United States of Mind under Uncertainty*

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Abstract

This paper investigates if heightened economic uncertainty raises concerns about mental health in the U.S. We first quantify such concerns by constructing a composite Mental Health Concerns index, using time series of the intensity of Google search queries related to mental disorders and distress. This index i) rises significantly during the three recessionary episodes and ii) comoves negatively with survey responses that reflect views on current consumer sentiment or on future economic conditions. We find that the concerns regarding mental health substantially increase after an unexpected hike in economic uncertainty; uncertainty not only channels through its negative impacts on economic activity, but also directly affects the level of concerns. Our findings suggest that an uncertainty shock can have a far-reaching impact on overall welfare of economic agents by leaving them more concerned about mental health.

JEL classification: E32, I31

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1 Introduction

Since the seminal work by Bloom (2009), real effects of a shock to uncertainty have been widely studied (see Baker et al. 2016; Bloom et al. 2018; Caggiano et al. 2014; Choi and Loungani 2015; Jo and Sekkel 2019; and Jurado et al. 2015, among others). In addition to such economic effects, uncertainty may further increase social anxiety (Boelen and Reijntjes 2009), stress (De Berker et al. 2016) as well as the numbers of suicides (Vandoros et al. 2019). These problems arising from mental distress and disorder likely impose material social costs. For instance, Frank and McGuire (2000) showed that mental disorders incur costs on the entire society, directly through treatment expenditures and indirectly via subsequent social implications such as violence and earnings' loss.[1] Therefore, it would be crucial to understand how uncertainty affects the mental health conditions, in order to have a full assessment of the impacts of uncertainty and to facilitate related policy discussions.

Nonetheless, empirical studies on quantifying the impacts of uncertainty over and above economic ones are scarce. Few previous literature takes microeconomic approaches, based on one-time survey responses (Boelen and Reijntjes 2009) or experiments (De Berker et al. 2016). These cross-sectional studies examine a possible association between the individual levels of uncertainty and mental health disorders. However, it is not straightforward to generalize their conclusions to the macro level for understanding dynamic relations between the two. Even if the effects of uncertainty over time was examined, these studies tend to focus on one specific mental health issue such as suicide (Vandoros et al. 2019). As such, it would be difficult to derive implications for overall mental health concerns.

The major hindrance in empirically understanding the spillover of uncertainty to mental health is that no indicator is readily available to quantify mental health concerns at the business-cycle frequency. Almost all of the surveys measuring the level of respondents' happiness are conducted annually and do not have sufficiently long time-series observations. Other indices based on social media can be constructed at higher frequencies. However, they may not accurately capture individuals' moods or well-being, as users may not truthfully reveal their mental status given the existence of viewers and readers (Wang et al. 2014; Wright et al. 2018). This paper thus aims to fill this gap in the literature by constructing an index that reflects concerns on mental health and by analyzing the effect of uncertainty

[1]Some studies showed that those with mental health problems are more likely to use violence (see Swanson et al. 1990, Link et al. 1992; Swanson et al. 2006). Bartel and Taubman (1986) found a negative effect of mental health problems on individuals' earnings. Doran and Kinchin (2017) reviewed that there is a high economic burden of mental health problems such as hampering educational attainment, employment, and life satisfaction, among others.

shock on aggregate mental health concerns from a macroeconomic perspective.

We construct the Mental Health Concerns (MHC) index as the search intensity of various keywords related to a range of mental disorders using the Google Trends data. The keywords are identified from the 12-item General Health Questionnaire (GHQ-12), similar in spirit to Brodeur et al. (2021). This questionnaire is a widely-used screening tool for risks for mental health conditions and psychological distress. We choose total 133 search terms under 14 broad categories describing mental health concerns, such as "anxiety", "depression", "stress" and "suicide". By carefully aggregating the search intensity of these terms, we construct a single composite index that represents overall concerns on mental health conditions.[2] An implicit assumption here is that the internet would be used as the main source of information within reach, when in need to get a prompt consultation or guidance on concerning issues about mental health. Consistent with this assumption, Fox (2011) shows that the internet serves an important role as a major source of health information. Other research also finds that those who search for online health information are indeed more likely to be in health needs (Houston and Allison 2002; Bundorf et al. 2006). In addition, previous studies have shown that search intensity information obtained from Google trends can successfully forecast the outbreaks of disease (Carneiro and Mylonakis 2009), tourism flows (Siliverstovs and Wochner 2018), unemployment (D'Amuri and Marcucci 2017) and trading behavior in financial markets (Preis et al. 2013; Da et al. 2015).[3]

Our index has advantages over alternative approaches based on surveys or on social media postings in terms of costs and veracity. First, the Google Trends data provide an instantaneous and efficient way to unveil where the public interest lies and what they care about. In contrast, survey-based approaches would require much more time and expense for their design and execution, to obtain similar information. Second, our internet search-based approach is likely capturing more accurate states of minds, compared to those measures drawing on social media, such as the Facebook Gross National Happiness Index and the Twitter-based Hedonometer happiness index (Dodds et al. 2011).[4] As Wright et al. (2018)

[2]This is distinct from the use of the Google Trends data in Brodeur et al. (2021), where the focus was on comparing changes in the search intensity of several queries.

[3]Choi and Varian (2012) showed that including Google Trends data can improve the predictive power of the models forecasting near-term values of economic indicators such as automobile sales, unemployment claims, travel destination planning, and consumer confidence. Da et al. (2015) constructed the FEARS index which is a measure of investor sentiment using Google search queries regarding household concerns. D'Amuri and Marcucci (2017) found that models incorporating job search intensity from Google tend to outperform others in predicting the monthly unemployment rate of the United States.

[4]A detailed description on the Facebook Gross National Happiness Index is available at https://www.nytimes.com/2009/10/12/technology/internet/12link.html. The Twitter-based Hedonometer happiness index is available at http://hedonometer.org.

demonstrate, social media users may not truthfully reveal their feelings, since interactions in social media presume the existence of viewers and readers on the other end. However, the behavior of putting in a query in an online search engine likely aims to obtain information in need, and as such, it is more plausible that users honestly unveil their states of mind.

Nonetheless, the Google Trends data do not come without limitations. First, one may question its representativeness, as the Google Trends database do not provide any information on its users' side. Hence, it is not feasible to further gauge underlying search motives and for whom the search queries are made. Second, it may over-represent certain demographics such as the young, as noted in Brodeur et al. (2021). Likewise, not all U.S. citizens have access to internet, although the share of individuals using internet in total U.S. population reached 91% in 2020 according to the World Bank data. Finally, other factors can drive up search intensity that are not necessarily related to concerns about mental health. For instance, increasing awareness about the risk of depression or other mental illness can trigger higher search volumes.

Despite these caveats, our subsequent analysis results show that the MHC index can reasonably capture the average level of concerns on the mental health. We assess its validity by examining its i) major peaks during our sample period and ii) comovement with a number of survey responses and economic indicators. First, we find that the MHC index shows three conspicuous hikes, which are in line with major economic distresses, i.e., the Global Financial Crisis in 2008-2009 and the debt-ceiling debate in 2011, as well as the outbreak of the COVID-19 pandemic in 2020. Furthermore, the MHC index is significantly negatively correlated with several series capturing respondents' views on their current sentiment and on future economic situations from the Michigan Survey of Consumers. The correlation likely reflects that concerns about mental health can be elevated, when more respondents retain pessimistic views.

We employ our index in a vector autoregressive (VAR) model by extending the framework in Baker et al. (2016) to analyze how an unexpected increase in uncertainty influences mental health concerns. We find that a positive uncertainty shock induces a significant rise in the MHC index. This is due to both the direct effects of the uncertainty shock on mental health concerns as well as the spillovers caused by the responses of real economic variables. The former highlights that elevated uncertainty can raise concerns about mental health, even without any material changes in the economy. In addition, as the economy deteriorates in response to the uncertainty shock, such concerns can intensify further.

Our work contributes to the literature of examining the effects of uncertainty shocks. We demonstrate that uncertainty can have far-reaching impacts on agents' welfare by compounding concerns on mental disorders, over and above its economic impacts highlighted in the previous literature. To the best of our knowledge, this is the first study to quantify the effect of uncertainty on mental health concerns at the aggregate level. Furthermore, our findings underscore the importance of considering mental health in studies on the welfare effects of uncertainty shocks. Our study is also related to the growing body of literature employing the Google Trends data.[5] We differ in that we focus on the investigation of the impacts of an economic shock rather than examining possible improvement in forecast ability from augmenting the information on search intensity changes.

The rest of this paper is organized as follows. We introduce the MHC index in Section 2 and examine its validity by comparing it to other available series. We then provide analysis on the transmission of uncertainty shocks to the MHC index in Section 3. Section 4 concludes.

2 The Construction of the Mental Health Concerns Index

In this section, we present how an index representing the level of mental health concerns is constructed. We then discuss its dynamics and compare it to other indicators capturing views on current consumer sentiment or future economic situations. Lastly, we examine the extent to which our index is insensitive to alternative ways of constructing the index.

2.1 Google Trends data We construct the monthly MHC index using Google Trends.[6] The Google Trends provides normalized series of search requests submitted to the Google search engine. Hence, one can find out how popularly a term is searched over time in Google. The normalization is done by applying the following steps. First, the number of search for each term i is divided by the number of total searches requested in a specific location during a certain period. Define the resulting number as keyword popularity:

$$\text{keyword popularity}_{i,t} = \frac{\text{number of searches for specific keyword}_{i,t}}{\text{number of total searches}_{i,t}} \tag{2.1}$$

[5] For instance, Castelnuovo and Tran (2017) constructed the Google Trends Uncertainty index with search terms related to uncertainties about future economic conditions. Brodeur et al. (2021) studied the effect of lockdown due to COVID-19 on well-being by employing Google Trends data. They chose well-being-related topics based on the questions in the GHQ-12.

[6] https://trends.google.com/trends/

Then, keyword popularity is further scaled from zero to 100 proportionally. More specifically, the data point where keyword popularity is the highest within the specified time interval is indexed to 100, while zero is assigned to the data point where the keyword popularity is relatively very low.[7] We call this scaled number a Search Volume Index (SVI henceforth) following Da et al. (2015). One issue with the scaling is that the process is highly dependent not only on the time period under investigation but on the group of keywords downloaded together from the Google Trends website. That is, Google Trends allows users to download up to five SVIs at once, and the magnitude of an SVI of one keyword may differ depending on the selection of the other four keywords. Define $\max_{i,t} \text{keyword popularity}_{i,t}$ as the maximal point among series of keyword popularity of multiple keywords downloaded together, i.e., $i \in J_n$ across all t in the period under investigation, i.e., $t = \{1, \ldots, T\}$. Then, the SVI of a search term i in time t is defined as,

$$SVI_{i,t} = \frac{100}{\max\limits_{i,t} \text{keyword popularity}_{i,t}} \times \text{keyword popularity}_{i,t}. \tag{2.2}$$

2.2 Mental Health Concerns Index

An implicit assumption for the construction of the MHC index with the Google Trends data is that searching activities of the Google users reflect their circumstances and need; they would use search queries related to mental health conditions, to gather information and references.

To identify search terms related to mental health conditions, we follow Brodeur et al. (2021) and select topics that could capture various types of mental disorders by referring to the questions in the GHQ-12. In particular, we start from topics specified in Brodeur et al. (2021).[8] After making some adjustments, we identify a total 14 topics to consider: *Anxiety, Boredom, Depression, Divorce, Irritability, Loneliness, Panic, Sadness, Self-esteem, Sleep, Stress, Suicide, Well-being*, and *Worry*.[9,10]

[7] A zero does not necessarily mean that there was no search activity for a keyword at all, since the Google Trends rounds the series to the nearest integers and provides a series of integers only. In fact, this rounding to integers creates additional issues for the construction of the MHC index. Details on how we address these issues are provided in the Appendix A.3.

[8] The topics are: *Boredom, Contentment, Divorce, Impairment, Irritability, Loneliness, Panic, Sadness, Sleep, Stress, Suicide, Well-being* and *Worry*.

[9] Specifically, we exclude two topics from the topic list of Brodeur et al. (2021), i.e., *Contentment* and *Impairment*. Based on related search queries to these two topics, we found that they appeared to reflect search attempts for finding information on marketing and finance; the top three-related queries are the followings: in the case of Contentment, satisfaction, customer satisfaction and contentment, and in the case of Impairment, impairment, goodwill and goodwill impairment. However, keeping the 13 topics as in Brodeur et al. (2021) yields a very similar index to our baseline one, as shown in Figure A6 in Appendix.

[10] We augment the list with three additional topics, i.e., *Anxiety*, *Depression*, and *Self-esteem*, which were not considered in Brodeur et al. (2021). *Anxiety* corresponds to question 5 ("Have you recently felt constantly under strain?") in the GHQ-12, *Depression* to question 9 ("Have you recently been feeling unhappy and depressed?") and that *Self-esteem* corresponds to question 3 ("Have you recently felt you were playing a useful part in things?").

Table 1: Subsets of Selected Search Terms

Topics	Top three-related queries
Anxiety	anxiety, anxious, depression
Boredom	bored, what to do, bored what to do
Depression	depression, depressed, anxiety
Divorce	divorce, divorced, divorce records
Irritability	irritable, irritability, symptoms
Loneliness	lonely, loneliness, quotes
Panic	panic, panic attack, panic attacks
Sadness	sad, sad quotes, quotes
Self-esteem	self, self esteem, esteem
Sleep	sleep, sleeping, sleep in
Stress	stress, stress disorder, traumatic stress
Suicide	suicide, suicidal, commit suicide
Well-being	well being, wellbeing, well-being
Worry	worry, worry about, worrying

Note: This table is based on top-related queries provided by Google Trends downloaded on March 1, 2023.

For each topic, we employ the top ten related search terms that Google Trends automatically provides for each topic, which hence amounts to total 140 search terms. By discarding seven duplicates, we include 133 search terms for the construction of the MHC index. Table 1 shows a subset of the selected search terms, i.e., the top three related queries of each topic. It is worthwhile to note here that we do not make any other ad-hoc adjustment to the 140 search terms chosen by Google Trends, except excluding duplicates. Adding judgements on the selection of the search terms might help increase the precision of the index. However, since Google Trends does not provide any information on the selection of these top ten related queries nor on individual users, it is not straightforward to argue that a specific adjustment would be appropriate. In addition, since the top ten related search terms vary over time, one would need to apply a different set of adjustments each time when updating the index. Hence, we keep as many related queries as possible, based on the assumption that any idiosyncrasy would be averaged out by the multiplicity of the terms. Table A1 in Appendix A.1 shows the complete list of the search terms.[11]

We download monthly data of search requests made in the U.S. from January 2004 to February

[11] Of note, Google Trends also provides search intensity information by subregions, i.e., 50 states and Washington D.C. The search intensity of our benchmark 133 search terms turns out to be heterogeneous across the subregions; about 70% of the terms are searched in all 51 subregions, while the rest does not have a full coverage. An alternative MHC index based only on the former terms is almost identical to our benchmark index with a correlation coefficient at 0.99. Details of the alternative series and its plot are provided in Appendix A.6.7.

2023 and construct the MHC index for the corresponding period. In particular, we aggregate the search intensity of the above-mentioned 133 search terms to construct a single time series representing the overall level of mental health concerns in the U.S.

We provide a detailed description regarding the construction of the MHC index in Appendix A.3. Nonetheless, a brief summary about the construction process is provided below:

Step 1 We re-scale all the SVI series to make them comparable across each other, using "depression" as the key base term.

Step 2 We then adjust the re-scaled series following Da et al. (2015). In short, we address seasonality using the X13-ARIMA-SEATS and remove outliers by winsorizing each series at the 5% level (2.5% in each tail).

Step 3 All the re-scaled and adjusted series are aggregated into a single series. Then, it is normalized so that the first data point (2004M01) is indexed to 100.

Figure 1 is the time series plot of the resulting MHC index.[12] The index sharply increases during key recessionary episodes (shaded regions).[13] The first hike coincides with the Global Financial Crisis and the second is associated with the heated political debates on U.S. debt ceilings in 2011. The latter may reflect heightened concerns of a possible U.S. government default: during this period, Standard & Poor's (currently known as S&P Global Ratings) downgraded the U.S. credit rating for the first time, and Dow Jones Industrial Average index dropped by about $2,000$ points during July and August 2011, showing the severity of an impending default risk.[14] The third jump is during the COVID-19 pandemic, especially during the lockdown period. It is notable that the index rises again after the mid-2021, which may reflect the impact of the prolonged COVID-19 pandemic and subsequent inflation surges. In sum, the search intensity of the terms regarding mental health concerns jumps greatly during these episodes, implying that the mental health concerns intensify greatly in bad times.

In addition, the MHC index appears to be on an increasing trend throughout the sample period. While this likely implies that overall concerns on mental health are continuously increasing, we construct

[12] The constructed MHC index is available on the authors' websites.

[13] Frasquilho et al. (2015) reviewed associations between times of economic recession and mental health.

[14] The seriousness of this episode also shows up in the Economic Policy Uncertainty (EPU) index (Baker et al. 2016); on the verge of a fiscal default, EPU jumped to the highest level since 1985 when the index starts until the Covid-19 outbreak in 2020.

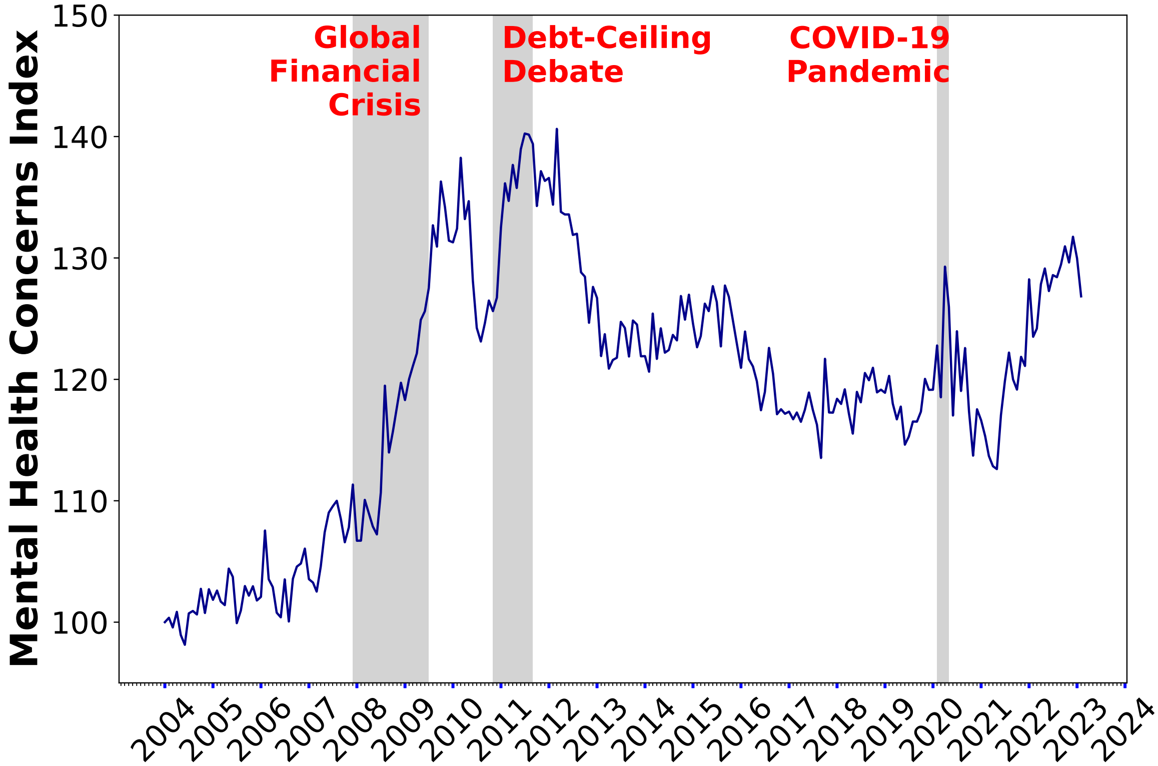

Figure 1: Mental Health Concerns Index

Note: 2004M01-2023M02. Shaded areas are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

disaggregated SVIs for 14 topics for a further investigation. We find that the SVIs of several topics such as *Anxiety*, *Irritability*, *Well-being* and *Worry* show a clear upward trend, likely driving the persistent increase in the composite MHC index. Appendix A.5 provides plots of all 14 topic-level SVIs.

2.3 What does the MHC index capture? To understand what is reflected in our MHC index, we first compute correlation coefficients between the MHC index and a variety of indicators that can possibly affect the mental health status of consumers. Table 2 reports the correlation coefficients for two different sample periods: the pre-COVID-19 era (end of 2019) and until February 2023 (2022 for yearly variables). The upper panel shows how much the MHC index is correlated with responses from the Michigan Survey of Consumers. In particular, we compare the MHC index to the Index of Consumer Sentiment, Current Financial Situation Compared with a Year Ago, Expected Household Income Change During the Next Year, and Probability of Losing a Job During the Next 5 Years. The degree of correlations with these various indicators is consistent with our priors; the more negative

Table 2: Correlation between the MHC Index and Various Indicators in the Pre-COVID-19 Period and All Periods

	2004M01 – 2019M12	2004M01 – 2023M02
Index of Consumer Sentiment	-0.41	-0.45
Current Financial Situation	-0.45	-0.46
Expected Household Income Change	-0.76	-0.71
Probability of Losing a Job	0.19	0.12
	2007 – 2019	2007 – 2022
Cantril ladder	-0.32	-0.38
Positive emotion	-0.39	-0.48
Negative emotion	0.44	0.37

Note: The data from the World Happiness Report (Cantril ladder, Positive emotion, and Negative emotion) are available from 2006-2022. The specific meanings of indicators are as follows: Cantril ladder = Life Evaluations; Positive emotion = Average of Three Measures of Positive Emotion, i.e., laugh, enjoyment, and doing interesting things; Negative emotion = Average of Previous Day Emotion Measures for Worry, Sadness, and Anger.

are sentiments about the overall economic condition, current financial situation or expected household income change during the next year, the more do consumers search terms regarding mental distress. On the contrary, our MHC index tends to rise when the chance of losing a job in the near future rises. This finding holds for both sample periods that are examined. It is surprising to find fairly high correlation coefficients overall, despite the fact that we did not include any search terms explicitly related to economic conditions for the construction of the MHC index, such as *unemployment* or *income*.

We also compare the MHC index with three other annual indices. These indices are obtained from the World Happiness Report (Helliwell et al. 2023) where various survey responses on subjective life satisfaction and happiness are collected starting from 2006. Each year, the survey is conducted to the representative sample of about $1,000$ U.S. citizens over the age of 15. The first indicator we use is called the *Cantril ladder*. A set of questions asks respondents to think of a ladder and evaluate their current lives on a scale from 0 (worst possible life) to 10 (best possible life). Secondly, we use *positive emotion*, defined as the average of responses to three questions that are related to laugh, enjoyment, and doing interesting things, respectively. Participants are asked to answer whether he/she smiled or laughed a lot yesterday, whether he/she experienced enjoyment a lot of the day yesterday, and whether he/she learned or did something interesting yesterday. The third indicator employed is *negative emotion*, which is also a part of the survey questions tracking the emotions experienced on the previous day. The negative emotion indicator is constructed as the average of answers indicating worry, sadness, and anger as what he/she experienced. We use the mean of the responses that are publicly accessible.

We compute the yearly averages of the MHC index for comparability. Due to time trends found in the survey responses, we use the growth rates of the above survey-based indicators for the calculation of correlation coefficients with the MHC index. As shown in the lower panel of Table 2, the annual average of the MHC index and the Cantril ladder as well as positive emotions are negatively correlated. Also, we find that the annual average of the MHC index and negative emotion are positively correlated. Based on these observations, we infer that the MHC index increases when people perceive that they are living unsatisfactory lives and experience less positive and/or intense negative emotions. Figure 2 shows the trajectories of the MHC index along with four selected indicators out of seven examined so far.

Finally, we conduct a sentiment analysis using Valence Aware Dictionary and sentiment Reasoner (VADER) presented by Hutto and Gilbert (2014). VADER is a widely-used lexicon- and rule-based sentiment analysis instrument, and provides four sentiment measurement as an output, i.e., positive, neutral, negative, and compound scores. The compound score is normalized to range between -1 and 1. We find that only around 10% of our 133 search terms reflect non-positive sentiment, as demonstrated in Figure A1. When we re-construct the MHC index using non-positive sentiment search terms only, its dynamics closely resemble those of our baseline index (Figure A2).[15]

Based on the findings from the above analyses, we conclude that the MHC index can be employed as an indicator capturing concerns on mental health conditions reasonably well.

2.4 Sensitivity of the MHC Index We modify our baseline MHC index in various ways and compare resulting alternatives to the benchmark to check its robustness. We i) make an adjustment in our topic selection by using identical topics from Brodeur et al. (2021), ii) include a smaller number of search terms (i.e., three and five) for each topic than the baseline setup of ten, iii) use the first factor from the Principal Component Analysis (PCA) instead of a simple aggregation for obtaining a composite index, iv) choose other search terms than "depression" as the baseline keyword for re-scaling and standardizing 133 SVIs, v) build a weekly index instead of monthly (covering periods from 2018

[15] It should be noted that VADER analysis is usually applied to a document, paragraph, sentence or clause; therefore, our results based on feeding search terms which consist of a few words at most should be interpreted with a grain of salt. Related, VADER classifies a word as "neutral" if there is no valid match in the lexicon (e.g., "divorce"). As such, we focus on search terms categorized in the negative and neutral groups in our main text, as these would not capture positive sentiment. Details of the VADER analysis results are provided in Appendix A.4.

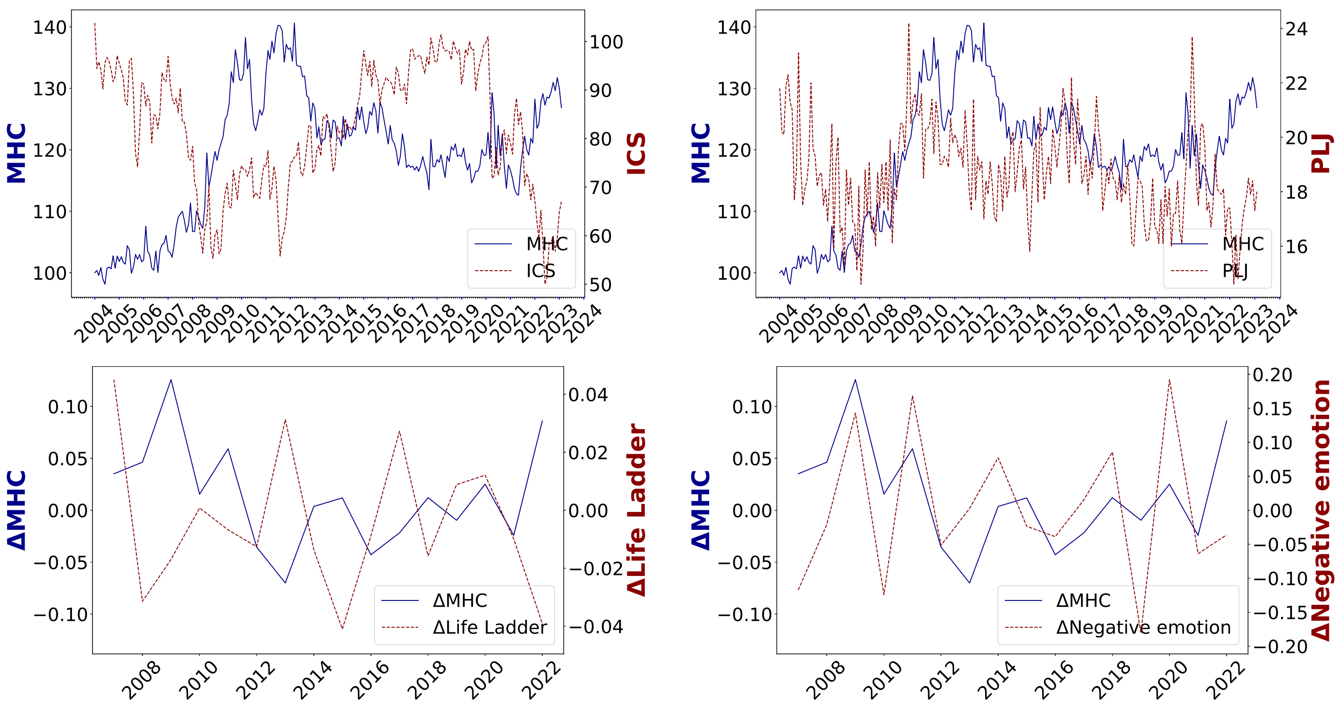

Figure 2: Correlation between the MHC Index and Various Indicators

Note: The blue solid line represents the time series of the MHC index. The red dashed line indicates the time series of other variables relevant to mental health. Labels of indicators are as follows: ICS = The Index of Consumer Sentiment; PLJ = Probability of Losing a Job During the Next 5 Years; Cantril ladder = Life Evaluations; Negative emotion = Average of Previous Day Emotion Measures for Worry, Sadness, and Anger.

to 2022), and vi) use underlying SVIs in changes from the previous months. Our baseline index turns out to be quite robust to these changes; all of the correlation coefficients between the baseline and alternative indices range between 0.77 to 0.99, except the one between the PCA-composite index and our benchmark (0.47). Details of the robustness checks along with plots of the alternative indices as well as correlation coefficient estimates are provided in the Appendix A.6.

3 The Impacts of Uncertainty on Mental Health Concerns

3.1 VAR Analysis In order to investigate the effect of uncertainty shocks on mental health concerns, we estimate a VAR model with monthly U.S. macroeconomic variables and the MHC index from January 2004 to December 2019.[16] We closely follow Baker et al. (2016) by setting the lag length to three

[16] We use the sample prior to the COVID-19 pandemic period in our baseline specification, as the pandemic likely influences the stability of parameters, particularly in a time-invariant model like ours (see, for example, Diebold 2020). Extending the sample period further, i.e., from January 2004 to December 2022, yields qualitatively similar results, but the size of the responses becomes smaller and the error bands wider, compared to our baseline impulse responses.

and employing the Cholesky decomposition to identify the uncertainty shocks. This identification scheme hinges on the ordering of variables, as it assumes that those that are ordered first tend to be exogenous and are not affected by variables ordered later within a month.[17] When applying the Cholesky decomposition to the analysis of the uncertainty shocks, a natural choice of the ordering of variables is not clear; a measure of uncertainty would react to real activity shocks within the same month, while it is also possible that other real variables included in the VAR would respond to uncertainty during the same time frame. As such, we keep the ordering of variables identical to that of Baker et al. (2016) and simply augment it with the MHC index. In particular, variables in our VAR are ordered as follows: an uncertainty index, the log of S&P 500 index, the shadow rate (Wu and Xia 2016), log employment, log industrial production, and the MHC index. The MHC index is ordered last because mental health concerns would likely be affected by other external circumstances; for instances, unemployment can increase the suicide rate through mental illness (Blakely et al. 2003). In addition, it is less likely that concerns for mental health affect macroeconomic variables in the same month at the aggregate level. For the measure of uncertainty, we consider macro uncertainty index developed by Jurado et al. (2015) (henceforth, JLN macro) and real uncertainty index constructed by Ludvigson et al. (2021) (LMN real) in our baseline specification. In Section 3.2, we extend our analysis to include other uncertainty measures such as VIX and the Economic Policy Uncertainty (EPU) index introduced in Baker et al. (2016).

Our baseline VAR specification can be described as follows:

$$Ay_t = c + \sum_{k=1}^{3} B_k y_{t-k} + u_t. \tag{3.1}$$

Here, y_t is the 6×1 vector of aforementioned endogenous variables; c is the 6×1 vector of constant terms; B_k are 6×6 matrices of coefficients; u_t is a 6×1 vector of orthogonalized shocks.

Equation (3.1) can be expressed in reduced form for estimation purposes:

$$y_t = A^{-1}c + \sum_{k=1}^{3} F_k y_{t-k} + A^{-1}\Sigma\epsilon_t, \qquad \epsilon_t \sim N(0, I_6), \tag{3.2}$$

[17] While existing empirical studies on the effects of uncertainty shocks have employed various identification methodologies such as an instrumental variable model (Baker et al. 2020) or a stochastic-volatility-in-mean-type model (Jo 2014; Carriero et al. 2018), the Cholesky decomposition in a VAR model has been one of the most commonly-used approaches.

where $F_k = A^{-1}B_k$ for $k = 1, 2, 3$, and

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & ... & 0 \\ 0 & \sigma_2 & ... & 0 \\ ... & ... & ... & 0 \\ 0 & ... & 0 & \sigma_6 \end{pmatrix},$$

where σ_i is the standard deviation of each of the orthogonal shocks. Since we use the Cholesky decomposition to identify uncertainty shocks, we further assume that

$$A = \begin{pmatrix} 1 & 0 & ... & 0 \\ a_{21} & 1 & ... & 0 \\ ... & ... & ... & 0 \\ a_{61} & ... & a_{65} & 1 \end{pmatrix}.$$

Figure 3 presents the impulse responses of log S&P 500 index, the shadow rate, log employment, log industrial production, and the MHC index to a one-standard deviation shock to uncertainty (an increase by about 0.01). The significantly negative responses of the S&P500 index, the shadow rate, employment, and industrial production to the uncertainty shocks are consistent with the findings from the previous literature (see Leduc and Liu 2016, as an example). Importantly, uncertainty shocks significantly raise the MHC index with a peak increase of about 1.20 (JLN macro) and 1.65 (LMN real). To illustrate, we consider an unexpected increase in uncertainty of a size equivalent to that from the 2005/06 average (before the Global Financial Crisis) level to the 2008/09 average, which is 0.20 for JNL macro and 0.11 for LMN real. In this case, the peak increase in the response of the MHC index is about 28.39 and 23.42 for the case of JNL macro and LMN real, respectively. Considering that the standard deviation of the MHC index in the period from January 2004 to December 2019 is 11.04, this is a substantial increase in the concerns for mental health.

We also calculate the forecast error variance decomposition, as reported in Table 3. Consistent with Figure 3, uncertainty shock explains a large share of the dynamics of macro variables, including the S&P 500 index, employment, and IP. The MHC index is also significantly affected by the uncertainty shock; about 30% (JLN macro) and 50% (LMN real) of the variance of the MHC index is explained by the uncertainty shocks after 2 and 3 years, a significant portion of its variations.

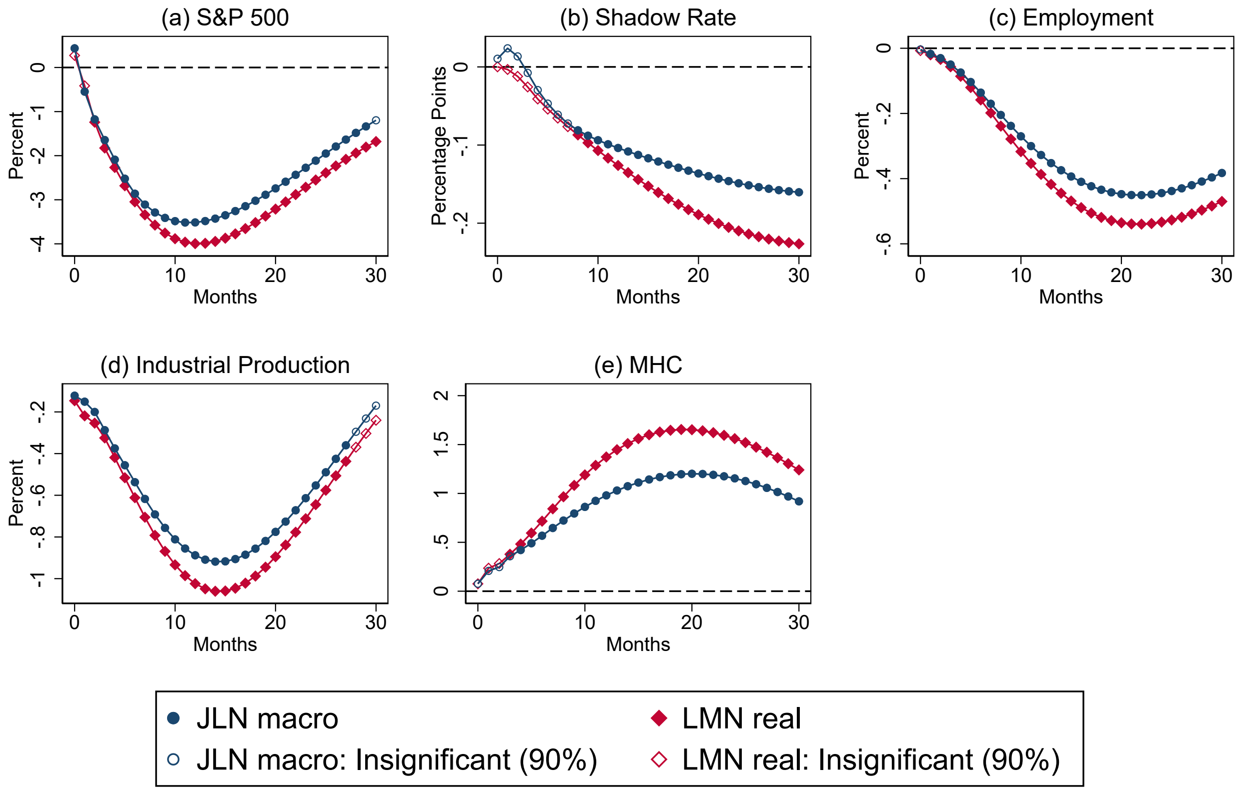

Figure 3: Impulse Response Functions to Uncertainty Shocks

Note: 2004M01-2019M12. The blue circles and the red diamonds represent responses to shocks to JLN macro uncertainty and LMN real uncertainty, respectively. The filled markers indicate responses that are significant at the 10% significance level, while the hollow ones represent those that are not. The 90-percent confidence intervals are obtained using 2,000 bootstraps.

Table 3: Forecast Error Variance Decomposition

	JLN macro					LMN real				
Horizon	S&P 500	SR	Employment	IP	MHC	S&P 500	SR	Employment	IP	MHC
1	0.02	0.00	0.00	0.06	0.00	0.01	0.00	0.01	0.08	0.00
6	0.31	0.01	0.19	0.35	0.04	0.26	0.02	0.21	0.37	0.06
12	0.63	0.05	0.54	0.69	0.14	0.57	0.06	0.55	0.65	0.23
24	0.68	0.12	0.69	0.76	0.32	0.71	0.18	0.76	0.79	0.48
36	0.65	0.17	0.68	0.73	0.36	0.71	0.29	0.80	0.79	0.53

Note: This table shows the share of forecast error variance of each variable explained by uncertainty shocks.

We further investigate the propagation mechanism of uncertainty to mental health concerns. The most likely candidate is the negative spillover from the responses of real economic variables to uncertainty shocks, such as employment and industrial production, which might be viewed as indirect effects. As demonstrated in Figure 3, employment and industrial production significantly decrease in response to the uncertainty shocks. This might further lead agents to face a higher level of mental distress, as they now need to adjust to the lower level of income and thus, consumption.

A natural follow-up question is if uncertainty shocks can directly influence mental health concerns. We thus perform two additional analyses. First, we run a bivariate VAR with uncertainty and the MHC index only. Second, we conduct a counterfactual analysis based on our benchmark VAR with six variables as in equation (3.1). Specifically, we block the spillover channels through other economic variables in the VAR by setting the coefficients of those variables to zero in the last equation of the MHC index. The upper and lower panels of Figure 4 depict the impulse responses of the MHC index to a one-standard deviation shock to uncertainty from the first and second analyses. Interestingly, in both cases, the MHC index significantly rises following a sudden increase in uncertainty, which indicates that there is a direct effect of uncertainty on the MHC index. The magnitudes of the responses are also comparable to that obtained from our baseline VAR model, which is noted in blue in the figure. These findings highlight that unexpected increases in macro uncertainty alone can result in heightened concerns about mental health status.

3.2 Robustness Checks We perform a battery of additional analyses to examine the robustness of our findings.

Alternative macroeconomic uncertainty measures While different uncertainty indices are closely related to each other and known to have similar effects on the aggregate economy (Jo and Sekkel 2019), each measure is constructed to reflect different aspects of underlying uncertainty. Thus, these indices may have varying effects on mental distress. We hence re-estimate our baseline VAR by using alternative measures for uncertainty, i.e., the EPU index from Baker et al. (2016), CBOE Volatility Index (VIX, monthly average of daily data), and the financial uncertainty index developed by Ludvigson et al. (2021) (LMN financial). Figure 5 plots the impulse responses of the MHC index to an uncertainty shock, measured with the different uncertainty proxies. Whereas the MHC index increases significantly in response to uncertainty shocks proxied by financial uncertainty indices (VIX and LMN financial, middle and right panels), EPU index does not show significant impacts (left panel).[18]

Survey-based uncertainty measure What we have used so far as baseline uncertainty indices are JLN macro and LMN real uncertainty indices, which are constructed based on state-of-the-art econometric

[18] In a companion paper (Bae et al. (2023)), we show that the shock to the EPU index does not also incur any significant impacts on the key macro variables when we consider the period between September 2008 and December 2019, unlikely other measures of uncertainty negatively affecting economic activity during the same period.

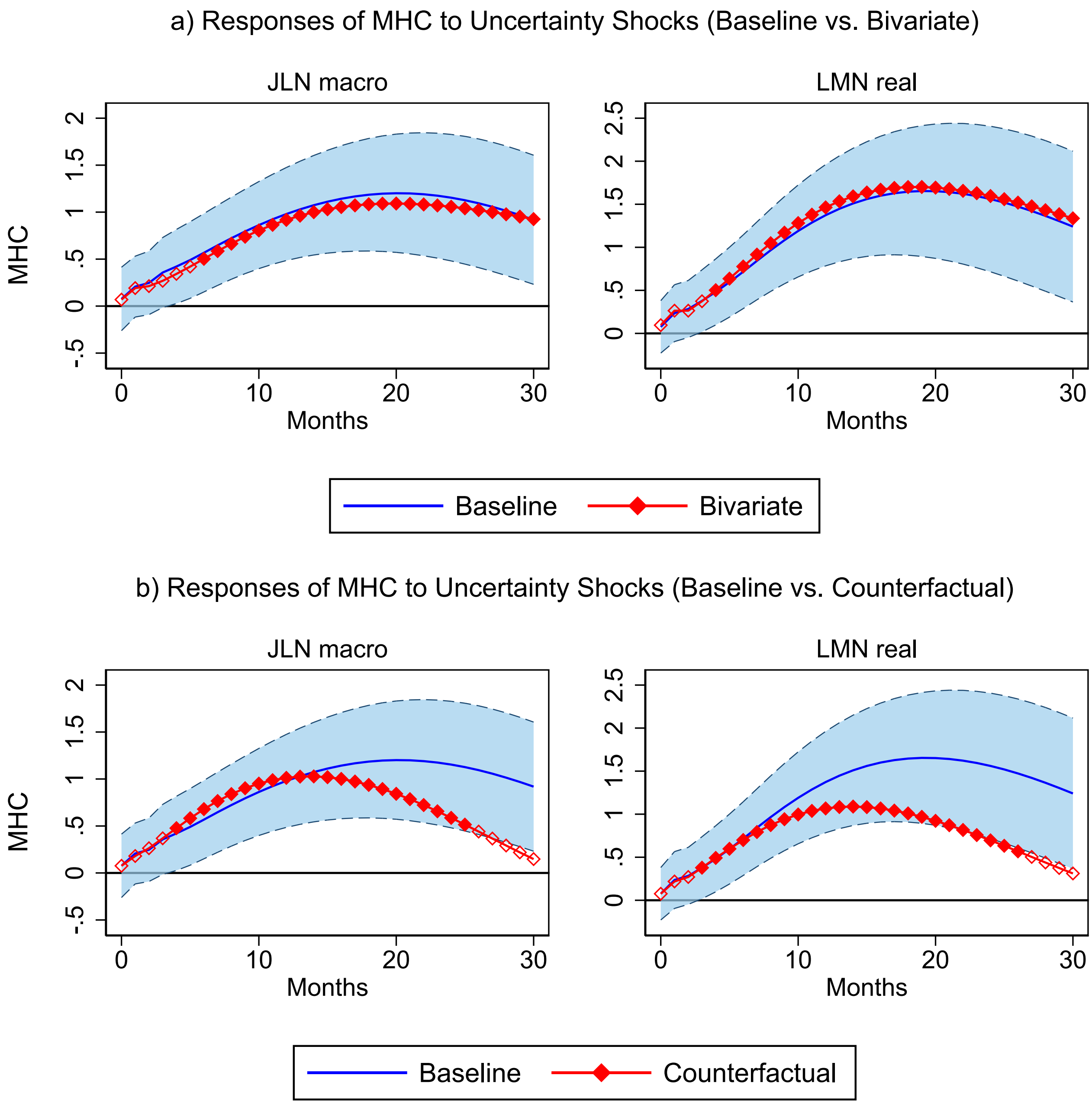

Figure 4: Direct Effects of Uncertainty Shocks

Note: 2004M01-2019M12. Each panel shows the responses of the MHC index to uncertainty shocks, with uncertainty quantified by JLN macro (left panels) and LMN real (right panels). In the upper panel, the red diamonds indicate impulse responses from a bivariate VAR (including uncertainty and the MHC index only). In the lower panel, the red diamonds indicate impulse responses from a counterfactual exercise, where the effects of other variables than uncertainty on the MHC index is "turned off" from the baseline model. Solid markers are significant responses, whereas hollow ones denote insignificant responses at the 10% significance level. The blue solid line represents impulse responses from the baseline VAR. Shaded areas represent 90-percent confidence intervals based on baseline VAR obtained using 2,000 bootstraps.

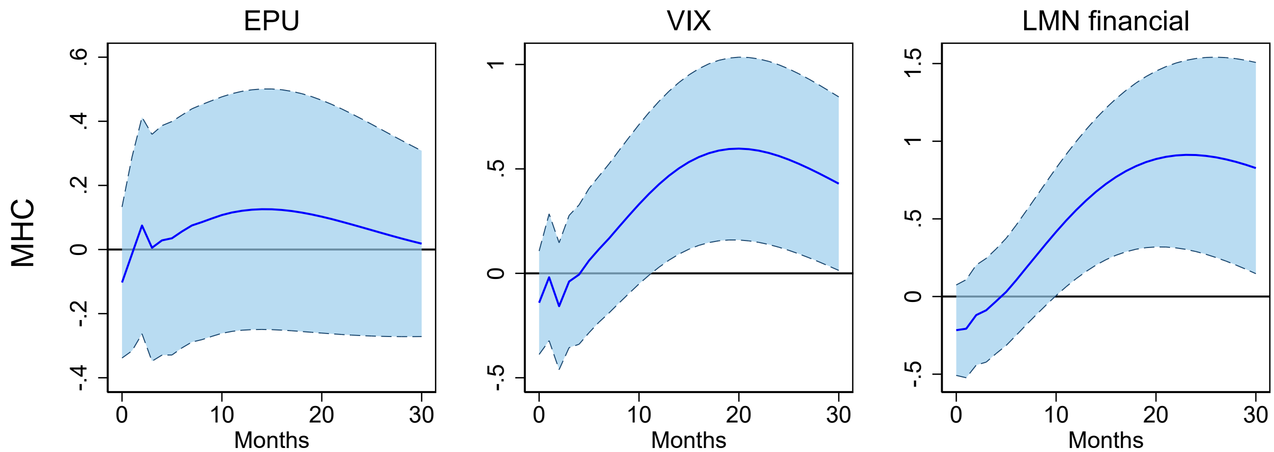

Figure 5: MHC Responses to Alternative Measures of Uncertainty

Note: 2004M01-2019M12. Each panel shows responses of the MHC index to uncertainty shocks represented by EPU, VIX, and LMN financial uncertainty, respectively, in the baseline VAR model. Shaded areas represent 90-percent confidence intervals obtained using 2,000 bootstraps.

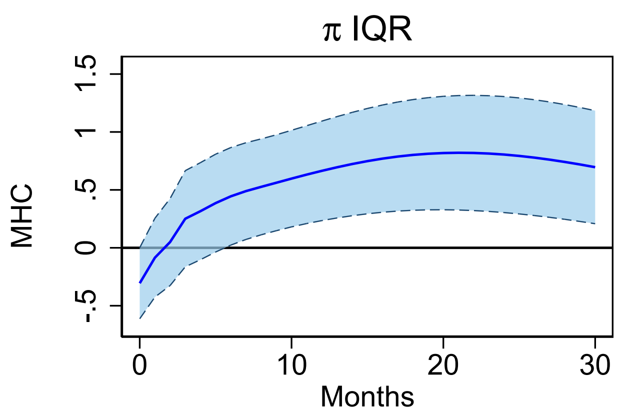

Figure 6: MHC Responses to a Survey-Based Uncertainty Index

Note: 2004M01-2019M12. This figure shows the responses of the MHC index to shocks to uncertainty represented by the IQR of one-year ahead inflation expectations. Shaded areas represent 90-percent confidence intervals obtained using 2,000 bootstraps.

models applied to numerous macro and financial indicators. However, these aggregate-level uncertainty may be different from what agents actually perceive. Hence, we consider a micro-level, survey-based uncertainty index, which is the dispersion in one year-ahead inflation expectations from the Michigan Survey of Consumers, measured as the interquartile ranges (IQR, 75th − 25th percentiles). This is based on the assumption that when the level of uncertainty is elevated, it would be more difficult to reach a consensus about future price conditions.[19] As shown in Figure 6, the MHC index significantly rises again, following a surprise increase in uncertainty measured as the IQR of expected inflation. Our baseline finding is hence robust to the changes in the uncertainty measure to a micro-level proxy.

Changes in VAR specifications Our results are also robust to alternative specifications of the baseline VAR model. In particular, we consider the cases with i) uncertainty index ordered fifth (right before the MHC index) instead of first in the Cholesky ordering and ii) six lags instead of three lags in the VAR. As reported in Appendix A.7, impulse responses change little.

Additional Analysis on the Uncertainty Transmission Mechanism Our baseline VAR model (equation (3.1)) does not allow a structural examination on how uncertainty shocks propagate to mental health concerns. However, we compare our MHC index to a range of other indices capturing economic agents' perception on uncertainty, in an attempt to understand underlying transmission channels.[20] The indices include i) survey responses from the Michigan Survey of Consumers noting that the current month is a bad time to purchase various durable goods due to uncertain future, ii) responses from the same survey showing consumers' perception on various economic conditions, iii) equity market volatility tracking indicators on different aspects, and iv) Twitter-based uncertainty index. We also compare a battery of macroeconomic indicators and compute the correlation coefficients. As shown in Table 4, indices reflecting agents' subjective perception show much higher correlation than economic indicators. This is consistent with the findings from Section 3.1 that uncertainty may affect the level of mental health directly, not necessarily through its negative impacts on economic activity.

4 Conclusion

This study examined the impact of uncertainty on aggregate mental health concerns. We first constructed the MHC index from January 2004 to February 2023, utilizing the Google Trends data. In particular, we quantified changes in search intensity of a number of phrases, such as "depression" and "stress", that can represent the mental status of U.S. citizens. We show that this index increased significantly during the Global Financial Crisis, the 2011 debt ceiling debate, and the COVID-19 pandemic. The MHC index was further shown to be correlated with alternative indicators that are potentially

[19] Previous studies hence used survey forecast dispersion as a measure of ex-ante uncertainty. See Bachmann et al. (2013), for example.

[20] We thank an anonymous referee for the suggestion.

Table 4: Correlation Coefficients between the MHC Index and Various Indicators

	Correlation Coefficients
A. Survey Data	
Bad time to buy Large Household Goods: uncertain future	0.46
Bad time to buy Vehicles: uncertain future	0.45
Bad time to buy House: uncertain future	0.45
Index of Current Economic Conditions	-0.49
Index of Consumer Expectations	-0.39
Probability of Personal Income Increase in Year Ahead	-0.61
Probability of Increase in Stock Market in Next Year	-0.40
Business Conditions Expected During the Next 5 Years	-0.35
Opinions About the Government's Economic Policy (Good-Poor)	-0.38
Buying Conditions for Large Household Goods (Good-Bad)	-0.44
B. Other Indicators Reflecting Volatilities	
Twitter-based Uncertainty	0.54
US Equity Market Volatility (Overall EMV Tracker)	0.11
Macro – Broad Quantity Indicators EMV Tracker	0.23
Macro – Labor Markets EMV Tracker	0.26
Financial Crises EMV Tracker	0.47
Fiscal Policy EMV Tracker	0.25
Government Spending, Deficits, and Debt EMV Tracker	0.37
C. Macroeconomic Indicators	
Unemployment Rate	0.50
ΔReal Final Sales of Domestic Product	-0.10
ΔGross Domestic Product	-0.10
ΔCorporate Profits after tax with IVA and CCAdj: Net Dividends	-0.08
ΔFederal Consumption Expenditures and Gross Investment	-0.28
ΔPersonal Consumption Expenditures	-0.06
ΔPersonal Consumption Expenditures: Nondurable Goods	-0.09
ΔPersonal Consumption Expenditures: Services	-0.08

Note: 2004M01-2023M02. For Twitter-based Uncertainty in panel B, we take the monthly average of daily data, and the correlation coefficient with the MHC index is calculated for the period from June 2011 to February 2023 because of the data availability. In panel C, Δ indicates the variables that are transformed to growth rates by taking the first difference of the natural logarithm. Real Final Sales of Domestic Product, Gross Domestic Product, Corporate Profits after tax with IVA and CCAdj: Net Dividends, and Federal Consumption Expenditures and Gross Investment are quarterly variables. Thus, we calculated correlation coefficients between the quarterly average of the MHC index and these variables from the first quarter of 2004 to the fourth quarter of 2022.

closely associated with the level of mental distress. We then analyzed the extent to which a shock to uncertainty affected the level of concerns about mental health by estimating a VAR model augmented with the MHC index: We found that unexpected increases in uncertainty significantly exacerbate mental health concerns. Our findings implied that heightened uncertainty could have a far-reaching effect to the overall welfare of economic agents through a channel often neglected by the previous literature.

It is worthwhile to note here again that we presumed that search terms would mirror the true mental status or concerns on mental health of the Google search engine users. We also considered this index to be able to capture the overall level of the concerns in the U.S. reasonably well. However, our index has a limitation in reflecting the state of those without access to internet, for example, who could be the ones with high mental health risks. More importantly, it would not be feasible for us to further validate whether internet users truly reveal their underlying concerns. For instance, their search demand could be i) due to families, friends, and acquaintances but not due to the searchers, ii) out of pure curiosity rather than specific needs, and iii) affected by external circumstances enabling a more frequent use of internet. Therefore, further research is needed to ensure the representativeness of the MHC index.

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A.1 Complete List of Selected Search Terms

Table A1: Complete List of Selected Search Terms

Topic	Top ten related queries
Anxiety	anxiety, anxious, depression, anxiety symptoms, anxiety depression, anxiety attack, anxiety disorder, social anxiety, anxiety medication, anxiety help
Boredom	bored, what to do, bored what to do, things to do, what to do when bored, things to do when bored, boredom, im bored, games, bored games
Depression	depression, depressed, anxiety, depression anxiety, anxiety and depression, depression symptoms, postpartum depression, postpartum, what is depression, depressing
Divorce	divorce, divorced, divorce records, marriage, divorce lawyers, divorce attorney, divorce lawyer, divorce court, divorce papers, texas divorce
Irritability	irritable, irritability, symptoms, anxiety, depression, irritable definition, irritability symptoms, anxiety irritability, irritable uterus, irritability depression
Loneliness	lonely, loneliness, quotes, lonliness, lonely quotes, feel lonely, lonely feeling, quotes loneliness, being lonely, alone
Panic	panic, panic attack, panic attacks, anxiety, panic disorder, anxiety attack, panic attack symptoms, anxiety panic attacks, anxiety attacks, panic anxiety disorder
Sadness	sad, sad quotes, quotes, sadness, sad songs, sad love, sad face, happy, sad movies, sad lyrics
Self-esteem	self, self esteem, esteem, low self esteem, low esteem, self-esteem, self worth, autoestima, respect, self respect
Sleep	sleep, sleeping, sleep in, how to sleep, asleep, sleep apnea, sleepy, sleep number, fall asleep, what is sleep
Stress	stress, stress disorder, traumatic stress, post traumatic stress, post stress disorder, post traumatic stress disorder, traumatic stress disorder, estres, stress ball, stress test
Suicide	suicide, suicidal, commit suicide, suicides, suicide hotline, suicide prevention, sucide, murder suicide, suicide rate, what is suicide
Well-being	well being, wellbeing, well-being, health, bienestar, health and wellbeing, well being definition, wellness, what is well being, mental health
Worry	worry, worry about, worrying, worried, to worry, worries, dont worry, stop worrying, not to worry, do not worry

Note: This table reports top ten related queries provided by Google Trends on March 1, 2023.

A.2 Data Sources

Table A2: Data Sources

Variable	Source	Notes
Mental Health Concerns Index	Google Trends	Constructed as described in Section 2
The Index of Consumer Sentiment	Survey of Consumers	
Current Financial Situation Compared with a Year Ago	Survey of Consumers	
Expected Household Income Change During the Next Year	Survey of Consumers	
Probability of Losing a Job During the Next 5 Years	Survey of Consumers	
Cantril Ladder	The World Happiness Report	
Positive Emotion	The World Happiness Report	
Negative Emotion	The World Happiness Report	
S&P 500	Yahoo Finance	Closing prices of monthly data
Shadow Rate	Wu and Xia (2016)	
All Employees, Total Nonfarm	FRED	
Industrial Production	FRED	
Economic Policy Uncertainty Index for United States	FRED	
CBOE Volatility Index: VIX	FRED	Monthly average of daily data
JLN Macro, LMN Real, and LMN Financial uncertainty Indices	Jurado et al. (2015); Ludvigson et al. (2021)	3-months forecast horizon
Bad Time to Buy Large Household Goods: Uncertain Future	Survey of Consumers	
Bad Time to Buy Vehicles: Uncertain Future	Survey of Consumers	
Bad Time to Buy House: Uncertain Future	Survey of Consumers	
Index of Current Economic Conditions	Survey of Consumers	
Index of Consumer Expectations	Survey of Consumers	
Probability of Personal Income Increase in Year Ahead	Survey of Consumers	
Probability of Increase in Stock Market in Next Year	Survey of Consumers	
Business Conditions Expected During the Next 5 Years	Survey of Consumers	
Opinions About the Government's Economic Policy (Good-Poor)	Survey of Consumers	
Buying Conditions for Large Household Goods (Good-Bad)	Survey of Consumers	
Twitter-Based Uncertainty	Baker et al. (2021)	
US Equity Market Volatility (Overall EMV Tracker)	Baker et al. (2019)	
Macro – Broad Quantity Indicators EMV Tracker	Baker et al. (2019)	
Macro – Labor Markets EMV Tracker	Baker et al. (2019)	
Financial Crises EMV Tracker	Baker et al. (2019)	
Fiscal Policy EMV Tracker	Baker et al. (2019)	
Government Spending, Deficits, and Debt EMV Tracker	Baker et al. (2019)	
Unemployment Rate	Bureau of Labor Statistics	
Real Final Sales of Domestic Product	FRED	
Gross Domestic Product	FRED	
Corporate Profits after tax with IVA and CCAdj: Net Dividends	FRED	
Federal Consumption Expenditures and Gross Investment	FRED	
Personal Consumption Expenditures	FRED	
Personal Consumption Expenditures: Nondurable Goods	FRED	
Personal Consumption Expenditures: Services	FRED	

A.3 Construction of the Mental Health Concerns Index

We construct the MHC index for the U.S. by integrating the search intensity of a variety of terms related to mental health concerns. Let $SVI_{i,t}^{sole}$ denotes the Google Search Volume Index of the term i and the period t downloaded individually from Google Trends; $SVI_{i,t}^{\text{“depression”}}$ denotes that of term i downloaded together with the term "depression" (total two keywords at a time); $SVI^{i}_{\text{“depression”},t}$ denotes that of the term "depression" downloaded together with term i (two keywords at a time). Note that $SVI_{i,t}^{\text{“depression”}}$ and $SVI_{i,t}^{sole}$ are the same if i is "depression". We proceed as follows.

The first step is to re-scale all of the SVI series. We need SVI series that are comparable across different search terms and groups. Here, we face a challenge inherent in Google Trends: only up to five SVIs are downloadable at once and a SVI downloaded with a different set of keywords is scaled differently. Hence, we set "depression" as a benchmark keyword and include it in every pair with other terms. We will re-scale SVI to be comparable with $SVI^{sole}_{\text{“depression”},t}$. By dividing $SVI_{i,t}^{\text{“depression”}}$ by $SVI^{i}_{\text{“depression”},t}$, we can get the ratio of keyword popularity of the two terms. This is because, as SVI of term i and the term "depression" are downloaded together, same $\max\limits_{i,t} \text{keyword popularity}_{i,t}$ is applied in the scaling process by Google Trends (see equation (2.2)).

$$ratio_{i,t} = \frac{SVI_{i,t}^{\text{“depression”}}}{SVI^{i}_{\text{“depression”},t}} = \frac{\text{keyword popularity}_{i,t}}{\text{keyword popularity}_{\text{“depression”},t}} \tag{A.3.1}$$

Note that $ratio_{\text{“depression”},t}$ is 1 for every t. We then calculate $ratio_{i,t} \times SVI^{sole}_{\text{“depression”},t}$, which is constant $\left(\frac{100}{\max_t \text{keyword popularity}_{\text{“depression”},t}}\right)$ multiple of keyword $\text{popularity}_{i,t}$.

$$\begin{aligned} ratio_{i,t} \times SVI^{sole}_{\text{“depression”},t} &= \frac{SVI_{i,t}^{\text{“depression”}}}{SVI^{i}_{\text{“depression”},t}} \times SVI^{sole}_{\text{“depression”},t} \\ &= \frac{\text{keyword popularity}_{i,t}}{\text{keyword popularity}_{\text{“depression”},t}} \times \frac{100 \times \text{keyword popularity}_{\text{“depression”},t}}{\max\limits_{t} \text{keyword popularity}_{\text{“depression”},t}} \\ &= \frac{100}{\max\limits_{t} \text{keyword popularity}_{\text{“depression”},t}} \times \text{keyword popularity}_{i,t} \end{aligned} \tag{A.3.2}$$

However, we face another challenge; Google Trends provides SVI rounded to an integer. Due to the rounding error, some $SVI_{i,t}^{\text{“depression”}}$s, especially those with very low keyword popularity compared to "depression", have the shape of an irregular step function. In addition, deseasonalizing these series is not starightforward. We hence take an alternative approach. Let $\tilde{t}_i$ denote the time when the $ratio_{i,t}$ becomes the highest.

$$\tilde{t}_i = \operatorname*{argmax}_t ratio_{i,t} = \operatorname*{argmax}_t \frac{SVI_{i,t}^{\text{“depression”}}}{SVI^i_{\text{“depression”},t}} \tag{A.3.3}$$

Then, define $SVI_{i,t}^{scaled}$ as follows:

$$SVI_{i,t}^{scaled} = SVI_{i,t}^{sole} \times \underbrace{\frac{ratio_{i,\tilde{t}_i} \times SVI^{sole}_{\text{depression},\tilde{t}_i}}{SVI^{sole}_{i,\tilde{t}_i}}}_{\text{Scaling Factor}_{\tilde{t}_i}\text{(constant)}} \tag{A.3.4}$$

Through this process, $SVI_{i,t}^{scaled}$ has the value of $ratio_{i,t} \times SVI^{sole}_{\text{“depression”},t}$, which we want, at time $\tilde{t}_i$. This means that SVI series are re-scaled to the same basis and can be compared to each other properly. On top of that, we can make use of ample dynamics of $SVI_{i,t}^{sole}$. Here, we use $ratio_{i,\tilde{t}_i}$ to avoid $SVI_{i,t}^{scaled}$ becoming 0 as possible as we can. This does not cause serious problems because the scaling factor for each term i should be the same regardless of time t mathematically if there were no rounding errors.

$$\begin{aligned}
\text{Scaling Factor}_t &= \frac{ratio_{i,t} \times SVI^{sole}_{\text{depression},t}}{SVI^{sole}_{i,t}} \\
&= \frac{SVI_{i,t}^{\text{“depression”}}}{SVI^{sole}_{i,t}} \times \frac{SVI^{sole}_{\text{depression},t}}{SVI^i_{\text{“depression”},t}} \\
&= \frac{\max_t \text{keyword popularity}_{i,t}}{\max_t \text{keyword popularity}_{\text{“depression”},t}}
\end{aligned} \tag{A.3.5}$$

From now on, we adjust $SVI_{i,t}^{scaled}$ series by drawing on Da et al. (2015). In the second step, all $SVI_{i,t}^{scaled}$ series are winsorized at the 5% level (2.5% in each tail) to remove outliers. This mitigates the concern of including inquiries of irrelevant keywords like “suicide squad” which is the title of an American superhero film. This is because this kind of term is searched for especially when specific events related to it, such as the release of the movie, happen.

Let us now turn to the third step. In this step, we address seasonality by de-seasonalizing each series with the X13-ARIMA-SEATS technique. To use this technique, we round winsorized $SVI_{i,t}^{scaled}$ series up to the fifth digit (for the sake of computation) and add 0.00001 to all data points (because this technique can be performed only on positive values). This is not a harmful transformation considering that the smallest nonzero value of winsorized $SVI_{i,t}^{scaled}$ is 0.01875. After seasonal adjustment, we bring the series back to the previous level by subtracting 0.00001 from all data points. Let $ASVI_{i,t}^{scaled}$ denote the re-scaled and adjusted (winsorized and de-seasonalized) SVI of each search term i and the period t.

Finally, we construct the MHC index by aggregating all the $ASVI^{scaled}$ into a single index and normalizing. We call the sum of $ASVI^{scaled}$ SUM:

$$SUM_t = \sum_{i=1}^{133} ASVI_{i,t}^{scaled} \tag{A.3.6}$$

Afterward, to index the first data point of the MHC index to 100, we define the MHC index as follows:

$$MHC_t = \frac{SUM_t}{SUM_0} \times 100 \tag{A.3.7}$$

In the equation (A.3.7), time 0 indicate the first point of time in our series, which is January 2004.[21]

A.4 Sentiment Analysis Results

We examine what our baseline MHC index captures by conducting a sentiment analysis using Valence Aware Dictionary and sentiment Reasoner (VADER) presented by Hutto and Gilbert (2014). VADER is a model to determine overall emotion contained in a document, paragraph, sentence, or clause. It relies on a dictionary that determines emotion intensities known as sentiment scores. The sentiment score of a text is obtained by summing up the intensity of each word in the text. Therefore, the following analysis we conduct using search terms, a majority of which consists of a single word, should be taken with caution. As shown in Table A1, the longest search term we use has five words only. In addition, a search term that is misspelled (e.g., “sucide”) that is still included for the construction of the MHC index will be classified neutral, because there is no valid match in the lexicon.

Table A3 provides keywords that are ranked at the bottom 20 in terms of compound scores. Figure A1 presents the result with a histogram: About 60% of total keywords are classified to be negative while only about 10% represents positive sentiment. Remaining 30% of the keywords are determined to be neutral. Of note, the convention is to view a word/phrase negative if its compound score is less than or equal to -0.05, neutral if it is in between -0.05 and 0.05, and positive if it is greater than or equal to 0.05. We further classify search terms that are non-positive (i.e. a compound score lower

[21] Google Trends provides data from 2004.

than 0.05). About 90% of our search terms falls in this category. Figure A2 plots an alternative MHC index constructed using only the terms with non-positive sentiments (the red dashed line) and another one using negative terms only (the blue dotted line). The former moves very closely with our baseline index, while the latter also peaks during similar times as our baseline index.

Table A3: Results from Sentiment Analysis (VADER): 20 Terms with Lowest Compound Scores

	negative	neutral	positive	compound
murder suicide	1.000	0.000	0.0	-0.8807
post traumatic stress disorder	0.902	0.098	0.0	-0.8481
traumatic stress disorder	1.000	0.000	0.0	-0.8481
anxiety panic attacks	1.000	0.000	0.0	-0.7845
panic anxiety disorder	1.000	0.000	0.0	-0.7717
post traumatic stress	0.867	0.133	0.0	-0.7579
traumatic stress	1.000	0.000	0.0	-0.7579
panic attack symptoms	0.865	0.135	0.0	-0.7506
panic attack	1.000	0.000	0.0	-0.7506
panic attacks	1.000	0.000	0.0	-0.7351
irritability depression	1.000	0.000	0.0	-0.7269
panic disorder	1.000	0.000	0.0	-0.7184
post stress disorder	0.846	0.154	0.0	-0.6705
stress disorder	1.000	0.000	0.0	-0.6705
suicidal	1.000	0.000	0.0	-0.6705
suicide	1.000	0.000	0.0	-0.6705
suicide hotline	0.818	0.182	0.0	-0.6705
what is suicide	0.692	0.308	0.0	-0.6705
suicide rate	0.818	0.182	0.0	-0.6705
suicide prevention	0.818	0.182	0.0	-0.6705

Note: 20 terms with the lowest compound scores among 133 keywords employed in constructing the MHC index. According to Hutto and Gilbert (2014), the negative, neutral, and positive scores (second, third, and fourth columns, respectively) are ratios indicating proportions of text classified as each category. The compound score (fifth column) is computed as the sum of the valence scores of each word in the lexicon, adjusted based on the rules, and then scaled to range between -1 (most negative) and +1 (most positive).

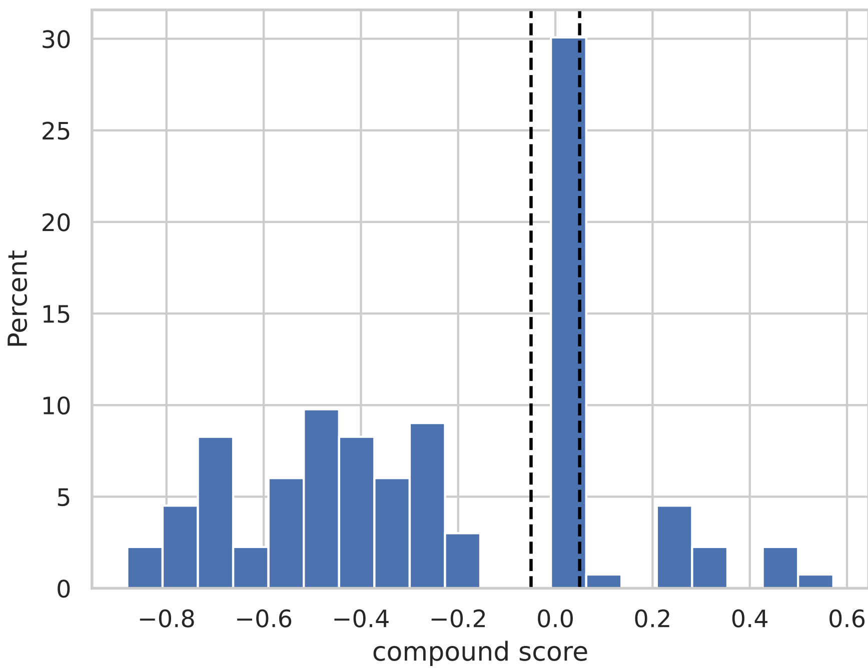

Figure A1: Histogram of Compound Scores

Note: Histogram of the compound scores of 133 keywords employed in constructing the MHC index. Dashed lines indicate -0.05 and 0.05, which are threshold values for negative (-0.05) and positive sentiment (0.05).

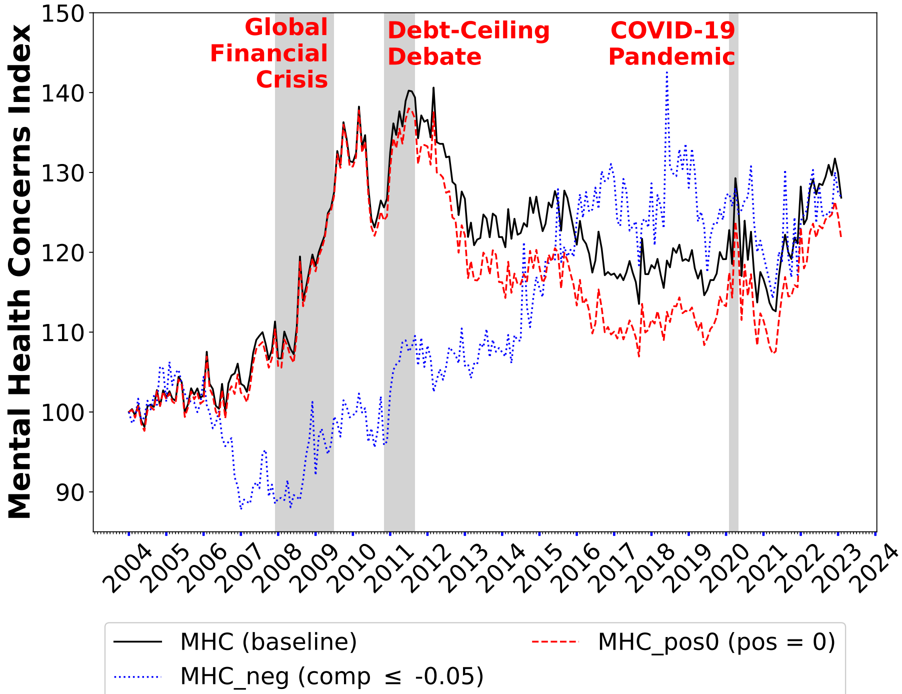

Figure A2: the MHC Index using Non-Positive Search Terms

Note: 2004M01 - 2023M02. The black solid line indicates baseline MHC index constructed using 133 keywords. The red dashed line and the blue dotted line represent variations of the MHC index constructed employing keywords whose positive scores are zero and keywords whose compound scores are less than or equal to -0.05, respectively. Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

A.5 Search Intensity Series of Individual Topics

In what follows, we show the dynamics of the search intensity of 14 topics consisting the baseline aggregate MHC index. Each series is scaled relative to the SVI of the topic "Depression". As such, we call them Adjusted Search Volume Indices (ASVIs).

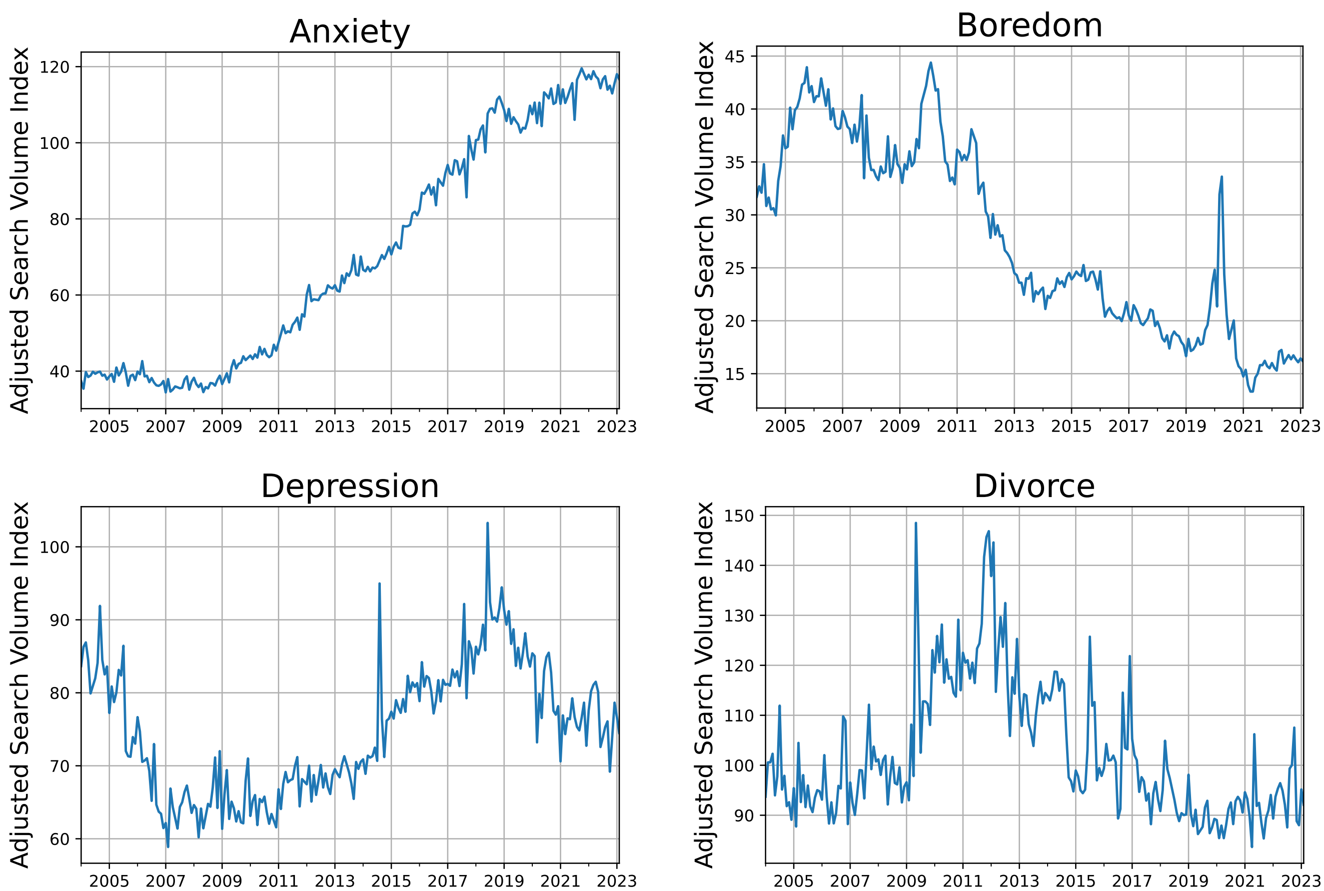

Figure A3: ASVI for Each Topic

Note: Each panel shows ASVI of each topic, which is scaled based on the SVI of "depression", winsorized at the 5% level (2.5% in each tail), and de-seasonalized with the X13-ARIMA-SEATS technique.

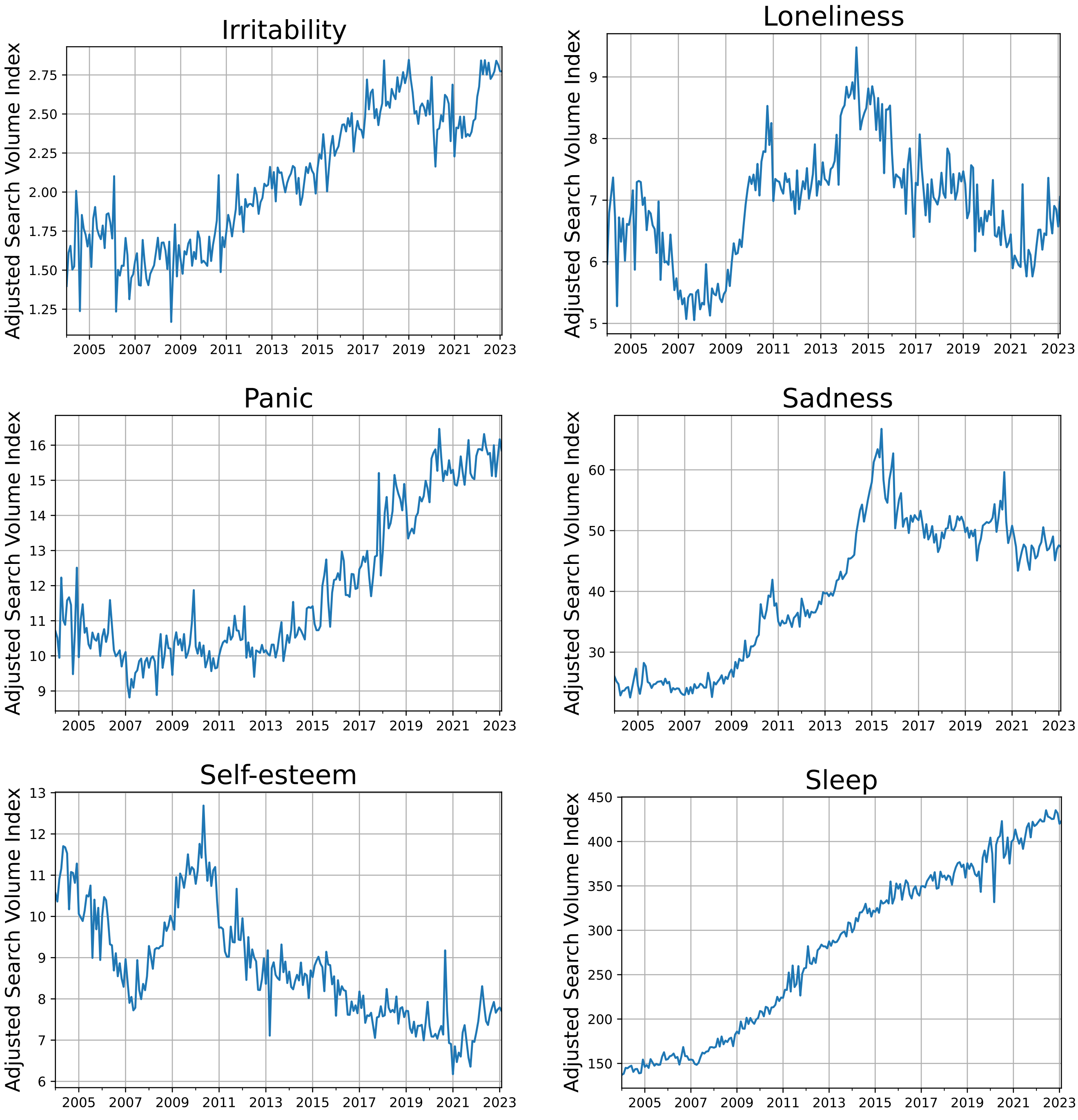

Figure A4: ASVI for Each Topic (continued)

Note: Each panel shows ASVI of each topic, which is scaled based on the SVI of "depression", winsorized at the 5% level (2.5% in each tail), and de-seasonalized with the X13-ARIMA-SEATS technique.

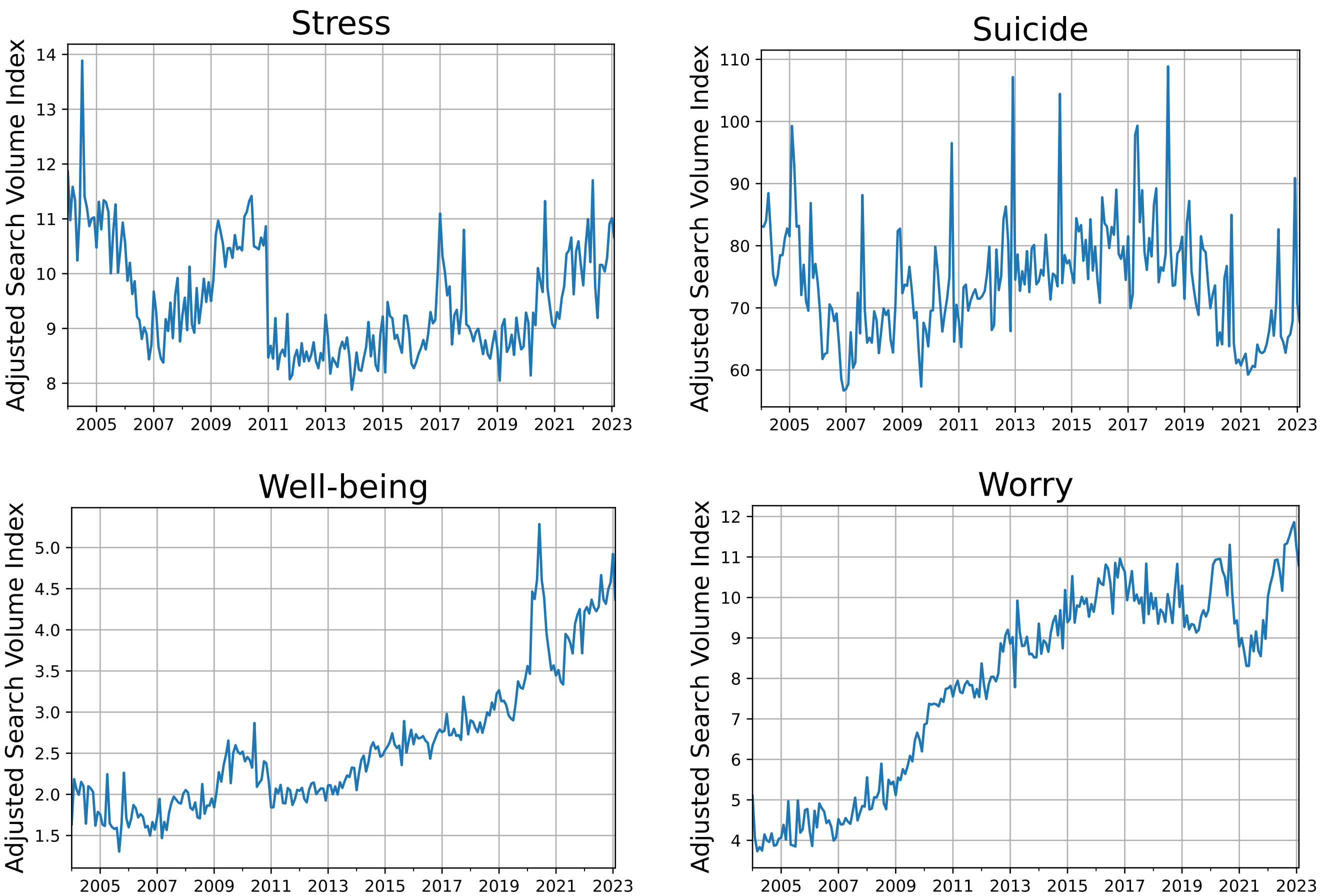

Figure A5: ASVI for Each Topic (continued)

Note: Each panel shows ASVI of each topic, which is scaled based on the SVI of "depression", winsorized at the 5% level (2.5% in each tail), and de-seasonalized with the X13-ARIMA-SEATS technique.

To gauge the relation between each topic and our baseline composite index, we further estimate a regression model where we regress the MHC index on each ASVIs and report relevant estimates in Table A4.

Table A4: Correlation Coefficients between the MHC Index and Individual ASVIs

Topic	(1) Correlation Coefficient	(2) R^2 (single topic)	(3) R^2 (all topics)	(4) Share of R^2
Anxiety	0.096	0.009	0.772	0.012
Boredom	0.420***	0.177	0.772	0.229
Depression	0.143*	0.020	0.772	0.026
Divorce	0.615***	0.378	0.772	0.490
Irritability	0.053	0.003	0.772	0.004
Loneliness	0.434***	0.188	0.772	0.244
Panic	0.412***	0.170	0.772	0.220
Sadness	0.210***	0.044	0.772	0.057
Sleep	0.405***	0.164	0.772	0.212
Suicide	0.069	0.005	0.772	0.006
Well-being	0.269***	0.072	0.772	0.093
Worry	0.357***	0.127	0.772	0.165
Stress	0.008	0.000	0.772	0
Self-esteem	0.553***	0.306	0.772	0.396

Note: Column (1) shows correlation coefficients between the MHC index and ASVIs for 14 topics, which are de-trended employing the Baxter-King filter. The significance of the correlation coefficient is tested based on Bonferroni-adjusted significance levels. Column (2) displays R^2 when regressing the MHC index on each ASVI separately. Column (3) illustrates R^2 when regressing the MHC index on ASVIs for 14 topics in the same regression. Column (4) represents the value in Column (2) divided by that in Column (3) for each topic.

A.6 Robustness of the MHC index

This section provides details of various checks we conduct, to investigate the sensitivity of our baseline MHC index.

A.6.1 Using Identical Topics from Brodeur et al. (2021)

Our baseline MHC index consists of 14 topics chosen based on the GHQ-12, which is a variation from the 13 topics specified in Brodeur et al. (2021). In particular, we exclude two from the selection of Brodeur et al. (2021), i.e., *Contentment* and *Impairment*, and append the list with three additional topics, i.e., *Anxiety*, *Depression*, and *Self-esteem*. Different from our baseline, here we construct the MHC index using the 13 topics identical to those noted in Brodeur et al. (2021).[22] As shown in Figure A6, the two indices exhibit very similar dynamics throughout the sample period, with the correlation coefficient amounting to 0.98. Still, the index based on the 13 topics from Brodeur et al. (2021) remains slightly higher, and the difference is most notable in the later part of the sample starting from 2014. To complete our analysis, Table A5 reports 20 related search terms that are included in the construction of the new index, as we additionally include the two topics of *Contentment* and *Impairment*.

[22] In particular, the 13 topics from Brodeur et al. (2021) are *Boredom, Contentment, Divorce, Impairment, Irritability, Loneliness, Panic, Sadness, Sleep, Stress, Suicide, Well-being* and *Worry*.

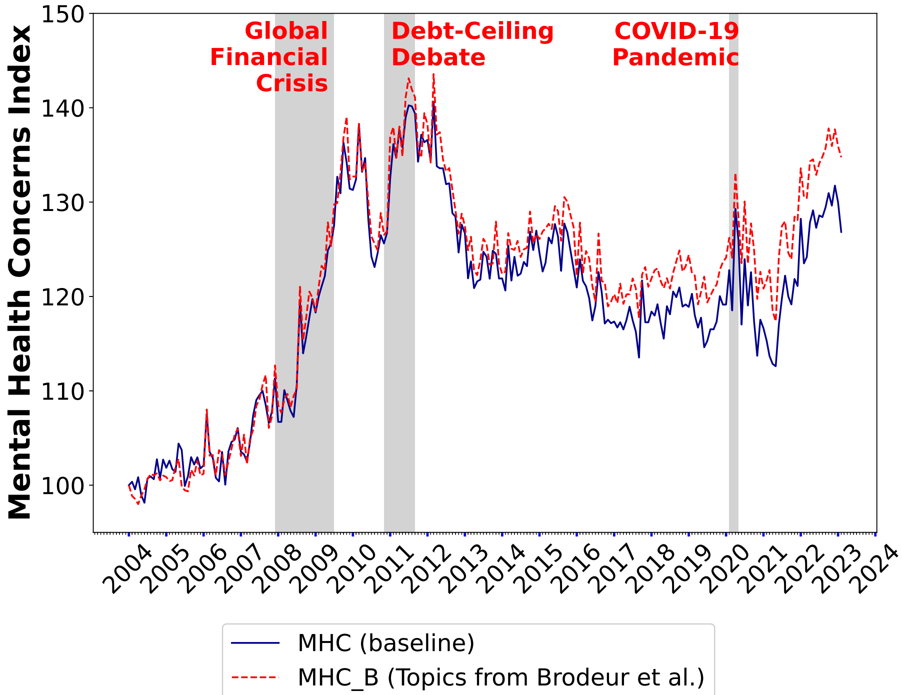

Figure A6: the MHC index using Topics from Brodeur et al. (2021)

Note: 2004M01-2023M02. The blue solid line indicates baseline MHC index constructed using keywords selected as top ten related terms for 14 topics, i.e., *Anxiety, Boredom, Depression, Divorce, Irritability, Loneliness, Panic, Sadness, Self-esteem, Sleep, Stress, Suicide, Well-being*, and *Worry*. The red dashed line represents a variation of the MHC index constructed employing keywords that are top ten related terms for 13 topics from Brodeur et al. (2021). Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

Table A5: Additional Topics and Respective Related Terms Considered as per Brodeur et al. (2021)

Topic	Top ten-related queries
Contentment	satisfaction, customer satisfaction, contentment, content, satisfaction survey, customer survey, customer satisfaction survey, contented, be content, customer service
Impairment	impairment, goodwill impairment, goodwill, what is impairment, impairment definition, asset impairment, impairment loss, impairment accounting, impairment test, impairment of assets

Note: This table is based on top-related queries provided by Google Trends on April 5, 2023.

A.6.2 Including Fewer Terms for the Construction of the MHC Index In the construction of our baseline MHC index, we use *ten* search terms for each topic. We consider an alternative approach of using a fewer number of search terms. As shown in Figure A7, MHC indices constructed from the first *three* (the blue dotted line) and *five* (the red dashed line) terms for a topic exhibit quite similar dynamics over all, with the correlation coefficients at 0.84 and 0.77, respectively, as shown in Table A7. The most notable difference would be the size of the drop in the newly-constructed indices before entering to the 2011 debt ceiling debate period, which further leads to differing sizes of the following peaks. While the levels remain differ across the indices, the overall dynamics afterwards are very close to each other.

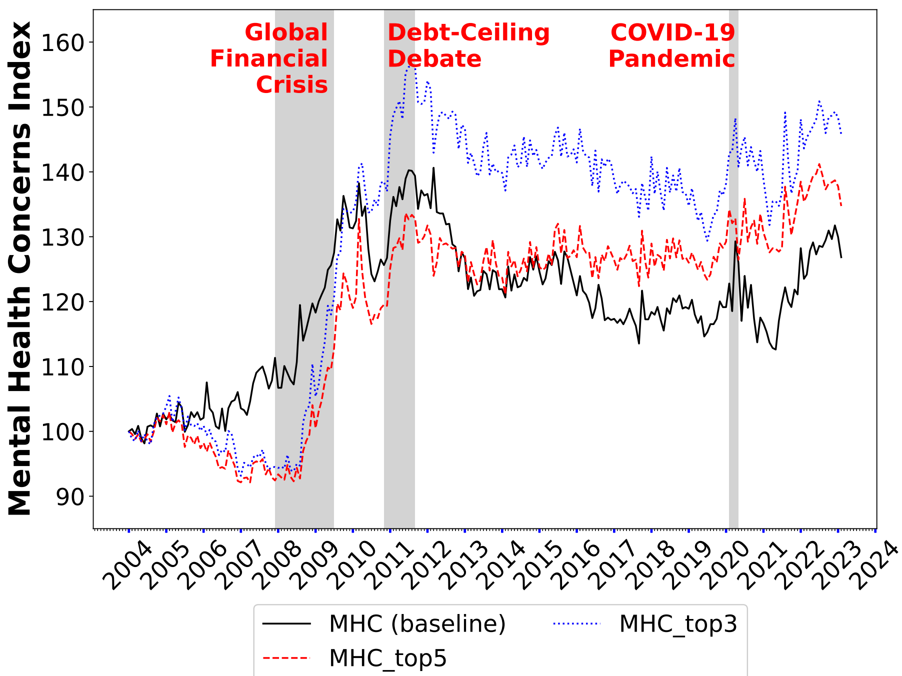

Figure A7: the MHC Index Constructed with a Fewer Number of Search Terms

Note: 2004M01-2023M02. The black solid line indicates baseline MHC index constructed using 133 keywords that are top ten related terms for 14 topics. The blue dotted line and the red dashed line represent variations of the MHC index constructed employing keywords that are top three related terms and keywords that are top five related terms for 14 topics, respectively. Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

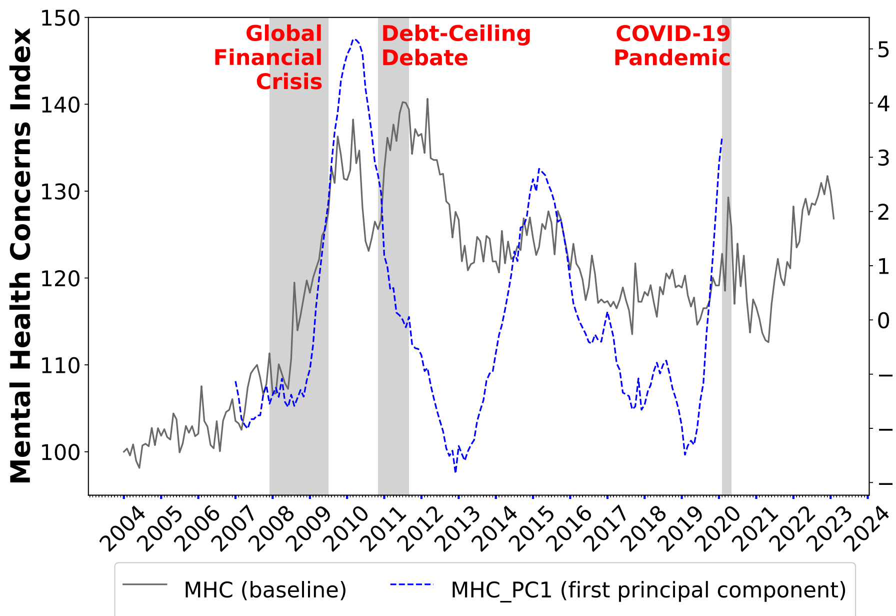

Figure A8: the MHC Index Constructed by PCA

Note: The gray solid line (2004M01-2023M02) indicates baseline MHC index constructed as overall search intensity of 133 keywords that are top ten related terms for 14 topics. The blue dotted line (2007M01-2020M02) represents variations of the MHC index constructed as the first principal component of ASVIs for 14 topics, which are winsorized at the 5% level (2.5% in each tail), de-seasonalized with the X13-ARIMA-SEATS technique, and then de-trended employing the Baxter-King filter (for ASVIs that are non-stationary as the results of the augmented Dickey-Fuller test). Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

A.6.3 Alternative Aggregation of Underlying SVIs For constructing the baseline MHC index, we simply sum up individual SVIs of all 133 search terms. Here, we instead apply the Principal Component Analysis (PCA) to the 14 topic series and obtain the first principal component, which captures the largest share of common variations in the underlying SVIs. It should be noted that we use a bandpass filter proposed by Baxter and King (1999) to remove trends from some non-stationary topic search series, based on the augmented Dickey-Fuller test results noted in Table A6, before applying the PCA.[23] The first principal component estimated using the PCA is much smoother than the baseline MHC index. It also shows extremely large jumps during the Global Financial Crisis and upon the arrival of the Covid-19 pandemic, while the component decreases during the debt-ceiling debate period. Overall, the first principal component and our baseline MHC index have a correlation coefficient of 0.45, as shown in Table A7. It is worthwhile to note here that the use of the Baxter-King bandpass filter

[23] This treatment is applied because PCA can be applied to stationary series only, in order to avoid components driven by trends of a few underlying non-stationary series. As such, one should remove trends from the underlying time series and standardize them to focus on common fluctuations before applying PCA.

Table A6: Augmented Dickey-Fuller Test Results

Topics	Test Statistic	p-value	AIC Lag
Anxiety	0.673	0.989	2
Boredom	-0.937	0.776	1
Depression	-1.775	0.393	11
Divorce	-2.733	0.069	2
Irritability	-0.181	0.941	5
Loneliness	-1.979	0.296	14
Panic	0.756	0.991	13
Sadness	-1.476	0.545	6
Sleep	-0.393	0.911	10
Suicide	-3.019	0.033	5
Well-being	-0.211	0.937	2
Worry	-1.237	0.657	14
Stress	-2.930	0.042	2
Self-esteem	-1.934	0.316	2

Note: Results of augmented Dickey-Fuller test with a constant term. The second column shows test statistics for ASVI for each topic, and the third column displays the p-value for the null hypothesis that the series has a unit root and the alternative that it does not have a unit root. Therefore, for the series whose p-value is above a critical size, we cannot reject that there is a unit root. The fourth column represents the number of lags used in testing.

results in a substantial loss of observations in the beginning and at the end of the sample period.

A.6.4 Use of Different Benchmark Keywords for Re-Scaling When constructing our benchmark MHC index, we set "depression" as the keyword to re-scale and standardize the dynamics of all 133 SVIs. As noted previously, this practice is to deal with a inherent challenge in Google Trends that allows downloading of up to five SVIs only at once. To see if our benchmark index is affected by the selection of a re-scaling keyword, we alternatively use "depression", "devorce", and "sad" as the benchmark keywords. From Figure A9 showing the resulting time series, we can observe that the three alternative series move very closely to our benchmark index. In addition, Table A7 reports the correlation coefficients of the alternative MHC indices with our benchmark, ranging from 0.98 to 0.99. Therefore, we conclude that our MHC index is robust to the selection of a re-scaling keyword.

A.6.5 Weekly MHC Index Higher frequency search volume data on a weekly basis can be downloaded from Google Trends, in addition to the monthly series we employ for our benchmark MHC index. This enables us to construct a weekly MHC index. However, one caveat with the weekly series is that one can download maximum 5-year worth of weekly data at a time, i.e., 160 weeks. Hence, it is not

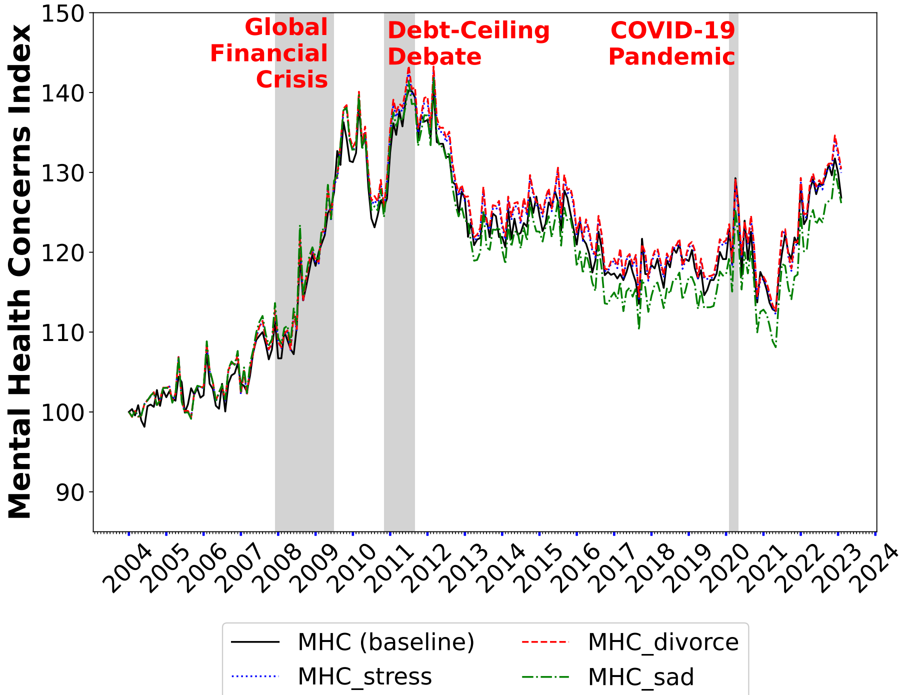

Figure A9: the MHC Index Constructed using Alternative Keywords for Re-Scaling

Note: 2004M01-2023M02. The black solid line indicates baseline MHC index constructed using 133 keywords scaled based on benchmark keyword "depression." The red dashed line, blue dotted line, and green dash-dotted line represent variations of the MHC index constructed by setting "divorce," "stress," and "sad," respectively, as benchmark keywords instead of "depression." Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M02-2020M04 (COVID-19 Pandemic).

straightforward how to merge multiple weekly indices covering 5-year separate windows, to create a continuous series for our entire sample period. Thus, we employ the identical construction methodology to the weekly data covering the most recent five years, and plot the resulting weekly MHC series in Figure A10, along with the VIX index capturing the stock market volatility. The weekly MHC series is surely more volatile than our benchmark monthly MHC index; however, when we compute the correlation coefficient of the monthly average of the weekly index and the original monthly index, it amounts to 0.87, indicating that our main index would not be sensitive to the selection of the data frequency. Its correlation with the weekly VIX is around 0.39.

A.6.6 MHC Index Capturing Monthly Changes in SVIs For the construction of our benchmark MHC index, we sum up 133 SVIs in levels that are re-scaled in comparison to the SVI of "depression." Alternatively, one can compute changes from the previous month and aggregate the resulting series. An advantage of this alternative approach would be that the MHC index in changes would be

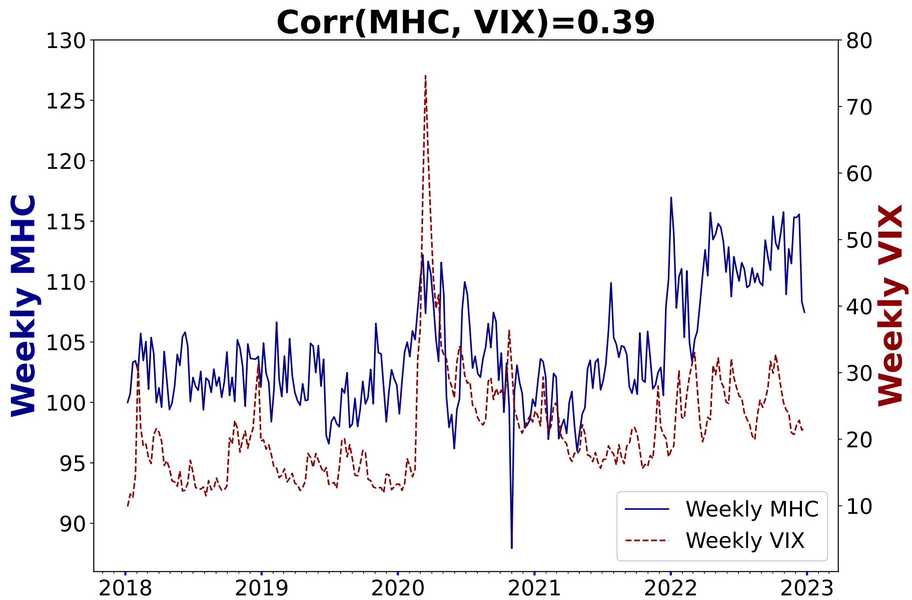

Figure A10: Weekly MHC Index and VIX

Note: 2018-2022. The blue solid line indicates the weekly MHC index constructed by using similar approach as described in Appendix A.3. As X13-ARIMA SEATS technique is not applicable for weekly data, we subtract (weekly average - mean) for each week in a year of each SVI to address seasonality. The red dashed line represents the weekly average of the daily CBOE Volatility Index. The correlation coefficient between the two series is 0.39.

positive when the concerns regarding mental health increase and negative, otherwise.[24] The alternative MHC index based on month-over-month changes in the SVIs together with the growth rate of the baseline MHC index are plotted in Figure A11. Both indices fluctuate around zero without a clear trend and take notably large positive values during the three episodes we highlighted above. Consistent with this observation, the correlation coefficient between the two is 0.87 (Table A7), reassuring that the benchmark index is robust.

A.6.7 Using Search Terms Covering All Sub-regions

Google Trends provides search intensity information by subregions. For the U.S., the subregions are 50 states and Washington D.C. More specifically, when one type in a search term, Google Trends returns a map of the U.S. where subregions are differently shaded according to the popularity of the term. Our 133 search terms turn out to show some heterogeneity in terms of geographical coverage. That is, some of the terms do not seem to be popularly searched in certain states, while about 70% of the terms are put in as queries in all 51 subregions. It should be noted here, however, that "[i]f a region on the map isn't highlighted, it doesn't

[24] We thank our anonymous referee for pointing this out.

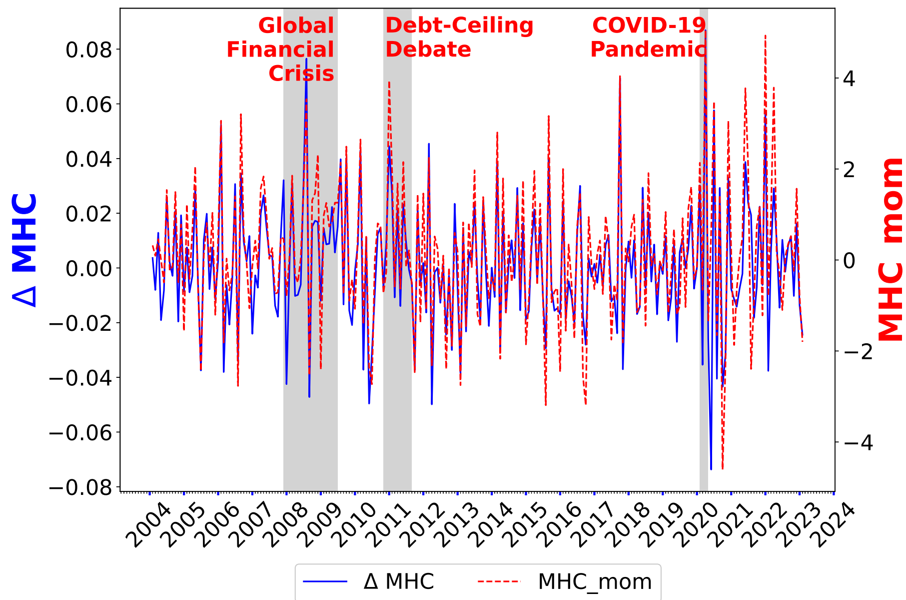

Figure A11: the MHC Index Constructed as Month-over-Month Growth

Note: 2004M02-2023M02. The blue solid line indicates a first difference of logged baseline MHC index. The red dashed line represents the variations of the MHC index constructed as the weighted sum of the month-over-month growth rate of ASVIs of 133 keywords by using the median value of each ASVI relative to ASVI of "depression" as weight. The correlation coefficient between the two indices is 0.87. Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M2-2020M04 (COVID-19 Pandemic).

mean there's no interest. Google Trends data is adjusted, so the term may be used in that region, but it's more popular in other regions."[25] The support page of Google Trends also notes that "[a] higher value means a higher proportion of all queries, not a higher absolute query count." Therefore, the relative popularity across subregions is affected by the total number of searches, i.e., the overall internet use intensity of residents.

We construct an alternative MHC index using SVIs that have a full geographical coverage, and plot the resulting series in Figure A12. We find that the alternative index remain almost unchanged from our benchmark series, with a correlation coefficient at 0.99.

[25] https://support.google.com/trends/answer/4355212

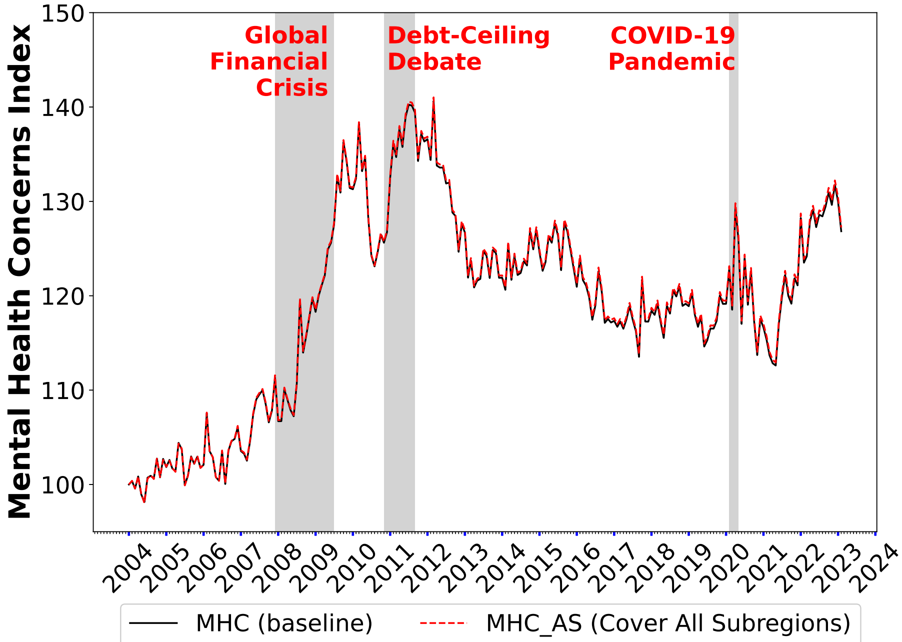

Figure A12: the MHC Index Constructed using Search Terms Covering All Sub-regions

Note: 2004M01-2023M02. The black solid line indicates baseline MHC index constructed using 133 keywords. The red dashed line represents a variation of the MHC index constructed by employing 88 keywords whose SVIs cover all of the 51 sub-regions in the U.S. The correlation coefficient between the two indices is 0.99. Shaded are 2007M12-2009M06 (Global Financial Crisis), 2010M11-2011M08 (Debt Ceiling Debate) and 2020M2-2020M04 (COVID-19 Pandemic).

Table A7: Correlation Coefficient between the MHC Index and its Variations

Index	Correlation Coefficient
MHC_B (topics from Brodeur et al.)	0.98
MHC_top3 (top 3 related terms)	0.84
MHC_top5 (top 5 related terms)	0.77
MHC_PC1 (first principal component)	0.45
MHC_stress (benchmark term: stress)	0.99
MHC_divorce (benchmark term: divorce)	0.99
MHC_sad (benchmark term: sad)	0.98
Weekly MHC	0.87
MHC_mom (weighted sum of mom growth)	0.87
MHC_AS (SVIs with full geographical coverage)	0.99

Note: This table shows the correlation coefficients of alternative MHC indices with the baseline MHC index. For weekly MHC, we take the monthly average of the weekly index from 2018 to 2022 to calculate the correlation coefficient with the baseline MHC index. For MHC_mom, we calculate the correlation coefficient with the first difference of the logarithm of the baseline MHC index. The specific meanings of alternative MHC indices are as follows: MHC_B = overall search intensity of keywords that are top ten related terms of topics from Brodeur et al. (2021); MHC_top3/top5 = overall search in overall search intensity of keywords that are top three/five related terms of topics; MHC_PC1 = first principal component of ASVIs of 14 topics; MHC_stress/divorce/sad = overall search in overall search intensity of keywords that are scaled based on benchmark term stress/divorce/sad; Weekly MHC = the MHC index constructed on a weekly basis; MHC_mom = weighted sum of the month-over-month growth rate of ASVIs of 133 keywords by using the median level of each series as weight; MHC_AS = index constructed with SVIs with full geographical coverge only.

A.7 Robustness Checks of the VAR results

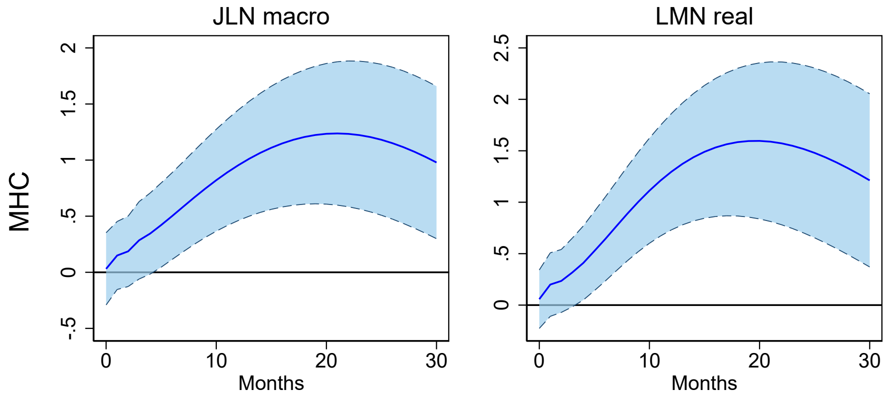

Figure A13: MHC Responses to Uncertainty Shocks with an Alternative Ordering

Note: 2004M01-2019M12. Each panel shows the responses of the MHC index to uncertainty shocks represented by JLN macro uncertainty and LMN real uncertainty, respectively, in the baseline VAR with uncertainty being ordered fifth. Shaded areas represent 90-percent confidence intervals obtained using 2000 bootstraps.

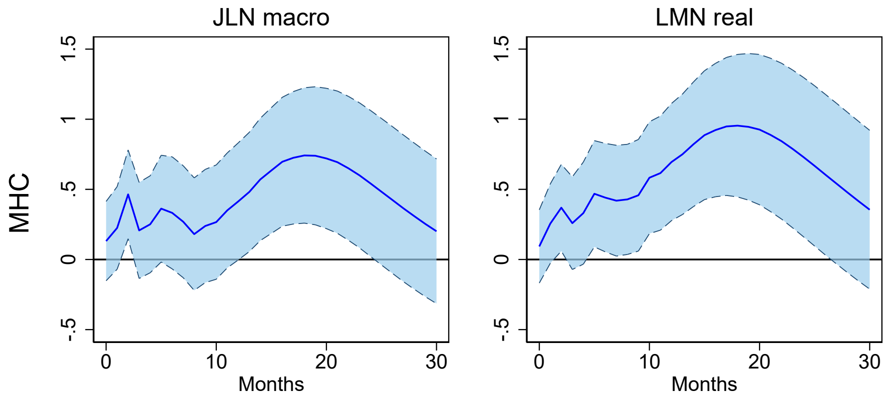

Figure A14: MHC Responses to Uncertainty Shock in VAR Model with Six Lags

Note: 2004M01-2019M12. Each panel shows responses of the MHC index to uncertainty shocks represented by JLN macro uncertainty and LMN real uncertainty, respectively, in the baseline VAR with six lags instead of three. Shaded areas represent 90-percent confidence intervals obtained using 2,000 bootstraps.

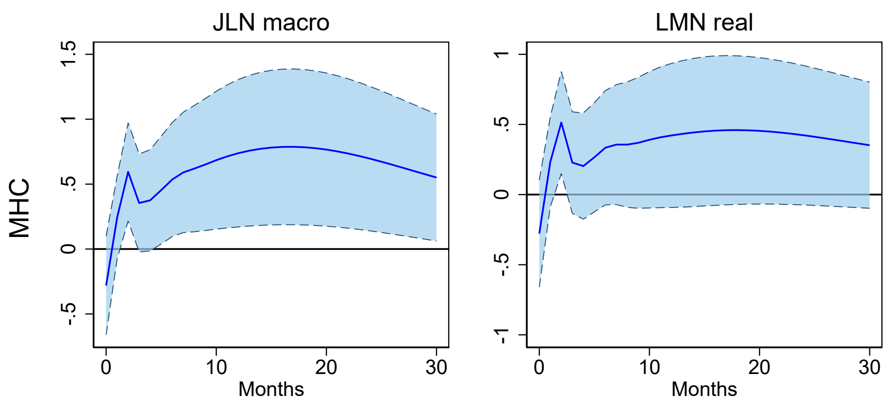

Figure A15: MHC Responses to Uncertainty Shock with Samples until 2022M12

Note: 2004M01-2022M12. Each panel shows responses of the MHC index to uncertainty shocks represented by JLN macro uncertainty and LMN real uncertainty, respectively, in the baseline VAR from January 2004 to December 2022. We extend the period until December 2022 due to the availability of the JLN macro and LMN real uncertainty indices. Shaded areas represent 90-percent confidence intervals obtained using 2,000 bootstraps.