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Working Paper Collective emotions and macro-level shocks: COVID-19 vs the Ukrainian war

GLO Discussion Paper, No. 1210

Provided in Cooperation with: Global Labor Organization (GLO)

Suggested Citation: Rossouw, Stephanié; Greyling, Talita (2022) : Collective emotions and macro-level shocks: COVID-19 vs the Ukrainian war, GLO Discussion Paper, No. 1210, Global Labor Organization (GLO), Essen

This Version is available at: https://hdl.handle.net/10419/267148

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Collective emotions and macro-level shocks: COVID-19 vs the Ukrainian war.

Stephanié Rossouw¹, Talita Greyling²

Abstract

We know that when collective emotions are prolonged, it leads not only to action (which could be negative) but also to the formation of identity, culture, or an emotional climate. Therefore, policymakers must understand how collective emotions react to macro-level shocks to mitigate potentially violent and destructive outcomes. Given the above, our paper's main aim is to determine the effect of macrolevel shocks on collective emotions and the various stages they follow. To this end, we analyse the temporal evolution of different emotions from pre to post two different types of macro-level shocks; lockdown, a government-implemented regulation brought on by COVID-19 and the invasion of Ukraine. A secondary aim is to use narrative analysis to understand the public perceptions and concerns that lead to the observed emotional changes. To achieve these aims, we use a unique time series dataset derived from extracting tweets in real-time, filtering on specific keywords related to lockdowns (COVID-19) and the Ukrainian war for ten countries. Applying Natural Language Processing, we obtain these tweets underlying emotion scores and derive daily time series data per emotion. We compare the different emotional time series data to a counterfactual to derive changes from the norm. Additionally, we use topic modelling to explain the emotional changes. We find that the same collective emotions are evoked following similar patterns over time regardless of whether it is a health or a war shock. Specifically, we find *fear* is the predominant emotion *before the shocks*, and *anger* leads the emotions after the shocks, followed by sadness and fear.

JEL codes: C55; I10; I31; H12; N40

Keywords: COVID-19; Big Data; Twitter; collective emotions; Ukraine; macro-level shock

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1. Introduction

Gaining insight into individual-level emotional reactions is important to understand how people anticipate and adapt to life events. However, when considering numerous people's interactions, macro-level affective processes occur and cannot be readily captured when one examines the individual-level alone. This is because macro-level affective processes differ from the individual-level responses in terms of their quality (reduced variability), magnitude (increased intensity), and time course (prolonged). Such macro-level affective processes seem to contribute to the unfolding of a variety of collective processes driven by both negative emotions (e.g., violent demonstrations, civil unrest, fear, and collective mourning) and positive emotions (e.g., excitement, hope, and collective celebrations such as sport teams winning) (Goldenberg et al. 2020:154).

In this paper, we define collective emotions as macro-level phenomena that emerge from emotional dynamics among individuals focused on a common event rather than emotional relationships between members of the society (de Rivera 1992, Goldenberg et al. 2020). We argue that it is important to study collective emotions because emotions influence our decisions, actions and cognition (Gallup 2022). As Lerner et al. (2015:816) state, "*emotions constitute potent, pervasive, predictable, sometimes harmful and sometimes beneficial drivers of decision making*". Additionally, we know that people's emotional levels influence their voting behaviour (Ward 2020), and according to the Gallup Global Emotions Report (Gallup 2022), our collective emotions and civil unrest. The global positive experience index has decreased, and the negative experience index has increased. And according to the Global Peace Index (GPI) (Institute for Economics & Peace 2022), violent demonstrations recorded the worst deterioration, changing by 49.6 per cent since 2008.

Furthermore, we note that the macro-level shocks (see section 2 for full discussion) we have seen over the past three years caused a surge of strong negative emotions such as anger and anxiety. Anger which signals that we are being threatened, injured, deprived, or robbed of rewards and expectancies, causes us to stand up and take care of ourselves and those we love. Studies such as Smith et al. (2021), Kubick et al. (2021) and Abadi et al. (2021) showed that measures, such as lockdowns, put in place to prevent the spread of COVID-19 in 2020 caused considerable tension since people reported feeling angrier, more aggressive and getting into confrontations with others. Likewise, we saw that at the national level, collective anger led to protests (sometimes violent) against lockdowns and governments across the globe (Belgium, New Zealand, Australia, Canada, and the USA). Similarly, we saw people take to the streets against President Putin and his security council when Russia invaded Ukraine in 2022 (nearly 1800 demonstrations between 4 February and 4 March 2022 (ACLED 2022)).

Given how emotions influence decision-making (sometimes in a harmful manner), more empirical studies must be conducted to help inform policymakers. Moreover, since we face a worsening

geopolitical climate and uncertainty regarding when the world will face the next pandemic, more information on the evolution of collective emotions is needed to suggest policy intervention to mitigate potentially violent and destructive outcomes as a consequence of macro-level shocks.

To our knowledge, few papers study collective emotions following a macro-level shock (see section 2 for discussion). During the first half of the 20th century, scholars such as Le Bon (1896), Durkheim (1912), Lewin (1947), and Taylor (1975) studied the effect of shocks. However, they did not consider *the stages of collective emotions* following a shock, which is essential when interpreting the associated consequences.

During the second half of the 20th century, we saw a move towards investigating individual-level responses to major life events such as divorce and death (see, for example, Brickman & Campbell 1971, Clarke et al. 2008, Clarke & Georgellis 2013, Frijters et al. 2011, Rudolf & Kang 2011). However, the emphasis is on the effect of *happiness (not emotions) at an individual-level*, with oversight regarding negative collective emotions following a macro-level event.

To this end, our primary aim is to determine the effect of macro-level shocks on collective emotions and the various stages they follow. A secondary aim is to use narrative analysis to understand the public perceptions and concerns that lead to the observed emotional changes.

To achieve our aims, we analyse the temporal evolution of Plutchik's (1980) wheel of negative emotions (anger, disgust, fear and sadness) and the positive emotion joy from pre- to post two different macro-level shocks; lockdown, which is the epimax against the backdrop of the COVID-19 pandemic (a health shock) (Morrison et al. 2022, Brodeur et al. 2021) and the invasion of Ukraine (a war shock). By doing the aforementioned, we will follow the evolution of emotions in anticipation of and in reaction to each shock. Additionally, we will identify the effects on and stages of emotions pre- and post-macro-level shocks.

Following the above, we contribute to the literature by being the first paper to determine the various stages collective emotions pass through in relation to macro-level shocks. We are also the first paper that compares collective emotions across different macro-level shocks in a cross-country analysis. Additionally, no topic modelling and narrative analysis were conducted to understand people's perceptions and concerns driving different emotional responses, which are needed to inform future policymaking.

In our analyses, we use a unique time series dataset derived from extracting tweets in real-time, filtering on specific keywords related to lockdowns (COVID-19) and the Ukrainian war, as well as a subset of tweets used as a counterfactual. The total number of tweets used in our analyses is more than 900 million at the country level. We use Natural Language Processing (machine learning) to code (score) the tweets' underlying emotions and derive the time series data using the daily means of the scores. The period

analysed relative to the lockdown is before and after the first lockdown in the ten countries in our study. The first lockdown in our sample of countries spreads across March 2020. The period analysed pertaining to the invasion of Ukraine is before and after the invasion on 24 February 2022. As a counterfactual time period, we used the same days in 2021. Furthermore, we use topic modelling of the original tweets to follow the narrative, which underpins the changes in emotions.

Our results show that regardless of the macro-level shock, there are clear effects on collective emotions. Moreover, the stages collective emotions pass through reveal the same pattern. Pre-lockdown and the invasion, we saw that fear was the leading emotion, followed by disgust. Post-shocks, anger was the leading emotion, followed by sadness and fear. Our results are limited to the analyses of two types of shocks (lockdown and invasion). However, similar results are observed within the whole sample, the subsamples of the Northern and Southern hemispheres and within the second lockdown in New-Zealand. Suggesting that the shocks similarly affect collective emotions and the stages of collective emotions.

Therefore, our findings explain the evolution of collective emotions related to specific types of macrolevel shocks and can inform policymakers about the pattern of increasing negative emotions, which can lead to violent and destructive outcomes.

The rest of the paper is structured as follows. The next section discusses relevant literature pertaining to macro-level shocks and collective emotion. Section 3 introduces the countries in our analyses, describes the data and outlines the methodologies used. The results and discussion follow in section 4, while the paper concludes in section 5.

2. Literature review

Before discussing COVID-19, the lockdown, and the invasion of Ukraine, let's first review literature related to other macro-level shocks and their effect on collective emotions.

Terrorism

Following the 11 September 2001 terrorist attacks in the United States (U.S.), an NBC News/Wall Street Journal poll conducted on 12 September revealed that the primary emotion felt was anger, followed by sadness and disbelief (Saad 2001). Fredrickson et al. (2003) also focused on the terrorist attack using survey data collected pre- (March and June 2001) and post-shock. U.S. college students' emotional responses were tested to see whether positive emotions act as 'active ingredients' in coping and thriving despite experiencing a shock. Mediational analyses showed that positive emotions experienced after the terrorist attack fully accounted for the relations between (a) pre-shock resilience and later development of depressive symptoms and (b) pre-shock resilience and post-shock growth in psychological resources. Metcalfe et al. (2011) found that the 9/11 attacks significantly negatively affected happiness in a country not directly impacted by the negative shock, the United Kingdom. Using

a quasi-experiment and survey data from the British Household survey, taken in September 2011, the authors produced one of the first studies to show the impact of a terrorist attack in one country on the well-being of another country.

Garcia and Rimé (2019) focused on the Paris terrorist attacks of November 2015, using approximately 62 000 Twitter users to investigate the relationship between collective emotions and solidarity in the communities affected by this shock. They found a collective negative emotional response followed by a marked long-term increase in solidarity-related lexical indicators. Expressions of social processes, prosocial behaviour, and positive affect were higher in the months after the attacks for the individuals who participated to a higher degree in the collective emotion. Coupe (2017) also investigated the Paris terrorist attacks using a quasi-experiment to determine the effect on the French's mood, expectations and trust. The author found evidence of increased trust in the national government and reduced optimism. However, there was no evidence that current life satisfaction nor political orientation was affected.

Buntain et al. (2016) studied the effect of the Boston Marathon Bombing on 15 April 2013 using a word-emotion association lexicon in the April 2013 Twitter feed. After analysing approximately 134 million tweets, they found a significant increase in the use of the word 'fear' on 19 April, the last day of a four-day manhunt for the two brothers from a Chechen family background, which suggests a heightened sense of fear.

Natural disaster

To analyse the effects of a combined disaster, a tsunami and nuclear accident at Fukushima in Japan, on people's subjective well-being, Rehdanz et al. (2015) used a quasi-experimental difference-indifferences approach. Using panel data for approximately 6000 individuals interviewed before and after the shocks, they found that proximity and spatial distribution played key roles. Moreover, they found that people who lived the closest to nuclear power stations experienced a drop in happiness. As the distance to the nuclear plant increased, the effect decreased. Additionally, they found no change in subjective well-being (measured as happiness with life) regardless of proximity. The authors equated the drop in happiness to 72 per cent of annual income and reached as high as 240 per cent for those closest to the Fukushima Dai-ichi power plant.

Economic shock

In a bid to better understand whether positive expectations can engender positive emotions and better social relations, which in turn provide support during times of difficulty, Arampatzi et al. (2020) studied the macro-level shock of the Greek bailout referendum. Additionally, the authors assessed the subjective well-being impact of the stress and anxiety generated by this shock. Using survey data collected from university students between May 2015–July 2015 (before, during and after the

referendum), they found subjective well-being levels were impacted significantly. Furthermore, they found that positive expectations have 'resilience-generating' capacities for subjective well-being. Individuals with more positive expectations before the referendum announcement experienced smaller decreases in subjective well-being. They adapted quicker to this negative macro-level shock than individuals who held negative expectations regarding the future—leading the authors to conclude that people with a more positive outlook on life are particularly more resilient in times of negative shocks.

COVID-19 and lockdown

Previous studies that focused on emotion analysis and COVID-19 include the work done by Metzler et al. (2022a), where the team investigated anxiety, sadness, anger and positive sentiment expressed during the first five weeks after the outbreak of the pandemic in 2020 for 18 countries. They found a strong and immediate increase in tweets containing anxiety but noted that it also decreased again before the end of the investigation period. In contrast, sadness and anger rose more gradually than anxiety but remained close to their highest level until the end of the investigation period. Interestingly, they also found that positive emotion did not significantly differ from its baseline in 2019 and remained relatively stable. Greyling and Rossouw (2022), using sentiment and emotion analyses, investigated the trend in positive attitudes towards vaccines from 1 February 2021 to 31 July 2021 across ten countries. Additionally, the researchers investigated those variables related to having a positive attitude, as these factors could potentially increase the uptake of vaccines. Jun et al. (2022) extended research by Greyling and Rossouw (2022) to the global level. They investigated social media discourse on the COVID-19 vaccine and its association with the vaccination rates of 192 countries worldwide. Sentiment and emotions of tweets and covariates (COVID-19 morbidity and mortality rates, GDP, population size and density, literacy rate, democracy index, institutional quality, human development index) were tested as predictors of vaccination rates in countries.

Lyu et al. (2021) used English vaccine-related tweets collected between March 2020 and January 2021 and categorised the tweets into 16 topics grouped into five overarching themes. Their emotion analysis found trust was the most prevalent emotion, followed by anticipation and fear. They found that fear was the most prevalent emotion before Moderna, one of the first to test their COVID-19 vaccine on humans in April 2020. Xue et al. (2021) analysed English vaccine-related tweets using a list of 20 hashtags from 7 March to 21 April. 2020. Their main aim was to identify popular unigrams (one word) and bigrams (two words), salient topics and themes, and sentiments in the collected tweets. Their emotion analysis showed that anticipation followed by fear, trust, and anger were prevalent across 12 of the 13 topics.

Chopra et al. (2021) collected 1.8 million English vaccine-related tweets across India, the United States, Great Britain, Brazil, and Australia from June 2020 to April 2021. They aimed to create ten lexical categories, split between two classes, namely emotions (6 categories) and influencing factors (4 categories) and study the temporal evolution of these categories across time. The lexical emotions category includes hesitation, sorrow, faith, contentment, anticipation and rage, while their influencing factors are misinformation, vaccine rollout, inequities, and health effects. The authors used the word-count approach to measure each category's strength in a tweet. They calculated the strength of the categories monthly and split their period under investigation into two; Before and After the date when each country's government approved the first COVID-19 vaccine. Kydros et al. (2021), using Greek tweets extracted between March and June 2020, found elevated levels of negative emotions such as fear and anger (at the end of their research period), whereas positive sentiment (happiness) decreased.

Codagnone et al. (2020) used a multi-country survey conducted in Italy, Spain and the United Kingdom to predict the level of stress, anxiety and depression associated with being economically vulnerable and having been affected by a negative economic shock due to COVID-19 and the subsequent lockdowns. They found that 42.8 per cent of the populations in the three countries were at high risk of stress, anxiety, and depression due to their exposure to a negative economic shock.

Cheng et al. (2020) used Singapore Life Panel (SLP) survey data which collected data on life satisfaction pre- and during COVID-19. Using a difference-in-difference model, they found a large decline in overall life satisfaction during the COVID-19 outbreak in Singapore. This decline coincided with the introduction of a nationwide lockdown in April and May 2020. Even after the lockdown was lifted in early June 2020, overall life satisfaction recovered to some extent but still remained lower than its pre-COVID-19 level.

War

Regarding the Ukrainian war, relatively few studies have used sentiment analysis, and the authors are unaware of studies focused specifically on analysing Plutchik's (1980) wheel of negative emotions. Sentiment analysis studies such as Blankenship et al. (2022) investigated responses posted on Twitter by users in Nevada from 14 February to 9 March and identified the most circulated narratives and disinformation topics. They found that most tweets supported Ukraine. The authors also analysed emojis and found that 36 per cent of the emojis correlated to happy emotions while 64 per cent corresponded to emotions of anger, fear, sadness, disgust, surprise, and neutral – most notably, fear. Chen et al. (2022) used 150 000 Chinese Weibo texts from 19 February to 5 March to study the opinion dynamics of the war in virtual reality. Ramírez and Vargas (2022) used a Twitter dataset from Kaggle to conduct sentiment analysis and found a high percentage of the tweets related to the war were negative. Additionally, they concluded that past tweets related to the war could continue to predict sentiment scores for new tweets. Shevtsov et al. (2022) used a dataset which started on 24 February and is available on GitHub to conduct sentiment analysis. They found a higher positive sentiment for Ukraine and a higher negative sentiment for Russia.

3 Data and methodology

3.1 Constructing time-series data using emotion analysis

To construct our time series, we use data from the *Gross National Happiness.today* (GNH) project, launched in April 2019 (Greyling et al. 2019). This project measures the evaluative mood of a country's citizens over time. As a measure of mood, the GNH captures the more volatile part of well-being, commonly referred to as happiness (Diener et al. 2009) and has been well-established and validated in previous studies (please refer to Greyling and Rossouw (2022), Morrison et al. (2022), Sarracino et al. (2022 a and b), Rossouw et al. (2021a and b), Greyling et al. (2021a and b)).

To derive our time series data that captures collective emotion, we construct variables using the Twitter API to extract and harvest original tweets within a geographic bounding box corresponding with the country in question. In our analysis, we extracted two sets of tweets based on keywords, one related to the first COVID-19 lockdown (2020) and the other related to the Ukrainian war (2022). Additionally, we extracted all tweets corresponding to the same period as those for the keywords but in the counterfactual year 2021, reflecting an assumed "normal" level of emotions. The tweets used in the analyses amounted to 905 414 260. Please see Figure 1, which shows a word cloud constructed of the extracted tweets for the counterfactual year 2021. As can be seen, no significant topics are dominating the conversation, such as COVID-19.



Fig 1. Word cloud constructed for the counterfactual year 2021 on all tweets.

To extract our two sets of tweets related to our macro-level shocks, we use the following keywords:

COVID-19 and the first lockdown include: *COVID*, *COVID-19*, *Lockdown*, *Stringency measures*, *Stay-at-home*, *SARS-CoV-2*, *Corona*, *Corona Virus*, *SARS*, *Travel ban*, *School closure near to COVID/Corona*, *Workplace closure near to COVID/Corona*, *Covid cases*, *Covid deaths*, *Hospital*, *ICU*, *Covid tests*, *Delta variant* (*B.1.617.2*), *Mortality* (wild cards?).

The Ukrainian war includes: *Ukrai*, War, Putin/Puten, Volodymyr / Vladimir OR Zelensky/Selenski, NATO, LPR, DPR

The first step in our analysis is to determine the tweets' language (we detected 64 different languages), and all non-English tweets were translated to English using Microsoft Azure and Google Translate. After the translation process, we performed necessary pre-processing to clean up the punctuation and remove @, #, the letters "https", control characters, digits, and emojis. We removed emojis because the lexicon used to determine emotions applies to words and is limited to only ASCII characters. We then use Natural Language Programming (the NRC lexicon (Turney & Mohammad 2010)) to extract eight emotions: anger, fear, anticipation, trust, surprise, sadness, joy and disgust (the so-called Plutchik (1980) wheel of emotions). From Turney and Mohammad (2010), we know that these eight emotions can be naturally paired into opposites – joy–sadness, anger–fear, trust–disgust, and anticipation–surprise.

Furthermore, anger, disgust, fear and sadness are negative emotions, and joy is positive, whereas surprise, anticipation and trust can be either negative or positive. Therefore, we only incorporate those emotions with a clear definition of negative or positive.

To test the robustness of coding the emotions of the translated tweets, we use lexicons in the original language, if available, and repeat the process. We compare the coded emotions of the translated and original text and find the results strongly correlated.

To ensure that the extracted tweets discuss the first COVID-19 lockdowns and the Ukrainian war, we first constructed word clouds per macro-level shock. For example, Figure 2 illustrates the word cloud generated regarding COVID-19 and Figure 3 regarding the Ukrainian war. After generating the word clouds, we returned to the original tweets and confirmed the context of the words with high frequencies.



Fig 2. Word cloud based on COVID-19-related tweets, all countries.

We determined that these COVID-19 lockdown and Ukrainian war-related tweets were relevant and related to the lockdown or the invasion of Ukraine and contained little noise (tweets irrelevant to the topics). For example, tweets that generated the word cloud in Figure 2 included:

" Even my friends gigs are getting cancelled! Honestly so fricken sad Coronavirus is taking the world by storm. Just hope everyone affected is okay I hope our world is okay" - Australia

"Prvention the spread of COVID19: confinement the home and always respect the barriers" - France

"Now that many people are being asked to do homeworking with coronavirus, just a reminder to BeKind, positive in." – United Kingdom

"My only fear is people who test positive for covid-19; intentionally want to spread it (like licking public bars, spitting on elevator buttons, etc) so they dont die alone" – South Africa



Fig 3. Word cloud based on the Ukrainian war-related tweets, all countries.

Tweets that generated the word cloud in Figure 3 included, for example:

"You can learn much about Putins personality and management style, as well as others reactions to him (this guy is shaking in his boots), by watching this brief clip. Speak directly!': Putin has tense exchange with his chief spy" – New Zealand

" Painful to see, kids in Ukraine who get lessons to do when the Russians attack nojournaal" – The Netherlands

"Adolf Putin is in total confusion. The problem becomes enormous when sick people have the command of nations " – Italy

" War is back." - Spain

Please note that the above tweets were taken directly from Twitter and do not represent the authors' views or their institutions.

Working with Big Data presents benefits such as an abundance of data, heterogeneous users, accounting for the moods of a vast blend of users, providing timely and internationally comparable data, zero non-response bias and the ability to "listen" and observe what people deem important in their lives. There are also limitations in working with Big Data in the form of tweets. Although representing a significant proportion of the population, it is not representative. Establishing convergent validity is also difficult as there are very few validated data sources to compare. In saying this, Garcia et al. (2021) compared weekly YouGov survey data to 1.54 billion tweets originating in the UK (June 2019 – June 2021) and found positive and consistent correlations between the survey and Twitter data. The authors argue that the emotions detected from Twitter data could possibly reflect the emotions of others around those who tweet. In this way, Garcia et al. (2021) argue social media users could serve as a way of 'social sensing' a larger population that could more closely match the composition of society at large. Additionally, working with Big Data extracted from tweets could include a drift in users, limiting how we apply this data, and the data is algorithm confounded (Metzler et al. 2022b).

3.2 The sample (countries and time periods)

We use the period 25 February -23 May 2020 (COVID-19 lockdown) and 1 February -30 April 2022 (Ukrainian war), thus 41 days, to indicate the changes in emotions over time. However, for a more indepth analysis, we focus on 10 days before and after the shock compared to a counterfactual for the same period in 2021.

The following ten countries are included in our analyses; three Southern hemisphere countries; Australia, New Zealand and South Africa and seven Northern hemisphere countries; Belgium, Germany, Great Britain, France, Italy, the Netherlands, and Spain. Primarily the choice of countries is determined by data availability. However, future studies can extend the dataset to include more countries. The current selection of countries from both hemispheres provides unique insights into the effect of two macro-level shocks (macro-level to the countries under investigation) on the evolution of emotions. Table 1 summarises key statistics for each country used in the current study.

Country	Total population	Date of Date of first		Date of Ukraine
		announcement	lockdown (2020)	invasion (2022)
Australia	25.5 million	15 March.	17 March*	24 February.
Belgium	11.6 million	17 March	18 March	24 February
France	66.99 million	16 March	17 March	24 February
Germany	83.02 million	22 March	22 March	24 February
Great Britain	66.65 million	23 March.	23 March.	24 February.
Italy	60.36 million	8 March	9 March	24 February
Netherlands	17.28 million	14 March	15 March [¶]	24 February
New Zealand	5.12 million	23 March	26 March	24 February
South Africa	57.7 million	23 March.	27 March.	24 February.
Spain	46.94 million	13 March	14 March	24 February

Table 1. Key summary facts of countries in this study.

* Australia never officially went into a complete lockdown like that in other countries. We used the day when the closure of international borders was announced as a proxy for "lockdown."

[¶]The Netherlands started a so-called 'intelligent lockdown' on this date.

Source: Greyling et al. (2019), Hale et al. (2020).

In the panel under investigation, the shock of the first COVID-19 lockdown directly impacted the countries through, for example, limiting people's movement (Fang et al. 2020). In contrast, the Ukrainian war indirectly impacted these countries, as the war did not take place in these countries, though the negative effects affected all countries worldwide. These shocks indirectly created upheavals in emotions and directly through increased instability in resources, food and other markets, leading to weaker economic growth, higher unemployment, higher inflation rates and increased poverty.

3.3 Methodology

3.3.1 Methodology related to the effect on and stages of collective emotions

As negative emotions have grave impacts on society and have increased over the last few years (Gallup 2022), we focus our analyses on anger, disgust, fear, and sadness; however, we also refer to joy representing a positive emotion.

To answer our research questions to analyse the anticipation and reaction of collective emotions to our two macro-level shocks, we consider data in 2020 centred around the first lockdown date of the different countries and data in 2022 centred around the invasion. As a counterfactual period, we use the year

2021, assumed to be the 'new normal' in which people have accepted that COVID-19 is a reality and part of their daily lives.

Using counterfactual data, we can assess the effect of shocks compared to the assumed normal time period (a baseline), thus ensuring that other factors, such as seasonal changes, do not drive our findings. In addition, the counterfactuals also control for the time-invariant heterogeneity of countries. We assume that the counterfactual dataset is stable³ and that the daily collective emotion score would be similar to the counterfactual without the macro-level shocks.

As we compare emotions across different years, we standardise the emotion time series data per year. The equation to derive the collective emotion time series data showing the difference between the shock and the counterfactual data is as follows:

$$Y_{dif} = Y_{i\pm 1} - Y_i \tag{1}$$

The collective emotion of interest in the calculations is denoted as Y. The difference in the collective emotion data in the year of the shock and the counterfactual is Y_{dif} (the outcome variable). The counterfactual year 2021 is denoted with *i*; thus, the counterfactual is denoted as Y_i , and the years of the shocks (2020 for the lockdown and 2022 for the invasion) are denoted as *i*-1 and *i*+1, respectively; thus the $Y_{i\pm 1}$ term in equation 1.

If the outcome is positive, the emotion in the year of the shock is greater than in the counterfactual year and vice versa. If the outcome is equal to zero (the norm), we assume that the emotions in the year of the shock and the counterfactual are similar.

Therefore, using the time series data explained by equation (1), we construct tables and graphs to visually analyse the effects and the evolution of emotions centred around the shocks. Additionally, we use the time series data to calculate and compare the effects of the shocks on the different collective emotions. Furthermore, we will split the sample into the Northern and Southern hemispheres and repeat the analysis to determine whether similar results are found. Lastly, to test the robustness of the stages of negative emotions, we will repeat our analysis focusing on the second lockdown experienced in New Zealand in August 2020⁴.

³ We make this assumption since after the macro-level shocks, even if COVID-19 numbers increased the collective emotions adapted to the norm; thus, the number of COVID-19 cases (deaths) itself is not a shock.

⁴ See Appendix C for a robustness test taking the difference between the emotions during New Zealand's second lockdown in August 2020 compared to a counterfactual of 2021. The results are similar to those reported in sections 4.1 and 4.2.

3.3.2 Topic modelling and narrative analysis

After determining the effect on and stages of collective emotions, we perform topic modelling on the extracted tweets and conduct narrative analysis to better understand these emotional responses.

Topic modelling can help organise a large collection of unstructured text into different themes. Topic modelling is often referred to as probabilistic clustering. It is more robust and usually provides more realistic results than hard clustering (e.g., k-mean clustering) (Blum et al. 2020). A typical clustering algorithm assumes a distance measure between topics. It assigns one topic to each document, whereas topic modelling assigns a document to a collection of topics with different weights or probabilities without any assumption of the distance measured between topics. Many topic models are available, of which we prefer the most widely used Latent Dirichlet Allocation (LDA) model (Blum et al. 2020), developed by Blei et al. (2003).

4. Results on collective emotions

In this section, we report the results of the research question defined in section 1. We start by visually inspecting the graphs showing the relationships in the collective emotions data to determine whether emotions reacted to the shocks compared to the counterfactual data (see equation 1). After establishing that the collective emotions did react to the shocks, we analyse the individual, collective negative emotions and joy before and after the macro-level shocks to determine any patterns or stages of interest. Next, we extend our investigation and divide our sample between the Northern and Southern hemispheres to determine if the evolution of emotions differs between these two regions and whether it reflects the stages of emotions found in the whole sample. Lastly, we report on our topic modelling and narrative analysis of the tweets to understand the observed changes.

Throughout the section, we report the results for the lockdown shock first, followed by the invasion shock.

4.1 The reaction of collective emotions to macro-level shocks.

Figure 4 (a) and (b) show the standardised daily emotion curves minus their standardised counterfactuals (smoothed using a three-day⁵ moving average) pre- and post-lockdown in 2020 and the invasion of Ukraine in 2022. In this section, we consider the emotions for a 41-day period, 20 days before and after the shocks, as well as the day of the shock. We use a day counter to number the days on the X-axis, with 0 the day of the shock. Thus, the day countries went into lockdown (these dates vary – see Table 1) and the day of the invasion (24 February 2022). On the Y-axis, the 0 line indicates the norm, a time when the daily counterfactual observation is equal to the observations in the year of the shock. Any deviation of the emotions above or below the normal line (y=0) is of interest in our analysis.

⁵ We use a three-day moving average, as the time-period we analyse is short and we would like to capture the volatility in the emotions.

Especially any negative emotions above the norm, as these are the collective emotions that can lead to actions. We also report on the opposing emotion joy, if below the norm. Additionally, our interest lies with when the emotions react to the shocks, thus the turning points of the emotions.







Fig 4 (a) and (b). Emotions (difference between shock year and counterfactual) before and after lockdown (top) and before and after the invasion (bottom).

From Figure 4 (a) and (b), we notice both shocks led to erratic movements in peoples' emotions, with increased deviations from the norm in anticipation and reaction to the shocks.

Furthermore, we notice the negative emotions show turning points (troughs) close to the days of the shocks. With lockdown, the turning points (troughs) are on the day of the shock, with sadness following with a one-day lag. Regarding the invasion, we notice these turning points for the negative emotions starting two days before the invasion, and in this instance, fear lags by one day. Considering joy, we notice similar changes with turning points closely centred on the shocks (see Appendix A).

Observing the patterns in collective emotions pre- and post-shocks differing from the norm and based on the negative emotions reaching their troughs in close proximity to the actual shocks, we can confidently assume the collective negative emotions react to the shocks.

Therefore, in the next section, we empirically investigate the reactions and the series of changes in collective emotions.

4.2 The effect on and stages of collective emotions pre-and post-macro-level shocks

To establish the effect of the shocks on collective emotions and whether there is a specific pattern of stages the emotions pass through, we consider a period of 21 days (ten days before and after the shock); as we know from the literature, emotions tend to change rapidly (Metzler et al. 2022 a and b).

We start our investigation by making use of Table 2. The last row of the table indicates the daily counter, ten days before and after the shock. The rest of the table is vertically separated into section (a) – showing the stages of the emotions during the lockdown shock, and section (b) – invasion – showing the stages of the emotions during the invasion shock. This summary table gives a visual image of the two shocks' evolution and changes in emotions. We read and interpret Table 2 as follows: anger (in red) was above the norm after the lockdown from day 3 to the end of the period under investigation, with a maximum value of 0.74 on day 10. Similarly, joy (in yellow) was below the norm before lockdown from day -10 to -3, with a minimum value of -0.99 on day -10.

	Anger											K										0.74
Lockdown	Disgust				0.58							НОС										
	Fear				0.25							ELS										0.48
	Sadness											LEV										0.35
	Joy	-0.99										,										
	Anger												0.58									
	Disgust											RO					0.05					
Invasion	Fear	0.69										MAC										0.38
	Sadness											0.22										0.11
	Jov	-0.82											-0.17									
Da	y	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10

Table 2: Negative emotions above (positive emotion, joy, below) the norm per day across the two shocks; lockdown and the invasion.

Source: Greyling et al. (2019)

Next, we turn to Figure 5, which graphically illustrates the relationships between the collective emotions during the lockdown period.



Source: Greyling et al. (2019)

Fig 5. Stages of negative emotions above the norm per day across the macro-level lockdown shock.

To determine the effect of the shocks on collective emotions, we calculate the difference between the value of the emotions at their turning point (trough) and their *peak after the shock*. We can compare these differences directly because the emotion time series are standardised (refer to section 3.3.1 and equation 1).

Anger changed with 1.87 units, sadness 1.76 units, fear 1.38 units and disgust with 0.42 units (from the trough to the highest point after the shock). Except for disgust, all the negative emotions peaked above the norm. Additionally, considering the standard deviation of the emotions, which can be interpreted as the volatility of the emotions, anger has the highest standard deviation of 0.56, sadness (0.51), fear (0.38) and disgust (0.30). Based on these results, the macro-level shock affected emotions, *with anger showing the greatest reaction, followed by sadness, fear and disgust.*

Considering the evolution of the emotions, we note that before the lockdown shock, disgust (dotted green line) at a maximum of 0.58 (7 days before the shock) and fear (black line) at a maximum of 0.25 (7 days before the shock) were above the norm up to day -4 (see reference line a), whereafter they decreased to below the norm. All negative emotions are below the norm until the day of the shock. On

the day of the shock, the negative emotions reached a turning point and started to increase (sadness shows a lag of one day). The first emotion to appear above the norm after the shock is anger (red line) (see reference line b) on day 3, sadness (blue line) (see reference line c) follows on day 6 and fear (black line, see reference line d) follows on day 7. We note that all the negative emotions are positively correlated, with fear and sadness having a correlation coefficient of more than r=0.90. Disgust correlations, although positively related to the other negative emotions, are not that strong.

During this period, joy follows an inverse pattern to negative emotions (see Figure 7 Appendix A). Joy reached a turning point on day -5 and moved to above the norm on day -3 before the lockdown and remained above the norm until day 8 after the lockdown when it moved sideways following the normal curve. Joy is significantly and negatively correlated with negative emotions. This confirms what we know about positive emotions in that they co-occur alongside negative emotions during stressful circumstances (Folkman & Moskowitz 2000).

We also consider the evolution of the collective emotions for the Northern and Southern hemispheres separately (see Figure 9 in Appendix B). Interestingly we notice a very similar pattern to the one observed for the whole sample. The difference is that in the South, negative emotions reached their turning point 2 days before the shock. We explain this by the Southern hemisphere countries anticipating what will come since several of their Northern counterparts went into lockdown first. Therefore, the negative collective emotions reacted in anticipation of the shock.

To summarise, following the evolution of collective emotions during the lockdown shock, we find that the negative emotions reached their tuning point on the day of the shock. After the shock, anger is the first emotion to move to levels above the norm (with a lag of three days), whereafter sadness and fear follow. Given these stages, a few questions come to mind. Why were fear and disgust above the norm before the shock, and why do we observe the negative emotions only appearing above the norm three days after the lockdown shock?

Although a macro-level shock, lockdowns were unique as they were regulations implemented to curb the spread of the virus. We assume that many people originally considered this a positive step since they feared contracting the virus; thus, the negative emotions decreased to below the norm. They also did not fully realise the negative effects of the lockdown and experienced the emotional turmoil brought on by the shock. Therefore, we notice the turning point on the day of the shock as opposed to before, with negative emotions moving above the norm only a few days after being in isolation. Next, we perform topic modelling to better understand the narrative underpinning the emotional response of fear and disgust before the lockdown and anger, sadness and fear after the lockdown. Table 3. Pre-lockdown topics based on keywords

TOPIC – COVID-19 lockdown	KEYWORDS – COVID-19 lockdown
NHS STAFF	Frontline; NHS; Priority; Staff; Test; Petition; Sign;
FRONTLINE NHS STAFF FOR COVID	NHS staff; Frontline NHS staff for COVID;
	TRAVEL; BAN; COUNTRIES; HIGH; RISK;
TRAVEL BAN HIGH RISK	TRAVEL BAN; HIGH RISK; HIGH RISK COUNTRIES
	Toilet; Paper; Buying; Panic;
TOILET PAPER	Toilet paper;
	Schools; Closed; Close; Restaurants; Closing; Wednesday; Easter; Open; April; Borders;
CLOSE SCHOOLS AND RESTAURANTS	Close schools; Schools closed; Schools will be closed; Schools are closed; Schools close; After Easter; Close combat Coronavirus; Amount of time amidst COVID; Close school colleges; Restaurants and clubs;
	Home; Stay;
STAY AT HOME	Stay at home; Stay home;

Source: Greyling et al. (2019)

From the topics identified in Table 3, the narrative analysis of the tweets suggests that fear was above the norm in Figure 5 because people feared for frontline medical staff not getting tested for COVID-19 and how that could impact incoming patients. There was a call for people to sign a petition to have medical staff tested and protected against COVID-19 since they could not isolate themselves under lockdown. Additionally, people feared that others from high-risk countries not under lockdown could enter their borders. Governments implementing travel bans made some people fearful of being separated from their families. Lastly, fear was expressed in terms of people potentially not adhering to lockdown regulations, such as staying home when sick and infecting others.

Additionally, the tweets' narrative analysis suggests that disgust was above the norm before the lockdown because people condemned others' selfish behaviour in panic buying toilet paper and other supplies. There was the feeling that the elderly and vulnerable would not have sufficient supplies to survive in lockdown if those with the means to did not stop hoarding necessities. Additionally, disgust was expressed about detestable behaviour where once again, the elderly succumbed to pushing and shoving when they tried to buy necessities for the upcoming lockdown.

When it comes to the period just before the imminent lockdown, days -4 to 0, when the announcements were made that countries would lockdown, the negative emotions decreased to below the norm (see section 4.1). Likely this is due to the expectations that the regulations will curb the spread of the virus; however, negative emotions start to increase on the day of the lockdown.

Next, we perform topic modelling to better understand the narrative of the public perceptions and concerns driving this emotional response of anger, fear and sadness after the lockdown.

TOPIC – COVID-19 lockdown	KEYWORDS – COVID-19 lockdown				
PEOPLE AND LOCK YOUR DOORS	March; Lockdown; Government; People; South; Police; God; Home;				
	Bible verse; Government arranged; People and lock your doors;				
	Stay; Home; After;				
STAY AT HOME	Stay at home; Stay home;				
	Virus; Corona; Pray; Hope; Pandemic; God; World;				
CORONA VIRUS	Good;				
	Corona virus;				
EMERGENCY MEDICAL	Emergency; Medical; Public; Quarantine; Health; Hospital; Time; Police; Pandemic;				
WORKING RISK	Working; Work; Risk; Sick; Hospital; IM People; After; Country;				

Table 4. Post-lockdown topics based on keywords

Source: Greyling et al. (2019)

From the topics identified in Table 4, the narrative analysis of the tweets suggests that the increase in anger to above the norm resulted from people not complying with implemented healthcare measures and displaying unacceptable behaviour in unprecedented times. Additionally, there was a sense that governments did not fully disclose all relevant information related to the COVID-19 virus, which influenced people's trust in what governments were telling them. Furthermore, the anger was driven by perceived political games being played during the pandemic and a lack of protection for healthcare and essential workers. Moreover, anger was also driven by people feeling that governments were controlling people's actions by unnecessary fear-mongering and not reporting the underlying conditions of people who succumbed to the virus. Lastly, people in financial distress seemed angry about not receiving government aid fast enough.

People were sad because health systems were overwhelmed, and people died without loved ones from what was seen as a preventable and treatable disease. Moreover, sadness increased because people were denied access to services and healthcare unrelated to the pandemic. Furthermore, people expressed sadness and fear about the number of lives and families destroyed by the lockdown through anxiety and panic attacks and the sudden loss of income, arguing that it would increase divorce and suicide rates. Fear was also expressed in what many people saw as imminent recessions in countries and how the number of new unemployed would be able to survive. Lastly, there was fear regarding governments using armed forces to ensure people followed their directives and how that would impact society.

Considering the narrative, it seems that the announcement of lockdown likely addressed the negative emotions caused by COVID-19 itself – but lockdown, although a method to stop the spread of the virus

was a shock in itself – lockdowns were at different stringencies – and included a combination of school closures, workplace closures, cancelling of public events, restrictions on gatherings, stay at home requirements, restrictions on internal movement, restrictions on international travel and restrictions on public information campaigns. With people fully realising the implications of the lockdown, it led to the observed stages of collective emotions of anger, sadness and fear increasing above the norm.



Source: Greyling et al. (2019)

Fig 6. Stages of negative emotions above the norm per day across the macro-level invasion shock. Turning to the second macro-level shock we analyse, namely, the invasion of Ukraine, we consider Table 2 and Figure 6.

Once again, we measure the effect of the invasion by each emotion's difference between the value at its turning point and its peaks after the shock. The patterns observed in Figure 6 are the same as we found for the lockdown in Figure 5. The only difference is that the turning point during the invasion already happened approximately three days before the invasion. Anger changed with 1.24 units, fear 1.14 units, sadness 0.90 units, and disgust, though only moving to above the norm fleetingly, with 0.07 units. Anger has the highest standard deviation of 0.4, followed by fear and sadness with 0.34 and 0.3, respectively. Disgust has the lowest volatility of 0.28. Based on these results, the macro-level shock invasion is related to changes in collective emotions, with anger showing the greatest reaction, followed by fear, sadness, and disgust after the shock.

We note that before the invasion shock, fear (black line) at a maximum of 0.69 (10 days before the invasion) was above the norm up to day -4 (see reference line a), whereafter it decreased to below the norm. All negative emotions are then below the norm. Interestingly, the negative emotions reached a turning point (trough) and increased (fear shows a lag of one day) three days before the shock itself. It would seem there was already some expectation that the invasion would become a reality, and emotions reacted to this expectation. One day before the invasion, anger, the first emotion to react, moved above the norm (red line) (see reference line b), followed by sadness (blue line) (see reference line c). On the day of the invasion, fear was at the norm (black line) (see reference line d).

After the invasion, anger remains above the norm and fleeting drops below the norm on day 8 (maximum on day 1 with 0.58) but moves back by day 9. Sadness and fear (on day 9) increased and peaked on day 10 at 0.11 and 0.38, respectively. Sadness and fear seem to follow the initial anger in response to the invasion. Interesting that the evolution and pattern of change in anger are very similar to that of sadness and fear. As with the lockdown, we find all the negative emotions are positively and significantly correlated. Fear and sadness once again show a very strong correlation of r=0.85, whereas disgust shows a much weaker correlation with the other negative emotions.

During this period, joy (Figure 8 Appendix A) was below the norm for days -10 and -9 (with a maximum of -0.82 on day -10). It recovered by day -8 but fell below the norm on day -6 and remained below until day 5 after the invasion. Interestingly, joy is not significantly correlated with negative emotions, unlike the lockdown shock. Joy seems to evolve independently from negative emotions.

Considering the Northern and Southern hemispheres (see Appendix B), we see that the turning point in the negative emotions mimics that of the total sample. The Northern hemisphere's figure generally mirrors that of the total sample. In terms of the Southern hemisphere, we note that it shows higher levels of fear in anticipation of the invasion of Ukraine. Anger in the Northern hemisphere towards the invasion was much stronger than in the South, most likely because of geographical proximity and the threat posed. Fear and sadness, while above the norm on the day of the shock in the Northern hemisphere, steadily decreased until below the norm by days 12 and 13, respectively. For the Southern hemisphere, we note that both emotions started below the norm on the day of the shock and, although increasing, stayed below the norm for the most part. Sadness and fear across both hemispheres seem to follow the initial anger in response to the invasion. The evolution and patterns of change after the shock are similar, with anger reacting first, followed by sadness and fear. However, in the South, the intensity of the negative emotions is not as strong regarding the invasion shock.

To summarise, following the evolution of collective emotions with the invasion, across the full sample and the Northern and Southern hemispheres, we note that fear is the strongest emotion before the shock and anger the strongest emotion after the shock. The turning point of the negative emotions in the full sample and the sub-samples are before the shock, which is different from the lockdown shock implying the shock was anticipated even before the invasion. After the turning point, we notice the same pattern or evolution of collective emotions, with anger leading, closely followed by sadness and fear.

The topics identified in Table 5 and our narrative analysis of the tweets suggest that fear was from Putin using Eastern Ukraine to bolster his despotic rule. Additionally, there was fear of the possibility that Putin was set to recognise Ukraine's rebel regions and how that would further threaten the sovereignty of Ukraine. Putin ordering 'peacekeeping operations' in parts of Eastern Ukraine was met by underlying fear in terms of what he really meant to do in this part of Ukraine. Furthermore, people were fearful about Putin sending in his Russian troops and the potential devastation they would wreak on Ukrainians.

TOPIC - Invasion	KEYWORDS - Invasion					
	Regions; Breakaway; Independence; Separatist; Recognises; Recognise; Eastern; Republics; Recognition; Donetsk; Orders; Donbass; Putin; Kremlin;					
BREAKAWAY REGIONS	Breakaway regions; Separatists regions; Putin recognises; Regions of Ukraine; Eastern Ukraine; Vladimir Putin; Breakaway regions of Ukraine; Putin recognises the independence; Donetsk and Lugansk; Regions in Eastern Ukraine; Regions in Ukraine; Separatist regions of Ukraine; Ukraine separatist;					
RUSSIAN TROOPS	Russian; Troops; Ukrainian; Orders; Border; Forces; Soldier Pro; Peace;					
PUTIN ORDERS	Russian troops; Putin orders; Putin orders Russian; Russian forces; Ukrainian border;					
RUSSIAN OLICARCHS	Oligarchs; Banks; Russian; Sanction; Sanctions; London;					
BANKS	Russian oligarchs; Russian banks; Russia must be shitting; Russian oligarchs sanctioned.					
	Council; Security; Meeting;					
SECURITY COUNCIL	Security council; National security;					
INTEDNATIONAL LAW	International; Law;					
INTERNATIONAL LAW	International law; Violation of international law;					

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Table 4	`	Pre-1	nvasion	tonics	hased	on	keywords
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Source: Greyling et al. (2019)

From the topics identified for the invasion in Table 5, the narrative of the tweets suggests that the increase in anger we saw in Figure 6 resulted from people not agreeing with the imminent invasion of Ukraine. Anger was expressed for what the invasion meant for the Russian people – increased poverty and fear. Additionally, people were angry about the potential that Ukraine's regions would be split and President Putin would start a campaign to occupy all the previous Russian-dominated Soviet Union countries that broke away from Russia's command. Furthermore, anger was directed at Russia for not abiding by international law and governments seemingly not doing enough to stop the invasion –

sanctions placed on 'already sanctioned individuals'. Naturally, anger was expressed in terms of people not recognising that this could turn into World War III and how we have not learned from past wars and allowing history to repeat itself.

After the invasion, anger, as understood from the topics in Table 6 and the narrative analysis, was expressed by people who did not agree with the invasion of Ukraine. Being called a fascist, Putin received a lot of anger for violating the sovereignty of Ukraine. Lastly, anger was expressed in terms of what this meant for the Russian people, and there was a sense that these unwilling participants in Putin's war would experience an increase in poverty and live in fear.

TOPIC - Invasion	KEYWORDS - Invasion					
	Ukraine; Russian; Invasion; Russia; Forces; Armed; Ukrainian;					
INVASION OF LIZDAINE	Government; Fascist; Free; News;					
INVASION OF UKKAINE DUSSIAN						
KUSSIAN	Invasion of Ukraine; Russian invasion; Russian invasion of Ukraine;					
	Free Ukraine; Free Ukraine from fascist; Ukraine invasion;					
	Letter; Open; Signing; Viral; World; Signed; Sign; People;					
OPEN LETTER	Open letter; Open letter against the war; World are signing; World					
	sign; Letter open against the war; World are signing this world;					
	World have already signed; World they are signing; Million people;					
	Deny; Boris; Johnson; Leaders; Europe;					
BORIS JOHNSON						
LEADERS IN EUROPE TO DENY	Boris Johnson; Leaders in Europe to deny; Putin and Boris Johnson					
	Cheap for comrade Boris Johnson;					
ADD VOUD VOICE	Voice; Add; Stand;					
STAND WITH THE PEOPI						
STAND WITH THE LEOIL	Add your voice; Stand with the people; Add your voice in solid;					
	Sweden; Finland; Join; NATO;					
FINLAND AND SWEDEN	Finland and Sweden; Sweden and Finland; Join NATO; Enter					
	NATO; Joining NATO; Part of Otan; Putin has threatened the					
	military; Threatens Sweden and Finland; NATO immediately;					

Table 6.	Post-invasion	topics	based	on	keywords
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Source: Greyling et al. (2019)

After the invasion, sadness and fear, as understood from the topics identified in Table 6 and the narrative of the tweets, resulted from people's reactions to the invasion of Ukraine. Fear was expressed regarding the world abandoning the Ukrainian people and the fate awaiting those Russian individuals who defied Putin. Sadness came in many forms. It related to the Ukrainian people and the horrors they would face, the lack of action taken by countries, world leaders and coalitions and how everyone loses in a war. Additionally, people were urged to sign an open letter against the war's brutalities and demand it be seized immediately.

We note that after the invasion, disgust was briefly above the norm on day 5 but then decreased below its norm by day 6, where it remained. From the topics identified for the invasion in Table 6, the narrative of the tweets suggests disgust resulted from people's reactions to the invasion of Ukraine. Disgust was

expressed towards leaders and countries choosing to remain neutral and not directly getting involved in the conflict.

In summary, when considering both shocks, we see that after the turning point, the emotion anger leads. In terms of the war shock, something unannounced, anger had already started increasing before the invasion in anticipation of what was to come. Anger stayed above the norm for seven days after the war shock before it started to dissipate. With the lockdown, people were warned that the measures would be put in place and the turning point was on the day of the lockdown. Anger only moved above the norm three days after the lockdown was implemented. Furthermore, we notice that anger, the emotion to react first, is also the first to dissipate. In contrast, the emotions of sadness and fear that follow anger do not react as strongly but seem to remain above the norm for a longer time. We note that for the lockdown period under investigation, all emotions seemed to linger longer after the shock compared to the invasion and the results found in previous literature (Metzler et al. 2022 a and b). A possible explanation could be that the lockdown itself lasted much longer. These observations also hold considering the Northern and Southern hemispheres as well as our robustness test concerning the second lockdown in New Zealand for August 2020 (Appendix C).

5 Conclusions

In this paper, our primary aim was to determine the effect of two different macro-level shocks on collective emotions and the various stages they subsequently follow. The macro-level shocks investigated in this paper were the lockdown, the epimax against the backdrop of the COVID-19 pandemic (a health shock) and the invasion of Ukraine (a war shock). Plutchik's (1980) negative emotions anger, disgust, fear and sadness, and the positive emotion joy were considered. After analysing our ten countries, we divided the sample into Northern and Southern hemispheres to determine if our findings for the full sample hold. Lastly, we conducted topic modelling and narrative analyses to understand what drove the observed changes in our negative emotions.

By doing the above, we contributed to the literature by being the first paper to determine the various stages collective emotions pass through in relation to macro-level shocks. We were also the first paper that compared collective emotions across different macro-level shocks in a cross-country analysis. Additionally, our topic modelling and narrative analysis conducted to understand people's perceptions and concerns that drove different emotional responses were novel in the collective emotion literature. Furthermore, whereas Metcalfe et al. (2011) produced one of the first studies to show the impact of a negative macro-level shock (terrorist attack) in one country on the well-being of another country, we were the first study to successfully show the impact of a negative macro-level shock (invasion) in one country on the collective emotions of another country.

Our results showed that the turning point of negative emotions centred around the date of the shock. However, we found that the turning point during the lockdown shock was on the day of the shock, whereas it was three days before the invasion for the war shock. Additionally, we found that anger was the emotion that showed the biggest effect after the turning point, followed by sadness and fear. We find that the stages of the negative emotions stayed the same across the shocks, with anger the first to move above the norm, followed by sadness and then fear. The observed patterns held across hemispheres and New Zealand's second lockdown of 2020.

Our results lead us to hypothesise that collective emotions follow specific and similar stages regardless of macro-level shock. Before macro-level shocks, fear dominates. In contrast, after macro-level shocks, anger reacts first, followed by sadness and fear. Positive emotions do not disappear during times of stress and shocks, and we argue this could mitigate the negative impact of shocks.

The insight we gained from determining which collective emotions respond counter to the norm and the stages they follow because of macro-level shocks at the national level are important since when groups pass a certain emotional threshold, action follows (Granovetter 1978). In cases in which negative collective emotion is prolonged, it leads not only to action but also to forming a negative identity, culture, or a toxic emotional climate. Therefore, our results show governments what to expect when the next shock happens. Policymakers can potentially mitigate the effect of an increase in negative emotions by nurturing positive emotions since these can foster trust and effective coping. Additionally, positive emotions build durable personal resources, the so-called *broaden-and-build theory* of positive emotions (Fredrickson 1998, 2000, 2001).

Apart from the limitations discussed in section 3.1, we highlight the following pertaining to our study. First, neither Ukraine nor its surrounding neighbours are included in our sample of countries. Our results could have been stronger with more significant and prolonged negative collective emotions if they were. Second, we acknowledge that social media measures of emotions are not perfect. However, this analysis demonstrates that they provide a useful complementary source of information about collective emotions. Metzler et al. (2022b) argue that the relationship between social media and survey emotion measures becomes most visible in times of large variations of emotions, such as during the COVID-19 outbreak. Third, our analyses could not be corrected for personality components likely to affect a person's susceptibility to participate in a collective emotion. Fourth, it should be noted that our analysis was purely observational, so we are careful not to make any causal claims. Lastly, we only considered two types of macro-level shocks. In the future, as additional macro-level shocks occur, we will investigate whether the current observed effects and stages of collective emotions continue to hold.

References

Abadi, D., Arnaldo, I., & Fischer, A. (2021). Anxious and Angry: Emotional Responses to the COVID-19 Threat. *Frontiers in Psychology*, *12*, 676116.

Armed Conflict Location & Event Data Project (ACLED). (2022). Fact Sheet: Global Demonstrations Against the Russian Invasion of Ukraine. Available from <u>https://reliefweb.int/report/russian-federation/fact-sheet-global-demonstrations-against-russian-invasion-ukraine</u>

Arampatzi, E., Burger, M., Stavropoulos, S., & Tay, L. (2020). The Role of Positive Expectations for Resilience to Adverse Events: Subjective Well-Being Before, During and After the Greek Bailout Referendum. *Journal of Happiness Studies*, 21, 965–995.

Blankenship, M., Saladino, C. J., Brown, W. E. (2022). Ukraine-Russia War: Nevada Twitter and Disinformation Trends. Elections & Governance Fact Sheet No. 3 1-4. Available at: https://digitalscholarship.unlv.edu/bmw_lincy_elect/3

Blei, D., Ng, A., & Jordan, M. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993-1022

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, 193, 104346.

Brickman, P., & Campbell, D. T. (1971). Hedonic relativism and planning the good society. In M. H. Appley (Ed.), Adaptation level theory: A symposium (pp. 287-302). New York: Academic Press.

Blum, A., Hopcroft, J., & Kannan, R. (2020). *Foundations of Data Science*. Cambridge, UK: Cambridge University Press.

Buntain, C., McGrath, E., Golbeck, J., & La Free, G. (2016). Comparing Social Media and Traditional Surveys Around the Boston Marathon Bombing. Published as part of the #Microposts2016 Workshop proceedings, available online as CEUR Vol-1691. Available at: <u>https://ceur-ws.org/Vol-1691/paper_02.pdf</u>

Chen, B., Wang, X., Zhang, W., Chen, T., Sun, C., Wang, Z., & Wang, F. (2022). Public Opinion Dynamics in Cyberspace on Russia–Ukraine War: A Case Analysis With Chinese Weibo. IEEE Transactions on Computational Social Systems, 9(3), June 2022.

Cheng, T. C., Kim, S., & Koh, K. (2020). The Impact of COVID-19 on Subjective Well-Being: Evidence from Singapore. *IZA Discussion Paper* No. 13702.

Chopra, H., Vashishtha, A., Pal, R., Ashima, A., Tyagi, A., & Sethi, T. (2021). Mining Trends of COVID-19 Vaccine Beliefs on Twitter with Lexical Embeddings. *arXiv*:2104.01131.

Clarke, A. E., Diener, E., Georgellis, Y., & Lucas, R. (2008). Lags and leads in life satisfaction: a test of the baseline hypothesis. *Economic Journal*, *118*, F222–F243.

Clarke, A. E., & Georgellis, Y. (2013). Back to Baseline in Britain: Adaptation in the British Household Panel Survey. *Economica*, *80*, 496–512.

Codagnone, C., Bogliacino, F., Gómez, C., Charris, R., Montealegre, F., Liva, G., et al. (2020) Assessing concerns for the economic consequence of the COVID-19 response and mental health problems associated with economic vulnerability and negative economic shock in Italy, Spain, and the United Kingdom. *PLoS ONE 15*(10),: e0240876.

Coupe, T. (2017). The impact of terrorism on expectations, trust and happiness – the case of the 13 November attacks in Paris, France. *Applied Economics Letters*, 24(15), 1084-1087.

de Rivera, J. (1992). Emotional climate: Social structure and emotional dynamics. In K. T. Strongman (Ed.), *International review of studies on emotion* (pp. 199–218). New York, NY: John Wiley.

Diener, E., Lucas, R. E., & Scollon, C.N. (2009). *Beyond the Hedonic Treadmill: Revising the Adaptation Theory of Well-Being*. In: Diener, E. (eds) The Science of Well-Being. Social Indicators Research Series, 37. Springer, Dordrecht.

Durkheim, É. (1912). The elementary forms of religious life. New York, NY: The Free Press.

Fang, H., Wang, L., & Yang, Y. (2020). Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China. *NBER Working Paper*, 26906.

Folkman, S., & Moskowitz, J. T. (2000). Positive affect and the other side of coping. *American Psychologist*, 55, 647–654.

Fredrickson, B. L. (1998). What good are positive emotions? *Review of General Psychology*, 2, 300–319.

Fredrickson, B. L. (2000). Cultivating positive emotions to optimise health and well-being. *Prevention & Treatment, 3*(1), Article 1. Available from <u>https://doi.org/10.1037/1522-3736.3.1.31a</u> Accessed 0n 17 November 2022.

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist*, *56*(3), 218–226.

Fredrickson, B. L., Tugade, M. M., Waugh, C. E., & Larkin, G. R. (2003). What good are positive emotions in crises? A prospective study of resilience and emotions following the terrorist attacks on the United States on 11 September 2001. *Journal of Personality and Social Psychology*, 84(2), 365-76.

Frijters, P., Johnson, D., & Shields, M. A. (2011). Life satisfaction dynamics with quarterly life event data. *Scandinavian Journal of Economics*, *113*, 190–211.

Gallup. (2022). Global Emotions Report 2022. Available from <u>https://www.gallup.com/analytics/349280/gallup-global-emotions-report.aspx</u>

Garcia, D., Pellert, M., Lasser, J., & Metzler, H. (2021). Social media emotion macroscopes reflect emotional experiences in society at large. *ArXiv*:2107.13236.

Garcia, D., & Rimé, B. (2019). Collective Emotions and Social Resilience in the Digital Traces After a Terrorist Attack. *Psychological Science*, *30*(4), 617–628.

Goldenberg, A., Garcia, D., Halperin, E., & Gross, J. J. (2020). Collective emotions. *Current Directions in Psychological Science*, 29(2), 154–160.

Granovetter, M. S. (1978). Threshold models of collective behavior. *American Journal of Sociology*, *83*, 1420–1443.

Greyling, T., & Rossouw, S. (2022). Positive attitudes towards COVID-19 vaccines: A cross-country analysis. *PLOS ONE*, 17(3), e0264994.

Greyling, T., Rossouw, S., & Adhikari, T. (2021a). The good, the bad and the ugly of lockdowns during Covid-19. *PLOS ONE*, 16(1), e0245546.

Greyling, T., Rossouw, S., & Adhikari, T. (2021b). A tale of three countries: How did Covid-19 lockdown impact happiness? *South African Journal of Economics*, 89(1), 25-43.

Greyling, T., Rossouw, S., & Afstereo. (2019). *Gross National Happiness.today Index*. Available at <u>http://gnh.today</u>

Hale, T., Angrist, N., Cameron-Blake, E., Hallas, L, Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H., & Webster, S. (2020). *Oxford COVID-19 government response tracker*. Available from <u>https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker</u>

Institute for Economics & Peace. (2022). Global Peace Index 2022: Measuring Peace in a Complex World, Sydney, June 2022. Available from <u>http://visionofhumanity.org/resources</u> Accessed on 21 July 2022.

Jun, J., Zain, A., Chen, Y., & Kim, S.H. (2022). Adverse Mentions, Negative Sentiment, and Emotions in COVID-19 Vaccine Tweets and Their Association with Vaccination Uptake: Global Comparison of 192 Countries. *Vaccines*, 10(735). https://doi.org/10.3390/vaccines10050735

Kubick, N., Milanesi, E., Dobre, M., Łazarczyk, M., Wijas, B., Sacharczuk, M., & Mickael, M. (2021). Trends of Anger and Physical Aggression in Russian Women During COVID-19 Lockdown. *Frontiers in Global Women's Health*. <u>https://doi.org/10.3389/fgwh.2021.698151</u>

Kydros, D., Argyropoulou, M., & Vrana, V. A (2021). Content and Sentiment Analysis of Greek Tweets during the Pandemic. *Sustainability*, 13, 6150.

Le Bon, G. (1896). The crowd: A study of the popular mind. New York, NY: Viking.

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and Decision Making. *Annual Review of Psychology*, 66(1), 799-823.

Lewin, K. (1947). Group decision and social change. Readings in Social Psychology, 3, 197-211.

Lyu, J.C., Han, E. L., & Luli, G. K. (2021). COVID-19 Vaccine–Related Discussion on Twitter: Topic Modeling and Sentiment Analysis. *Journal of Medical Internet Research*, 23(6), e24435.

Metcalfe, R., Powdthavee, N., & Dolan, P. (2011). Destruction and Distress: Using a Quasi-Experiment to Show the Effects of the September 11 Attacks on Mental Well-Being in the United Kingdom. *The Economic Journal*, *121*(550), F81–F103.

Metzler, H., Rimé, B., Pellert, M., Niederkrotenthaler, T., Di Natale, A., & Garcia, D. (2022a). Collective emotions during the COVID-19 outbreak. *Emotion*. <u>https://doi.org/10.1037/emo0001111</u>

Metzler, H., Pellert, M., & Garcia, D. (2022b). Using Social Media Data to Capture Emotions Before and During COVID-19. In World Happiness Report 2022. New York: Sustainable Development Solutions Network.

Morrison, P. S., Rossouw, S., & Greyling, T. (2022). The impact of exogenous shocks on wellbeing. New Zealanders' reaction to Covid-19. *Applied Research in Quality of Life Studies*, 17, 1787–1812.

Plutchik, R. (1980). *A general psychoevolutionary theory of emotion*. In: Robert P, Henry K, editors. Theories of Emotion. Cambridge, MA: Academic Press, pp 3-33.

Ramírez, L. I. G. & Vargas, M. V. (2022). A sentiment analysis of the Ukraine-Russia conflict tweetsusingRecurrentNeuralNetworks.Availablefromhttps://www.researchgate.net/publication/361275253_A_sentiment_analysis_of_the_Ukraine-Russia conflict tweets using Recurrent Neural Networks

Rehdanz, K., Welsch, H., Narita, D., & Okubo, T. (2015). Well-being effects of a major natural disaster: The case of Fukushima. *Journal of Economic Behavior & Organization*, 116, 500-517.

Rossouw, S., Greyling, T., & Adhikari, T. (2021a). The implied volatility of happiness pre and peri-COVID-19: a Markov Switching Dynamic Regression Model. *PLOS ONE*, 16(12), e0259579. Rossouw, S., Greyling, T., & Adhikari, T. (2021b). Happiness-lost: Did Governments make the right decisions to combat Covid-19? *South African Journal of Economic and Management Sciences*, 24(1), a3795.

Rudolf, R., & Kang, S. J. (2011). *The baseline hypothesis revisited. Evidence from a neo-confucianist society*. University of Göttingen, mimeo.

Saad, L. (2001). Personal impact on Americans' lives: Women express much more fear of terrorism than do men. Gallup news service. Available from <u>https://news.gallup.com/poll/4900/personal-impact-americans-lives.aspx</u>. Accessed on 17 November 2022.

Sarracino, F., Greyling, T., O'Connor, K., Peroni, C., & Rossouw, S. (2022a). A year of pandemic: levels, changes and validity of wellbeing data from Twitter. Evidence from ten countries. *Forthcoming in PLOS ONE*.

Sarracino, F., Greyling, T., O'Connor, K., Peroni, C., & Rossouw, S. (2022b). Trust predicts compliance with COVID-19 containment policies: Evidence from ten countries using big data. *IZA Discussion Paper* No. 15171.

Shevtsov, A., Tzagkarakis, C., Antonakaki, D., Pratikakis, P., & Ioannidis, S. (2022). Twitter Dataset on the Russo-Ukrainian War. *arXiv*:2204.08530v1 [cs.SI] 7 April. 2022. Available from https://arxiv.org/pdf/2204.08530.pdf

Smith, L. E., Duffy, B., Moxham-Hall, V., Strang, L., Wessely, S., & Rubin, G. J. (2021). Anger and confrontation during the COVID-19 pandemic: a national cross-sectional survey in the UK. *Journal of the Royal Society of Medicine*, *114*(2), 77-90.

Taylor, C. (1975). Hegel. Cambridge, England: Cambridge University Press.

Theology of Joy & the Good Life Overview. (2018). Retrieved from https://faith.yale.edu/joy/about

Turney, P., & Mohammad, S. (2010). Emotions evoked by common words and phrases: using Mechanical Turk to create an emotion lexicon. 2010. In: Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. Presented at: NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text; Los Angeles, CA p. 26-34 URL: <u>https://www.aclweb.org/anthology/W10-0204</u>

Ward, G. (2020). Happiness and Voting: Evidence from Four Decades of Elections in Europe. *American Journal of Political Science*, 64(3), 504–518.

Xue, J., Chen, J., Hu, R., Chen, C., Zheng, C., Su, Y., & Zhu, T. (2021). Twitter Discussions and Emotions About the COVID-19 Pandemic: Machine Learning Approach. *Journal of Medical Internet Research*, 22(11), e20550.

Appendix A. Joy.



Source: Greyling et al. (2019)





Source: Greyling et al. (2019)

Fig 8. Stages of joy per day across the macro-level invasion shock.



Appendix B. Northern and Southern hemispheres.



Source: Greyling et al. (2019)

Fig 9. Stages of negative emotions above the norm per day across the macro-level lockdown shock split into the Northern (top) and Southern hemispheres (bottom).





Greyling et al. (2019)

Fig 10. Stages of negative emotions above the norm per day across the macro-level invasion shock split into the Northern (top) and Southern hemispheres (bottom).

Appendix C. Robustness test.



Source: Greyling et al. (2019)

Fig 11. The difference between the emotions during the second lockdown – August 2020 – compared to a counterfactual of 2021, New Zealand.