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# Markov switching models for happiness during a pandemic: The New-Zealand experience

Stephanie Rossouw[1], Talita Greyling[2], Tamanna Adhikari[3], Phillip S. Morrison[4]

**Abstract** This paper estimates Markov switching models with daily happiness (GNH) data from New Zealand for a period inclusive of the Covid-19 global health pandemic. This helps us understand the dynamics of happiness due to an external shock and provides valuable information about its future evolution. Furthermore, we determine the probabilities to transition between states of happiness and estimate the duration in these states. In addition, as maximising happiness is a policy priority, we determine the factors that increase happiness, especially during the pandemic to ensure rapid restoration of happiness levels post the Covid-19 shock. The results show New Zealand is currently in an unhappy state which is lasting longer than predicted. To increase the happiness levels to pre-pandemic levels, policymakers could allow free mobility, create economic stimuli, and allow international travel between New Zealand and low-risk Covid-19 countries.

**Keywords:** Happiness; Covid-19; Big data; Markov switching model; New Zealand
**JEL classification codes:** C55, I12, I31, J18

[1] Corresponding author. Faculty of Business, Economics and Law, Auckland University of Technology, E-mail: stephanie.rossouw@aut.ac.nz

[2] School of Economics, University of Johannesburg, South Africa, E-mail: talitag@uj.ac.za

[3] School of Economics, University of Johannesburg, South Africa, E-mail: tamanna.adhikari@ucdconnect.ie

[4] School of Geography, Environment and Earth Sciences, Victoria University of Wellington, New Zealand, Email: philip.morrison@vuw.ac.nz

## 1. Introduction

Research related to happiness and the global pandemic, Covid-19, has shown that during the pandemic peoples' happiness decrease (Greyling et al. 2020) and the number of reported negative emotions increase (Sibley et al. 2020, Brodeur et al. 2020). New Zealand's government was one of the only countries in the world that decided to *'go fast and go hard'* in an attempt to curb the spread of Covid-19. In May 2020, New Zealand has succeeded in beating the virus with zero new cases reported on most days. However, the negative effect of the pandemic and lockdown regulations on happiness lingers. To restore New Zealand's happiness levels, it is important to understand both the dynamics of happiness as well as the factors most likely to increase happiness levels post-pandemic. Understanding the dynamics of happiness will undoubtedly allow policymakers greater insight into its implications for economic behaviour.

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 identify the states of happiness as well as the likelihood of switching between states. This allows us to estimate the duration in these happiness states. Lastly, we determine the factors that are related to happiness for the time period after the pandemic began. The result will help direct future government policy.

Against this backdrop, the current study makes the following contributions: i) it investigates the dynamics of happiness, using the *Markov switching model*, not done before and ii) it conducts this during the time period including a *pandemic*. In addition, it is also one of the first studies to use Big Data methods combined with other data collection methods in the analysis (for comparative studies see Brodeur et al. (2020) and Hamermesh (2020)).

The rest of the paper is structured as follows. The next section contains a short discussion on happiness and relevant studies. Section 3 describes the data and outlines the methodology used. The results follow in section 4, while the paper concludes in section 5.

## 2. Background and relevant literature review

According to Algan et al. (2019), there is an increasing demand to use measures of well-being to move beyond the classical income-based approach to measuring human development and progress. Gross domestic product does not measure non-market social interactions, such as friendship, family, happiness, moral values or the sense of purpose in life. Additionally, Bryson et al. (2016) and Piekalkiewicz (2017) states that happiness may act as a determinant of economic outcomes: it increases productivity, predicts one's future income and affects labour market performance. New Zealand has embraced this move as expressed in the Treasury's Living Standards Framework (LSF) alongside the LSF Dashboard, which the Treasury developed to inform its policy advice (McLeod 2018).

Studies that investigated *subjective well-being* during previous pandemics found that community-connectedness and not isolation was a mitigating factor on subjective well-being during the SARS outbreak (Jones & Salathe 2009). Additionally, anxiety levels waned along with the perception of the H1N1 virus being less of an immediate threat (Lau et al. 2008).

More recently, Sibley et al. (2020) investigated the effect of lockdown regulations on institutional trust, attitudes, health and *well-being*, using survey data collected at two points in time (1003 respondents). Their preliminary results showed a small increase in people's sense of community and trust. However, they also found an increase in anxiety/depression post-lockdown and hinted at longer-term challenges to mental health. Brodeur et al. (2020) found that after a lockdown was implemented, an increase in searches for loneliness, worry and sadness, using Google Trends data, which indicated a negative effect on *well-being and mental health*. Greyling et al. (2020) used the GNH to investigate the *determinants of happiness* before and after Covid-19 and found that the factors implemented to curb the spread of the virus negatively affected happiness and that the threat of Covid-19 dissipated over time. Hamermesh (2020) used *Google Trends data* to predict the satisfaction of married and single people while in government-imposed lockdown by running simulations. Not surprisingly, married people were more satisfied with life than single people.

## 3. Data and methodology

### *3.1. Data*

In the analyses, we make use of high frequency daily data. The time period under consideration is from 1 January to 25 May 2020 (146 days). However, to determine what matters most to happiness for the period after the first confirmed Covid-19 case, we consider the period from 28 February 2020 to 25 May 2020 (88 days).

#### *3.1.1 Selection of variables (covariates)*

To select the covariates included in the models we were led by the literature and data availability. However, we were challenged by the limited number of covariates we could include in estimations, due to the short time period (limited observations), to avoid overfitting of the models.

To represent the importance of economic factors on happiness (Sacks et al. 2010), we selected:

i. economic sentiment[5] (a confidence measure),
ii. border crossings (daily arrivals and departures into New Zealand) which is a proxy for international travel (Statistics New Zealand 2020),

[5] The economic sentiment measures the tone 'at the news article level, as well as coding the articles themes' and geographic mentions. For full details see GDELT Project (2020).

iii. daily searches on Google Trends for "jobs" as a proxy for job uncertainty in the future (Brodeur et al. 2020, Simionescu & Zimmermann 2017) and
iv. data on weekly job seekers allowance payments (JSAP) to proxy benefit payments (Statistics New Zealand 2020). We impute daily figures from weekly data using a cubic spline interpolation methodology.

After performing diagnostic tests, we found that (iii) and (iv) are highly correlated, and therefore we only included, JSAP, as it was the better fitting variable.

To represent factors important to happiness other than economic, we selected:

i. lack of mobility (significant from analysis of tweets). Here we use data derived from the Covid-19 Community Mobility Reports (Google 2020). The reports show the percentage change in visits to certain destinations. We construct a mobility variable by making use of Principal Components Analysis (PCA) of which we use the first extracted component as the index.
ii. number of tweets per day for New Zealand (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, Helliwell and Huang 2013).
iii. number of Covid-19 cases (exogenous shock) (European Centre for Disease Prevention and Control (ECDC) 2020).

See table 1 for the descriptive statistics of the variables included in the models.

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

| Variable | Mean | Std Dev. | Min | Max | N |
|---|---|---|---|---|---|
| Daily Covid-19 Cases | 13.11 | 22.7 | 0 | 95 | 88 |
| Economic sentiment | -1.12 | 0.20 | -1.48 | -0.72 | 79 |
| Border crossings (Log) | 5.20 | 2.56 | 0 | 9.44 | 88 |
| Tweets (Log) | 8.59 | 0.18 | 7.77 | 8.93 | 88 |
| Lack of mobility | -0.99 | 1.61 | -3.79 | 1.73 | 78 |
| Job Seekers Assistance Payments (Log) | 11.96 | 0.93 | 11.87 | 12.14 | 88 |

Source: Authors' calculations.

### *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 May 2019 for New Zealand. The GNH measures the happiness (mood) of New Zealand's citizens during different economic, social and political events, using a live feed of tweets, extracted from Twitter. The happiness index assigns scores that range between 0 and 10, with five being neutral, thus neither happy nor unhappy. The index is available live on the GNH website. For a full description of the methodology followed, read Greyling et al. (2020). As happiness varies over the day of the week, with a Monday low and a Friday high, we adjust the time-series to remove the average day of the week effect (figure 1 in Appendix B) (Kelly 2018, Helliwell & Wang 2011).

New Zealand has 400600 active Twitter users who are approximately 8.37 per cent of the population (Omnicore 2020). Although the number of tweets is extensive and represents a significant proportion of the population, 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 a negative and significant relationship (*r*>0.5); therefore, it seems that the GNH index derived from Big Data and the 'depression' and 'anxiety; variables derived from survey data give similar trends, though in opposite directions.

## ***3.2 Methodology***

### *3.2.1 Markov switching model*

To determine the dynamics of happiness during the different states, we fit a Markov switching model to the daily GNH data for the period from 1 January 2020 to 25 May 2020 (see appendix A for full description). We begin by assuming that GNH follows an AR(1) process given by:

$$GNH_t = \mu_s + \sigma_s GNH_{t-1} + bsCovid\ Cases + e_{st} \tag{1}$$

Where S represents the unknown states and t = (0,1,2….).

Parameters μ and σ are state-dependent and represent the stochastic trend as well as the volatility of the states, such that:

$$E(S_{t-1}) = \mu_s \quad (2)$$

$$Var(S_t) = \sigma_s^2 Var(GNH_{t-1}) \quad (3)$$

We further assume that the Markov chain S is ergodic with transition probabilities between states given by:

$$P_{ij} = P(S_t = i) \quad (4)$$

where i,j=(1,2)

The priori of 10 parameters (2 transition probabilities, 2 trends, 2 volatility parameters, 2 AR parameters, and 2 state-dependent parameters on COVID cases) are estimated using an Expectation Maximisation algorithm. As the number of parameters estimated increases rapidly as the number of states increases and given the relatively small number of observations for our sample, we decided to keep the minimum of 2 states; 1 state-dependent autoregressive term and 1 state-dependent covariate (Covid-19 cases). We limited our choice to only Covid-19 cases as we assume, within reason that the majority of the transmission of the variation in happiness during the period could be through Covid-19 cases. Naturally, we are also limited in adding additional covariates due to the limited number of observations. We report robust standard errors to correct for heteroscedasticity inherent to high-frequency data.

The classification of the states is largely subjective and can be inferred upon observing state-dependent μ and $\boldsymbol{\sigma}$. In this way, it still seems that we can classify *unhappy* and *happy* states.

Finally, given the estimated transition probabilities, we compute the expected duration (D) in each of the two states through the following equation:

$$E(D_S) = \frac{1}{1-P_{ij}} \quad (5)$$

*where i,j=(1,2)*

### *3.2.2 OLS regression*

To address our second objective to determine which factors are related to happiness, we make use of a linear model and OLS estimations. This is appropriate since we are only considering the time period after the first Covid-19 case was announced and not the entire period:

$$GNH_t = \alpha_0 + \alpha_2 X_t + \mu_t \quad (6)$$

We include a vector of covariates encapsulated in $X_{t.}$ (see section 3.1) with $\mu_t$ the error term.

Some of our independent variables may be correlated with the error term, leading to endogeneity concerns, which implies that a coefficient could be biased upwards or downwards. In the absence of panel data or an appropriate instrument, it is difficult to assess the likelihood of endogeneity and also to make predictions related to causality. Therefore, in interpreting the results, we should be conscious of these limitations. However, after conducting diagnostic tests, the model, as outlined in equation (6) and the selection of variables (see section 3.1.1), seems to be most efficient.

## 4. Results and analysis

### *4.1 Results on the unobserved states of happiness*

Table 2 gives the parameters of the MSAR model, which describe the two states of happiness, for the period from 1 January to 25 May 2020, controlling for the number of Covid-19 cases and past happiness. The switching between the states is a priori unobserved. However, if we consider the data (see also figure 1 in Appendix C), we notice that the average levels of happiness were significantly higher (7.08) before the pandemic than thereafter with 6.49. In our opinion, it seems that the switch in the states arises from exogenous factors governed by an autonomous latent process.

**Table 2: Markov switching model parameters**

| | **Unhappy State** | **Happy State** |
|---|---|---|
| Mean | 6.49 (0.110) | 7.08 (0.029) |
| 95% Confidence Interval | (6.25, 6.79) | (7.03, 7.14) |
| GNHt-1 | 0.434* (0.332) | 0.264*** (0.088) |
| Covid-19 cases | 0.004 (0.004) | -0.002** (0.001) |
| Sigma | 0.191 (0.141) | |
| N | 145 | |

Source: Authors' calculations. Standard errors in parenthesis

We describe the period before the switch, as classified by the Markov model, as *happy* and the period thereafter as *unhappy*. We can potentially associate the lower state of happiness over this period, largely to the effect of the exogenous shock, due to the pandemic observed. In saying this, we do recognise that other local concomitant factors might have also affected happiness during this time. The lower state of happiness, although significantly associated with past levels of happiness, is not significantly related to the number of daily Covid-19 cases. This finding supports the Markov classification of the two states, thus independent of Covid-19 cases there seems to be two states, which likely is due to the exogenous shock. Furthermore, it seems that in the *unhappy* state, the number of Covid-19 cases per day is not such a big threat, likely due to the measures that were implemented to curb the spread. During this time period, it might be that other factors, such as economic concerns and uncertainty about future employment, play a bigger role.

In the time period before the switch, the *happy* state, we find, as in the *unhappy* state, that past happiness significantly explains happiness levels. However, contradicting the *unhappy* state, we find that the number of Covid-19 cases is negative and significantly related to happiness. This could potentially be explained by the increase in the emotion *fear* before regulations were implemented, and people's happiness was significantly negatively influenced as a result.

**Table 3: Transition Probabilities of Switching between States**

| | Unhappy | Happy |
|---|---|---|
| Unhappy | 0.78 (0.11) | 0.21 (0.11) |
| Happy | 0.03 (0.23) | 0.97 (0.23) |

Source: Authors' calculations.

Table 3 gives the four probabilities to transition between the two states. We can see that for New Zealanders' the happier state is quite persistent, reflective of the overall high happiness levels in the country. However, the probability of moving from an *unhappy* state to a *happy* state is only 21 per cent. In addition, the probability of staying in an *unhappy* state is relatively high, at 78 per cent. Thus, we can conclude, once New Zealander's achieve an *unhappy* state (the state of happiness during the pandemic), the likelihood to become happy is relatively small, and the likelihood to stay unhappy is relatively big. Therefore, policy intervention is a priority to ease the *unhappy* state.

**Table 4: Expected duration in each state (in days)**

| | Unhappy | Happy |
|---|---|---|
| Mean Duration | 4.6 | 31 |
| Standard Error | 2.5 | 23.5 |

Source: Authors' calculations.

Table 4 shows that the higher state of happiness has a higher expected duration of 31 days than the unhappy state, which is, on average, only 4.6 days. This is expected, due to the high persistence observed in the transition probabilities in Table 3. However, the expected duration of the happy state has a high standard deviation (23.5 days) conveying greater uncertainty in the number of days New Zealanders’ are expected to remain in this state vis-á-vis the unhappy state. The *unhappy* state that New Zealand currently finds itself in is expected not to last for long. Still, due to the exogenous shock of the pandemic, it can be that this state is prolonged and could last beyond the expected duration. This once again emphasises the need for affirmative policy intervention.

### *4.2 Regression results*

The factors significantly related to happiness after the first Covid-19 case was announced include job seeker assistance payments, border crossings and mobility (see table 5). We notice, considering the standardised coefficients, that what matters most to the happiness of New Zealanders' is international travel (border crossings). International travel restrictions have a double impact on the happiness of New Zealanders, first an economic- and second a social shock. Those impacted directly by the lack of international and domestic tourism experience a significant economic shock that negatively influences their livelihoods. New Zealanders are known for their international travelling. In the year 2019, over 1.6 million New Zealanders (35.21 per cent of the total population) travelled abroad (Statistics New Zealand 2020). Not being able to go and travel the world is a social shock causing a decrease in happiness.

**Table 5 OLS estimation results for GNH after the first confirmed Covid-19 case**

| | **(1)** | **(2)** | |
|---|---|---|---|
| **Covariates** | **Coefficients** | **Standardised Coeff** | **SE** |
| Covid-19 Cases | -0.0019 | -0.1677 | (0.0019) |
| Economic sentiment | 0.2024 | 0.1526 | (0.1923) |
| Border cross (log) | $0.005^{***}$ | $0.8102^{***}$ | (0.0000) |
| Job seeker assistance | $1.526^{***}$ | $0.5799^{***}$ | (0.7473) |
| Mobility | $-0.0785^{**}$ | $-0.4724^{**}$ | (0.0408) |
| Cons | -11.4273 | | (9.1194) |
| *N* | 78 | 78 | |
| adj. $R^2$ | 0.377 | 0.377 | |

Source: Authors' calculations. Note: to account for heteroscedasticity we report robust standard errors in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Thus, based on the probability of moving to a *happy* state during the pandemic being only 21 per cent, policymakers should address the factors that matter most to restore happiness to pre-pandemic levels.

## 5. Conclusions

The Markov switching model showed New Zealand has two states of happiness; *happy* and *unhappy*, and it seems as if the switch from one state to the other was due to the pandemic. Furthermore, New Zealanders currently finds itself in the *unhappy* state, and the probability of moving to a *happy* state is relatively small. In addition, the current *unhappy* state, due to the pandemic, might be lasting longer than expected. We found the factors significantly related to happiness after the first Covid-19 case was announced to be: job seeker assistance payments, border crossings and mobility.

For happiness levels to return to pre-pandemic levels, policymakers could possibly intervene in the form of lifting lockdown regulations and opening the borders. This could restore mobility and encourage border crossings, thereby increasing tourism to rekindle the economy. The possibility of establishing a 'Trans-Tasman bubble' to encourage international travelling and tourism could be one of the possible areas for government to focus one. The extended bubble could go further than just Australia and include other low-risk nations. There are 21 island nations and territories in Oceania that have reported no Covid-19 cases including Samoa, American Samoa, Tonga, Tuvalu, Tokelau, Niue, Nauru, Kiribati, the Cook Islands and the Solomon Islands. In saying this, government should only consider this option without increasing the Covid-19 risk again. Additionally, government could also create employment opportunities to decrease the fear of losing jobs and the dependency on job-seekers assistance. Failure to increase happiness levels could have further negative spill-over effects in various domains such as economic, social and political.

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## Appendix A

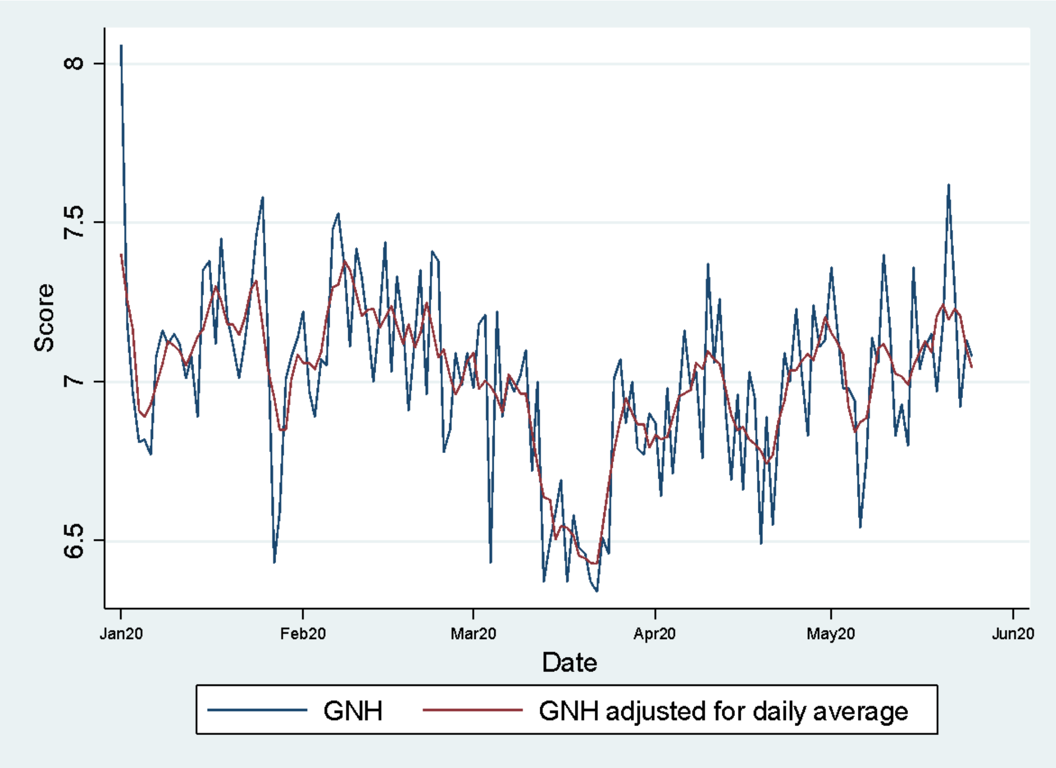
Previously models most often employed to analyse the dynamic behaviour of economic variables were linear of nature, such as autoregressive (AR) models, moving average (MA) models, and mixed ARMA models. However, linear models do have limitations, although adequate to estimate linear equations, they are not able to capture nonlinear dynamics such as asymmetry, amplitude dependence and volatility clustering. Furthermore, they cannot estimate models for variables that move through significant different states, such as GDP growth rates, during periods of expansion and contraction, or in the current paper, happiness levels increasing and decreasing before and after a pandemic.

Therefore, nonlinear models have been developed to address these shortcomings (see Granger and Terasvirta 1993). One of these models, the model applied in the current analysis, is the Hidden State Markov Switching Autoregressive Model (MSAR) model (Hamilton, 1989; Buckle et al. 2004), as it can address many of the pre-mentioned challenges. Furthermore, the model has the benefit that it can encapsulate more than one equation that characterises time-series behaviours in different states, as it allows for switching between states. In addition, the switching mechanism of the Markov model is controlled by an unobservable state variable that follows a first-order Markov chain. In particular, the Markovian property regulates that the current value of the state variable depends on its immediate past value (a lagged GNH variable). Thus, a specific structure (state) only prevails for a random time period, after which it will "switch" to another structure (state). Thus, using the Markov model, we do not need to make subjective judgements on the state we are in, a priori, as the switch is determined by the Markov model itself. From the model, we derive the probabilities of the happiness time series from transitioning from one state to another and the length of time it takes to move between the different states of happiness.

Except for the one-period lag of GNH, we also include the number of Covid-19 cases as a covariate in the model, seeing that it most likely impacts the transition probabilities. In choosing the best fitting model, we ran several diagnostic tests with different states and also included other likely covariates. We were dictated both by a lower information criterion (AIC and BIC), as well as concerns for parsimony in the final model selection.

**Appendix B**

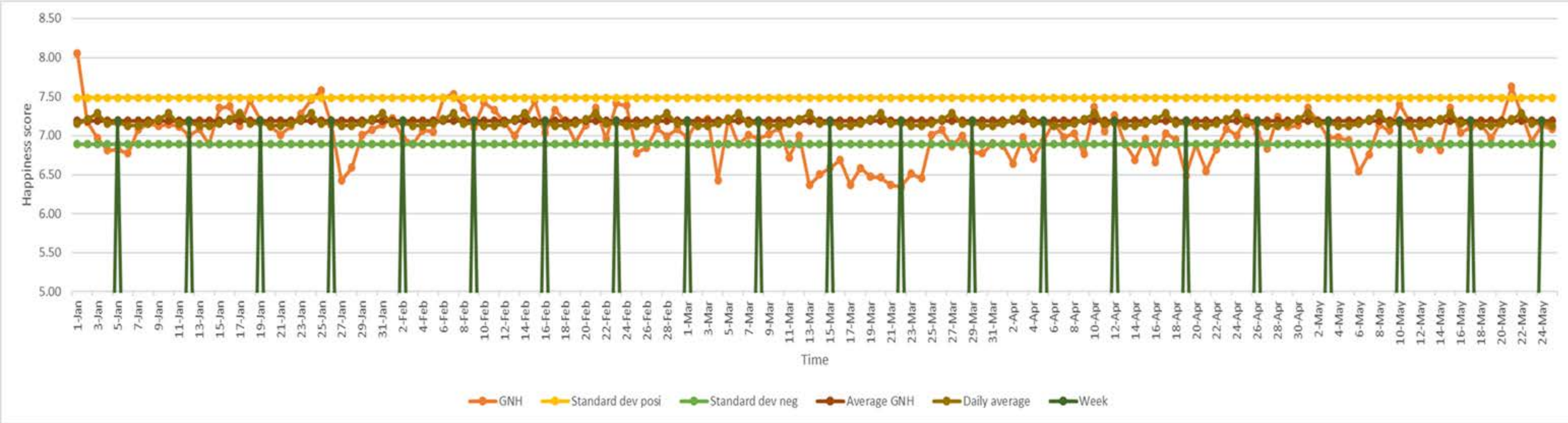
**Figure 1: GNH adjusted for day of the week effect.**




Source: Greyling et al. (2019).

## Appendix C

**Figure 1: New Zealand's happiness levels for January – May 2020.**




Source: Greyling et al. (2019).