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ORIGINAL RESEARCH

Portfolio decision analysis for pandemic sentiment assessment based on finance and web queries

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Abstract
COVID-19 has spread worldwide, affecting people's health and the socio-economic environment. Such a pandemic is responsible for people's deteriorated mood, pessimism, and lack of trust in the future. This paper presents a portfolio decision analysis framework for policymakers aiming at recovering the population from psychological distress. Specifically, we explore the relative relevance of a country to the overall "mood of the world" in light of pursuing predefined targets through optimization criteria. Toward this aim, we design a statistical indicator for measuring the mood by considering the financial markets' outcomes and the people's online searches about COVID-19. Then, we adapt existing portfolio selection models to evaluate the role of an extensive collection of countries and stock markets based on different criteria. More precisely, such criteria are established assuming "rational" goals of a policymaker, namely to aspire to a general and stable optimism and avoid waves of opposite moods or excess pessimism. Empirical experiments validate the theoretical proposal. The employed dataset contains 39 countries selected on the basis of data reliability and relevance in the context of COVID-19. Data on daily Google Trends searches of the term "coronavirus" (and its translations) and closing prices of relevant domestic stock indexes are considered for 2020 to develop the statistical mood indicator. Results offer different insights based on the selected optimization criteria. The practical implications of the proposed models have been illustrated through arguments based on a National Recovery and Resilience Plan-type normative framework.

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1 Introduction

The current period is characterised by one of the most significant pandemics in the modern era—the so-called COVID-19. This disease, caused by a coronavirus, was officially identified for the first time in China towards the end of 2019 (Li et al., 2020; Zhu et al., 2020). The world is grappling with the dramatic effects of COVID-19 on health, evidenced by an increasing number of infections and numerous fatalities. Additionally, the non-pharmaceutical interventions to curb the spread of the pandemic share a common underlying principle: the reduction of social interactions (see, e.g., Dave et al., 2021, Lewnard & Lo, 2020). In this context, COVID-19 has also precipitated economic and financial crises, leading to widespread unemployment (see, e.g., Kong & Prinz, 2020, Susskind & Vines, 2020, Milani, 2021, and the monograph by Gans, 2020).

Generally speaking, the global pandemic situation has had deleterious effects on people's behaviour, manifesting in widespread anxiety and a diminishing trust in a positive future outlook (see, e.g., Lee et al., 2020, Mann et al., 2020). In this regard, Asmundson and Taylor (2020) coined the term *coronaphobia*.

This paper presents an operational research perspective to explore global citizens' responses to the pandemic. The conceptualisation of this response is based on two immediately interconnected aspects: the anxiety induced by the pandemic and the confidence in the future performance of financial markets. We henceforth refer to the term "mood" to describe the sentiment of a country's citizens. As we shall see, mood is measured through a combination of the aforementioned aspects.

Specifically, we integrate and complement the financial aspect of pandemic-induced anxiety using data from Google Trends related to COVID-19, as supported by the literature (see Sect. 2). The mood of a country's citizens is examined by jointly considering the prices of one or more stock indices linked to it and the respective Google Trends indicator for the term *"coronavirus"* within that country. When necessary, the term "coronavirus" has been appropriately translated. The proposed synthetic mood indicator increases (decreases) when prices rise (fall) and the Google search index diminishes (escalates).

The period under review spans 1 year, from January 1st, 2020, to December 31st, 2020, and we consider daily data. Notably, this period was predominantly marked by the implementation of non-pharmaceutical measures to combat COVID-19. By analysing this timeframe, we exclude the influence of vaccines introduced at the end of 2020, as it would require a separate analysis in the context of population mood swings. We select relevant stock indices for each country based on Bloomberg's relevance score R and the Human Development Index (HDI, 2019). For more details, see Sect. 5.1.

The process of selecting stock indices results in one index per country, with the exceptions of China and Finland, which have two each. Therefore, with the aforementioned exceptions in mind, we will refer to the index, market, or country interchangeably in the following sections.

The global mood indicator is defined as the weighted mean of the moods of each stock index, where a weight represents the relative importance of a stock index/country to the world's mood. From a modelling perspective, these weights can also be interpreted as the shares of a portfolio. Consequently, one can suitably select the portfolio's weights to pursue a specific target mood for the world or, alternatively, a specific target for its fluctuation—for example, maximising the expected world's mood while minimising its variance.

More specifically, the aim of this paper is twofold. Firstly, we propose a mood indicator based on both financial data and Google Trends concerning COVID-19. Secondly, we determine each country's contribution to the global mood when specific targets are set—thereby guiding policymakers in developing strategies to mitigate the psychological distress caused by COVID-19. This issue can be seen as a project selection process to achieve a predefined target.

In this paper, we employ Portfolio Decision Analysis (PDA) to investigate the global reaction to COVID-19. We consider and compare different portfolio models, each tailored to specific criteria for evaluating the relevance of indices in optimally describing the world's mood in relation to specific targets.

In the first approach, a high and stable mood is considered positive, representing a condition of general unperturbed optimism. The target is to elevate the level of the global mood while curtailing its fluctuations. This approach is supported by empirical evidence suggesting that an increase in countries' mood tends to bolster their economic, financial, and social prosperity. Furthermore, minimal fluctuations in the global mood are believed to enhance the stability of financial markets by mitigating economic imbalances caused by the so-called "animal spirits" (see De Grauwe, 2011). In this context, we propose a well-known Risk-Gain model based on symmetric risk measures, namely the Mean-Variance (MV) model (Markowitz, 1952, 1959).

In the second approach, the focus shifts from minimising mood fluctuations to avoiding low mood levels associated with an overly pessimistic environment. In this regard, we observe that waves of negative mood and pessimism might contribute to deteriorated economic performances (see, e.g., Jouini & Napp, 2011). Thus, we explore a different Risk-Gain model, the Mean-CVaRD (Conditional Value-at-Risk Deviation) portfolio problem (Rockafellar & Uryasev, 2000; Sarykalin et al., 2008; Filippi et al., 2020).

Under a third perspective, we utilise the Risk Parity (RP) approach for conceptualising the optimal portfolio model (see Maillard et al., 2010, Roncalli, 2014, Cesarone & Tardella, 2017, Cesarone & Colucci, 2018, Bellini et al., 2021). This strategy focuses on the concept of equal risk contribution and aims to ensure that all indices associated with countries contribute equally to mood fluctuations. The rationale behind this approach is to prevent any single country from predominantly influencing high and low mood waves, thereby fostering a sense of shared belonging among the countries linked to the stock indices. This could promote solidarity and facilitate a swifter psychological recovery from the crisis.

Lastly, we propose a risk diversification model, introduced by Choueifaty and Coignard (2008), which consists of maximising the relative distance between the volatility of the world's mood and that associated with the worst scenario. Here, the policymaker's objective transcends merely maximising the mood level or reducing its fluctuations. This approach aligns with the notion that mood extremes might be associated with economic distress—see, for instance, Lowe and Ziedonis (2006) for the economic analysis of overoptimism and unjustified self-confidence, and Jouini and Napp (2011) for the impact of excessive pessimism.

Several noteworthy results emerge from our empirical analysis, offering valuable insights for policymakers.

The MV optimal portfolios with low target levels for the expected mood allocate more relevance to indices associated with a set of countries of the European continent, namely Greece, Turkey, Norway, and Denmark. This reflects the model's tendency to mitigate pessimism and optimism waves in the world's mood. Conversely, stock indices related to Hong

Kong, Qatar, and Singapore assume significant roles in the optimal portfolios when targeting a high world mood level.

The Mean-CVaRD optimal portfolios, focusing on low expected mood targets, assign greater importance to indices related to Saudi Arabia, South Korea, Norway, and Malaysia, aiming to temper fluctuations towards a low-level mood of the world.

The aforementioned portfolio models are comparable in terms of the expected mood target. In both cases, there is greater diversification when the expected mood target is low compared to when it is high. However, in the MV case we have a penalization of high fluctuations of the mood, disregarding their sign. Differently, the Mean-CVaRD model specifically penalises countries having only high deviations from the expected mood from the negative side. So, the MV model curbs countries exhibiting high levels of pessimism and optimism—essentially moderating extreme mood behaviours—whereas the Mean-CVaRD model focuses solely on high levels of pessimism. This outcome is more evident when the expected mood target is low, in agreement with standard features of the Risk-Gain analysis á la Markowitz.

The RP portfolio, by construction, includes all countries/stock indices in the composition of the world's mood. As a result, the scores associated with each index within a country tend to be relatively uniform, precluding any single country from assuming a dominant role and promoting a sense of unity among the countries.

For the Most Diversified (MD) portfolio, we observe a high relevance for indices linked to Denmark, Oman, Greece, and Chile. This allocation aims to minimise fluctuations caused by pessimism and optimism waves and to distance them as much as possible from the worst-case scenario (where the imbalances in financial markets and the countries' moods are perfectly correlated). We note that, despite the appealing theoretical aspects of the Gain-Risk models, their results are quite sensitive to variations in the preselected expected gain of the optimal portfolio. In contrast, the RP and MD strategies exhibit less sensitivity to estimation errors of the model inputs (see Cesarone et al., 2020, and references therein).

The methodology we adopt for modelling pandemic-related anxiety aligns with Cerqueti and Ficcadenti (2023), where the authors develop mood indicators based on a combination of Google searches for the term "coronavirus" and the financial market performances at a country level. However, the referenced paper focuses solely on illustrating the country-based situation of anxiety, without delving into portfolio decision problems. Therefore, our paper has a more strategic objective, guiding policymakers towards different mood targets under various portfolio model characterisations. In this respect, our paper has practical implications. Indeed, we can suggest a reliable identification of a supra-national entity acting as a portfolio optimiser, giving tangible meaning to the optimal portfolio shares. Specifically, we draw a parallel with the recent global action to recover from the pandemic, the so-called National Recovery and Resilience Plan (NRRP). In the NRRP, the European Union allocated funds to individual countries for developing actions and policies to support the socio-economic environment post-pandemic shock. Among these interventions, healthcare played a crucial role. However, some countries lacked a focus on the psychological well-being of citizens. This underscores the importance of considering psychological recovery as a critical target (see, e.g., Ussai et al., 2022). Our work fits within a framework akin to the NRRP, but with a specific focus on psychological recovery from COVID-19. In this context, the European Union can be viewed as a policymaker deeply invested in determining the frustration levels of EU state citizens. To this end, one could introduce a mood indicator—like the one we propose in this paper—to represent the general mood state of a given country's inhabitants. The mood indicators of individual countries are then aggregated to form a global (European) mood—analogous to the world mood in our context. The European Union would then establish actions to achieve specific targets related to this global mood by optimally allocating resources to individual countries—as already executed for the NRRP. These policies are formalised through the establishment of portfolio problems in various contexts—as explained in this paper. The optimal portfolio shares give the percentage of the capital to be allocated to the individual countries to achieve the proposed goal. In our model, the shares capture the relevance of the countries (in terms of indices and searches) in achieving specific targets. These shares can also be suitably scaled to account for the differing population sizes of the countries. As with the NRRP, the European Union provides guidelines for explicit actions by institutions, universities, and research centres. The inclusion of non-European countries such as China—whose relevance in the context of COVID-19 is undeniable, see Sect. 5.1—can be interpreted as the establishment of strategic interactions between the European Union and other countries, envisaging an extended version of the NRRP specifically targeting psychological recovery from the pandemic.

The remainder of the paper is organised as follows. Section 2 reviews relevant literature for our study. Section 3 defines the statistical indicator for measuring mood, introducing its main properties and characteristics. In Sect. 4 we develop the employed concept of portfolio and present the four portfolio selection models considered. Section 5 is dedicated to empirical experiments, presenting the dataset used and critically analysing the study's results. The final section offers some concluding remarks.

2 Literature review

There is a wide literature showing that financial markets are vulnerable to catastrophic and unexpected events of non-financial nature like aviation disasters (see, e.g., Kaplanski & Levy, 2010), terrorist attacks (see, e.g., Goel et al., 2017), or, recently, COVID-19 (see, e.g., Štefan Lyócsa et al., 2020). Importantly, there is evidence that the occurrence of disasters tends to generate approximately instantaneous dramatic collapses in prices (see, e.g., Barro, 2006, Gabaix, 2012, Gourio, 2012). In the particular context of the pandemic, Goodell (2020) highlights the existence of an explicit parallelism between COVID-19 and terrorism, disasters of ecological nature and nuclear conflicts. Undoubtedly, intuitive psychological reasons explain the link between disasters and the approximately instantaneous fall in financial indices, being disasters associated with anxiety, panic, and consequent loss of confidence in the financial markets. In Da et al. (2014), the authors found that online searches of locutions attributable to the sense of *fear* are instantaneously related to financial returns (some aspects of the timing in the relationship have been recently confirmed in Nikkinen and Peltomäki, 2020), and in Da et al. (2011) a proposal for detecting investors' attention in a timely manner is made, and it is based on Google searches.

We are in line with this strand of literature, and we adopt the view that the collapse of the stock index prices might effectively contribute to measuring the effect of the pandemic on the mood of the citizens of the related country. We then align with recent literature showing that COVID-19 has led to anxiety and pessimistic expectations about economic performance. Binder (2020) provides a survey study showing that the anxiety about the pandemic mirrors the loss of confidence in positive future outcomes of macroeconomic variables. Fetzer et al. (2020) extend the perspective offered by Binder (2020) by including time dependence and exploring the causal effect of COVID-19 on the growth of anxiety of economic nature. Interestingly, when reporting the results of Binder's survey, she wrote, "Nearly all participants follow news about coronavirus, 50% somewhat closely and 43% very closely". Concerning the expectations related to the pandemic, she reports: "concerns about economic effects are most prevalent, with 52% somewhat concerned and 38% highly concerned. Consumers who follow news about the coronavirus more closely tend to be more concerned about the effects of the virus”. Furthermore, “respondents who own stocks or follow news about the stock market seem more attentive to coronavirus news, more concerned [...]”. Under the same perspective, Fetzer et al. (2020) focus on sentiment information by highlighting the interrelation between Google Trends data and the measurement of how people react to the pandemic. Google Trends data are also used by Nikolopoulos et al. (2021) for implementing forecasting exercises on the “excess and intermittent demand” that leads to “panic buying” (see Tsao et al., 2019) of “different products and services including groceries, electronics, automotive and fashion” for timely adjustments of the logistics in supply chains management. Garfin et al. (2020) clearly state that online searches and exposure to media are strongly connected to the fear of such a pandemic disease. More specifically, a large (small) amount of coronavirus-related searches on the web is associated with a high level of pessimism (optimism).

We now discuss relevant contributions related to PDA being the employed methodological framework chosen for this paper.

Taking portfolio selection models whose optimal shares represent a measure of the relevance of the associated alternatives is also the ground of the well-known and widely used Composite Indicator of Systemic Stress (CISS). It is a portfolio-based systemic risk assessment device developed by the European Central Bank (ECB, see the research paper Hollo et al., 2012). The authors consider five stress measures—based on five categories—in the context of systemic risk; then, they identify the relative weights of such measures for detecting the relevance of the related stress categories—the higher the weight, the more relevant the category for minimising systemic risk.

In general, the need to make optimal decisions under uncertain conditions—eventually subject to specific constraints—is one of the main drivers of OR-based studies. Recently, in Salo et al. (2011), the idea of taking decisions within a set of available alternatives has been translated into mathematical methods and models, defining the Portfolio Decision Analysis (PDA). Such a theoretical framework is the approach adopted in this paper for facing our research objectives. Liesiö et al. (2020b) contains a recent review of developments and prospects of PDA, and it is the paper from which we grasp motivations for adopting a PDA approach in our study. Indeed, quoting Liesiö et al. (2020b), one reads “Typical PDA analyses provide recommendations for the selection of projects or the allocation of resources”. Furthermore, our work falls in the “two-thirds of articles in the sample of the methodologically oriented PDA papers reporting realistic applications” (again from Liesiö et al., 2020b, where 148 articles related to PDA are reviewed).

In general, PDA is helpful for formalising rational decision-making processes and identifying straightforward optimal solutions. PDA helps in obtaining a view and consequent management insights throughout the analysis of the resulting efficient sets of solutions. In this respect, such a methodological framework supports decisions among multiple scenarios by evaluating the individual contributions to pre-identified objectives.

PDA has been widely employed in several applied contexts. Baker et al. (2020)’s authors take the government as the policymaker and deal with the analysis of research and development expenses for designing the energy technology in the context of climate change. In the same vein, the authors in Liesiö et al. (2020a) and Toppila et al. (2011) present a decision model for allocating resources in portfolios of decision-making units and research and development activities. Differently, Grushka-Cockayne et al. (2008) explore a problem of air traffic flow optimisation by clearly illustrating the various elements of the reference PDA context. In Barbati et al. (2020), the authors identify the optimal combination of facilities by considering their multi-attribute nature, with a particular reference to their locations and activating times. Mild et al. (2015) adopt a PDA approach for the selection of the maintenance projects of the bridges and apply their study to the data of the Finnish Transportation Agency. Kangaspunta et al. (2012) evaluate the cost-efficiencies of weapon systems portfolios, while Chowdhury and Quaddus (2015) select "the most satisfactory efficient portfolio of supply chain resilience strategies" for the case of three Bangladesh companies. More in general, research involving PDA applications can be found in the IT sector (Gemici-Ozkan et al., 2010), energy management (Cranmer et al., 2018), health care field (Mastorakis & Siskos, 2016; Phillips & e Costa, C. A. B., 2007) and many others. In Barbati et al. (2018), the authors advance a portfolio decision problem by also considering the qualitative satisfaction level of the policymaker's choices as the objective function to be maximised. We are close to the perspective of Barbati et al. (2018), in that we here consider the mood—which is undoubtedly a qualitative variable—as the objective function. As stated above, we offer a quantitative translation of mood to be used in the optimisation process. Castellano et al. (2021) also define the shares of a portfolio as relative relevance scores assigned to units for pursuing a predefined target. They use countries as units, and the target is the systemic risk minimisation. However, to the best of our knowledge, our paper is the first to address the optimal selection of units for analysing COVID-19 and its consequences in the context of sentiment formation.

3 Statistical indicator for the mood

This section provides formal definitions of reliable measures of the mood of citizens in various countries when dealing with pandemics and financial markets. As previously discussed, our scientific basis is grounded in the evidence—well-established in recent authoritative literature—that a simultaneous increase in Google searches and a decrease in stock index prices capture a sense of pessimism, while a concurrent decline in Google searches and a rise in prices indicate an optimistic mood.

To address the optimal portfolio problem, we have designed a statistical indicator that captures the interplay between anxiety about the pandemic and expectations regarding the future performance of financial markets—in brief, the *mood*.

3.1 Preliminaries and notation

Consider J countries. In a country j, there are $K(j)$ stock indices, so that the generic stock index of country j is denoted by $k(j) = 1, \ldots, K(j)$—with the majority of their components linked to the country in question. The total number of considered stock indices is denoted by

$$K = \sum_{j=1}^{J} K(j).$$

By construction, $K \geq J$.

We consider a common observation period of T days for both the stock indices' prices and the Google searches data. Specifically, we excluded Google search results that do not correspond with financial data for the same date. When the market is closed in a country, there are no values for price; thus, the corresponding Google searches cannot be used in constructing the mood indicator.

For country j, the daily prices of stock index $k(j)$ are denoted by $\mathbf{p}_{k(j)} = (p_{k(j)}(1), \ldots, p_{k(j)}(T))$, while the volume of Google searches for the term "*coronavirus*" (and its translations) in country j is represented by $\mathbf{w}^j = (w^j(1), \ldots, w^j(T))$.

Note that prices are nonnegative quantities, and Google searches—sourced from Google Trends, as detailed in Sect. 5.1—range from 0 to 100. A value of $w^j(t) = 0$ indicates no Google searches reported at time t in country j. Hence, null values of ws are not always observed. Indeed, there may be a nonnull amount of searches every "day"—by taking "days" as the time units—so a value of 0 is rarely achieved. Conversely, a value of 100 certainly appears in correspondence with the day having the highest level of searches. However, when querying a large volume of data from Google Trends, careful attention is required due to Google's scaling system for the search volume index. During data download from Google Trends, the geographical area of interest is selected, leading to normalization within that geographical area. This means that each query to download the search volume of a word in a country is normalized between 0 and 100, allowing for comparisons among countries. For 1-year data requests, as in our case, the most granular accessible data is weekly (a common limitation noted by scholars, see Maggi & Uberti, 2018, 2021). In this scenario, the index value of 100 corresponds to the week with the maximum searches over the queried period. Conversely, for a 1-month request, daily data is normalized for that month. Therefore, a value of 100 obtained from a monthly query and a value of 100 derived from yearly data normalization are not directly comparable. To address this issue, we implemented the following procedure to derive daily observations from weekly data (in line with methods used in other studies, such as Vollmer et al., 2021). Initially, for each country, monthly search volumes are downloaded, providing daily volumes for each month—as Google permits daily data downloads for 1-month periods. Subsequently, weekly data are downloaded for the entire period (01/01/2020–31/12/2020, see Sect. 5.1), yielding 52 observations, one per week. The weekly data are then multiplied by the corresponding daily values obtained in the first phase, and the resultant figure is divided by 100.

For comparison purposes, we also normalize the series of observed daily prices to the range of [0, 100], converting $p_{k(j)}(t) \in [0, +\infty)$ to a corresponding $\bar{p}_{k(j)}(t) \in [0, 100]$. To achieve this, we identify $\bar{t} \in \{1, \ldots, T\}$ such that $p_{k(j)}(\bar{t}) = \max\{p_{k(j)}(t) : t = 1, \ldots, T\}$ and set

$$\bar{p}_{k(j)}(t) = \left[100 \times \frac{p_{k(j)}(t)}{p_{k(j)}(\bar{t})} \right], \quad \forall t = 1, \ldots, T, \tag{1}$$

where $[\bullet]$ denotes the integer part of number $\bullet$. This Formula (1) sets the $\bar{p}_{k(j)}$'s value to 100 for the highest price observed in the period $\{1, \ldots, T\}$; $\bar{p}_{k(j)}(t) = 0$ when $p_{k(j)}(t) = 0$.

The daily variations of the normalized daily prices $\bar{p}$'s and the Google searches w's are denoted as follows:

$$\Delta \bar{p}_{k(j)}(s) = \bar{p}_{k(j)}(s+1) - \bar{p}_{k(j)}(s), \quad \forall s = 1, \ldots, T-1, \tag{2}$$

and

$$\Delta w^j(s) = w^j(s+1) - w^j(s), \quad \forall s = 1, \ldots, T-1, \tag{3}$$

3.2 Definition and properties of the mood indicator

We propose a time-dependent mood indicator based on the comparison of variations in daily prices and Google searches, as given in Eqs. (2) and (3). First, we define the indicator; then, we discuss its properties and relevant observations.

Consider $t \in \{1, \ldots, T-1\}$, $j = 1, \ldots, J$ and $k(j) = 1, \ldots, K(j)$. We define

$$m_{t,k(j)} = \frac{1}{4 \times 10^4} \cdot \Big[\alpha(\bar{p}_{k(j)}(t)) \cdot \Delta\bar{p}_{k(j)}(t) - \alpha(w^j(t)) \cdot \Delta w^j(t) + 2 \times 10^4\Big], \quad (4)$$

where, given $H = \bar{p}_{k(j)}, w^j$, we have

$$\alpha(H(t)) = \begin{cases} H(t), & \text{if} \quad \Delta H(t) \geq 0; \\ 100 - H(t), & \text{if} \quad \Delta H(t) < 0. \end{cases} \quad (5)$$

The indicator in Formula (4) jointly evaluates the stock index price $\bar{p}_{k(j)}$ and the extent of Google searches w^j. The former serves as a proxy for confidence in the performance of index $k(j)$; the latter reflects the level of pandemic-related anxiety experienced by the citizens of country j.

The daily prices in the $\bar{p}_{k(j)}$ result from investments in $k(j)$. Empirical evidence suggests that transactions based on index $k(j)$ are predominantly made by citizens of country j—the host country of $k(j)$. Nevertheless, the involvement of foreign investors cannot be discounted. Thus, investing in $k(j)$ also signifies trust in the economic status and prospects of country j.

Therefore, from a general perspective, a thoughtful combination of the prices of $k(j)$ and the Google searches in country j enables us to interpret the mood of country j. More specifically—as mentioned in the Introduction—we explore the link between financial mood and trust in the performance of stock indices in country j, and the anxiety surrounding the pandemic. Pessimism is indicated when trust in financial performance is low, and anxiety is high; conversely, optimism is signalled by high economic confidence and low pandemic-related anxiety.

For analysing the financial aspect of country j's mood, we rely on the stock indices $k(j) = 1, \ldots, K(j)$; thus, as detailed later, the mood of country j is also represented through aggregated confidence in the performance of stocks within the indices related to country j (see Formula (7) in Sect. 4).

By (4), we find $m_{t,k(j)} \in [0, 1]$. Indeed, the construction of (4) is informed by the variation range of the Google Trends data, which is [0, 100]. We have retained this range and accordingly set the range of variation for the financial component to [0, 100]. The components of the indicator are quadratic so that 10^4 acts as a scale factor for normalisation, setting the range to [0, 1].

This indicator comprises terms of two different types: the Δ's represent daily variations, while the function α acts as a variation weight. To elucidate the meaning of $m_{t,k(j)}$, let's delve into the details.

One has $\Delta\bar{p}_{k(j)}(t) > 0$ when the daily price of the stock index labelled $k(j)$ has increased from day t to $t+1$. This signifies rising investor confidence in its future performance, reflecting optimistic behaviour. In the same way, $\Delta w^j(t) < 0$ is a signal of optimistic behaviour; indeed, this case is associated with a decreasing interest in the pandemic as reflected in Google searches, suggesting a reduction in related anxiety. In the former scenario, optimism is amplified by a high level of price $\bar{p}_{k(j)}(t)$. Specifically, for a given fixed level of $\Delta\bar{p}_{k(j)}(t) > 0$, the optimism is more pronounced when the initial price $\bar{p}_{k(j)}(t)$ is higher. The rationale behind this condition lies in the evidence that when the increasing confidence in the stock market moves from a good performance, optimism is persistent, and it is more radicated. By following the same argument, the optimism described in the latter case is amplified when $w^j(t)$ is small, i.e., when $100 - w^j(t)$ is large. In the same way, we have that $\Delta\bar{p}_{k(j)}(t) < 0$ and $\Delta w^j(t) > 0$ describe situations of pessimism. Such moods are exacerbated when price $\bar{p}_{k(j)}(t)$ is low and the Google searches $w^j(t)$ are large. Indeed, these cases are associated with the persistence of pessimism.

The indicator $m_{t,k(j)}$ is a normalised measure reflecting the level of optimism in country j for index $k(j)$; $m_{t,k(j)}$ increases as the level of optimism grows. In particular, such an indicator approaches one when, *ceteris paribus*, $\Delta\bar{p}_{k(j)}(t)$ and $\bar{p}_{k(j)}(t)$ approach 100, $\Delta w^j(t)$ approaches -100 and $w^j(t)$ approaches zero. Conversely, $m_{t,k(j)}$ gravitates towards zero when, *ceteris paribus*, $\Delta\bar{p}_{k(j)}(t)$ goes to -100, $\bar{p}_{k(j)}(t)$ approaches zero while $\Delta w^j(t)$ and $w^j(t)$ approach 100. The former scenario is indicative of high optimism, while the latter is symptomatic of strong pessimism.

4 Optimal portfolio models

This section outlines the considered optimal allocation models. First, we provide the definition of the portfolios. Then, we present the portfolio selection strategies analysed.

4.1 Definition of the portfolio

The starting point of the analysis is a concept of time-dependent (non-financial) portfolio, whose definition is formally given as follows.

Definition 4.1 Consider $t = 1, \dots, T-1$. The K-ple of real numbers $\pi(t) = (\pi_1(t), \dots, \pi_K(t))$ is said to be a portfolio at time t when $\sum_{i=1}^{K} \pi_i(t) = 1$ and $\pi_i(t) \geq 0$, for each $i = 1, \dots, K$. The π's are the shares of the portfolio. Vector $\pi = (\pi(1), \dots, \pi(T-1))$ is a portfolio trajectory—or, simply, a portfolio.

The mathematical definition of portfolio π in Definition 4.1 is the same as the standard financial one in Markowitz (1952, 1959), when short-selling is not allowed. However, the interpretation of the shares of the portfolio is radically different here. By employing the notation introduced in the previous sections, we say that $\pi_{k(j)}(t)$ is the share of the portfolio associated with the j-th country—with specific reference to the $k(j)$-th index—at time t, for each $j = 1, \dots, J$ and $k(j) = 1, \dots, K(j)$. Such a share provides a measure of the relevance of country j and, specifically, index $k(j)$ for pursuing the targets formalised in the proposed portfolio models. After stating the optimisation models, we will provide several details on the meaning of the portfolio below.

The proposed portfolio models are based on the evaluation of the aggregated moods of the considered countries—briefly, the *mood of the world*—on the basis of the time-dependent statistical indicator introduced in the Formula (4).

Definition 4.2 Fix a time $t = 1 \dots, T-1$ and a portfolio $\pi(t) = (\pi_1(t), \dots, \pi_K(t))$. The mood of the world at time t associated to the portfolio $\pi(t)$ is

$$M(t,\pi) = \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \pi_{k(j)}(t) m_{t,k(j)}. \tag{6}$$

Definition 4.2 clarifies the meaning of the shares of the portfolio $\pi(t)$. Indeed, the term $\pi_{k(j)}(t)$ represents the relative contribution of the index $k(j)$ in country j to the mood of the world. Indeed, Formula (6) claims that the mood of the world is a weighted mean of the moods based on the consider stock indexes, and the shares of the portfolio represent the weights.

Furthermore, given $j = 1, \ldots, J$, one can identify the relative contribution of country j in $\pi(t)$ by aggregating the shares of the portfolio related to the indexes linked to country j, so that one has

$$\pi^j(t) = \sum_{k(j)=1}^{K(j)} \pi_{k(j)}(t). \tag{7}$$

Interestingly, vector $\pi(t; j) = (\pi^1(t), \ldots, \pi^J(t))$ is still a portfolio according to Definition 4.1, whose shares represent the relative relevance of the countries for the mood of the world. Such a portfolio has intuitively relevant informative content. However, the term $\pi^j(t)$ in Formula (7) is an aggregated quantity; therefore, one does not have the possibility of identifying from it its granular components—i.e., the relative contribution of an individual index $k(j)$ linked to country j.

4.2 Portfolio selection models

COVID-19 has a vast impact on countries' moods (and therefore on the world's mood), affecting social, political and economic aspects of the citizens' lives. An analysis of these impacts is essential to understand and manage the effects of the world's mood on society and the economy. Indeed, waves of generalised optimism and pessimism—i.e., the behaviour of the world's mood—might be driven by the anxiety of the citizens in specific countries. Thus, the action for leading the world's mood towards a target has to provide the relative contributions to be assigned to stock indexes and countries, i.e., the optimal portfolio. We aim to identify the weights of a given set of stock indexes and countries so that the selected world's mood portfolio is the best one according to specific criteria. To accomplish this objective, we exploit several concepts of portfolio optimisation. As a consequence, these selected portfolios could give the policymaker an indication of which stock indexes and countries are more relevant to achieve prefixed goals in terms of global mood. For this purpose, we introduce the optimal portfolio models used for this analysis. More precisely, we investigate two classes of models for selecting a portfolio: the classical Risk-Gain analysis á la Markowitz and risk diversification approaches. The first class consists of maximizing the expected value of the world's mood while simultaneously minimizing its fluctuations. Such fluctuations are evaluated by means of two deviation risk measures (see Rockafellar et al., 2006), volatility and Conditional Value-at-Risk Deviation. In fact, in portfolio selection, typically, we can distinguish a first step of the Risk-Gain analysis where the efficient portfolios, namely the Pareto-optimal solutions, are identified. Then, among the Pareto-optimal portfolios, we can adopt preference criteria, for instance, by requiring specific target levels in terms of portfolio risk or gain, which, therefore, are eventually introduced in the second step of the Risk-Gain analysis (see, e.g., Cesarone, 2020). In this specific case, we know *a-priori* that when the required level of the expected value of the world's mood increases, the number of countries involved in the Pareto-optimal solutions typically tends to decrease. For the second class, we consider two relatively recent risk-focused portfolio selection approaches. The Risk Parity (RP) strategy aims to achieve a balanced portfolio in terms of mood fluctuation. This risk diversification approach is based on the general notion of equal risk contribution from each asset. It can be shown that the fluctuation of the RP portfolio is bounded between the fluctuation of the minimum risk portfolio and that of the Equally Weighted portfolio (Cesarone & Tardella, 2017; Cesarone et al., 2020; Cesarone & Colucci, 2018). The Maximum Diversification ratio approach consists in maximizing the relative distance between the portfolio risk in the worst-case scenario, namely when risk is additive, and the generic portfolio risk. Note that risk is additive when the risk drivers are highly dependent (see, Cesarone et al., 2023, Ararat et al., 2024, Bellini et al., 2021).

We assume that the country moods are discrete random variables distributed in a discrete state space, and that there are T states of nature, each with probability q_t with $t = 1, \ldots, T$. We use a look-back approach where the outcomes of the discrete random variables correspond to past realised data. More precisely, the choice of the relative contributions of stock indexes and countries to the world's mood is made using T historical scenarios, each with probability $q_t = 1/T$, if there are no ties (see, e.g., Carleo et al., 2017, Cesarone, 2020, and references therein). In so doing, we start from Formulas (4) and (6) and consider the related random variables $m_{k(j)}$ and $M(\pi)$, respectively.

The optimal allocation models' formalizations follow the arguments of the Introduction, related to optimal criteria based on what is expected by the value of the mood and on its fluctuations. A location parameter captures the former quantity, i.e., the expected value of the mood of the world $\mu(\pi) = \mathbb{E}[M(\pi)]$, whilst the latter one is given by a dispersion parameter (e.g., the variance of $M(\pi)$), that yields an indication of the amplitude of the oscillations around the location.

4.2.1 Pareto-optimal risk-gain portfolios

In this section, we describe two portfolio selection models focused on the Risk-Gain analysis, namely the study of the best trade-off between the maximisation of the gain—i.e., the expected value—and the minimisation of the risk—i.e., the fluctuations of the mood. In particular, we consider two well-known Risk-Gain models based on both symmetric and asymmetric risk measures. In the former case, we seek the stability of the mood, while the latter is associated with avoiding overpessimism.

The symmetric framework is the classical MV model (Markowitz, 1952, 1959). With it, we aim to determine the relative contribution of each index $k(j)$ linked to country j, $\pi_{k(j)}$, to the total mood of the world that minimises the whole portfolio mood instability represented by its variance while binding the expected mood of the portfolio to attain at least a fixed target level of the mood. Thus, denoting by $\sigma^2(\pi)$ the variance of the world's mood, the MV model can be expressed by the following optimisation problem

$$
\begin{aligned}
&\min_{\pi} \ \sigma^2(\pi) = \sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \sigma_{h(i)k(j)} \pi_{h(i)} \pi_{k(j)} \\
&s.t. \\
&\qquad \mu(\pi) = \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \pi_{k(j)} \mu_{k(j)} = \eta \\
&\qquad \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \pi_{k(j)} = 1 \\
&\qquad \pi_{k(j)} \geq 0 \quad k(j) = 1, \ldots, K(j) \quad \text{and} \quad j = 1, \ldots, J
\end{aligned}
\tag{8}
$$

where $\mu_{k(j)}$ represents the expected mood of the index $k(j)$ in country j, and $\sigma_{h(i)k(j)}$ is the covariance between moods of the index $h(i)$ (of country i) and $k(j)$ (of country j) with $i, j = 1, \ldots, J$. Furthermore, $\eta \in [\eta_{min}, \eta_{max}]$ is the required level of the portfolio expected mood, where η_{min} denotes the value of the portfolio expected mood $\mu(\pi)$ at an optimal solution of the problem obtained by deleting the first constraint in Formula (8), whilst $\eta_{max} = \max\{\ldots, \mu_{k(j)}, \ldots, \mu_{K(j)}, \ldots\}$ with $j = 1, \ldots, J$ (see, e.g., Cesarone et al., 2013, Cesarone, 2020).

The second model is based on an asymmetric risk measure, the Conditional Value-at-Risk (CVaR) (Rockafellar & Uryasev, 2000) at a specified confidence level $\varepsilon > 0$, $CVaR_\varepsilon$, i.e., in financial terms, the mean of losses in the worst $100\varepsilon\%$ of the cases (Acerbi & Tasche, 2002), where losses are defined as negative outcomes. Therefore, it makes sense to minimize $CVaR_\varepsilon$ only if it is positive (Sarykalin et al., 2008). Since our quantity of interest is the *world's mood portfolio* $M(\pi)$, that is a nonnegative random variable—more precisely, $M(\pi) \in [0, 1]$—we use CVaR Deviation (CVaRD) as a risk measure, namely $CVaRD_\varepsilon(\pi) = CVaR_\varepsilon(\mu(\pi) - M(\pi))$. A formal definition of CVaRD is

$$CVaRD_\varepsilon(\pi) = \frac{1}{\varepsilon}\int_0^\varepsilon Q_{\mu(\pi)-M(\pi)}(\alpha)d\alpha\,, \tag{9}$$

where $Q_{\mu(\pi)-M(\pi)}(\alpha)$ is the α-quantile function of the deviation of the portfolio mood $M(\pi)$ from its mean $\mu(\pi)$.

Similar to the MV model, the Mean-CVaRD model can be expressed by the following optimization problem:

$$\begin{aligned} &\min_{\pi}\ CVaRD_\varepsilon(\pi) \\ &s.t. \\ &\quad \mu(\pi) = \sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)} \pi_{k(j)}\mu_{k(j)} = \eta \\ &\quad \sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)} \pi_{k(j)} = 1 \\ &\quad \pi_{k(j)} \geq 0 \quad k(j) = 1, \ldots, K(j) \quad \text{and} \quad j = 1, \ldots, J \end{aligned} \tag{10}$$

Unlike Model (8) where both positive and negative deviations of the world's mood portfolio from its mean are penalized, Model (10) aims to identify those portfolio weights that minimize the mean of the world's mood portfolio in the worst $100\varepsilon\%$ of the cases, namely the cases of greatest "pessimism" in the world.

From a computational point of view, Model (10) can be reformulated as a linear programming problem using the same approach of Rockafellar and Uryasev (2000). Thus, we have

$$\begin{aligned} &\min_{(\pi,\zeta,d)}\ \zeta + \frac{1}{\varepsilon T}\sum_{t=1}^{T} d_t \\ &\text{s.t.} \\ &\quad d_t \geq \sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)} (\mu_{k(j)} - m_{t,k(j)})\pi_{k(j)} - \zeta \quad t = 1, \ldots, T \\ &\quad d_t \geq 0 \quad t = 1, \ldots, T \\ &\quad \mu(\pi) = \sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)} \pi_{k(j)}\mu_{k(j)} = \eta \\ &\quad \sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)} \pi_{k(j)} = 1 \\ &\quad \pi_{k(j)} \geq 0 \quad k(j) = 1, \ldots, K(j) \quad \text{and} \quad j = 1, \ldots, J \\ &\quad \zeta \in \mathbb{R} \end{aligned} \tag{11}$$

This reformulation is obtained by considering T auxiliary variables d_t defined as the deviation of $\sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)}(\mu_{k(j)} - m_{t,k(j)})\pi_{k(j)}$ from ζ when $\sum_{j=1}^{J}\sum_{k(j)=1}^{K(j)}(\mu_{k(j)} -$

$m_{t,k(j)})\pi_{k(j)} > \zeta$ and 0 otherwise, and by adding the following constraints: $d_t \geq 0$, $d_t \geq \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} (\mu_{k(j)} - m_{t,k(j)})\pi_{k(j)} - \zeta \forall t$. Note that when solving this optimisation problem, the optimal value of the variable ζ coincides with $VaR_{\varepsilon}(\pi^{\star})$, where $\pi^{\star}$ is the optimal solution of Problem (11).

4.2.2 Risk diversification strategies

In this section, we present two relatively recent portfolio selection approaches focused on risk diversification. More precisely, we are looking for portfolios that can be interpreted as indicative scores associated with each stock index in a country and that allow us to obtain the goals described through the two risk-focused portfolio selection strategies described below. One of the main methodological reasons why we examine models based on risk diversification strategies is that, as shown by the extensive empirical analysis of Cesarone et al. (2020), generally, they are less sensitive to estimation error of the inputs to the model.

The Risk Parity (RP) strategy, developed by Maillard et al. (2010), in the case where the volatility measures the risk $\sigma(\pi) = \sqrt{\sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \sigma_{h(i)k(j)} \pi_{h(i)} \pi_{k(j)}}$, requires that each asset equally contributes to the total risk of the portfolio. In this way, one pursues the target of avoiding the existence of a country with a leading role in generating waves of optimism and pessimism, hence fostering a shared sense of belonging. The standard approach used for decomposing the portfolio volatility is the Euler allocation, namely $\sigma(\pi) = \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} RC_{k(j)}(\pi)$, where

$$RC_{k(j)}(\pi) = \pi_{k(j)} \frac{\partial \sigma(\pi)}{\partial \pi_{k(j)}} = \frac{1}{\sigma(\pi)} \sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} \sigma_{h(i)k(j)} \pi_{k(j)} \pi_{h(i)}$$

is the risk contribution of the $k(j)$th index in country j. The RP approach requires equality of all total risk contributions

$$RC_{h(i)}(\pi) = RC_{k(j)}(\pi) \Leftrightarrow \sum_{l=1}^{J} \sum_{k(l)=1}^{K(l)} \sigma_{h(i)k(l)} \pi_{h(i)} \pi_{k(l)} = \sum_{l=1}^{J} \sum_{k(l)=1}^{K(l)} \sigma_{k(j)k(l)} \pi_{k(j)} \pi_{k(l)} \quad \forall h(i), k(j).$$

Then, a possible method for finding an RP portfolio is to solve the following system of linear and quadratic equations and inequalities

$$\begin{cases} \sum_{l=1}^{J} \sum_{k(l)=1}^{K(l)} \sigma_{h(i)k(l)} \pi_{h(i)} \pi_{k(l)} = \lambda & h(i) = 1, \ldots, K(i) \quad \text{and} \quad i = 1, \ldots, J \\ \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \pi_{k(j)} = 1 & \\ \pi_{k(j)} \geq 0 & k(j) = 1, \ldots, K(j) \quad \text{and} \quad j = 1, \ldots, J \end{cases} \tag{12}$$

that has a unique solution when the covariance matrix Σ is positive definite (Cesarone et al., 2020). Therefore, applying the RP strategy to the world's mood portfolio leads to the search of the weights of all indexes in such a way that their contributions to the total volatility of the world's mood are equally distributed among all indexes.

An alternative strategy based on risk allocation has been introduced by Choueifaty and Coignard (2008) and consists in maximising the so-called diversification ratio

$$DR(\pi) = \frac{\sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \pi_{k(j)}\sigma_{k(j)}}{\sqrt{\sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \sigma_{h(i)k(j)}\pi_{h(i)}\pi_{k(j)}}}, \tag{13}$$

where $\sigma_{k(j)}$ is the mood volatility of $k(j)$. Note that $DR(\pi)$ represents the ratio between the portfolio volatility in the worst case—i.e., where the indexes are all perfectly positively correlated with each other—and the generic portfolio volatility for any correlation structure of the market. Clearly, employing the convexity property of volatility, we have that $DR(\pi) \geq 1$.

As shown by Choueifaty et al. (2013), the Most Diversified (MD) portfolio, namely the optimal portfolio that maximizes the diversification ratio (13), can be found by solving the following (convex) quadratic programming problem

$$\begin{aligned} \min_{y} \; & \sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} \sigma_{h(i)k(j)} y_{h(i)} y_{k(j)} \\ s.t. \; & \\ & \sum_{j=1}^{J} \sum_{k(j)=1}^{K(j)} y_{k(j)}\sigma_{k(j)} = 1 \\ & y_{k(j)} \geq 0 \quad k(j) = 1, \ldots, K(j) \quad \text{and} \quad j = 1, \ldots, J \end{aligned} \tag{14}$$

The normalized portfolio weights are $\pi_{k(j)}^{MD} = \frac{y_{k(j)}^*}{\sum_{i=1}^{J} \sum_{h(i)=1}^{K(i)} y_{h(i)}^*}$ with $k(j) = 1, \ldots, K(j)$ and $j = 1, \ldots, J$, where y^* is the optimal solution of Problem (14). Hence, the optimal portfolio choice π^{MD} identifies the relative contribution of each index to the world's mood, so that the distance between the volatility of the world's mood and the volatility relative to the worst scenario (i.e., the case where all moods are perfectly correlated) is maximum.

5 Empirical experiments

This section proposes the empirical validation of the theoretical setting described above. We first present the data used and then report the results.

5.1 Data

This section discusses the data collected and organized for implementing the optimal allocation models proposed in this study. Our experiment focuses on countries with a development level that ensures access to online sources and financial markets. We have chosen a set of countries based on the Human Development Index (HDI) used by the United Nations Development Programme (UNDP)'s Human Development Report Office. This index includes indicators of life quality, education, and standard of living. We selected countries categorised as "very high human developed countries" in Table 1 of UNDP (2019), based on 2018 data, namely those with an HDI greater than 0.8. Additionally, China, with an HDI of 0.75, is included due to its central role in the pandemic's spread, bringing the total to 63 countries.

In each selected country, the term "*coronavirus*" is translated into the most spoken language using Google Translate. These translations are listed in Table 1. Online searches for

Table 1 The table reports the country name, translation from English of "*coronavirus*", in the most used language in the respective country. A statistical summary of the volumes of searches (from Google Trends) along the period of reference

Country	Terms	μ	σ	Skew	Kurt	μ/σ
Andorra	Corona virus	1.789	8.699	6.988	57.651	0.206
Argentina	coronavirus	12.769	15.724	2.985	10.410	0.812
Australia	coronavirus	13.080	16.993	2.583	6.574	0.770
Austria	Coronavirus	8.962	13.481	3.859	17.115	0.665
Bahamas	coronavirus	7.794	14.121	3.133	11.283	0.552
Bahrain	فيروس كورونا	4.957	9.470	4.647	33.664	0.523
Barbados	coronavirus	9.378	16.913	2.705	7.234	0.554
Belarus	корона вирус	5.910	14.094	3.568	13.643	0.419
Belgium	coronavirus	12.036	15.742	2.669	7.336	0.765
Brunei	Virus korona	1.082	9.713	9.456	90.811	0.111
Bulgaria	коронавирус	14.403	14.626	2.329	7.197	0.985
Canada	coronavirus	11.507	15.649	2.684	7.167	0.735
Chile	coronavirus	8.961	13.358	3.411	14.141	0.671
China	新冠 病毒	5.815	12.446	3.113	11.741	0.467
Croatia	koronavirus	17.143	16.323	1.718	3.959	1.050
Cyprus	κορων οϊόσ	1.910	9.601	6.297	43.759	0.199
Czech Republic	koronavirus	10.777	14.553	3.800	16.216	0.741
Denmark	coronavirus	8.694	14.878	3.626	14.068	0.584
Estonia	koroona viirus	2.443	9.918	6.181	46.038	0.246
Finland	koronaviirus	1.889	8.788	7.327	64.551	0.215
France	Corona virus	5.949	13.429	4.043	18.379	0.443
Germany	Coronavirus	11.088	14.463	2.719	7.708	0.767
Greece	κορωνοϊόσ	2.342	7.974	9.592	101.357	0.294
Hong Kong	新冠 病毒	13.900	16.678	2.091	5.531	0.833
Hungary	koronavírus	14.084	16.162	2.499	6.742	0.871
Iceland	kórónaveira	2.183	13.242	6.082	36.013	0.165
Ireland	coronavirus	13.695	16.672	2.547	6.975	0.821
Israel	נגיף קורונה	8.341	16.722	2.818	8.615	0.499
Italy	coronavirus	13.731	16.933	2.882	9.239	0.811
Japan	コロナウイルス	16.255	18.273	2.154	4.644	0.890
Kazakhstan	коронавирус	15.540	20.284	1.813	2.662	0.766
Kuwait	فيروس كورونا	6.102	10.521	3.805	21.492	0.580
Latvia	koronavīruss	4.778	12.392	4.206	20.845	0.386
Liechtenstein	Coronavirus	5.380	12.513	3.817	17.307	0.430
Lithuania	koronavirusas	11.839	17.571	2.632	6.801	0.674
Luxembourg	Corona virus	4.563	12.499	4.416	22.394	0.365
Malaysia	virus korona	3.664	10.643	4.898	28.955	0.344
Malta	koronavirus	0.818	7.302	9.821	104.445	0.112
Montenegro	вирус корона	1.279	7.956	8.016	77.539	0.161
Netherlands	coronavirus	10.071	16.422	2.886	8.424	0.613

Table 1 continued

Country	Terms	μ	σ	Skew	Kurt	μ/σ
New Zealand	coronavirus	10.707	17.530	2.935	8.504	0.611
Norway	koronavirus	3.542	11.088	5.951	40.026	0.319
Oman	فيروس كورونا	7.119	10.359	3.358	19.464	0.687
Palau	coronavirus	1.821	6.520	4.758	26.743	0.279
Poland	Korona wirus	5.002	11.522	5.440	35.266	0.434
Portugal	coronavírus	7.176	11.911	4.367	22.652	0.602
Qatar	فيروس كورونا	7.539	12.359	2.802	11.217	0.610
Romania	coronavirus	11.143	15.777	2.953	9.574	0.706
Russia	коронавирус	10.164	13.017	3.618	17.458	0.781
Saudi Arabia	فيروس كورونا	6.659	9.910	3.768	23.378	0.672
Seychelles	coronavirus	5.865	12.682	3.442	15.934	0.462
Singapore	新冠 病毒	6.360	12.693	3.086	12.676	0.501
Slovakia	koronavírus	12.509	16.508	3.268	11.438	0.758
Slovenia	Corona virus	4.323	11.763	5.043	30.816	0.368
South Korea	코로나 바이러스	3.850	8.926	5.788	39.068	0.431
Spain	coronavirus	11.478	14.580	3.351	13.594	0.787
Sweden	coronavirus	9.004	14.758	3.067	10.214	0.610
Switzerland	Coronavirus	11.462	14.167	3.054	11.081	0.809
Turkey	koronavirüs	20.009	16.292	1.687	4.490	1.228
United Arab Emirates	فيروس كورونا	8.329	11.265	3.004	14.179	0.739
United Kingdom	coronavirus	13.036	16.150	2.759	8.223	0.807
United States	coronavirus	11.081	16.652	2.883	8.644	0.665
Uruguay	coronavirus	9.727	12.777	3.435	13.926	0.761

these translations within each country are sourced from Google Trends, resulting in 63 time series from 01/01/2020 to 31/12/2020.

By applying the method described in Sect. 3.1, we compile a time series of daily data for each country, tracking the daily search volume for the term "*coronavirus*" in various languages, over the specified period.

Table 1 and Fig. 1 illustrate the search patterns in each country.

Regarding financial data, we identify at least one stock index for each country listed in Table 1.

Utilising Bloomberg's "*SECF*" function, these indexes are identified and ranked using Bloomberg's proprietary relevance indicator, "*R*", which ranges from 0 to 4, increasing with relevance. We select stock indexes with the highest relevance ($R=4$) and exclude countries with indexes having $R < 4$. As a result, Andorra, Bahamas, Bahrain, Barbados, Belarus, Brunei, Bulgaria, Croatia, Cyprus, Estonia, Iceland, Kazakhstan, Kuwait, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Montenegro, Palau, Seychelles, Slovakia, Slovenia, and Uruguay are excluded. Notably, China and Finland each have two stock indexes with $R=4$, referred to as China 1, China 2, and Finland 1, Finland 2. The final dataset comprises 39 countries and 41 stock indexes, detailed in the first two columns of Table 2.

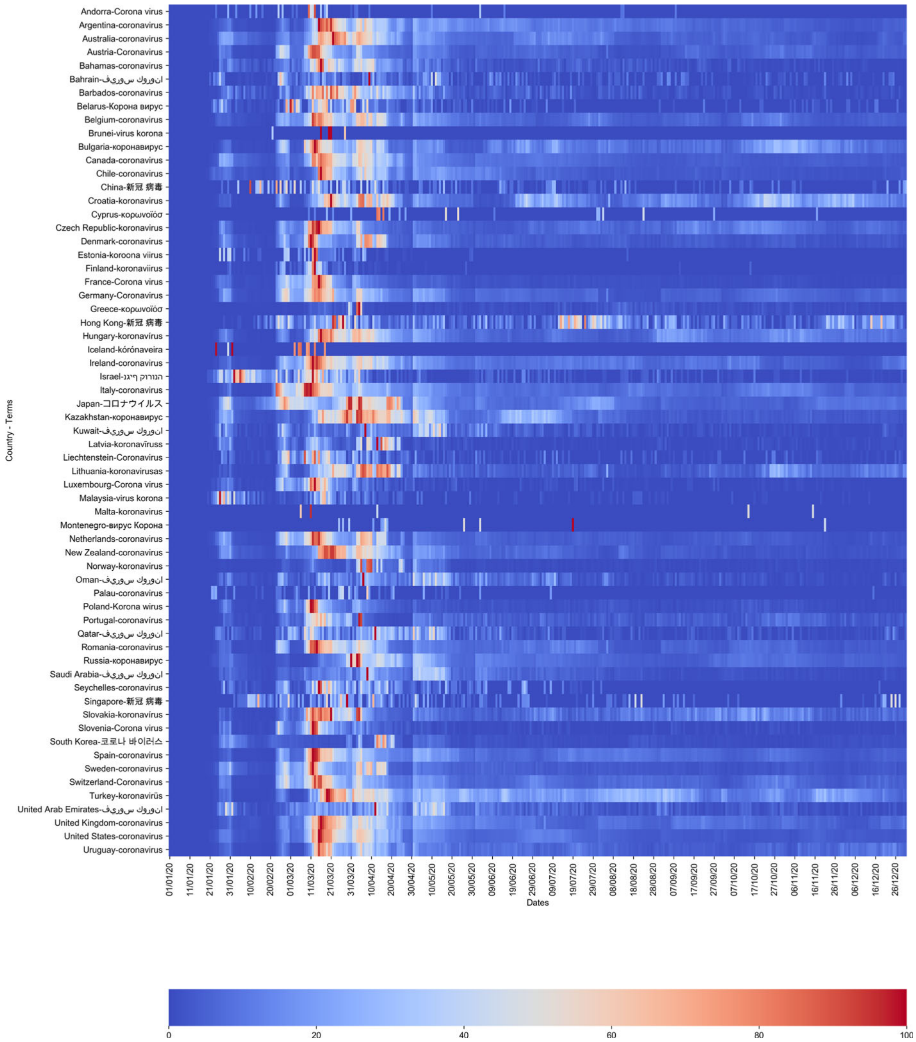

Fig. 1 Google Trends volumes of "*coronavirus*" translations in the most spoken languages of the respective countries. The white areas at the beginning of each row in the heat map indicate the onset of interest in COVID-19 in each country

The closing levels of these indexes, sourced from Bloomberg for the period 01/01/2020–31/12/2020, are normalized as per Formula (1). Table 2 presents a statistical summary of these normalized closing prices.

To calculate the mood indicator as per Formula (4), we exclude data corresponding to non-trading days from each country/stock index's time series. Due to the asynchronous nature of global trading (e.g., Chinese indexes not traded during the Chinese New Year), the mood index is not available for every day between 01/01/2020 and 31/12/2020. To address this, we omit days where mood data is unavailable, resulting in a matrix A containing daily moods across 106 days and 41 stock indexes. Table 3 provides a statistical summary of the mood index for each stock index.

Table 2 Country names, stock indexes, Bloomberg's tickers, and a statistical summary of the normalized indexes' closing prices (according to Formula 1) for the reference period

Country	Bloomberg ticker	μ	σ	Skew	Kurt	μ/σ
Argentina	MERVAL Index	76,463	13,669	−0.587	−0.084	5594
Australia	AS51 Index	85,193	7943	−0.071	−0.413	10,726
Austria	ATX Index	74,682	11,725	0.950	−0.160	6369
Belgium	BEL20 Index	81,295	8503	0.209	−0.228	9561
Canada	SPTSX Index	89,259	7555	−1.014	0.894	11,814
Chile	IPSA Index	79,883	7923	0.329	0.567	10,082
China	SHSZ300 Index	84,108	8670	−0.063	−1.510	9701
China	SHCOMP Index	90,077	6689	−0.214	−1.498	13,466
Czech Republic	PX Index	81,585	8303	0.597	0.072	9826
Denmark	OMXC25 Index	81,969	9273	−0.354	−0.540	8839
Finland	HEX Index	87,660	8698	−0.996	0.314	10,078
Finland	HEX25 Index	88,715	8726	−1.070	0.449	10,167
France	CAC Index	83,091	8871	0.234	−0.518	9367
Germany	DAX Index	89,477	8901	−1.250	0.710	10,052
Greece	ASE Index	72,587	12,084	1.044	0.010	6007
Hong Kong	HSI Index	87,079	5165	0.459	−0.258	16,859
Hungary	BUX Index	80,301	9012	0.707	−0.638	8910
Ireland	ISEQ Index	84,251	9851	−0.474	−0.430	8553
Israel	TA-35 Index	82,338	7571	0.940	0.130	10,875
Italy	FTSEMIB Index	78,801	9306	0.285	−0.498	8468
Japan	TPX Index	87,787	6814	−0.552	−0.057	12,884
Malaysia	FBMKLCI Index	89,865	5466	−0.817	0.301	16,440
Netherlands	AEX Index	88,983	7361	−0.795	0.755	12,089
New Zealand	NZSE50FG Index	87,170	6544	−0.743	0.660	13,320
Norway	OSEBX Index	86,819	7817	−0.622	−0.051	11,106
Oman	MSM30 Index	87,346	5170	1.215	0.189	16,896
Poland	WIG20 Index	81,385	8600	0.264	−0.197	9464
Portugal	PSI20 Index	82,335	7804	0.701	−0.237	10,550
Qatar	DSM Index	89,622	6312	−0.273	−0.943	14,200
Romania	BET Index	87,044	6869	−0.039	−0.292	12,672
Russia	RTSI$ Index	76,471	9935	0.424	0.097	7697
Saudi Arabia	SASEIDX Index	88,224	8391	−0.461	−0.862	10,515
Singapore	STI Index	82,554	7715	1.038	−0.119	10,701
South Korea	KOSPI Index	77,261	9562	−0.030	0.093	8080
Spain	IBEX Index	75,460	10,186	1057	−0.090	7408
Sweden	OMX Index	89,239	7584	−0.886	0.055	11,767
Switzerland	SMI Index	90,058	4881	−1.059	1.919	18,451
Turkey	XU100 Index	76,827	8700	0.158	0.202	8830
United Arab Emirates	DFMGI Index	78,363	10,495	0.424	−0.670	7467
United Kingdom	UKX Index	81,779	7879	0.922	0.266	10,380
United States	SPX Index	85,671	8482	−0.702	0.189	10,100

Table 3 Country names, stock indexes, Bloomberg's tickers, and a statistical summary of the mood index calculated using Formula (4)

Country	Bloomberg ticker	μ	σ	Skew	Kurt	μ/σ
Argentina	MERVAL Index	0.5004	0.0135	− 5.4665	44.5997	37.0107
Australia	AS51 Index	0.5017	0.0090	− 1.9556	28.9805	56.0020
Austria	ATX Index	0.5016	0.0058	− 1.4123	13.3691	85.8751
Belgium	BEL20 Index	0.5014	0.0119	− 7.3179	69.4856	41.9649
Canada	SPTSX Index	0.5006	0.0105	− 5.5138	48.1026	47.7653
Chile	IPSA Index	0.4995	0.0228	− 9.2079	90.9126	21.9058
China	SHSZ300 Index	0.5042	0.0339	− 0.8187	17.8851	14.8817
China	SHCOMP Index	0.5043	0.0339	− 0.8015	17.8303	14.8800
Czech Republic	PX Index	0.5016	0.0074	− 5.9728	52.9433	67.6568
Denmark	OMXC25 Index	0.5014	0.0135	− 0.3399	34.4556	37.1294
Finland	HEX Index	0.5020	0.0133	0.5475	30.5426	37.7080
Finland	HEX25 Index	0.5021	0.0133	0.5619	30.3767	37.6361
France	CAC Index	0.5010	0.0084	− 5.3866	44.9941	59.3906
Germany	DAX Index	0.5020	0.0069	0.5139	15.8341	72.4869
Greece	ASE Index	0.5019	0.0083	1.5563	35.6850	60.5857
Hong Kong	HSI Index	0.5073	0.0255	− 0.4115	6.9257	19.9027
Hungary	BUX Index	0.5006	0.0138	− 7.3394	66.6646	36.3924
Ireland	ISEQ Index	0.5016	0.0084	− 2.3469	19.8482	59.3838
Israel	TA− 35 Index	0.5014	0.0203	− 1.9593	14.3032	24.6684
Italy	FTSEMIB Index	0.5021	0.0065	1.4757	10.9006	77.5981
Japan	TPX Index	0.5017	0.0166	− 4.2209	44.9289	30.2284
Malaysia	FBMKLCI Index	0.5033	0.0118	3.7398	19.7559	42.7125
Netherlands	AEX Index	0.5017	0.0098	− 4.7745	47.9132	51.0409
New Zealand	NZSE50FG Index	0.5016	0.0121	− 3.0266	35.4076	41.3005
Norway	OSEBX Index	0.5021	0.0067	8.2774	78.8757	75.3277
Oman	MSM30 Index	0.5045	0.0153	5.8698	47.2990	32.9650
Poland	WIG20 Index	0.5017	0.0135	− 2.2056	42.5489	37.2614
Portugal	PSI20 Index	0.5030	0.0098	2.3569	14.3185	51.5228
Qatar	DSM Index	0.5057	0.0147	2.5489	13.2770	34.3981
Romania	BET Index	0.5019	0.0086	− 3.3010	38.1974	58.0270
Russia	RTSI$ Index	0.5026	0.0066	3.3604	22.7373	76.7256
Saudi Arabia	SASEIDX Index	0.5028	0.0060	4.9223	32.5224	83.4407
Singapore	STI Index	0.5049	0.0186	1.1760	5.8426	27.1833
South Korea	KOSPI Index	0.5025	0.0083	6.2256	50.5340	60.3632
Spain	IBEX Index	0.5013	0.0091	− 5.7556	52.7410	55.2326
Sweden	OMX Index	0.5017	0.0104	1.0803	21.5532	48.2034
Switzerland	SMI Index	0.5018	0.0066	− 1.1947	18.9062	76.2267
Turkey	XU100 Index	0.5014	0.0151	− 2.7749	14.3304	33.2976
United Arab Emirates	DFMGI Index	0.5036	0.0074	3.2388	16.2601	67.6691
United Kingdom	UKX Index	0.5004	0.0122	− 5.4345	45.8719	40.9221
United States	SPX Index	0.5002	0.0117	− 5.1739	34.6032	42.6016

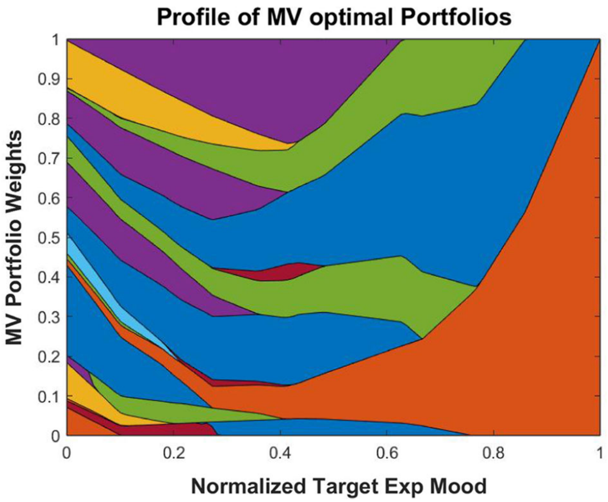

Fig. 2 MV efficient frontier in terms of relative portfolio weights with respect to the *normalized* target level of the expected world's mood

5.2 Results and discussion

In Fig. 2, we display the composition profile of the MV efficient frontier, showing the variation in the portfolio composition as the target level of the expected mood η shifts from $\eta_{\min}$ to $\eta_{\max}$. For enhanced readability, the x-axis of Fig. 2 denotes the normalized target level $\tilde{\eta} = \frac{\eta-\eta_{\min}}{\eta_{\max}-\eta_{\min}} \in [0, 1]$. Specifically, we present the Pareto-optimal solutions of Problem (8), illustrating the relative contribution of each index to the world's mood. These configurations optimally balance maximizing the expected mood of the world and minimizing its variance. According to the mathematical properties of the MV model, the diversification of stock indexes generating the lowest volatility of the world's mood is high. While approaching the highest targets of the expected world's mood portfolios become more concentrated, particularly in the Hong Kong and Qatar indexes. Increasing the world's expected mood level in Model (8) tends to prioritize countries with higher expected mood values in the efficient solutions, that happens because of the model design.

To further elucidate the behaviour of optimal MV portfolios in terms of the world's mood, Fig. 3 depicts the time evolution of the world's mood for three distinct portfolios: the Minimum Variance (MinV) portfolio, the Pareto-optimal portfolio with maximum expected mood (MaxExpMood, that corresponds to a portfolio with only one country, in this case, Hong Kong), and the Equally Weighted (EW) portfolio, which distributes the contribution to the global mood equally among all indexes. Here, $\pi^{EW}_{k(j)} = \frac{1}{n}$ for $k(j) = 1, \ldots, K(j)$ and $j = 1, \ldots, n$. The MinV portfolio, chosen to minimize volatility, contrasts starkly with the MaxExpMood portfolio, which, while offering the highest expected mood, exhibits considerable instability over time.

Figure 4 uses a heatmap to visualize each country's relative contribution to the total mood of the world for the MV Pareto-optimal portfolios. The y-axis lists the countries, while the x-axis displays 100 equally-spaced target levels of the world's expected mood between η_{min} and η_{max}. The colour spectrum from light yellow to dark red represents low to high impact on the world's mood, respectively. White blocks indicate minimal impact of a country's financial

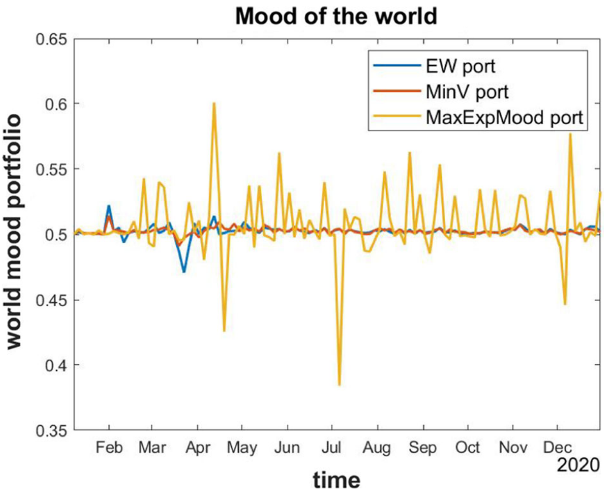

Fig. 3 Daily time evolution of the world's mood for the MinV, EW, and MaxExpMood portfolios during the pandemic year

markets and COVID-19 anxiety on the global mood. Policymakers can use this visualisation to discern which countries significantly influence the global mood. Again, we observe that to achieve less fluctuation in world mood values, more countries should be considered relevant in Pareto-optimal solutions.

In Fig. 5, we present the profile of the Pareto-optimal portfolios obtained by Problem (11), varying the normalized target level of the mood $\tilde{\eta} = \frac{\eta - \eta_{min}}{\eta_{max} - \eta_{min}} \in [0, 1]$. In this empirical experiment, the confidence level is set at $\varepsilon = 0.10$. At a fixed $\tilde{\eta}$, the portfolio weights minimize the mood values in the most pessimistic scenarios without penalizing the optimistic ones. Notably, as observed by Cesarone et al. (2013); Mansini et al. (2007) for equity portfolios, the portfolio with minimum CVaRD tends to be less diversified compared to the minimum variance portfolio.

Figure 6 illustrates the time evolution of the world's mood for the Minimum CVaRD (MinCVaRD) portfolio, the MaxExpMood portfolio, and the EW portfolio. The results mirror those in Fig. 3, with the risk-minimization portfolio leading to a relatively stable mood around the fair value of 0.5.

Figure 7 offers a heatmap visualization of each country's relative contribution to the total mood of the world for the Mean-CVaRD Pareto-optimal portfolios (similar to Fig. 5 but with a different visualization technique). In line with the representation in Fig. 4, on the y-axis we report the countries, and on the x-axis, 100 equally-spaced target levels of the expected mood of the world, assuming the same meaning for the colour of the blocks. Different from the MV model, the Mean-CVaRD optimal portfolios with low target levels of the expected mood assigns more relevance to Saudi Arabia, South Corea, Norway and Malaysia to reduce pessimistic fluctuations of the world's mood. Model (11) suggests that fewer countries are relevant in Pareto-optimal solutions to contain downside fluctuations of world mood values compared to those obtained by solving Model (8).

In Fig. 8 we compare the relevance of countries in the world's mood as determined by the RP model (12) and the Most Diversified Portfolio (MDP, namely the normalized optimal solution of Model (14)), along with the MinV and MinCVaRD portfolios. By construction, the RP portfolio includes all countries in composing the world's mood. Thus, the resulting

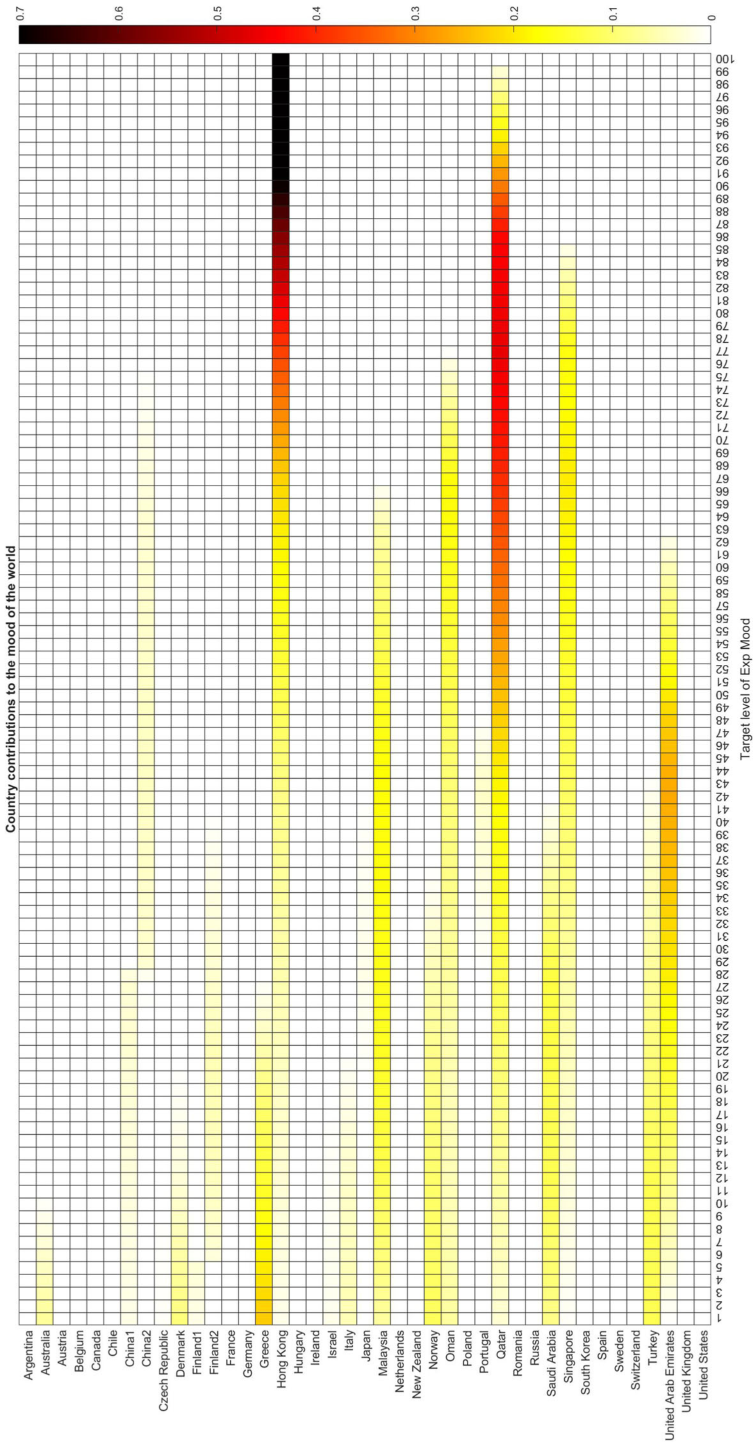

Fig. 4 Heatmap visualization of the MV Pareto-optimal contributions of all countries to the global mood

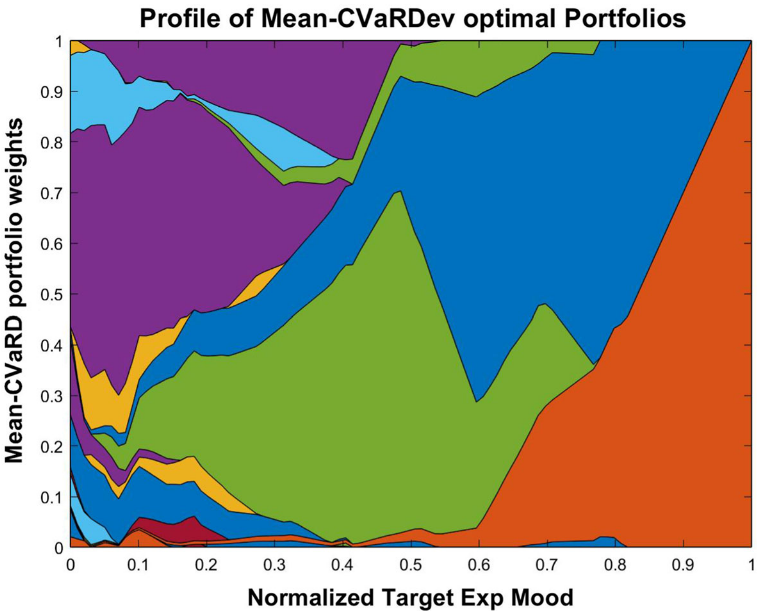

Fig. 5 Mean-CVaRD efficient frontier showing relative portfolio weights with respect to the *normalized* target level of the expected world's mood

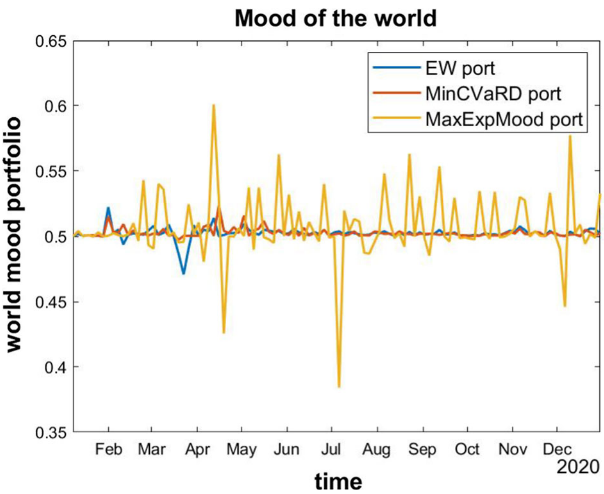

Fig. 6 Daily time evolution of the world's mood for the MinCVaRD, EW, and MaxExpMood portfolios during the pandemic year

scores (i.e., the weight in percentage shown in Fig. 8) associated with each market in a country tend to have uniform weights across markets, preventing any single country from dominating. In MDP, countries like Denmark, Oman, Greece, and Chile are most relevant. This allocation ensures that the fluctuations caused by waves of pessimism and optimism are as small as possible, and also as far as possible from the worst case where the turbolences of the stock markets and the mood of the countries are perfectly correlated. We point out that

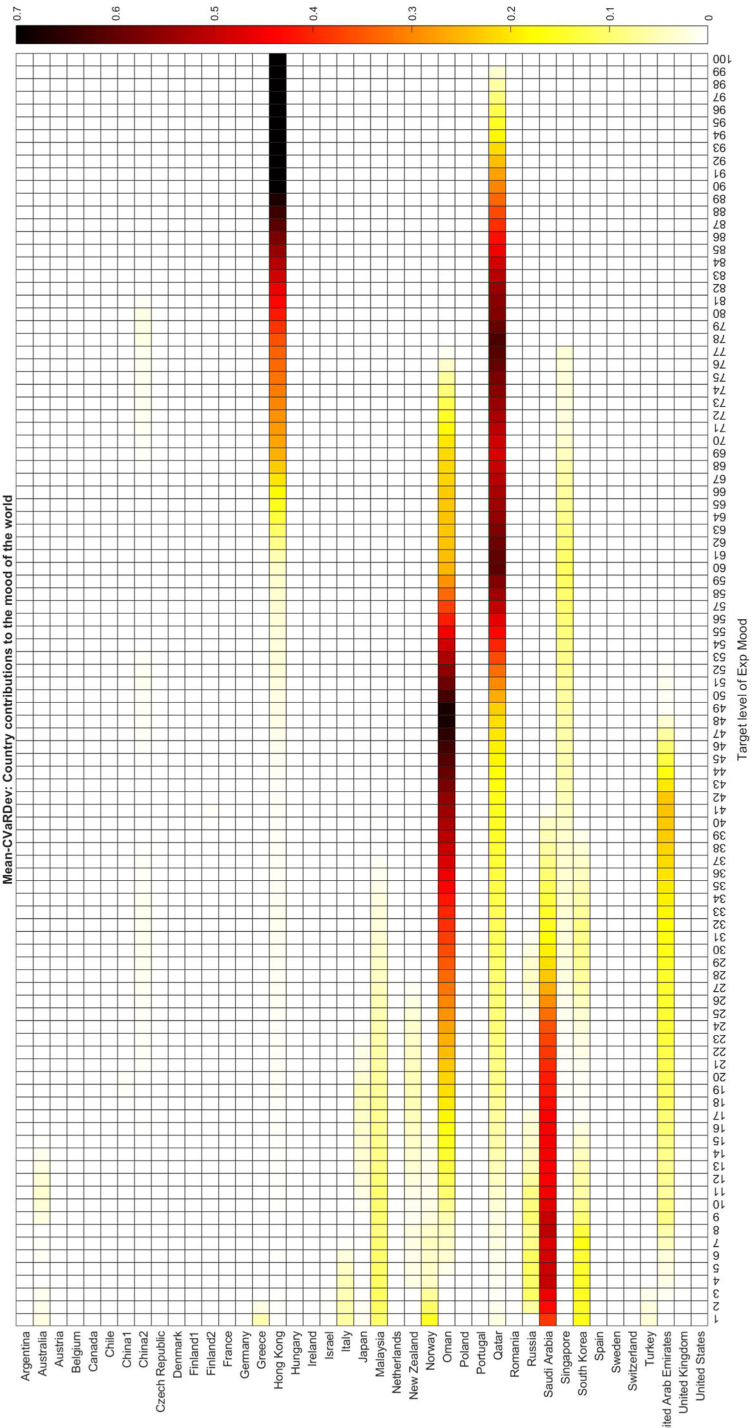

Fig. 7 Heatmap visualization of the Mean-CVaRD Pareto-optimal contributions of all countries to the global mood

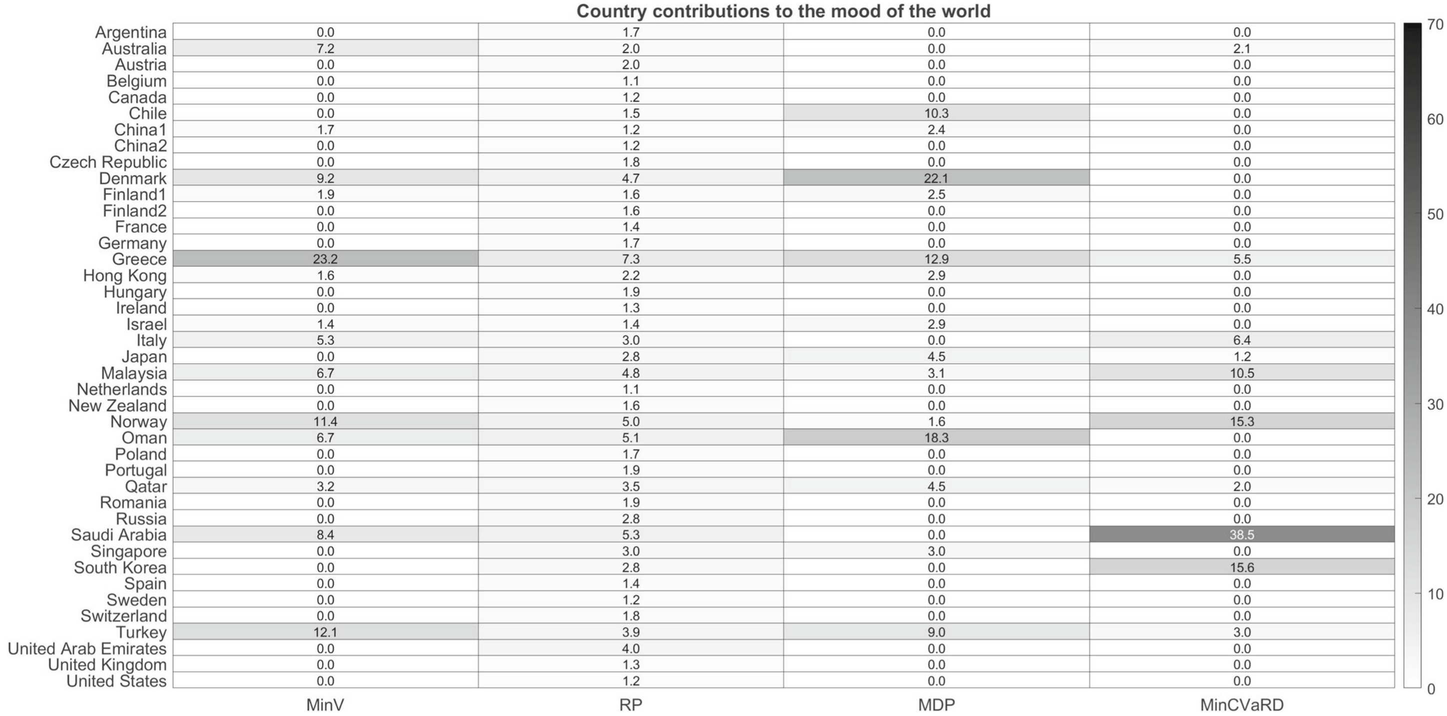

Fig. 8 Heatmap visualization showing relative weights (percentage) for the MinV, RP, Most Diversified (MD), and MinCVaRD portfolios

Table 4 Descriptive statistics of the daily mood of the world for the EW, the MinV, the MinCVaRD, the MaxExpMood, the RP, and the MDP strategies

	μ	σ	Skew	Kur	Min	Max
EW	0.50217	0.0048	− 2.21	22.7	0.471	0.522
MinV	0.50243	0.0025	0.36	9.9	0.491	0.514
MinCVaRD	0.50260	0.0035	3.21	16.4	0.497	0.524
MaxExpMood	0.50725	0.0256	− 0.41	9.5	0.384	0.601
RP	0.50244	0.0034	− 0.77	16.6	0.484	0.519
MDP	0.50248	0.0029	− 0.22	12.5	0.487	0.516

the MinCVaRD model tends to favour countries with high mood kurtosis levels (see Table 3) induced by a noticeable number of days where the Google searches decrease, and the stock indexes' prices increase. Thus, such a selection seems to link with the model's focus on penalizing pessimistic fluctuations.

Finally, Table 4 highlights important features of the daily mood of the world when the considered portfolio models are implemented. Such a table can also be interpreted along with Figs. 3 and 6. Specifically, we notice that all the models are associated with an average mood close to 0.5. The skewness oscillates between positive and negative values, to illustrate different symmetry properties of the models. In all the cases the skewness is around zero, except for EW—showing a remarkably negative value of the skewness—and MinCVaRD—that presents a high level of positive skewness. Interestingly, MaxExpMood is the strategy with the highest level of fluctuations, hence leading to extreme values of the mood as *standard ones*. For this reason, this model does not present the highest level of kurtosis. Differently, we notice that EW has quite stable behavior, with values around 0.5. However, the presence of some specific deviations from the mean level leads to a high level of kurtosis.

6 Conclusive remarks

This paper proposes a portfolio decision analysis framework to analyse the world's reaction to COVID-19. We measure this reaction by combining the anxiety generated by the pandemic with the stock markets' perception of performance.

We applied and compared different portfolio selection models, each tailored to describe the world's mood optimally under the assumption of "rationality", that is, a preference for prosperity over decline. Our goals included pursuing a high and stable level of mood, but also for avoiding extremes of overpessimism. We also explored a target aimed at fostering solidarity, cooperation, and a shared sense of belonging. Supranational institutions, such as the European Commission, the World Health Organization, or the World Bank, can utilise our findings to analyse various scenarios and guide their focus, especially when the relevance of certain countries is paramount. For instance, the European Union can employ our portfolio decision analysis in the context of the National Recovery and Resilience Plan, to strategically allocate funds to countries for developing actions and policies supporting the socio-economic environment post-pandemic (refer to the Introduction for a thorough discussion).

The outcomes highlight regional differences when the adopted portfolio strategy varies. For example, European countries play a leading role in the MinV context, while Asian countries are predominant in the MinCVaRD portfolio.

Our approach disentangles the challenge of selecting countries based on their unique mood realisations, facilitating a global analysis of the world's reaction to COVID-19. It enables analysts to focus on countries with assigned relevance according to the predetermined target. The empirical experiment showcases the informative content of our proposal, revealing different clusters of countries driven by weight distributions, depending on the chosen model and target.

This study's foundation lies in the selected data type for describing citizens' mood and the proposed mood indicator; these elements represent a clear limitation. However, the validity of the models' components is supported by existing studies (see Cerqueti & Ficcadenti, 2023).

New data-based conceptualizations of anxiety and novel indicators might lead to alternative portfolio decision models, offering results comparable to ours.

Several research ideas emerge from this study. Firstly, developing a set of portfolio models with an entropy-based objective function could describe the world's mood in terms of closeness to a uniform distribution. In so doing, one can analyse the assigned relevance to the individual stock markets/countries for concentrating attention on a few paradigmatic realities—e.g., by minimising the Shannon entropy of $M(\pi)$, one can focus on the most critical situations, maintaining vigilance over the pandemic and mitigating COVID-19 spread due to fear-driven defensive behaviour. Secondly, a data science approach could provide detailed insights into citizens' reactions at the country level. For example, conducting a rank-size analysis might reveal inner structures within disaggregated data and allow for forecasting the evolution of the world's mood. Significantly, the outcomes of the portfolio models can be interpreted through cluster analysis, optimising a similarity-based distance between countries. This approach can yield meaningful classifications of countries in terms of their reaction to the pandemics. These challenging topics are reserved for future research.

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