainly focuses on a relatively short 111-day COVID-19 period (14<sup>th</sup> of February to 14<sup>th</sup> of June 2020), it is instructive, to begin with the way the Twitter series behaved over a 548 day longer period in order to set the context. Over this one-and-a-half-year period, the number of tweets issued in New Zealand fluctuated around a mean of 4,527 tweets per day. The count began to increase in January 2020, just before the first COVID-19 cases were reported and they increased

<sup>21</sup> At least one other Twitter based series also use the term Gross National Happiness (Mitchell et al., 2013).

<sup>22</sup> Social Media 101 Guide. <https://www.marketing.org.nz/social-media-101#:~:text=In%20New%20Zealand%2C%20Twitter%20has,range%20with%20a%20female%20skew.>

<sup>23</sup> Our own untested suspicion is that the temporal changes in volume and shifts in the emotional mix of tweets are likely to be common to all New Zealanders, whether they tweet or not.

steadily to exceed 5,000 tweets per day in late February 2020. The day the number of COVID-19 cases reached its peak and the country went into lockdown (March 26, 2020) the number of tweets reached its maximum of 7,652 tweets. Over the ensuing weeks, the number of daily tweets gradually decreased and by early May 2020 had returned to their long-run mean.

Our measure of wellbeing, the mean GNH over the one-and-a-half-year period, was 7.14 from an approximately normally distributed set of daily scores. The mean GNH score decreased by about 0.027 units per month over this period, with the estimated downward trend accounting for just under one-quarter of the variance in the series ( $t = 11.02$ ; effect size,  $\eta^2 = \omega^2 = 0.238$ ).<sup>24</sup> Although the cause of this slow fall in the GNH index is unclear, the decline itself remains an important contextual feature and we have therefore removed it from the series we use below.<sup>25</sup>

De-trending the GNH series exposed another source of variation, namely the day-of-the-week effect. Each week the index increased from its lowest point on Monday through to its peak on Friday, after which the mean mood decreased in anticipation of the coming work week. The magnitude of the day-of-the-week effect was almost two points on the de-trended scale, -1 to +1, from the Monday low through to the Friday high. It is a pattern that replicates very closely the international results based on more conventional measures of wellbeing (Akay & Martinsson, 2009; Helliwell & Wang, 2014; Kelly, 2018; Taylor, 2006; Tsai, 2019). That the Twitter-based wellbeing series picks up this day of the week pattern so clearly is one indication of its sensitivity to daily changes in national mood.

Two further characteristics of the GNH series stand out. The first is the high noise to signal ratio. The second is the frequent appearance of outliers, both positive and negative. There is no reason to expect the residuals from the adjusted GNH index to relate to each other and we therefore applied a suitable smoother to pick up only the underlying systematic movements. Since moving averages based on the mean have little resistance to the outliers we adopted a resistant five-day smoother based on running medians.

<sup>24</sup> The eta-squared estimate is equivalent to R-squared estimates and the omega-square to the adjusted R-squared estimates. In our bivariate case the two effect sizes are the same. This long-term decline in the GNH closely approximates the end of the much longer secular decline evident in the major international sentiment based series, Hedonometer, see [http://hedonometer.org/timeseries/en\\_all/](http://hedonometer.org/timeseries/en_all/)

<sup>25</sup> As Shah et al., (2019 p. 11) advised, “When applying sentiment analysis tools to Twitter data to characterize a population over time, it is useful to account for baseline spatiotemporal differences before attempting to detect deviations in mood”.

## Results and analysis

### GNH and the COVID-19 epidemic curve

As discussed in Section 1, our primary aim is to demonstrate the sensitivity of a national wellbeing index to changes in daily reported COVID-19 cases.<sup>26</sup> In practical terms, this involves comparing the national wellbeing index (GNH) with the curve formed by the succession of COVID-19 cases. The comparison is undertaken descriptively in Fig. 1. The left axis identifies the recorded number of COVID-19 cases per day, and the right axis defines the de-trended five-day smoothed Gross National Happiness index.

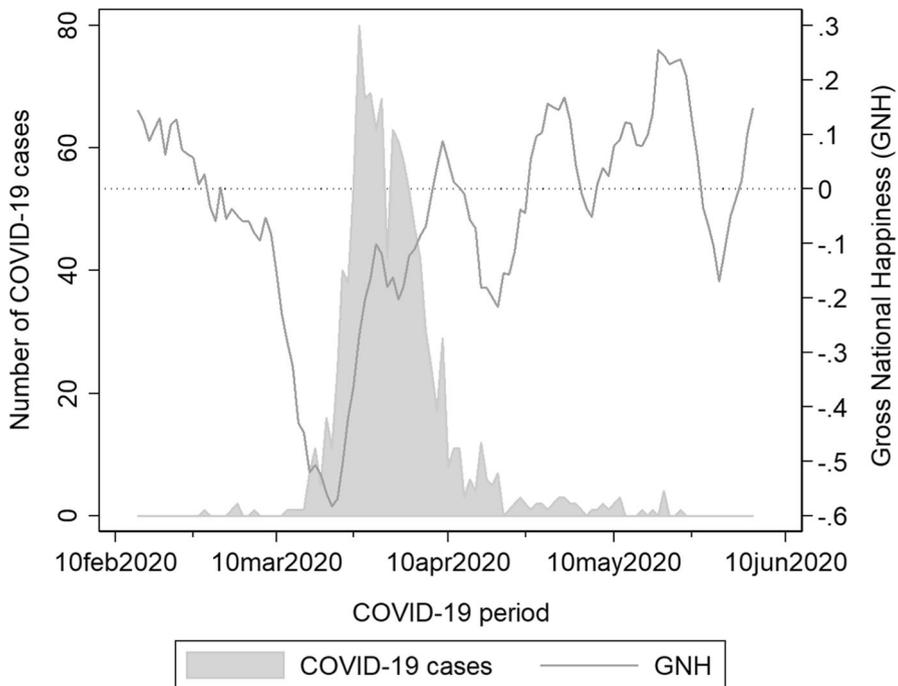
Figure 1 shows the detrended GNH index decreasing from above its long-term average (0) even before the first case of COVID-19 was recorded in New Zealand. The index continued to decrease until just after the government announced that New Zealand was moving to alert level 2 on the 21<sup>st</sup> of March 2020. This proved to be the turning point after which the country's average wellbeing began to increase even though the number of cases of COVID-19 were also increasing. Except for the brief period between the 10<sup>th</sup> and 26<sup>th</sup> of April, the country's wellbeing continued to increase. There was a collective relief at the government's response coupled with a growing faith that the state had taken the right steps, so by the time New Zealand moved down to alert level 3 on the 28<sup>th</sup> of April, the GNH had already returned to its long-term mean.

There has been considerable speculation about the timing and magnitude of the country's wellbeing response to COVID-19. Most of the 'evidence' came from reported case studies in the media, usually made up of small non-random studies of selected groups who presented with symptoms. This was leavened only by a few cross-sectional surveys, which described the wide variation in wellbeing across their point in time samples (see Sibley et al., 2020; Every-Palmer et al., 2020; Prickett et al., 2020). What has been lacking in the evidence presented to date is a consistent series capturing the country's level of wellbeing that could be tracked on a daily basis. Using the GNH Index at hand we begin by asking whether the nation's wellbeing preceded (led), aligned or followed (lagged) the COVID-19 series.

### Cross-correlations

The temporal relationship between COVID-19 and the GNH index can be described using the cross-correlogram applied in Fig. 2. Each dot depicts the correlation between the GNH index and the number of COVID-19 cases at different leads and lags. The vertical line at zero is the correlation that applies without any lead or lag. The negative correlation,  $r = -0.372$ , shows how the wellbeing index was decreasing over most of the period when the number of COVID-19 cases were increasing. There

<sup>26</sup> In terms of the COVID-19 series utilised in our analyses, we use the New Zealand Ministry of Health's publicly available data (Ministry of Health, 2020).

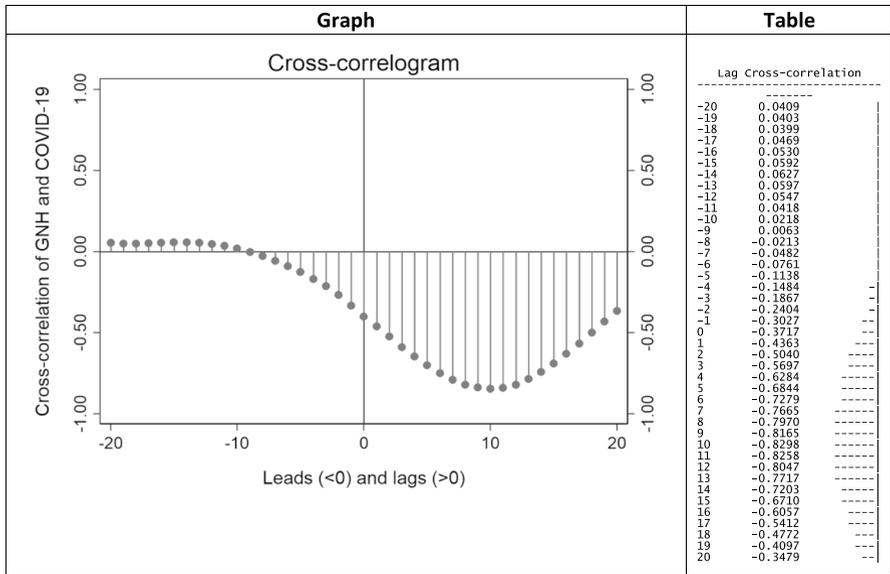


**Fig. 1** The Gross National Happiness Index and COVID-19 cases. 14- Feb - 14 June 2020. New Zealand. *Source:* The COVID-19 case series (Ministry of Health, 2020) and the GNH index (Greyling et al., 2019)

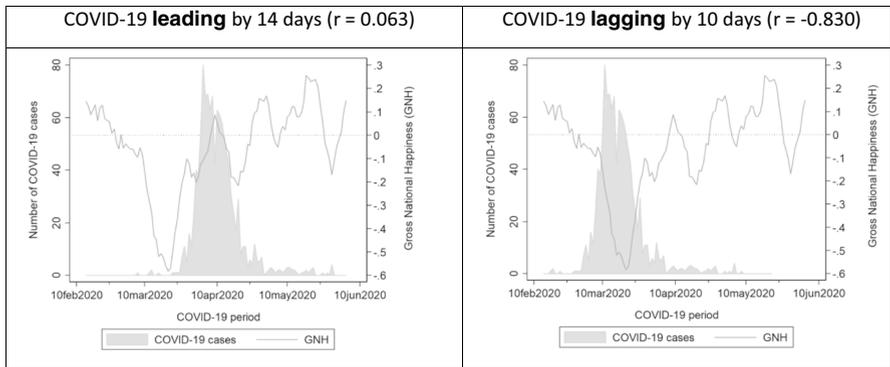
was a brief period when the two series were increasing together, but the series was inversely related over most of the period. The correlations themselves are presented in the accompanying table, which shows that wellbeing was most strongly inversely related to the number of COVID-19 cases ten days after they were reported.

To gain an intuitive feel for the difference between the 14-day *lead* when the positive correlation was highest and the 10-day *lag* when the negative correlation was highest, we reran our first figure, Fig. 1, again to generate the two panels in Fig. 3. In the left panel, we have allowed the pandemic to *lead* wellbeing by 14 days, graphically pulling the COVID-19 series to the *left* of its original position resulting in a low correlation of  $r=0.063$ . In the right panel, we have *lagged* the ‘epidemic curve’ to the point where the *negative* correlation reaches a maximum ( $r=-0.830$ ) some ten days later. The evidence clearly shows that the changes in national wellbeing were largely in response to turning points in the ‘epidemic curve’.

In summary, the GNH time series exposes the dynamic nature of the relationship between our measure of national wellbeing and the path taken by the ‘epidemic curve’. Instead of simply counting levels of psychological distress in the population before and after the event as cross-sectional studies have done, the time-series approach enabled by the GNH series permits the identification of a rather weak anticipation curve that gradually changed to a much stronger reactive response as the pandemic took hold. At the end of the day, the strong negative reaction to the



**Fig. 2** Cross-correlogram. GNH and COVID-19. 5 14 Feb -14 June 2020. New Zealand. *Source:* The GNH (Greyling et al., 2019) and COVID-19 series (Ministry of Health, 2020)



**Fig. 3** The lead in COVID-19 at which the positive correlation is maximised (left) and the lag when the negative correlation is maximised (right). *Source:* The GNH (Greyling et al., 2019) and COVID-19 series (Ministry of Health, 2020)

destructive effect of the virus and acceptance of the sacrifices the policy response required to contain it determined the country’s wellbeing response.

At the same time, the anticipation and the response have only been described as averages, as a single index. As we will now recognise a range of emotions that are juxtaposed within the GNH index, and collectively they determine its average. A closer look at the temporal sequences of these emotions allows us to address our second research question, the way in which the relative ranking of emotions changed as the national wellbeing index fell then rose.

## The emotional impact of COVID-19

We expected that the arrival of the virus would generate a range of emotions. In this section we ask whether those associated with an increase in wellbeing, such as ‘joy’ and ‘trust’, prevail over those emotions likely to decrease wellbeing, such as ‘anger’, ‘disgust’ and ‘sadness’.<sup>27</sup>

In order to explore the shift in emotions that underpin the Gross National Happiness Index, Greyling et al. (2019), using Natural Language Processing (NLP), derived the emotions underlying the same set of tweets used to calculate the GNH. They distinguish between eight categories of emotion: anger, fear, anticipation, trust, surprise, sadness, joy and disgust.

Box 1 offers three examples of how underlying emotions are derived from the text. Each tweet is scored according to the presence and intensity of one or more emotions. In the first example, the tweet—“I love dogs: they are such good companions”, a score of 1 is assigned to the emotion called ‘trust’, and a score of 2 is assigned to the emotion called ‘joy’. Scores are assigned to the other two examples in a similar manner; “Judith’s doing a good job ....” and “Mask-wearing is really .....”.

### Box 1 Examples of coding tweets for emotion

#### “I love dogs; they are such good companions”

Anger	Fear	Anticipation	Trust	Surprise	Sadness	Joy	Disgust
0	0	0	1	0	0	2	0

#### “Judith’s doing a great job boosting the party vote in her new role as leader of the Nat Party, hope they get rid of that Bridges guy now”

Anger	Fear	Anticipation	Trust	Surprise	Sadness	Joy	Disgust
4	0	1	2	0	0	5	0

#### “Mask-wearing is really reducing in inner Auckland – I’ve been virtually the only one I’ve seen today. (Lack of) distancing pretty much the same... #COVID19NZ”

Anger	Fear	Anticipation	Trust	Surprise	Sadness	Joy	Disgust
6	0	2	0	2	0	0	4

Source: Emotion time-series based on the GNH (Greyling et al., 2019)

If only these three messages were tweeted in one day, then the daily mean of the emotion ‘joy’ would be 2.3, i.e.  $(2+5+0)/3$ , and ‘disgust’ would be 1.33  $(0+0+4=4/3)$ , and so on. Therefore, the daily averages for each of the eight emotions reflect both the emotion and the weighting they receive within the coding algorithm.

Using the scores assigned to each emotion and deriving the daily mean of each emotion allows us to track the fluctuation in the emotions over the COVID-19 period and these are presented in Table 1. ‘Trust’ is exposed and weighted at 0.856, followed by ‘anticipation’ at 0.739 and ‘joy’ at 0.675. Each of these three emotions

<sup>27</sup> We are aware of the debate in psychology on whether trust is an emotion or not but working from a linguistic approach and sentiment analysis perspective we adopt their treatment of trust as an emotion and present it as such in our text. In related research Li et al. (2020) sought the consequences of COVID-19 via almost 18,000 posts by active Weibo users. The results showed that negative emotions (e.g., anxiety, depression and indignation) and sensitivity to social risks increased, while the scores of positive emotions (e.g., Oxford happiness) and life satisfaction decreased.

is not only more likely to be recorded, but they also vary more widely about their mean as their standard deviations, minimum and maximum scores show.

The five remaining emotions are less likely to be present in the tweets and are less heavily weighted: ‘fear’ followed by ‘sadness’, ‘anger’, ‘surprise’ and ‘disgust’. This is almost in the same order as their variance, with ‘fear’ varying most and ‘surprise’ varying least over the 111-day COVID-19 period.

Based on what we have learned from the literature and the GNH series, we expected that the pending arrival of COVID-19 would be accompanied by a marked decrease in ‘joy’ and an increase in ‘anticipation’, ‘fear’ and ‘sadness’. As the country gained control of the spread of the pandemic, we expected an increase in ‘trust’, ‘anticipation’ and ‘joy’ and a diminution in ‘sadness’, ‘anger’ and ‘disgust’.

We graph the series in two figures to facilitate their identification—the top scoring ‘trust’, ‘anticipation’ and ‘joy’ in Fig. 4 and the rest in Fig. 5. Together they suggest a complex mix of reactions to the passage of the pandemic. Figure 4 shows that after a variable start, all three daily means fell a few days after the announcement of the first recorded case in New Zealand on 28 February 2020 (dashed vertical line). An ambiguous reaction to the first COVID-19 case in the case of all three emotions suggests uncertainty which helps explain the marked decrease in ‘trust’, ‘anticipation’ and ‘joy’ as the virus spread within the community. However, well before the government announced the first level 3 lockdown on the 23<sup>rd</sup> of March 2020 (light grey shading), these three emotions began to appear more frequently in the Twitter posts and continued to do so, albeit irregularly, when the lockdown was raised to alert level 4 (dark grey shading).<sup>28</sup> Particularly noticeable was the increase in expressions of ‘trust’ from <0.8 to 0.9+, while those for ‘joy’ and ‘anticipation’ began to level off.<sup>29</sup>

Figure 5 graphs the remaining emotions. These daily mean scores initially increased then decreased fairly steadily after the first case of COVID-19 but decreased less severely in the days prior to the sustained increase in cases. The singular exception was ‘sadness’, which maintained its presence as the number of COVID-19 cases increased while all other emotions decreased. By the time of the level 4 lockdown, all five emotions had begun to increase, headed by ‘fear’, ‘sadness’ and ‘anger’ and less emphatically by ‘surprise’ and ‘disgust’. A notable feature of these last five emotions was their diminished amplitude compared with those appearing in Fig. 4.

When investigating the emotion time series, we found that the emotions ‘fear’, ‘sadness’ and ‘anger’ increased markedly in the days preceding the exit from lockdown and the country’s return to level 1 during the first week of June 2020. In order to understand what caused this increase in these emotions we turned to the contents of the tweets themselves. We discovered that the marked increase in the emotions

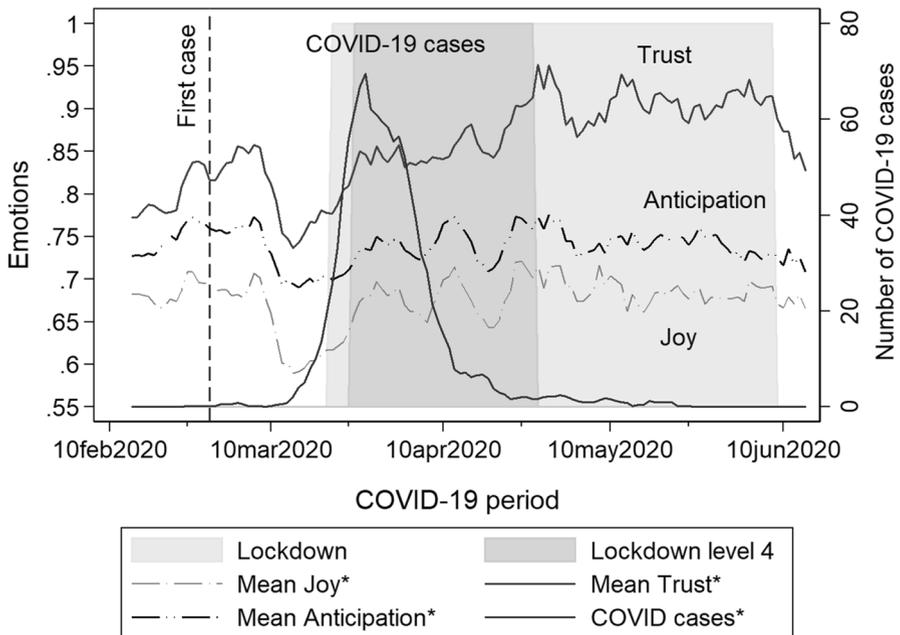
<sup>28</sup> The shading approximates the more detailed depiction of stringency as assembled by the Oxford COVID-19 Government Response Tracker reported in Our World in Data: <https://ourworldindata.org/coronavirus/country/new-zealand>

<sup>29</sup> In support of our findings note how de Pedraza, using a continuous voluntary web survey, find that “a growing number of confirmed COVID-19 cases increases dissatisfaction and anxiety but that this effect levels off with a higher number of cases” (de Pedraza et al., 2020, p. 1).

**Table 1** Means and standard deviations of emotion scores extracted from Twitter over the COVID-19 period. New Zealand

Variable	Mean	Std. Dev	Min	Max
Trust	0.856	0.067	0.711	1.055
Anticipation	0.739	0.036	0.661	0.843
Joy	0.675	0.045	0.576	0.802
Fear	0.481	0.041	0.392	0.608
Sadness	0.398	0.026	0.333	0.471
Anger	0.360	0.032	0.303	0.478
Surprise	0.336	0.016	0.294	0.371
Disgust	0.285	0.023	0.227	0.357

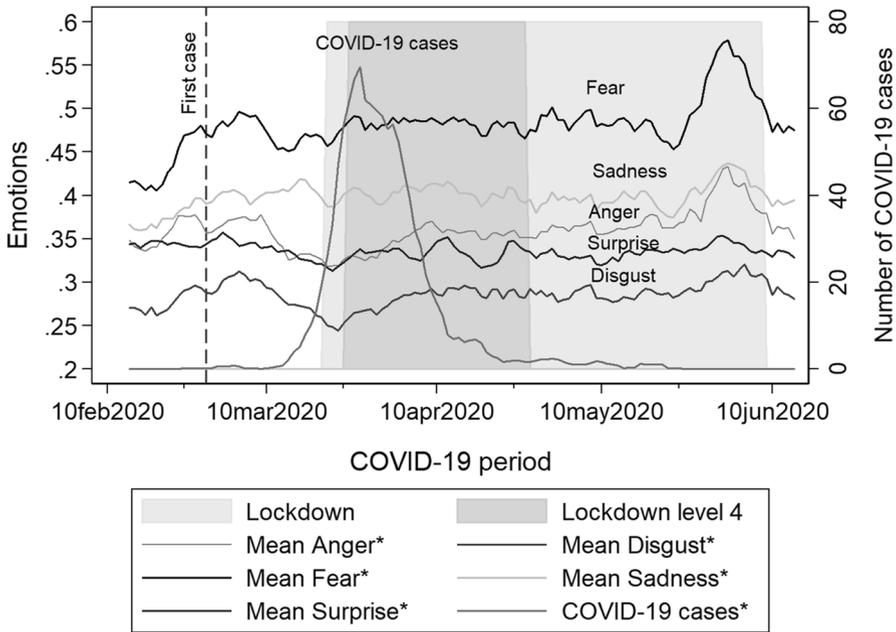
Source: Emotion time-series based on the GNH (Greyling et al., 2019)



**Fig. 4** First set of emotional responses to COVID-19 in New Zealand. Source: Emotion time-series based on the GNH (Greyling et al., 2019). Note: \* denotes the application of a five-day moving average

‘fear’, ‘sadness’ and ‘anger’ over the 10 days did not relate to New Zealand being liberated from lockdown but reflected instead a sympathy with the protests in the United States over the killing of George Floyd on 25 May 2020. The first week of June was also marked by protests within New Zealand in support of the *Black Lives Matter* movement.

When investigating the correlation of our emotions, we also found that instead of ‘trust’ and ‘joy’ tracking inversely with ‘fear’, ‘sadness’ and ‘anger’, they actually correlated positively. Of the 28 possible correlations across the



**Fig. 5** Second set of emotional response to COVID-19. *Source:* Emotion time-series based on the GNH (Greying et al., 2019). *Note:* \* denotes the application of a five-day moving average

eight emotions, almost all returned a significant positive correlation, and none reported a statistically significant negative correlation. Whether this reflected the appearance of various emotions in the same or different tweets is not identifiable from the data at hand. Still, the positive correlation of the emotion series suggests that both are likely given the differential scoring and weighting system described in Box 1 above.

The predominance of the increase in ‘trust’, ‘anticipation’ and ‘joy’ over the relative stability of the remaining emotions following the increase in COVID-19 cases accounts for the marked increase in the GNH index back to its long-run mean in mid-April, as shown in Fig. 1.<sup>30</sup> Clearly, the GNH reflects a complex set of emotions whose temporal behaviour reflects both anticipation and reaction. Furthermore, the lockdowns imposed in New Zealand forced people to have more “me time”, explore alternatives to commuting and spend more time with their families. It is possible that this not only generated higher levels of positive emotions and hedonic happiness but opened up extended opportunities for greater creativity and productivity in ways that caused a rise in eudaimonia as well.

<sup>30</sup> These results are quite consistent with the noticeable increase in trust observed in two cross sections drawn from the New Zealand Attitudes and Values study (Sibley et al., 2020). There is mixed evidence in our series for the post-lockdown anxiety and depression they recorded.

## Limitations

Scholarship based on tweets is still at an early stage despite well over a decade of experimentation. At least four unresolved issues are worth noting. The first is the way our enquiry has exposed the presence of a wide mix of emotions. Happiness and unhappiness may be present within the same person, as well as there being happy and unhappy people. They are both present to unknown degrees in the daily mean of the index used here. Being able to separate the two in the future would add to their policy relevance.

A second unresolved issue concerns the sampling bias characteristic of Twitter feeds. While the presence of demographic bias is widely acknowledged, the degree and nature of that bias remain quite uncertain. Whether an older population would have reacted very differently in wellbeing terms over the COVID-19 period compared to the younger members who are more likely to tweet is unclear. Since the number of tweets varies positively with the number of COVID-19 cases, it is also possible that the composition of tweets changes with the volume of tweets.

A third issue has to do with the distributional consequences of COVID-19. The Twitter series is not accompanied by any demographic characteristics of the tweeters themselves. Therefore it is not possible to monitor changes in emotions by age, education or disadvantage. However, the ability to tie the location of tweets to separate geographic areas within the country offers an enticing future opportunity to explore the distributional implications in geographical terms, as demonstrated in studies focusing on Italy and the USA. For example, see Iacus et al. (2019) and Mitchell et al. (2013).

Fourthly, our study has been confined to what we called the ‘COVID-19 period’, the 111 days between the 14th of February and the 14th of June 2020. However, the economic repercussions of the pandemic in New Zealand, which experienced a record decrease in GDP in the June quarter and an increase in unemployment to 5.3 per cent in the second quarter, have generated their own secondary impacts on national wellbeing. These are likely to have had a much longer and wider range of downstream distributional implications. Reactions to these secondary wellbeing effects of the pandemic still have to be investigated. They are likely to be highly conditional on an individual’s personal circumstances, the nature of their employment, social support, their personal resilience and where they live within the country.

## Conclusion

This paper has demonstrated the sensitivity of a national wellbeing index constructed from Big Data to changes in the number of COVID-19 cases over time. We posed two research questions: would the national wellbeing response lead or lag the passage of the pandemic in New Zealand, and how would the composition of emotions change as the country passed through the ‘epidemic curve’ and the policy steps taken to control its spread.

Our literature search showed we still know relatively little about how the national wellbeing of countries responds to exogenous shocks. The knowledge now being assembled world wide on the epidemiology of happiness and the composition of emotions that underlie indices of national wellbeing is important because, as other studies have shown, reductions in a country's happiness is often associated increases in stress, domestic violence, hospitalisations, decreased labour productivity, increased road deaths, lower immune systems, poorer eating habits, and other shifts in consumption. From such a perspective the Gross National Happiness index (GNH) we have applied to the New Zealand's experience with COVID-19 may serve as a broad macro level indicator of unrest as well as serving as a guide to the country's reaction to the pandemic.

In terms of our first research question, we found that the GNH displayed a rather weak anticipation curve (lead) that gradually changed to a much stronger reactive response (lag) as the pandemic took hold. In terms of the second research question, we found that the pending arrival of COVID-19 was accompanied by a marked decrease in the emotion 'joy' and an increase in the emotions 'anticipation', 'fear' and 'sadness'. However, as the country gained control of community transmission of the virus, we witnessed an increase in the emotions 'trust', 'anticipation' and 'joy' and a decrease in the emotions 'sadness', 'anger' and 'disgust'. While the scores on all eight emotions moved in the same direction, what differed was their relative degree of change with scores on 'trust' and 'joy' in particular increasing faster than the remaining emotions.

The results of this study are most likely applicable to other countries although their greater exposure to neighbouring influences and their as yet incomplete 'epidemic curves' means this may take longer to determine. Even at this stage however there may be lessons to be learned from the New Zealand experience. The New Zealand government adopted a 'go hard and go fast' approach in order to severely restrict community transmission as well as the introduction of COVID-19 across the boarder. Clearly, this was the correct response. Whereas New Zealanders did not appreciate their liberties being taken from them they understood that adhering to the stringent level 4 lockdown (and to a lesser degree, level 3) would restore those liberties sooner rather than later. This is a major reason why national wellbeing rose rather than declined during lockdown. As part of its response, the New Zealand government implemented a COVID-19 wage subsidy scheme which helped employers and self-employed people keep paying staff in jobs impacted by government-mandated lockdowns under alert levels 3 and 4, steps which further contributed to the general rise in national wellbeing as the number of COVID-19 cases fell and lockdown came into effect.

The New Zealand economy is heavily dependent on international tourism and the government established a Trans-Tasman quarantine free travel bubble as soon as was practicable. This meant that New Zealanders and Australians could travel between the countries without entering government quarantine facilities for 14 days upon arrival in New Zealand. By the end of May 2021, the government will be looking to extend the quarantine free travel bubble to the Cook Islands, which has not recorded a single COVID-19 case since the start of the pandemic.

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**Contributions** The first author conceptualised the paper and undertook the analysis that appears in the text. The second and third authors prepared the Gross National Happiness Index series and provided expert advice and editorial comments.

## Declarations

**Conflict of interest/Ethical statement** There are no conflicts of interest. However note that the New Zealand academic community is very small and that any reviewer in the field will be able to guess the authors.

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