Journal of Data Science 0 (0), 1–20
??? 2022
DOI: 10.6339/22-JDS1066
Data Science in Action

The Impact of COVID-19 on Subjective Well-Being: Evidence from Twitter Data

Tiziana Carpi[1], Airo Hino[2], Stefano Maria Iacus[3,*], and Giuseppe Porro[4]

[1]*Department of Studies in Language Mediation and Intercultural Communication, University of Milan, Piazza Indro Montanelli 1, 20099 Milan, Italy*

[2]*School of Political Science and Economics, Waseda University, 1-6-1 Nishiwaseda Shinjuku-ku, Tokyo 169-8050, Japan*

[3]*Institute for Quantitative Social Science, Harvard University, 1737 Cambridge St, Cambridge, MA 02138, USA*

[4]*Department of Law, Economics and Culture, University of Insubria, Via Sant'Abbondio 12, 22100 Como, Como, Italy*

Abstract

This study analyzes the impact of the COVID-19 pandemic on subjective well-being as measured through Twitter for the countries of Japan and Italy. In the first nine months of 2020, the Twitter indicators dropped by 11.7% for Italy and 8.3% for Japan compared to the last two months of 2019, and even more compared to their historical means. To understand what affected the Twitter mood so strongly, the study considers a pool of potential factors including: climate and air quality data, number of COVID-19 cases and deaths, Facebook COVID-19 and flu-like symptoms global survey data, coronavirus-related Google search data, policy intervention measures, human mobility data, macro economic variables, as well as health and stress proxy variables. This study proposes a framework to analyse and assess the relative impact of these external factors on the dynamic of Twitter mood and further implements a structural model to describe the underlying concept of subjective well-being. It turns out that prolonged mobility restrictions, flu and Covid-like symptoms, economic uncertainty and low levels of quality in social interactions have a negative impact on well-being.

Keywords *COVID-19; subjective well-being; Twitter data*

1 Introduction

This study focuses on the impact of the COVID-19 pandemic on a Twitter subjective well-being indicator that has been previously proposed in the literature and that is available for Italy (Iacus et al., 2019, 2020a,b) (SWB-I) and Japan (SWB-J) (Carpi et al., 2022) only and based on the ISA supervised machine learning algorithm (Ceron et al., 2016b). It turns out that SWB-I has dropped by 11.7% and SWB-J by 8.3% during the first nine months of 2020 compared to the end of 2019, and even more compared to the previous years. This evidence is not shared by other Twitter-related studies (Rossouw and Greyling, 2020; Greyling et al., 2020; Dodds et al., 2011) in which only few isolated deviations from the mean of the indicators have been reported, contrary to our evidence of a structural change. The only the exception in the literature is that of Guntuku et al. (2020), though its work focuses more on change in emotions (anxiety, etc)

*Corresponding author. Email: siacus@iq.harvard.edu.

Received January 14, 2022; Accepted September 16, 2022

rather than on a composite well-being indicator.

Building from the evidence of a substantial decay of the Twitter mood, this work proposes a new framework to analyse the impact of external factors on Twitter indicators based on a dynamic elastic net approach combined with a random forest (Carammia et al., 2022) that produces a new concept called the Importance-Frequency (IF) space. This space makes easy and intuitive the analysis of the relative importance through time of a set of external factors on a dependent variable. This concept of IF space is widely applicable in other contexts of data science and we believe it makes a contribution in its own.

To accomplish our goal, we collected data on several factors, namely: socio-economic and public health indicators; Google search data on the virus and its spread, on economy and unemployment, on stress-related symptoms; Facebook survey data on flu and Covid-like symptoms as well as fears for own future; Google mobility data and governmental containment measures.

We then model the underlying concept of subjective well-being and test several hypotheses about causes and effects of well-being. We test these assumptions through a structural equation model (Bollen, 1989). It turns out that prolonged mobility restrictions, flu and Covid-like symptoms, economic uncertainty and low levels of quality in social interactions have a negative impact on well-being, and that low level of well-being tend to increase consumption of adult content, which confirms the evidence from the literature of subjective well-being based on survey data (Mestre-Bach et al., 2020; D'Orlando, 2011; Döring, 2020). But it also proves that the selected Twitter indicator is capable to capture part of this latent notion of well-being.

The paper is organized as follows: Section 2 presents a Twitter subjective well-being indicator, its trajectory during the first wave of the pandemic and a comparison with other available Twitter indicators. Section 3 gives some context on the impact of the pandemic on well-being measured through traditional methods and describes the set of potential determinants of the Twitter mood. Section 4 introduces and comments the results of the short term analysis. Section 5 presents a model to test the some assumptions on structural determinants of the Twitter indicators. The Supplementary Material is provided to contain all technical details and additional support material.

2 Twitter Mood During the First Wave of the Pandemic

In this study we discuss in details the behaviour of a particular Twitter subjective well-being indicator introduced by the the authors of the present study in Iacus et al. (2019, 2020a,b) for the Italian case (SWB-I), and in Carpi et al. (2022) for the Japanese case (SWB-J). Our aim is to estimate the Twitter mood and its evolution over time, during the first wave of the pandemic. We are aware of the fact that the Twitter users are not representative of the demographic population of a country. Nevertheless, our opinion is that social networking sites provide an (almost) freely available and just-in-time updated source of information about the tendencies of public sentiment and may serve as an informative tool for the design and monitoring of public policies. It should be made clear that we do not pretend to be able to reconstruct the subjective well-being of the real demographic populations of Italy and Japan with our indicators. Our focus is just on the Twitter mood.

Our indicators are the Twitter-based counterparts of the one proposed by the New Economic Foundation (NEF) think-tank spurring governments to build national accounts of well-being New Economic Foundation (2009, 2012) that were based on survey data. The NEF well-being indicator is a multidimensional index based on eight aspects of well-being and further grouped into three main areas called *personal*, *social*, and the one related to self-perception of well-being at *work*. These eight components are described below:

- **Personal well-being**
  - `emo`-tional well-being: the overall balance between the frequency of experiencing positive and negative emotions, with higher scores showing that positive feelings are felt more often than negative ones
  - `sat`-isfying life: having a positive assessment of one's life overall
  - `vit`-ality: having energy, feeling well-rested and healthy while also being physically active
  - `res`-ilience and self-esteem: a measure of individual psychological resources, of optimism and of the ability to deal with life stress
  - positive `fun`-ctioning: feeling free to choose and having the opportunity to do it; being able to make use of personal skills while feeling absorbed and gratified in daily activities
- **Social well-being**
  - `tru`-st and belonging: trusting other people, feeling treated fairly and respectfully while experiencing sentiments of belonging
  - `rel`-ationships: the degree and quality of interactions in close relationships with family, friends and others who provide support
- **Well-being at work**
  - quality of `wor`-k: feeling satisfied with a job, experiencing satisfaction with work-life balance, evaluating the emotional experiences of work and at work conditions

The eight indicators vary in the interval $[0, 100]\%$ and the SWB-I/J index is the simple average of the eight components. Full details on how our subjective well-being indicator is constructed from Twitter data can be found in Iacus et al. (2019, 2020a,b); Carpi et al. (2022).

2.1 The Twitter data

The data were collected through the Twitter search API's using the filter on language = `Japanese` and country = `Japan` for Japan, and similarly for Italy (`Italian` and `Italy`). The Twitter search API only provides a 10% sample of all tweets though the company does not disclose any information about the representativeness of this sample. Nevertheless, according to the large scale experiment by Hino and Fahey (2019), the coverage of topics and keywords is quite accurate and appears to be randomly selected. As said, we do not pretend to reconstruct the well-being of the real demographic populations as our focus is just the reaction of Twitter to the pandemic.

Please remark that the construction of training set for the evaluation of the Twitter indexes does not include any tweet from 2019 or 2020, so there is no specific COVID-19 information in the training data.

According to Statista (https://statista.com), there are about 8 million accounts active daily in Italy whilst about 52 millions are in Japan. To keep the volumes of tweets comparable between the two countries we set the maximum number of tweets downloaded daily to 50,000. As a result, the total volume of tweets is 13,975,242 for Italy and 12,907,902 for Japan and the data were collected from 2019-11-01 till 2020-10-11 for Italy and till 2020-09-20 for Japan. For this reason, this study is limited to the first wave of the COVID-19 pandemic. These tweets are part of two separate repositories that were collected for Italy since 2012 and for Japan since 2015. For both projects, systematic download of data was stopped in 2018 and resumed on late 2019 with alternate fortune, due to changes in Twitter API limits. For Italy some historical data were

Table 1: Average values of SWB-I and SWB-J from 2015 till 2020. For Italy, data in 2015 were not available for the whole year.The statistics for 2019 are referred only to the months of November and December. For 2020, the average refers to period from 1st January up to 11th October for Italy and 20th September for Japan. Standard errors in parentheses.

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	Nov-Dec 2019 vs 2020
SWB-I	48.9	52.2	49.7	48.7	50.5	57.7	55.7	54.1	42.4	−11.7
	(4.2)	(3.8)	(4.9)	(9.8)	(7.5)	(4.5)	(7.1)	(5.6)	(6.4)	–
SWB-J	–	–	–	54.4	53.6	53.2	52.5	35.3	27.0	−8.3
	–	–	–	(13.4)	(11.1)	(13.1)	(12.7)	(15.2)	(5.5)	–

collected ex-post for the year 2019 for other research repositories and included in this data collection.

2.2 The Trajectories of the Twitter Indicators

Table 1 shows some summary statistics of the SWB-I and SWB-J indexes since 2012. The trend of the two time series is captured through the limiting behaviour a dynamical system as the Chan-Karolyi-Longstaff-Sanders (CKLS) model (Chan et al., 1992), which is in fact a stochastic differential equation (SDE) (Iacus, 2008; Iacus and Yoshida, 2018) of the form

$$\mathrm{d}X_t = \alpha(\beta - X_t)\mathrm{d}t + \sigma X_t^\gamma \mathrm{d}W_t, \quad X_0 = x_0 \tag{1}$$

Social media indicators are time series that usually have high variability in the short term but they may exhibit a medium or long term trend like our SWB-I/J indicators as shown in Figure 1. Indeed, the two indicators fall by a certain amount and tend to oscillate stabilty around this new mean. where $0 < \gamma < 2$, β represents the long term mean around which the time series X_t oscillates and α is called the *speed* of mean reversion: the higher α, the faster the process is pushed back to (or attracted towards) its long run mean. Equation (1) represents a dynamical system with noise, where $\mathrm{d}W_t \sim N(0, \mathrm{d}t)$ represents the increment of the Gaussian noise and x_0 is the initial state of the process. Using a model selection approach it turned out that the SWB-I index has an estimated long term mean of about 39.28 and SWB-J of 28.41, those values being statistically different. (See section “Stochastic analysis” in the Supplementary material.)

It is then visually but also statistically clear that these indicators declined during the first wave of the pandemic. We also see from this analysis that the decline of the Twitter indicator has been larger in Italy than Japan.

It is worth noticing that other Twitter indicators related to well-being or happiness did not seem to show a persistent decline as in our case. For example, the *hedonometer* (https://hedonometer.org/timeseries/en_all/) indicator (Dodds et al., 2011) has shown no particular trend or shift through the year 2020, if not a negative peak around the 15th of March, after which the hedonometer went immediately back to its previous level. Similarly, the *Gross National Happiness index* (GNH; https://gnh.today) (Rossouw and Greyling, 2020; Greyling et al., 2020) also shown no substantial shift if not on one very specific date around March 2020. On the contrary, the results of the World Well-Being Project (WWBP; http://www.wwbp.org) (Guntuku et al., 2020), that focused specifically on tracking mental health symptoms during the first wave of the pandemic, seems more in line with our evidence.

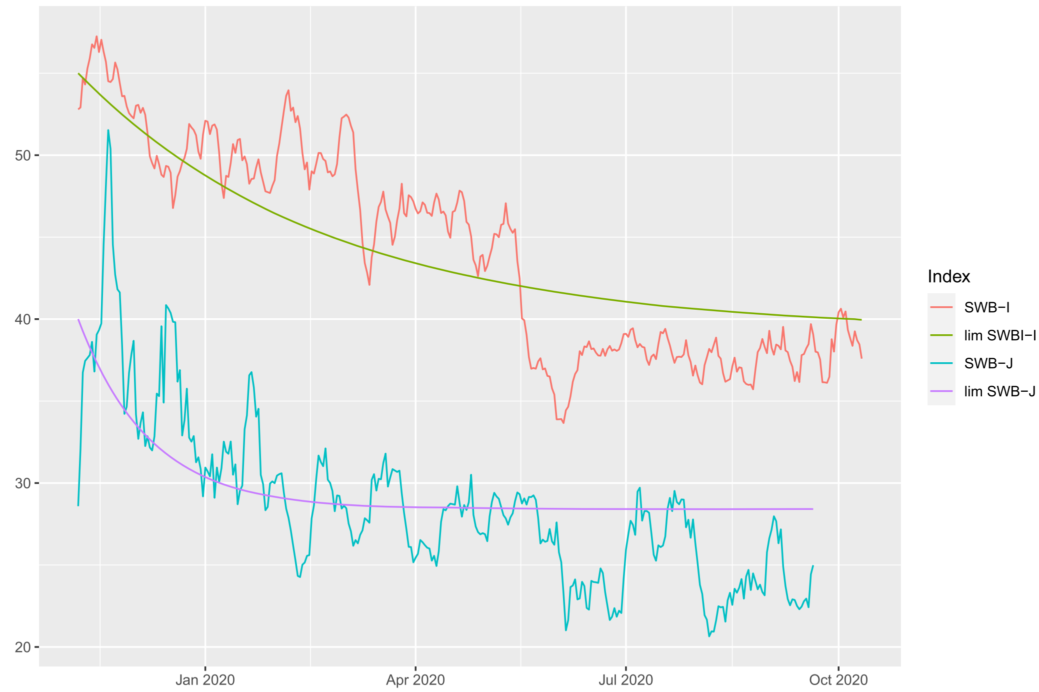

Figure 1: **The trend estimation.** SWB-I and SWB-J indexes from November 2019 till 10th October 2020 for Italy and 20th September for Japan with estimated limiting dynamical systems.

It is then worth investigating which factors have impacted our Twitter indicators. We conjecture that the Twitter community reacts to exogenous facts and news on how well/badly the economy is progressing, how bad the pandemic is unfolding, how much the news stress certain aspects of the pandemic, how well is one's health, how severe are the mobility restrictions, etc. We also assume that some facts may have a temporary impact, others may have persistent relationships. To this aim we perform two different analyses. At first we use a dynamic elastic net approach (Carammia et al., 2022) to select a subset of potential causes from a pool of several observable variables through the Importance-Frequency (IF) space (see Section 4). Then we propose some hypotheses to be tested via structural equation models (Bollen, 1989) about the persistent impact of several causes on subjective-well being and how this reverberates in our Twitter indicators (see Section 5).

3 What May Have Impacted the Twitter Mood?

Many recent studies have examined the effect of the COVID-19 outbreak on feeling, mood and health status – in particular, on mental health – both among Italian (Coppola et al., 2021; Marazziti et al., 2020; Maugeri et al., 2020; Rossi et al., 2020; Sani et al., 2020; Gualano et al., 2020) and Japanese people (Koda et al., 2022; Yamamoto et al., 2020; Qian and Yahara, 2020; Ueda et al., 2020). Some of these studies, moreover, focus on specific population targets such as elderly and young people or unemployed workers (Gallè et al., 2021; Orgilés et al., 2020; Shigemura et al., 2020). Particular attention is devoted to vulnerable categories and people involved in COVID-care activities: e.g., health care workers, who may suffer heavy emotional distress and even discrimination and stigmatization effects (Kotera et al., 2022; Rossi et al., 2021;

Shigemura and Kurosawa, 2020; Asaoka et al., 2020; Torricelli et al., 2021); pregnant women and newborns (Matsushima and Horiguchi, 2022; Ravaldi et al., 2021; Haruna and Nishi, 2020); patients with specific pathologies (Capuano et al., 2020).

All these studies aim at evaluating the impact of the pandemic on individual and collective well-being and suggesting intervention priorities. Yet, we do not know to what extent precariousness feelings, fears of possible impoverishment or the restrictions imposed to social interactions are going to yield temporary or permanent aftermaths on our perception of life. Studies are still on-going (OECD, 2021).

On the other hand, all the economic forecasts agree on the heavy consequences the pandemic is going to have on global GDP (Gross Domestic Product), consumption and employment (Yeyati and Filippini, 2021; Chudik et al., 2020; Baldwin and Weder di Mauro, 2020).

It is also know that factors such as temperature (Curini et al., 2015) and exposition to pollution are determinants of well-being, likewise media amplification of bad news (Ceron et al., 2016a), etc. Building on the above remarks, this section presents a pool of potential candidates as determinants of the Twitter mood.

Data on COVID-19 Spread We collected World Health Organization (WHO) data on the number of confirmed COVID-19 cases and deaths. We considered a 7-days moving average to reduce the impact of weekend days late reporting, that induces artificial periodicity in the data.

Financial Market Data We include the main stock market indexes of both countries, specifically the Nikkei (more precisely the Japan's Nikkei 225 Stock Average) and FTSE MIB (the primary benchmark index for the Italian equity markets), for Japan and Italy respectively, to take into account high frequency economic data. Daily adjusted closings data are taken from Yahoo! Finance (https://finance.yahoo.com) through the `quantmod` package (Ryan and Ulrich, 2020).

Air Quality Data We obtained air quality data called World Air Quality Index (WAQI; https://aqicn.org/data-platform/Covid19/) and, in particular, the PM2.5 (the fine particulate matter that are 2.5 microns or less in diameter) pollutant concentration and the temperature. Also in this case we considered a 7-days moving average and aggregate data at country level. The two variables roughly capture, on one hand, the amount of pollutant reduction during the pandemic due to the lockdown and, on the other hand, the effect of high/low temperature on mood (Curini et al., 2015).

Internet Searches As in Choi and Varian (2012), we make use of several Google search data as proxies of macro-economic variables (data available through the Google Trends https://www.google.com/trends portal and downloaded through the **`gtrendsR`** package (Massicotte and Eddelbuettel, 2020)). Google Trends offers two types of search statistics: one is based on the exact keyword and one is based on the concept of *topic*, where topics include all search terms related to that topic and are normalized across countries. We distinguish between general web searches (blogs, forum, etc) and specific news-related searches. We selected terms related to the pandemic, real economy and job market, health conditions and searches for adult content. Remark that, *"Pornhub, one of the largest pornography sites, has reported increased pornography use in multiple countries, with global traffic increasing over 11% from late February to March 17, 2020"* (Mestre-Bach et al., 2020). The happiness literature also seems to consider the link between well-being and boring living conditions (D'Orlando, 2011) as well as COVID-19 specific stress conditions (Döring, 2020).

Table S2 in the Supplementary Material contains the complete list of topics used in this study. Topics and keywords are the same for the two countries with two differences: 1) for Japan only we added the search for the keyword Corona 'コロナ' in katakana alphabet, as we noticed a remarkable difference between the topic and this exact search in terms of time series patterns; 2) for Italy only we included the keyword '`Rt`' for *reproduction number*, as this was daily reported in the news and in the official statements of the Italian government. The search term '`Rt`' for Japan is not associated to the virus, therefore it is not included in the analysis.

Human Mobility Data We also consider the human mobility data from the Google COVID-19 Community Mobility Reports (Google LLC "Google COVID-19 Community Mobility Reports", https://www.google.com/Covid19/mobility/). We considered a 7-days moving average data of the "residential" and "workplace percent change from baseline" statistic available in the data to capture, roughly, the effect of lockdown restrictions on human mobility.

Survey Data Since late April 2020 Facebook has conducted the "COVID-19 World Survey Data". The survey asks respondents how many people in their household are experiencing Covid-like symptoms, among other questions. Using this survey response data, it has been estimated the percentage of people in a given geographic region on a given day who:

- have COVID-like illness (FB.CLI): fever and cough, shortness of breath, or difficulty breathing;
- have influenza-like illness (FB.ILI): fever and cough or sore throat;
- have reported to use mask cover (FB.MC);
- have reported had direct contact (FB.DC), longer than one minute, with people not staying with them in last 24 hours;
- are worried about themselves and their household's finances in the next month (FB.FH).

Instead of direct counts that may have missing data for some date, we use the smoothed versions of the indicators based on a seven-day rolling average. Data have been collected through the COVID-19 World Symptom Survey Data API (Fan et al., 2020).

Policy Measures Finally, we constructed a dummy variable `lockdown` for both countries, taking value 1 when lockdown or other types of restrictions were in force in each country. For Italy (see https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Italy), a national lockdown was enforced since 9 March 2020 and lifted on 3 June 2020. For Japan (see https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Japan), there was no strict lockdown, but the state of emergency has been declared starting from 8 April 2020 and lifted on 21 May 2020 for most prefectures. But, as the remaining five prefectures had to wait till 25 May 2020, we decided to set our dummy equal to 1 for Japan for the whole period 2020-04-08/2020-05-25.

Table S3 in the Supplementary Material reports the complete list of variables used in the analysis. Remark that in the subsequent analyses the variables will have the prefix "`i`" or "`j`" according to the country to which they refer: e.g., "`iCases`" for Italy and "`jCases`" for Japan, and so on. It is worth mentioning that, due to the different time coverage of the data, we extended the analysis to 10 October 2020 for Italy and to 20 September 2020 for Japan.

4 The Impact of External Factors on the Twitter Indicators

As the impact of the external factors on the SWB-I and SWB-J indicators may vary through time we perform the analysis of the impact of these factors via the dynamic elastic net approach (Carammia et al., 2022).

At each date, we take the previous 30 days of time series of SWB-I/J and fit an Elastic Net model (Zou and Hastie, 2005), which is a regularized estimation method that performs estimation and model selection at the same time. It is basically a linear model estimated under both an L_1 and an L_2 penalization on the coefficients of the linear model. Details on how we implemented the Elastic Net for these data are given in the Supplementary material.

In order to assess the importance of each variable, we need to create a relative measure of importance, because the Elastic Net model is applied on a time-moving window and the variables selected, as well as their number, may and do change through time. Therefore it is important to take into account the *frequency* ($Freq$) at which each explanatory variable is selected. In addition to that, even the absolute values of the coefficients of these variables, no matter if standardized, is of little help as the variance/covariance matrix of the model changes through time. So in practice, absolute values of coefficients cannot be compared through time. To solve this issue, we perform two additional steps. At first, we extract the variables importance measure (Imp) of a Random Forests model (Breiman, 2001) run on the selected variables. Then, as Imp is based on the explained deviance of the model and this also changes through time, we need to transform it into a relative one. We first rank the variables according to the variables importance measure Imp, and then construct their relative rank, setting it equal to 1 for the most important variable and 0 if the variable has not been selected. The Imp variable is calculated at after each iteration of the dynamic elastic net estimation. Figure 5 shows this workflow while Figures 2 and 3 show the heat maps generated by this procedure. In both plots we can see how patterns of correlation emerge through time.

4.1 The "Importance-Frequency" space

In order to summarize the overall patterns that emerge from Figures 2 and 3, we introduce now the "Importance-Frequency" (IF) space. Each point in the IF space represents a variable/factor and its coordinates (x, y) on the space correspond to the average rank of the variable ($y = Imp$) when selected by dynamic elastic net model and the number of times ($x = Freq$) this variable has been selected. So that in the upper right corner of the IF space we find the most important and highly frequently selected variables and in the bottom left corner the less important and rarely selected variables. The advantage of this representation is that, in addition to summarizing the overall impact of the variables on the SWB-I/J indicator, it makes possible to compare the importance of those factors across countries.

Figure 4 represents the IF space for our data while Figure 5 shows the entire workflow of the dynamic short term analysis proposed in this work.

Analysis of the Importance-Frequency Space The IF space shows that, for example, the variables `Deaths` and `Cases` are more important in Japan than in Italy, as well as the fact that the number of deaths is more important – compared to the number of cases – to explain SWB-I, while the number of cases is more important to explain SWB-J. Notice, moreover, that `iRt` – the reproduction number of the infection – is recurrently important to SWB-I, and this likely due to the fact that the Italian media as well as the weekly bulletins issued by the Italian government, repeatedly report this number rather than the number of cases.

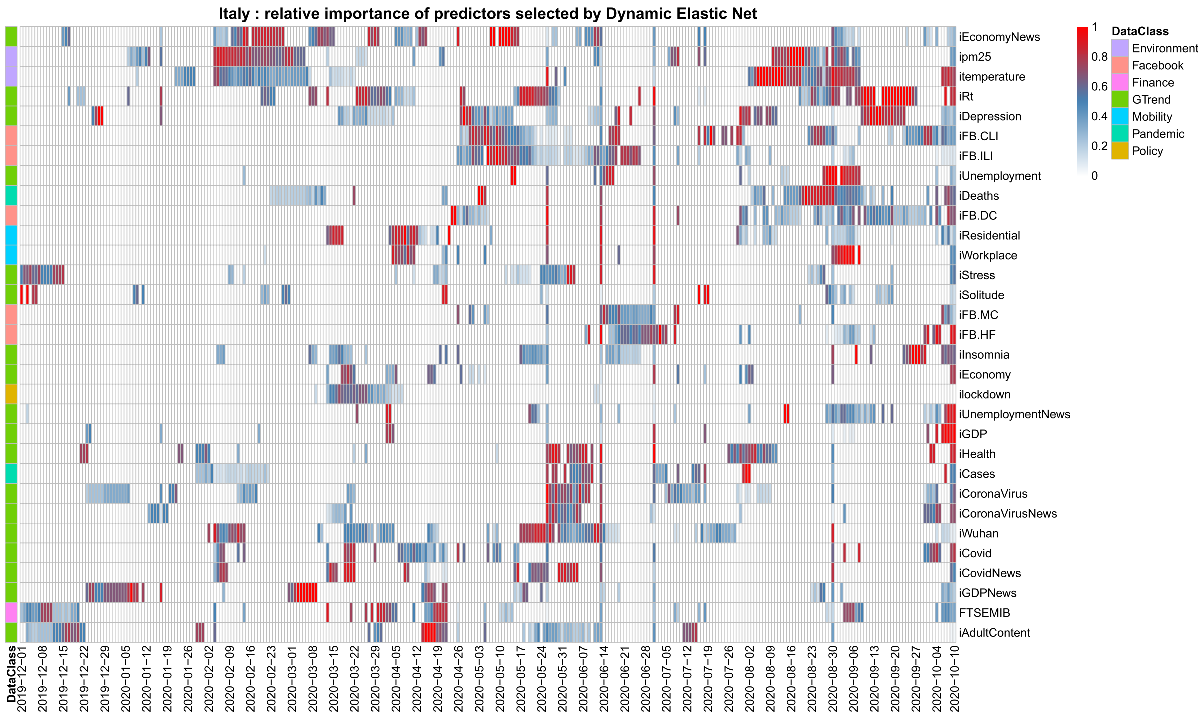

Figure 2: **Selection of external factors in the SWB-I analysis.** Relative importance (1 = maximum, 0 = variable not selected) of the covariates selected by Elastic Net to explain the SWB-I through time.

The factor `temperature` is frequently selected in both countries, but this is not the case for the air quality proxy `pm2.5` which seems to be relevant for Italy only.

In general, the economic variables are more often selected in the Japanese case: see, for instance, `NIKKEI`, `jEconomyNews`, `jUnemployment` compared to the corresponding `FTSEMIB`, `iEconomyNews` and `iUnemployment` variables. On the contrary, `lockdown` is relatively important for Italy and rarely for Japan. As a matter of fact, Italy applied more restrictive mobility measures than Japan.

Further, the Covid-like symptoms variable `iFB.CLI` is more frequently selected than `jFB.CLI`, meaning that own personal health condition is more important to Italian than Japanese Twitter users. The variables `jsolitude` and `jAdultContent` are prominent compared to the Italian counterparts.

The above results show that the dynamic elastic net analysis is a good tool to study the Twitter mood at high frequency, contrary to a single static model. Next section moves the focus to a low frequency and aggregated analysis to test some hypotheses on the persistent relationship between Twitter mood and socio-economic factors.

5 Testing for Structural Overall Associations

In this section we try to study the overall association of the external factors collected in Section 3 to the concept of subjective well-being and our Twitter indicator. We model the real subjective well-being as a latent variable and assume that it is affected by some other observ-

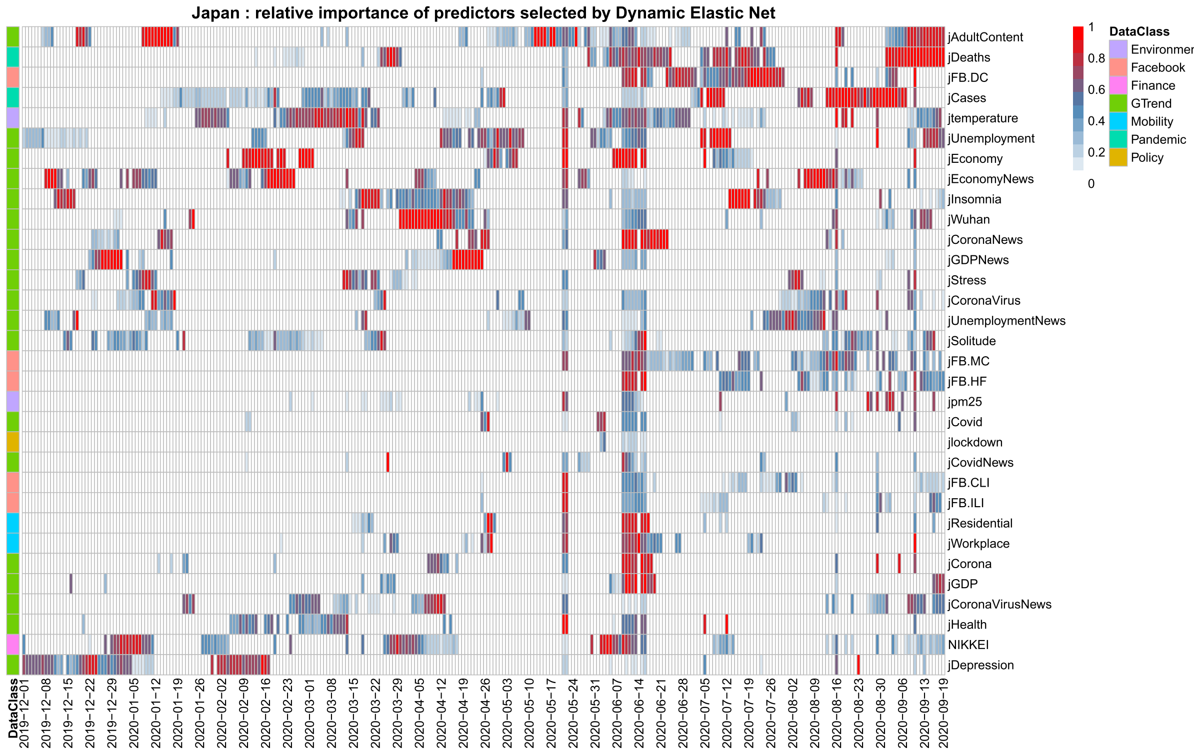

Figure 3: **Selection of external factors in the SWB-J analysis.** Relative importance (1 = maximum, 0= variable not selected) of the covariates selected by elastic Net to explain the SWB-J through time.

able variables and that it affects, in turn, some observable behaviours, including the Twitter mood. Figure 6 is a formal representation of the set of hypotheses we are going to model. As input factors we include “`Social interaction`”, “`Mobility restrictions`”, “`Financial insecurity`”, “`Physical conditions`” and “`Panic` or fear about the unfolding pandemic as search on news related to COVID-19. As output behaviours, we include the consumption of “`Adult content`”, on-line search of symptoms related to “`Psychological stress`” and Twitter mood (the `SWB-I/J` indicator). Each of the input factors will be modeled as concepts through latent variables as well. So, for example, `Financial insecurity` will be modelled as a linear combination of search for unemployment terms, stock market index values and Facebook survey data on perception of financial insecurity; as well as `Mobility restrictions` will be taken as a linear combination of “residential” and “workplace” Google mobility indicators and enforcement of “lockdown” measures; etc. We now present the set of eight hypotheses (H1–H8) that correspond to the conceptualization in Figure 6 and that we are going to test through the structural equation model in the next section.

H1: `Social interaction`. “The higher the quality of social interaction, higher the well-being”, (positive correlation);

H2: `Mobility restrictions`. “The stricter the implementation, the lower the well-being”, (negative correlation);

H3: `Financial insecurity`. “The higher the financial insecurity, the lower the well-being”, (negative correlation);

Figure 4: **The “Importance-Frequency” (IF) space.** Each point of coordinates (x, y) in this plot represents an explanatory variable where y is the average relative rank and x is the number of times each variable has been selected (over 315 dates for Italy and 294 dates for Japan) by the dynamic elastic net.

H4: `Physical conditions`. “The better the physical conditions, the higher the well-being”, (positive correlation);
H5: `Panic/Fear`. “The higher the panic, the worse the well-being”, (negative correlation);
H6: `Psycological stress`. “The higher the well-being, the lower the search for stress-related topics”, (negative correlation);
H7: `Adult content`. “The higher the well-being, the lower the consumption of adult content”, (negative correlation);
H8: `SWB-I/J`. “The higher the well-being, the higher the Twitter mood”, (positive correlation).

Notice that `Well-being` is the abstract concept of well-being, `Psycological stress`, `Adult content` and `SWB-I/J` are “caused” by it, while the rest of the variable cause `Well-being`.

5.1 A structural equation model

To test the hypotheses **H1-H8**, we use a Structural Equation Model (SEM) with continuous response variable (Bollen, 1989). We test separately the hypotheses for Italy and Japan and

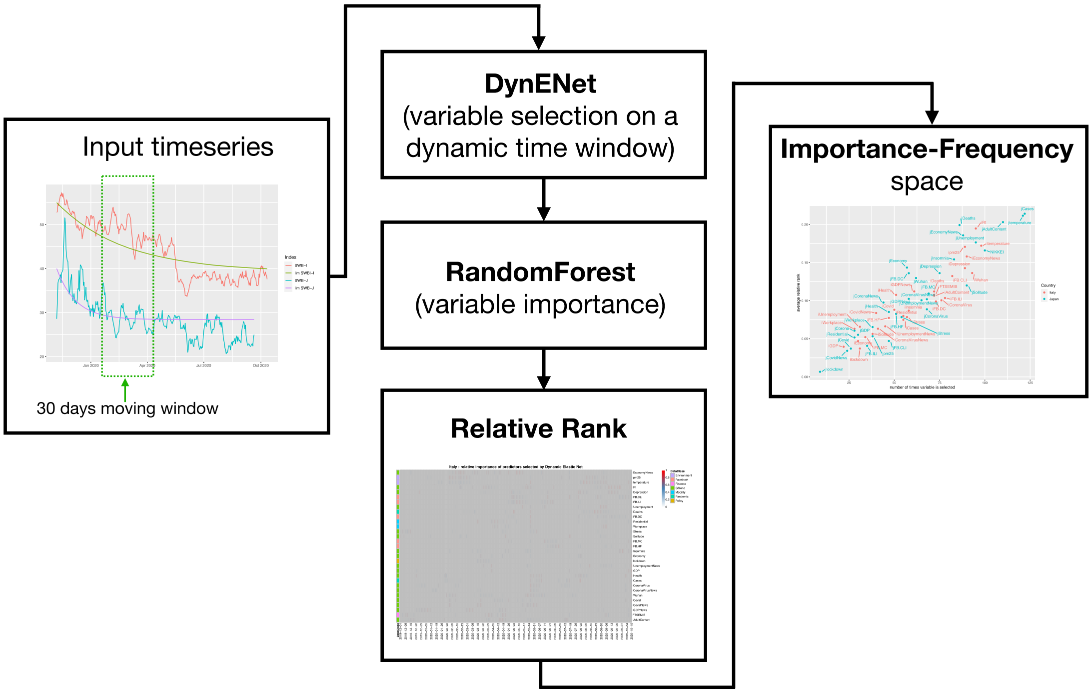

Figure 5: **Workflow of the dynamic short term analysis.** After fitting an Elastic Net model on a 30-days moving window, a Random Forest is applied to the selected variables to extract rank. Then rank are normalized to [0,1] for comparison over time and number of variables selected. Finally the Importance-Frequency space is built to assess the overall relative importance of each variable in explaining the Twitter indicators.

construct the model as follows:

$$
\begin{aligned}
\text{WellBeing} &\leftarrow \text{VirusSearch} + \text{HealthStatus} + \text{Mobility} + \text{Finance} + \text{SocDist} \\
\text{PsySearch} &\leftarrow \text{WellBeing} \\
\text{AdultContent} &\leftarrow \text{WellBeing} \\
\text{SWB-I/SWB-J} &\leftarrow \text{WellBeing}
\end{aligned}
$$

Where $B \leftarrow A$ means A impact/determines B. Further, the residual correlations among some of the observed variables are inserted in the model to take into account cross-correlation, for example between `Mobility` and `Cases`. Notice that there is not a one-to-one correspondence between the names of the latent variables in the SEM model and the factors in Figure 6. Although this seems confusing at first glance, it allows for more flexibility in interpreting the results of the SEM model in the following sense. The SEM model is nothing but a path analysis of artificially built latent variables.) The latent variables are built as linear combinations of observable variables whose coefficients determines their interpretation, but the latent space in which those latent variables live is a mere numerical artifact) as we will see during the discussion of the results of the analysis (see e.g. the discussion of hypotheses H3). More precisely, the latent variables in SEM model are built as follows:

- `VirusSearch`: captures the compulsive search for Covid-related information. We built them as linear combination of the following observable covariates: `CoronaVirus`, `Covid` and – only

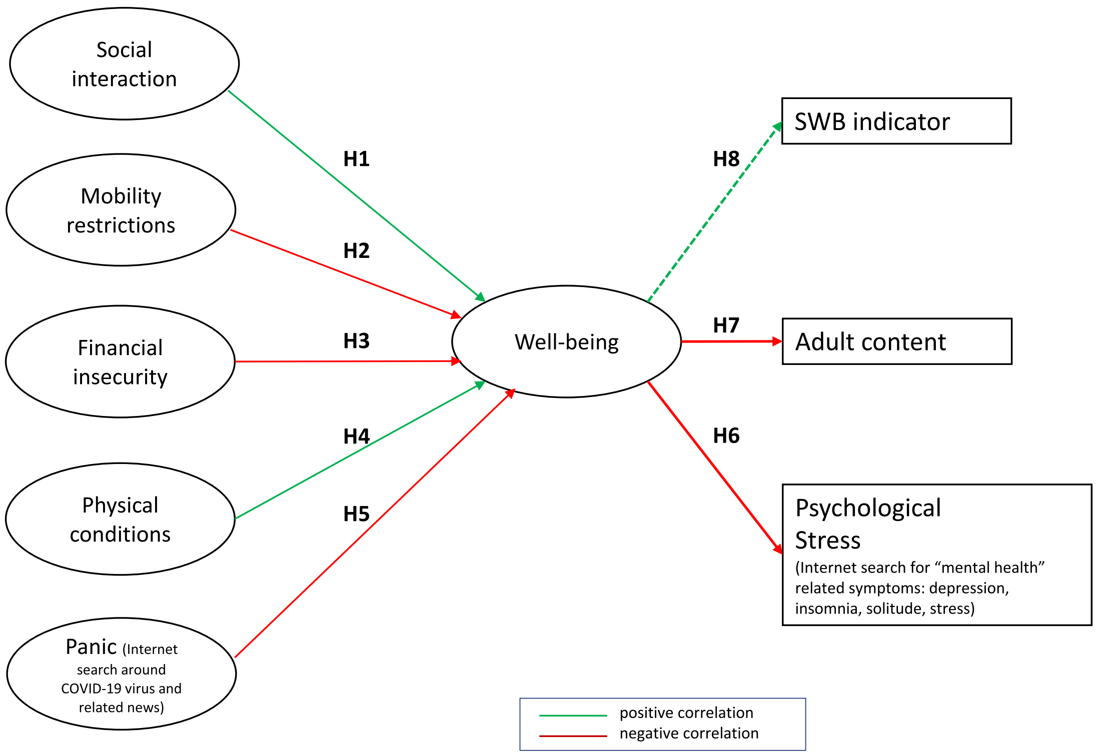

Figure 6: **Modelling the hypotheses around well-being.** Overall relationships that affect or are produced by the latent well-being variable. See text for an interpretation of the variables.

for Italy – by `Rt`, and – only for Japan – by `Corona`;

- `PsySearch`: captures the web search for symptoms related to psychological stress like `Stress`, `Insomnia`, `Solitude` and `Depression`;
- `HealthStatus`: captures the declared health status, whose observables are `FB.CLI` and `FB.ILI`.
- `Mobility`: captures the mobility restrictions enforcement, measured through the Google variables `Residential` and `Workplace` and `lockdown` measures;
- `Finance`: accounts for the effect of the financial and economic variables: `FTSEMIB`/`NIKKEI`, `FB.HF` and `Unemployment`.
- `SocDist`: represents the social distancing factor, measured by `FB.MC` and `FB.DC`.

We do not include the COVID-19 cases and deaths variables, as we assume their effect is captured by several of the other behavioural factors like `HealthStatus` and `PsySearch`. For the same reason we do not include the temperature as this is, in general, highly correlated with the virus spread.

5.2 The results of testing of the hypotheses through the SEM model

The results of the fitted model for SWB-I (respectively SWB-J) are reported in Table S4 (resp. Table S5) in the Supplementary material, while Fig. 7 (resp. Fig. 8) give a graphical representation of the same fitting, also in the Supplementary material. Let's focus on each individual hypothesis.

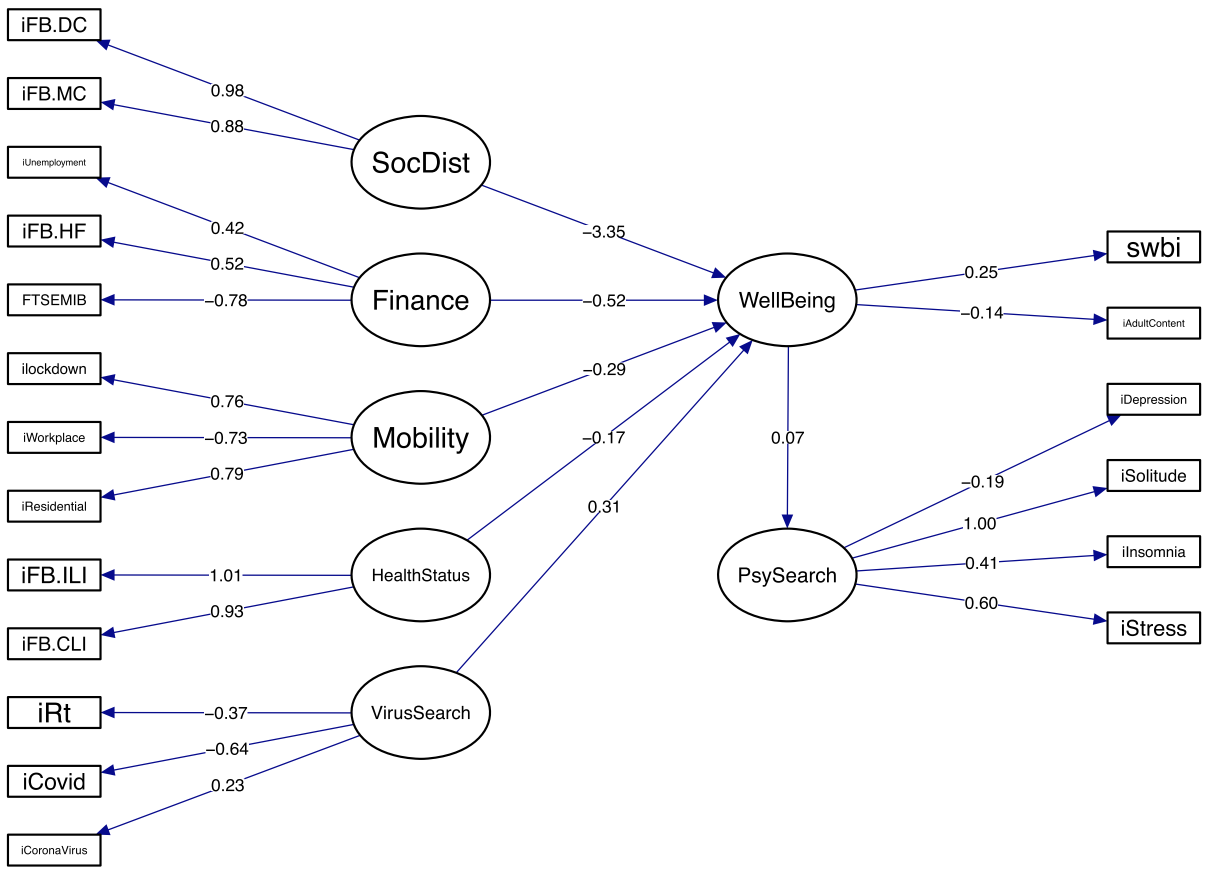

Figure 7: Output of the SEM fitting for SWB-I. Modelled covariances and their values are not shown to keep the plot clean but they appear in full in Table S4.

H1: Social interactions. *"the higher the quality of social interaction, the higher the well-being"*. The SEM latent variable `SocDist` is built on `FB.DC` and `FB.MC`, so it is about people wearing masks all the time and having had contact with external people with social distancing. Both components have positive coefficients. Looking at what it means to have interactions wearing masks and keeping distance, this might be interpreted as reduction of quality of social interaction compared to pre-pandemic habits (e.g. in Italy people hugs, kisses, etc when they meet; but in Japan as well, people are used to meet a lot after work in closed space to drink and chat freely). The correlation with `WellBeing` is negative, so we can say that when social interaction happens through wearing masks and keeping distance, the well-being deteriorates. We can conclude that **H1 is verified for both Italy and Japan**.

H2: Mobility Restrictions. *"the stricter the implementation, the lower the well-being"*. The SEM latent variable `Mobility` is built on `lockdown`, `workplace` and `residential`. While `lockdown` and `residential` have positive signs, `workplace` has negative sign. This applies to both Italy and Japan. This means that this variable represents the actual *mobility restrictions*. The correlation with `WellBeing` is negative. We can conclude that **H2 is verified for both Italy and Japan**.

H3: Financial insecurity. *"the higher the financial insecurity, the lower the well-being"*. The SEM latent variable `Finance` is built on `FB.HF`, `Unemployment` and `FTSEMIB` for Italy,

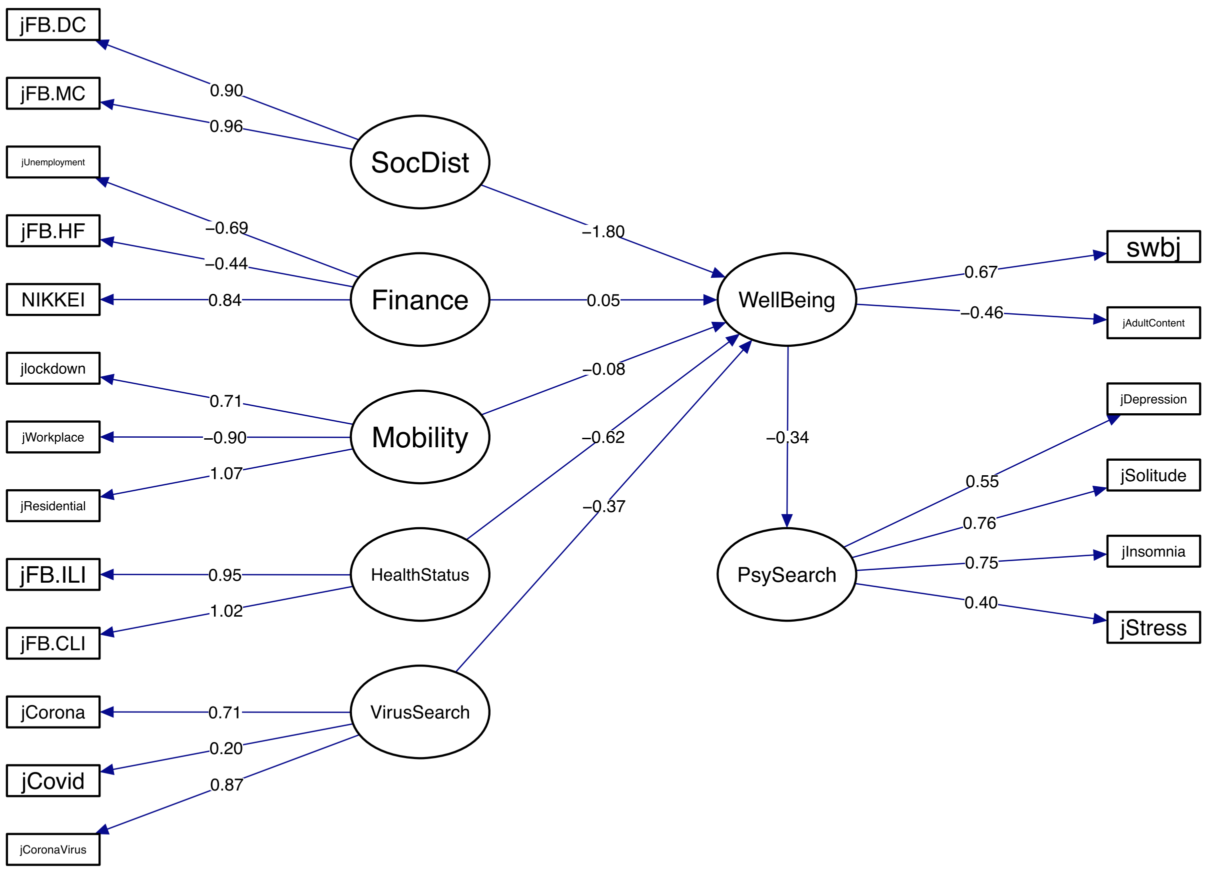

Figure 8: Output of the SEM fitting for SWB-J. Modelled covariances and their values are not shown to keep the plot clean but they appear in full in Table S5.

respectively `NIKKEI` for Japan. For Italy, this variable represents *financial insecurity* because `FB.HF` and `Unemployment` have positive signs while `FTSEMIB` has negative sign. The correlation with `WellBeing` is also negative, therefore **H3 is verified for Italy**. For Japan, this variable represents *financial stability* because `FB.HF` and `Unemployment` have negative signs while `NIKKEI` has positive sign. The correlation with `WellBeing` is in fact positive, therefore **H3 is verified also for Japan**.

H4: Physical conditions. *"the better the physical conditions, the higher the well-being"*. The SEM latent variable `HealthStatus` is built on `FB.ILI` and `FB.CLI`. Coefficients are positive for both variables in both countries, so this variable represents *bad physical conditions*. The correlation with `WellBeing` is negative, therefore we can say that **H4 is verified for both Italy and Japan**.

H5: Panic/Fear. *"the higher the panic, the worse the well-being"*. For Italy, the SEM latent variable `VirusSearch` is built on `Covid` and `Rt` with negative coefficients (resp -0.64 and -0.37), and `CoronaVirus` with a positive coefficient (0.23). Overall this component has a negative sign ($-0.64-0.37+0.23$) when these Google search increase by the same amount and the correlation with `WellBeing` is positive, therefore as these search increases, the combined impact on `WellBeing` is negative, therefore we can say that **H5 is verified for Italy**. For Japan, the SEM latent variable `VirusSearch` is built on `Corona`, `Corona` and `CoronaVirus`

Table 2: Summary of the results of hypotheses tested through the SEM model. The '✓' means that the corresponding hypothesis has been successfully verified.

Hypotheses	Italy	Japan
H1: Social interactions	✓	✓
H2: Mobility restrictions	✓	✓
H3: Financial insecurity	✓	✓
H4: Physical conditions	✓	✓
H5: Panic/Fear	✓	✓
H6: Psychological stress	–	✓
H7: Adult content	✓	✓
H8: SWB-I/J	✓	✓

all with positive coefficients and the correlation with `WellBeing` is negative, therefore as these search increases, the overall impact on `WellBeing` is negative, therefore we can say that **H5 is verified for Japan**.

H6: Psychological stress. *"the higher the well-being, the lower the search for stress-related topics"*. For Japan, the correlation between `WellBeing` and the SEM latent variable `PsySearch` is negative. This variable is built on `Depression`, `Solitude`, `Insomnia` and `Stress` all with positive coefficients. Meaning that as `WellBeing` improves, the search for stress-related topics decreases. Therefore **H6 is verified for Japan**. For Italy, the correlation between `WellBeing` and the SEM latent variable `PsySearch` is positive. All coefficients are positive but `Depression` and overall, this latent variable grows when the search grows. Therefore **H6 is not verified for Italy**.

H7: Adult Content. *"the higher the well-being, the lower the consumption of adult content"*. The correlation between `WellBeing` and the variable `AdultContent` is negative for both Japan and Italy, meaning that when the well-being improves the consumption of adult content decreases. Therefore **H7 is verified for both Italy and Japan**. This result is in line with the current literature that relates the consumption of these products to unsatisfactory levels of happiness (Mestre-Bach et al., 2020; D'Orlando, 2011; Döring, 2020).

H8: SWB-I/J. *"the higher the well-being, the higher the Twitter mood"*. The correlation between `WellBeing` and the twitter indicators `SWB-I` and `SWB-J` are both positive. So **H8 is verified for both Italy and Japan**.

In summary (see also Table 2) most of the hypotheses are verified through the SEM model with one exception: H6 is not verified for Italy. This assumption is based on the Google search volume on psychological stress symptoms, but ultimately fails to capture what we expected. This analysis also show that, under the hypothesized model, the Twitter indicator is able to capture the underlying subjective well-being, at least partially (as the coefficients are not equal to one in both countries).

6 Concluding remarks

This study shows that the COVID-19 pandemic has had a negative impact on Twitter mood as measured through a particular subjective well-being indicator proposed in the literature (Iacus et al., 2020a; Carpi et al., 2022). This decay has been statistically assessed also through a dynamic system approach.

Although such behaviour would have been somehow expected, and still being investigated by other scholars through other more traditional approaches, this decay does not seem to be observed in most other Twitter-related studies. Given the high volatility of social media indicators, we proposed a complete data science workflow (see Figure 5) to study the relative impact of external factors that may have determined this behaviour. This workflow can be applied in many other studies and we think it is an useful contribution at the service of the applied data science community.

We further modeled more structural causes and effects of the underlying concept of subjective well-being and showed that most expected relationships seem to hold true. As a byproduct of this analysis we also gave evidence that the Twitter indicators capture, at least, partially this underlying concept of well-being.

Supplementary Material

The supplementary material consists of the following sections: Construction of the Twitter indicators; Stochastic analysis; Dynamic Elastic Net and Dynamic variable selection for the SWB-I/J indicators; Structural equation models. As well as information on authors' contribution and data availability.

Acknowledgements

The data collection has been performed within the Japan Science and Technology Agency CREST (Core Research for Evolutional Science and Technology) project, grant n. JPMJCR14D7. This work was performed also in collaboration with the Waseda Institute of Social Media Data (WISDOM), especially for the part concerning the training set human coding.

References

Asaoka H, Koido Y, Kawashima Y, Ikeda M, Miyamoto Y, Nishi D (2020). Post-traumatic stress symptoms among medical rescue workers exposed to COVID-19 in Japan. *Psychiatry and Clinical Neurosciences*, 74(9): 503–505.

Baldwin R, Weder di Mauro B (2020). *Economics in the Time of COVID-19*. CEPR Press.

Bollen K (1989). *Structural Equations with Latent Variables*. Wiley, New York.

Breiman L (2001). Random forests. *Machine Learning*, 45(1): 5–32.

Capuano R, Altieri M, Bisecco A, d'Ambrosio A, Docimo R, Buonanno D, et al. (2020). Psychological consequences of COVID-19 pandemic in Italian MS patients: Signs of resilience? *Journal of Neurology*, 268(3): 743–750.

Carammia M, Iacus SM, Wilkin T (2022). Forecasting asylum-related migration flows with machine learning and data at scale. *Scientific Reports*, 12(1): 1457.

Carpi T, Hino A, Iacus SM, Porro G (2022). A Japanese subjective well-being indicator based on Twitter data. *Social Science Japan Journal*, 25(2): 273–296.

Ceron A, Curini L, Iacus SM (2016a). First- and second-level agenda setting in the twittersphere: An application to the Italian political debate. *Journal of Information Technology & Politics*, 13(2): 159–174.

Ceron A, Curini L, Iacus SM (2016b). iSA: A fast, scalable and accurate algorithm for sentiment analysis of social media content. *Information Sciences*, 367(C): 105–124.

Chan KC, Karolyi GA, Longstaff FA, Sanders AB (1992). An empirical comparison of alternative models of the short-term interest rate. *The Journal of Finance*, 47(3): 1209–1227.

Choi H, Varian H (2012). Predicting the present with Google trends. *Economic Record*, 88(s1): 2–9.

Chudik A, Mohaddes K, Pesaran MH, Raissi M, Rebucci A (2020). A counterfactual economic analysis of COVID-19 using a threshold augmented multi-country model. *Working Paper 27855*, National Bureau of Economic Research. http://www.nber.org/papers/w27855.

Coppola I, Rania N, Parisi R, Lagomarsino F (2021). Spiritual well-being and mental health during the COVID-19 pandemic in Italy. *Frontiers in Psychiatry*, 12(626944): 1–15.

Curini L, Iacus S, Canova L (2015). Measuring idiosyncratic happiness through the analysis of Twitter: An application to the Italian case. *Social Indicators Research*, 121(2): 525–542.

Dodds PS, Harris KD, Kloumann IM, Bliss CA, Danforth CM (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *PLoS ONE*, 6(12): 1–26.

Döring N (2020). How is the COVID-19 pandemic affecting our sexualities? An overview of the current media narratives and research hypotheses. *Archives of Sexual Behavior*, 49(8): 2765–2778.

D'Orlando F (2011). The demand for pornography. *Journal of Happiness Studies*, 12(1): 51–75.

Fan J, Li Y, Stewart K, Kommareddy AR, Bradford A, Chiu S, et al. (2020). COVID-19 world symptom survey data api, *Technical report*, University of Maryland. https://covidmap.umd.edu/api.html.

Gallè F, Sabella EA, Roma P, Ferracuti S, Da Molin G, Diella G, et al. (2021). Knowledge and lifestyle behaviors related to COVID-19 pandemic in people over 65 years old from southern Italy. *International Journal of Environmental Research and Public Health*, 18(20): 1–11.

Greyling T, Rossouw S, Adhikari T (2020). Happiness-lost: Did governments make the right decisions to combat COVID-19? *Repec preprint*, Global Labor Organization. https://ideas.repec.org/p/zbw/glodps/556.html.

Gualano MR, Lo Moro G, Voglino G, Bert F, Siliquini R (2020). Effects of COVID-19 lockdown on mental health and sleep disturbances in Italy. *International Journal of Environmental Research and Public Health*, 17(4779): 1–13.

Guntuku SC, Sherman G, Stokes DC, Agarwal AK, Seltzer E, Merchant RM, et al. (2020). Tracking mental health and symptom mentions on Twitter during COVID-19. *Journal of General Internal Medicine*, 35(9): 2798–2800.

Haruna M, Nishi D (2020). Perinatal mental health and COVID-19 in Japan. *Psychiatry and Clinical Neurosciences*, 74(9): 502–503.

Hino A, Fahey RA (2019). Representing the Twittersphere: Archiving a representative sample of Twitter data under resource constraints. *International Journal of Information Management*, 48: 175–184.

Iacus SM (2008). *Simulation and Inference for Stochastic Differential Equations. With R Examples*. Springer, New York.

Iacus SM, Yoshida N (2018). *Simulation and Inference for Stochastic Processes with YUIMA: A Comprehensive R Framework for SDEs and Other Stochastic Processes*. Springer, New York.

Iacus SM, Porro G, Salini S, Siletti E (2019). Social networks data and subjective well-being. An innovative measurement for Italian provinces. *Scienze Regionali, Italian Journal of Regional*

Science, 2019(Speciale): 667–678.

Iacus SM, Porro G, Salini S, Siletti E (2020a). Controlling for selection bias in social media indicators through official statistics: A proposal. *Journal of Official Statistics*, 36(2): 315–338.

Iacus SM, Porro G, Salini S, Siletti E (2020b). An Italian composite subjective well-being index: The voice of Twitter users from 2012 to 2017. *Social Indicators Research*, 161: 1–31.

Koda M, Harada N, Eguchi A, Nomura S, Ishida Y (2022). Reasons for suicide during the COVID-19 pandemic in Japan. *JAMA Network Open*, 5: e2145870.

Kotera Y, Ozaki A, Miyatake H, Tsunetoshi C, Nishikawa Y, Kosaka M, et al. (2022). Qualitative investigation into the mental health of healthcare workers in Japan during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, 19(1): 568.

Marazziti D, Pozza A, Di Giuseppe M, Conversano C (2020). The psychosocial impact of COVID-19 pandemic in Italy: A lesson for mental health prevention in the first severely hit European country. *Psychological Trauma: Theory, Research, Practice, and Policy*, 12: 531–533.

Massicotte P, Eddelbuettel D (2020). gtrendsR: Perform and display Google trends queries. *R package*, R Foundation for Statistical Computing. https://CRAN.R-project.org/package=gtrendsR.

Matsushima M, Horiguchi H (2022). The COVID-19 pandemic and mental well-being of pregnant women in Japan: Need for economic and social policy interventions. *Disaster Medicine and Public Health Preparedness*, 16: 449–454.

Maugeri G, Castrogiovanni P, Battaglia G, Pippi R, D'Agata V, Palma A, et al. (2020). The impact of physical activity on psychological health during COVID-19 pandemic in Italy. *Heliyon*, 6: 1–8.

Mestre-Bach G, Blycker GR, Potenza MN (2020). Pornography use in the setting of the COVID-19 pandemic. *Journal of Behavioral Addictions*, 9(2): 181–183.

New Economic Foundation (2009). National accounts of well-being: bringing real wealth onto the balance sheet. *NEF report*, New Economics Foundation. https://neweconomics.org/uploads/files/2027fb05fed1554aea_uim6vd4c5.pdf.

New Economic Foundation (2012). Measuring well-being. A guide for practitioners. *NEF report*, New Economics Foundation. https://neweconomics.org/uploads/files/measuring-wellbeing.pdf.

OECD (2021). *COVID-19 and Well-Being: Life in the Pandemic*. OECD Publishing.

Orgilés M, Morales A, Delvecchio E, Mazzeschi C, Espada JP (2020). Immediate psychological effects of the COVID-19 quarantine in youth from Italy and Spain. *Frontiers in Psychology*, 11: 1–10.

Qian K, Yahara T (2020). Mentality and behavior in COVID-19 emergency status in Japan: Influence of personality, morality and ideology. *PLoS ONE*, 15: 1–16.

Ravaldi C, Wilson A, Ricca V, Homer C, Vannacci A (2021). Pregnant women voice their concerns and birth expectations during the COVID-19 pandemic in Italy. *Women and Birth*, 34: 335–343.

Rossi R, Socci V, Talevi D, Mensi S, Niolu C, Pacitti F, et al. (2020). COVID-19 pandemic and lockdown measures impact on mental health among the general population in Italy. *Frontiers in Psychiatry*, 11: 1–6.

Rossi R, Socci V, Jannini TB, Pacitti F, Siracusano A, Rossi A, et al. (2021). Mental health outcomes among Italian health care workers during the COVID-19 pandemic. *JAMA Network Open*, 4: 1–11.

Rossouw S, Greyling T (2020). Big data and happiness. In: *Handbook of Labor, Human Resources* *and Population Economics* (K Zimmermann, ed.), 1–35. Springer.

Ryan JA, Ulrich JM (2020). quantmod: Quantitative financial modelling framework. *R package*, R Foundation for Statistical Computing. https://CRAN.R-project.org/package=quantmod.

Sani G, Janiri D, Di Nicola M, Janiri L, Ferretti S, Chieffo D (2020). Mental health during and after the COVID-19 emergency in Italy. *Psychiatry and Clinical Neurosciences*, 74: 372.

Shigemura J, Kurosawa M (2020). Mental health impact of the COVID-19 pandemic in Japan. *Psychological Trauma: Theory, Research, Practice, and Policy*, 12: 478–479.

Shigemura RJ, Ursano J, Morganstein JC, Kurosawa M, Benedek DM (2020). Public responses to the novel 2019 coronavirus (2019-nCoV) in Japan: Mental health consequences and target populations. *Psychiatry and Clinical Neurosciences*, 74: 281–282.

Torricelli L, Poletti M, Raballo A (2021). Managing COVID-19 related psychological distress in health workers: field experience in northern Italy. *Psychiatry and Clinical Neurosciences*, 75(1): 23–24.

Ueda M, Stickley A, Sueki H, Matsubayashi T (2020). Mental health status of the general population in Japan during the COVID-19 pandemic. *Psychiatry and Clinical Neurosciences*, 74: 505–506.

Yamamoto T, Uchiumi C, Suzuki N, Yoshimoto J, Murillo-Rodriguez E (2020). The psychological impact of 'mild lockdown' in Japan during the COVID-19 pandemic: A nationwide survey under a declared state of emergency. medRxiv preprint, 1(1): 1–24. https://www.medrxiv.org/content/medrxiv/early/2020/07/30/2020.07.17.20156125.full.pdf.

Yeyati EL, Filippini F (2021). The economic effects of COVID-19 containment measures. *Brookings global working paper n. 158*, Global Economy and Development Program at Brookings. https://www.brookings.edu/wp-content/uploads/2021/06/Social-and-economic-impact-COVID.pdf.

Zou H, Hastie T (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society, Series B*, 67: 301–320.