J. Int. Financ. Markets Inst. Money 81 (2022) 101692

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

When central bank research meets Google search: A sentiment index of global financial stress☆

Mikhail Stolbov [a,*], Maria Shchepeleva [b], Alexander Karminsky [c]

[a] *Department of Applied Economics, Professor of the Department of Economics and Banking Business, Moscow State Institute of International Relations (MGIMO University), Russia*

[b] *Department of Theoretical Economics, National Research University Higher School of Economics (NRU HSE), Russia*

[c] *School of Finance, National Research University Higher School of Economics (NRU HSE), Professor of the Department of Economics and Banking Business at MGIMO University, Russia*

ARTICLE INFO

JEL codes:
G15
G41

Keywords:
Financial stability
Financial stress
Google trends
Sentiment index
Sparse principal component analysis

ABSTRACT

We construct a sentiment-based index of global financial stress (s-GFS index) for the period January 2004-December 2020. It builds on a novel methodological approach, which synthesizes the intensity of Google search for specific terms and word collocations related to financial instability and their prior selection based on the titles and abstracts of more than 2,000 working papers posted on the Basel Bank for International Settlements Central Bank Research Hub. The s-GFS index obtained by means of sparse principal component analysis (PCA) accurately captures major episodes of global financial instability during the observation period, playing a pivotal role for the US financial stress as well as industrial production in the USA, the Eurozone and China. It also Granger causes several well-known measures of global financial instability based on sentiment and "hard" data, e.g. the VIX index, as well as the overall dynamics of the global financial cycle, thereby emphasizing the usefulness of sentiment-based measures in monitoring worldwide financial stress.

1. Introduction

The role of "soft information", e.g. sentiment, has increased substantially in economic and financial research over the past years. Specific econometric techniques and software appear to quantify qualitative sentiment data, leading to the emergence of a new research field, *sentometrics* (Algaba et al., 2020; Gentzkow et al, 2019; Larsen and Thorsrud, 2019; Shapiro et al., 2022). The sentometric analysis deals with sentiment embedded in different textual, audio and visual sources to construct quantitative sentiment variables. They serve as proxies to assess the relationship between sentiment and conventional economic variables. The sentometric approach has penetrated many research programs, ranging from measuring economic policy uncertainty (Baker et al., 2016) to nowcasting and forecasting various economic and financial indicators (Ardia et al., 2019; Ellingsen et al., 2022; Kalamara et al., 2022).

This approach, inter alia, allows to develop sentiment indices capturing financial stress at the national and global level, which complement the existing measures based on "hard" data, thereby contributing to monitoring financial instability. The extant literature

☆ We thank a subject editor and an anonymous reviewer for the comments which helped improve the original manuscript. The remaining errors are our own.

* Corresponding author at: 76 Vernadskogo prospect, Moscow 119454, Russia.
E-mail addresses: stolbov.m@my.mgimo.ru (M. Stolbov), mshchepeleva@hse.ru (M. Shchepeleva), akarminsky@hse.ru (A. Karminsky).

https://doi.org/10.1016/j.intfin.2022.101692
Received 13 February 2022; Accepted 14 November 2022
Available online 21 November 2022
1042-4431/

shows that such sentiment indices can build on the information about systemically important financial institutions provided by leading international newswire services, e.g. Thompson Reuters (Borovkova et al., 2017; Chen et al., 2020), article titles in major business newspapers (Püttmann, 2018; Huang et al., 2019), Twitter messages related to major financial institutions and financial shocks (Fernandez et al., 2021), informational contents of US congressional hearings (Wischnewsky et al., 2021), US Fed FOMC members' speeches (Istrefi et al., 2021), financial stability reports released by standalone national central banks (Moreno and González Pedraz, 2020) or by their samples as well as international financial institutions (Blix Grimaldi, 2011; Correa et al., 2017, 2021).[1]

In this paper, we propose a sentiment measure of global financial stress (s-GFS index) between January 2004 and December 2020, exploiting the intensity of *Google Trends* queries about specific terms and word collocations which capture the perception of Internet users that the global financial stability stance is deteriorating. As far as we know, this is the first study using *Google Trends* to construct a sentiment index of global financial stress, though such data source is well-entrenched in adjacent literatures, for example, the one measuring investor sentiment around the world, e.g. Gao et al. (2020).

Nonetheless, the novelty of our approach goes beyond the choice of data source. Since it is reasonably hard to pin down an accurate and comprehensive list of terms and world collocations capturing the buildup of financial risks, we begin by compiling our own dictionary on financial (in-)stability. It builds on our reading the titles and abstracts of the working / discussion papers posted on the Bank for International Settlements (BIS) Central Bank Research Hub during January 2001-December 2020 and covering financial stability issues. We identify 2,080 papers out of 21,043 posted on this repository, and, based on them, compile a dictionary which includes 128 terms and word collocations conveying negative sentiment about financial stability. To our knowledge, this is a novel source of textual information to create a dictionary on financial (in-)stability.

After obtaining the *Google Trends* series which capture the dynamics of their Internet searches in the "Finance" category across the world between January 2004 and December 2020, we extract the first principal component from them, using sparse principal component analysis (PCA). This method outperforms the standard PCA in terms of the interpretability of components, since loadings on less important input variables are set to zero. This feature of sparse PCA is quite useful in a research setting with a lot of input variables. The composite measure we derive is the sentiment index of global financial stress.

Based on the component loadings, our s-GFS index primarily depends on the search intensity of the terms and word collocations describing disruptions in the banking system, e.g. "credit crisis", "banking crisis", "bank failure", "bank run", "credit bubble", etc. The s-GFS index accurately captures major crisis episodes during the observation period, reaching its maximum historical value in October 2008 as well as exhibiting local surges during the European financial crisis in the years 2010–2012 and at the onset of the COVID-19 pandemic in the early 2020.

We document correlations fully consistent with theoretical expectations and significant at the one percent level between the s-GFS index and a number of internationally recognized financial stress / systemic risk indicators based on both hard and qualitative data. Lead-lag relationships between them are studied in a linear and nonlinear framework, using conventional and nonlinear multivariate Granger (no) causality tests. We find that the s-GFS index Granger causes such indicators as the VIX index and the Office of Financial Research Financial Stress Index (OFR FSI) by Monin (2019) which both build on hard data and are widely used to monitor global financial instability. In the meantime, our index doesn't have any effect on global conditional capital shortfall (SRISK), a well-known systemic risk metric developed by Brownlees and Engle (2017), and receives no feedback from it either. In another horse race, our sentiment measure compares with its two publicly available peers: the global financial stability sentiment (FSS) index by Correa et al. (2021) and newspaper-based financial stress index (NpFSI) by Püttmann (2018). This exercise reveals that the three measures are not tightly connected, with the first statistically significant causal linkage running from the s-GFS index to the global FSS index in a linear framework and the other running from the latter to the newspaper-based FSI in the nonlinear setting. However, both linkages are marginally significant at the ten percent level.

The findings indicate that the s-GFS index is not driven by the rest of the metrics used in the two empirical exercises. Meanwhile, these competing metrics, the VIX index, in particular, underpin the global financial cycle (GFC) defined by Miranda-Agrippino and Rey (2020) as an international co-movement in asset and commodity prices, credit and capital flows. They also find that the GFC has implications for real economic activity. Besides, Püttmann (2018) examines the interaction of his sentiment-based FSI and US GDP and industrial production, reporting an adverse effect on them which persists for about two years. Against this backdrop, we examine whether there is any lead-lag relationship between the s-GFS index, the GFC proxy capturing the dynamics of more than one thousand asset and commodity prices, and the world industrial production index. By adopting linear and nonlinear Granger causality tests, we find that the s-GFS index helps explain movements in the GFC proxy at the conventional significance level. Based on generalized forecast error variance decomposition (GFEVD), our index accounts for nearly 25 % of the variance in the GFC proxy at the horizon of 12 months, which is an economically sizeable proportion. We also document a bidirectional relationship between the s-GFS index and world industrial production index.

We proceed by investigating the macrofinancial linkages for major economies, the USA, the Eurozone, and China, involving the s-GFS index. Using our baseline econometric methodology, we find that the s-GFS index appears to play a pivotal role for financial stress in the USA, while its relationships with the Eurozone and Chinese FSI run in both directions. In addition, the s-GFS index unilaterally

[1] There are studies which construct the metrics which are conceptually close to the sentiment-based indices of financial stress, but, unlike the latter, do not seek to capture all facets of financial instability. For instance, Manela and Moreira (2017) propose a news-implied volatility metric which is based on the contents of front-page articles from the *Wall Street Journal* and fares well as a forward-looking measure of the stock market volatility. In a recent paper, Dim et al. (2021) introduce a news-implied sovereign default risk index using 10 million news articles covering 100 countries.

leads industrial production in the USA, the Eurozone and China. Taking into account the macrofinancial spillovers which these major economic centers propagate to the rest of the world, the effects of the s-GFS index on financial stress and industrial production in these economies are spread worldwide as well. This mechanism is likely to underlie the robust performance of the s-GFS index versus its competing measures based on sentiment and hard data as well as its statistically significant impact on the GFC.

Additionally, we assess the interaction between the s-GFS index and central bank digital currency (CBDC) sentiment indices proposed by Lucey et al. (2021) and Wang et al. (2022).We find that global financial stress sentiment and the newly introduced sentiment measures for the CBDC are not connected. The result suggests that fears about global financial stress do not translate (at least) directly into uncertainty related to digital currencies, and vice versa.

Finally, we apply our baseline econometric methodology to examine if the s-GFS index has any predictive power for the changing frequencies of banking, sovereign debt and currency crises during January 2004-December 2017. We provide preliminary evidence that our index can be a leading indicator for the waves of currency crises and a coincident one for the frequency of banking crises. Besides, it appears to anticipate the worldwide trend towards macroprudential policy tightening.

The s-GFS index survives a threefold robustness check. First, we re-estimate the relationships reported above and involving more than two variables using structural VAR analysis. We corroborate the majority of the lead-lag linkages between the s-GFS index and other variables in this alternative framework. Second, we invite three independent readers coming from central banking and academia to validate our dictionary. Based on the same set of research papers, they suggest replacing seven terms and word collocations in our dictionary with alternative items which, according to our initial reading, do not exhibit strictly negative connotation with respect to financial stability. After making these changes in the dictionary, we construct an alternative version of the s-GFS index, s-GFS_alt, which appears strongly correlated with our baseline index. By applying our standard econometric methodology to test for lead-lag relationships, we show that the baseline s-GFS index Granger causes the alternative measure. Third, we create a reduced version of the s-GFS index, building only on the terms and word collocations from the working/discussion papers published by the major world central banks, i.e. the Fed, ECB, Bank of England and Bank of Japan. However, the baseline s-GFS measure appears to lead the reduced version as well.

Overall, our findings emphasize the relevance of sentiment-based measures to monitor financial instability worldwide, building on the intensity of Google searches of specific terms and word collocations related to financial stability and selected with the aid of "collective wisdom" concentrated in a vast sample of research papers posted on the BIS Central Bank Research Hub.

In a nutshell, our contribution to the literature is twofold. First, we extend the multi-faceted literature on financial stress measures[2] by proposing a new sentiment index of global financial stress which successfully withstands the horse race with the indicators based on hard data and its sentiment-based peers, also playing a pivotal role for the overall dynamics of the global financial cycle. Second, we make an innovation to the sentometric methodology by exploiting the synergy between two types of data – Google search intensity indices and textual information accumulated in a professional repository, which reduces bias in an *ex ante* selection of terms and word collocations used to derive the sentiment index of global financial stress by means of *Google Trends*. This methodological innovation adds to a strand of the sentometric literature dedicated to textual analysis in finance and surveyed by Loughran and McDonald (2016, 2020).

The rest of the paper proceeds as follows. Section 2 describes the data and presents the empirical design of the study. The findings are reported and discussed in Section 3, the robustness check is presented in Section 4, while Section 5 concludes.

2. Data and empirical design

2.1. Constructing the s-GFS index

The sentiment data based on Google searches and their aggregation via *Google Trends* have become widespread in many fields of economic and financial research, yielding promising results (Choi and Varian, 2012; Preis et al., 2013; Jun et al., 2018; Woloszko, 2020). Nonetheless, to the best of our knowledge, such data have not been used to gauge global financial (in-)stability sentiment, though Gao et al. (2020) exploit Google searches to tackle an adjacent research question by measuring investor sentiment worldwide. Google retains nearly 90 % of the world market for web search, which makes it an appropriate data source to assess financial (in-) stability sentiment.[3] However, an open question is which terms and word collocations need to be selected so that they capture Internet users' actual perception of financial (in-)stability. Without such a list compiled on the basis of pre-specified criteria, any analysis involving *Google Trends* data would be heavily biased. A possible solution is to create a comprehensive dictionary containing terms and word collocations capturing financial stability stance. Correa et al. (2017, 2021) argue that existing general purpose and finance-specific dictionaries, e.g. Loughran and McDonald (2011), Du et al. (2022), are unlikely to accomplish this goal, as words may have a completely different connotation in the financial stability context. Using financial stability reports published by 35 national central banks, the IMF and ECB, they create their own dictionary comprising 391 words, of which 96 have a positive connotation with respect to financial stability, while 295 have a negative one.

However, the dictionary compiled by Correa et al. (2017, 2021) does not allow us to identify genuinely informative terms and word collocations to capture financial stress sentiment worldwide. First, there are only 107 nouns out of 295 negative words. Consequently,

[2] See, for example, Kliesen et al. (2012) for a survey of the literature.

[3] Although there are major economies where Google is not the dominant search engine, e.g. China, Russia, we assume that it doesn't create a significant bias as regards the perception of global financial stress.

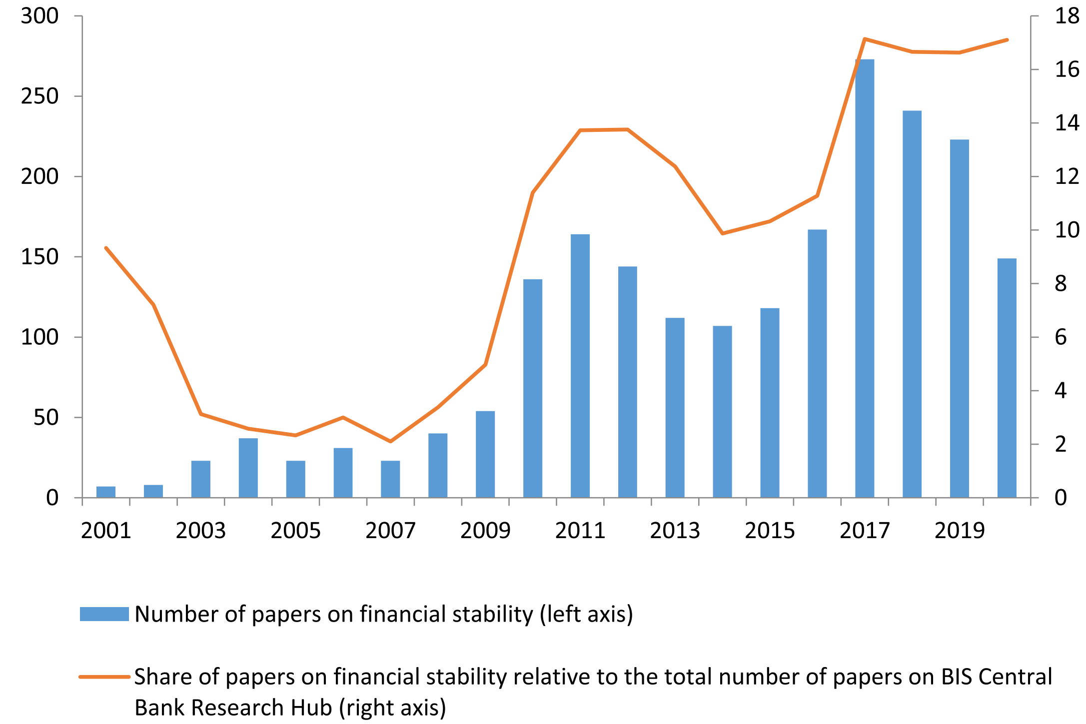

Fig. 1. Breakdown of working / discussion papers on financial stability on the BIS Central Bank Research Hub, by year, 2001–2020.

this dictionary includes quite general words related to financial stability, e.g. "contagion", "volatility", without covering more specific terms which are not only used by researchers and industry professionals, but also appear in the media and can therefore be searched by Internet users, e.g. "bank run", "moral hazard", "credit bubble", etc. Second, financial stability reports as a data source may not timely and fully reflect the financial stability sentiment, as they are usually published on quarterly, semi-annual and annual basis. Thus, Correa et al. (2021) have to apply statistical interpolation to make their financial stability sentiment index monthly. Third, there may be certain inertia in the coverage of topics and language usage in the financial stability reports, as they are prepared by relatively limited groups of central bank employees, often according to standardized templates.[4] As a result, market participants may anticipate the contents of financial stability reports, which makes them less relevant for predicting important market indicators, e.g. equity returns and CDS spreads, as shown by Harris et al. (2019).

Like Correa et al. (2017, 2021), Püttmann (2018) creates his own dictionary comprising 120 words and phrases to construct a newspaper-based indicator of financial stress. Nonetheless, he acknowledges (Püttmann, 2018, p. 7) that his selection does not rest on any particular rule, being largely heuristic. Moreover, his sentiment indicator is by default driven by the US financial stability stance, as his research is based on the newspapers published in this country (but distributed worldwide). Huang et al. (2019) apply semantic clustering to the news articles from *Financial Times* and compile the dictionaries describing a number of sentiments, including those which refer to "fear" and "crisis". Then, they construct sentiment-based indices to forecast financial crises in a sample of 20 emerging market economies and developing countries between 1980 and 2019. However, similar to Correa et al. (2017, 2021), their dictionaries mostly consist of verbs and adjectives and therefore can miss essential facets of financial instability.

Against this backdrop, we create our own dictionary of terms and word collocations conveying negative sentiment about financial stability. To mitigate selection bias, we consider the Bank for International Settlements (BIS) Central Bank Research Hub a natural reservoir of proper words and phrases describing financial stability. We carefully read the titles and abstracts of 21,043 working/ discussion papers written in English and posted on this repository between January 2001 and December 2020 and select all papers having something to do with financial stability broadly defined.[5] This is a novel source of textual information to compile a dictionary

[4] Our critical remarks are solely related to the usage of financial stability reports to create specific dictionaries on financial stability. However, these reports can be useful to reach alternative goals. For example, Oosterloo et al. (2007) and Čihák et al. (2012) find that well elaborated financial stability reports tend to be correlated with more resilient financial environments. In a similar vein, Born et al. (2014) conclude that central bank communication through financial stability reports decreases stock market volatility. Comelli and Ogawa (2021) argue that financial stability reports provide multi-faceted information about systemic risk buildup, thereby effectively complementing country-level reports issued under the IMF Financial Sector Assessment Program.

[5] At this stage of our search, we don't target only those papers which explicitly deal with financial instability, e.g. contagion, financial stress, systemic risk, etc., but also the works covering financial crisis resolution, changes in macro- and microprudential regulation, supervisory and regulatory design, etc.

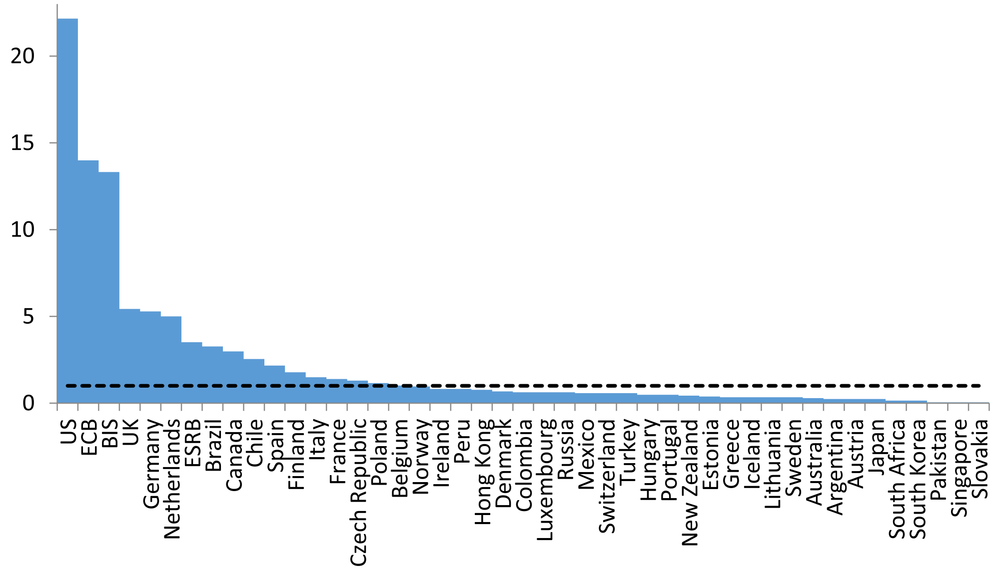

Fig. 2. Breakdown of working / discussion papers on financial stability on the BIS Central Bank Research Hub, by country and international financial institutions, %.

on financial (in-)stability.[6]

Although we recognize that the titles and abstracts of the papers may contain sophisticated terms and word collocations related to financial stability, there are still non-negligible odds that individuals can search for them in the Internet, as central bank communication, including that on financial stability, has made huge progress in recent years. For example, the findings published in central bank working papers are now often explained to the general public in the form of non-technical surveys in business newspapers, websites and other media. Properly designed central bank communication can enhance the targeted audience and increase the readability of professional texts. This assertion is consistent with Loughran and McDonald (2020) who argue that the complexity of financial texts does not necessarily undermine public interest in them and their usefulness in predicting financial outcomes. Based on the experimental evidence, Bholat et al. (2019) find that the impact of central bank communication can further increase if the information is made relatable to peoples' daily lives. Similar evidence is provided by Munday and Brookes (2021). As a result, central bank communication on financial stability can influence individuals' expectations and the perception of financial risks (Beutel et al., 2021), incentivizing them, among other things, to search for additional information on such risks via Internet search engines. Such conjecture accords with the recent research by Ehrmann and Wabitsch (2021) who, using the ECB as a case study, argue that central banks successfully reach non-experts with their communications.

Overall, we select 2,080 papers meeting our basic criterion, i.e. dealing with financial stability broadly defined. In general, there is an upward long-term trend in the share of papers on financial stability relative to the total number of papers posted on the BIS Central Bank Research Hub (Fig. 1).

During the period 2017–2020 this share is about 17 %, while being close to 2 % on the eve of the global financial crisis (GFC) in 2007. It is also worth noting that this share appears to rise significantly with a lag of two–three years after major crisis episodes, i.e. the GFC and the European financial crisis. The sample of 2,080 papers is internationally representative, as it contains the works on financial stability written by the researchers from 42 national central banks and three international financial institutions, i.e. the BIS itself, the European Central Bank (ECB) and European Systemic Risk Board (ESRB) (Fig. 2). These international bodies altogether

[6] In the literature on central bank communication, researchers have so far resorted to a BIS repository containing speeches by the officials from national central banks, but their studies are unrelated to constructing sentiment indices on financial (in-)stability. For example, Armelius et al. (2020) investigate cross-country spillovers in sentiment for a sample of 23 national central banks during the 2002–2017 period, emphasizing the role of the Fed as a primary generator of these spillovers. We decide not to compile our dictionary based on the speeches, as the language of speeches by central bank officials tends to be politically sensitive. Thus, the coverage of financial stability issues in the speeches may be selective and incomplete. In contrast, we believe that the working / discussion papers which are published by central bank researchers with a usual disclaimer stating that they reflect their personal views rather than those of the regulatory bodies are more impartial and comprehensive.

account for nearly 31 % of the papers in our sample, followed by the national central banks of the USA[7] (22.2 %), the UK (5.4 %), Germany (5.3 %) and the Netherlands (4.9 %).[8] Importantly, some emerging market economies (Brazil, Chile) also account for a notable fraction of the papers on financial stability posted on the BIS Central Bank Research Hub.

Based on the sample papers, we compile a raw list comprising 327 terms and word collocations capturing various dimensions of financial stability. Unlike the dictionary compiled by Correa et al. (2017, 2021), this list does not include adjectives as standalone items. We classify 128 items from this list as negative, i.e. capturing deterioration in the financial stability stance, while the rest can bear a positive or negative meaning, conditional on the context, or possess a neutral connotation. Such terms and word collocations as “macroprudential regulation”, “regulatory capital”, “credit rating” exemplify the ambivalent part of our raw list. Since we are interested in the dynamics of global financial stress, only the terms and word collocations with a strictly negative connotation are retained in the analysis, thereby constituting our dictionary on financial instability. We document a minor overlap between our dictionary and the list of words with negative connotation assembled by Correa et al. (2017, 2021), as they have only 23 common items. In case of the dictionary by Püttmann (2018) and “negative” sentiment dictionary by Huang et al. (2019), the degree of commonality is even less, as there are 9 and 11 coincident words, respectively. Thus, our dictionary appears notably different from the analogous sources both in terms of the procedures we follow to compile it and its contents.

Using *Google Trends*, a web application by Google, which estimates the popularity of queries in the Google search, we obtain the indices measuring the intensity of searches for each of the negative items from our dictionary for the period January 2004-December 2020.

In order to create a composite index synthesizing the information in these numerous indices of search intensity, we first standardize the series so that each of them has the mean equal to zero and standard deviation to one, and then adopt sparse principal component analysis (PCA). Similar to the conventional PCA, which is a common tool to construct financial stress indices,[9] this method performs dimensionality reduction, but is better suited to the environments with multiple input variables and where it is vital to secure the interpretability of resultant principal components. The sparse PCA achieves the interpretability by assigning zero component loadings to unimportant input variables.

Our sentiment index of global financial stress (the s-GFS index) is the first principal component extracted by means of the sparse PCA.[10] The descriptive statistics for our index as well as for the variables which it interacts with in Sections 2.2-2.6 below are reported in the Appendix, Table A2.

2.2. Estimating lead-lag relationships between the s-GFS index and alternative measures of global financial stress

At the next stage of our study, we conduct a horse race between the s-GFS index and two sets of competing indicators.

The first of them is made up of global financial stress indices based on hard data, including (i) the VIX index capturing global volatility and risk aversion; (ii) worldwide conditional capital shortfall, SRISK, a well-known systemic risk measure proposed by Brownlees and Engle (2017), which gauges the global shortage of equity in case of a severe world stock market decline[11]; (iii) the financial stress index proposed by Monin (2019) and published by the US Fed Office of Financial Research (OFR FSI).

The second set of indicators to be compared with our s-GFS index encompasses two sentiment-based measures which are publicly available, i.e. the financial stability sentiment index (FSS index) by Correa et al. (2021) and newspaper-based financial stress indicator (NpFSI) by Püttmann (2018).

The horse race aims to uncover in-sample lead-lag relationships between the s-GFS index and its contenders in each set of indicators. We study these relationships in a linear and nonlinear setting. To this end, we first specify a vector autoregression (VAR) for each set of indicators and then run Granger (no) causality tests.[12] The estimation period is January 2004-December 2020 for the first set of indicators, while for the second one it ends in December 2016, since this is the last time point available for the newspaper-based FSI (NpFSI) by Püttmann (2018). In addition to Granger (no) causality tests, we conduct generalized forecast error decomposition (GFEVD) to assess the effect of an orthogonalised shock to one of the variables on the rest in our VAR models. The GFEVD is based on Lanne and Nyberg (2016) whose procedure has an attractive property that the proportions of the impact accounted for by innovations

[7] The indicator includes the papers published under the auspices of the Federal Reserve Board of Governors and all Federal Reserve banks.

[8] We calculate the Herfindahl-Hirschman index (HHI) based on the countries and international financial institutions' shares in the total number of papers on financial stability posted on the BIS Central Bank Research Hub. The indicator yields the value of 950, which is significantly less than 1500, a benchmark below which any market is considered competitive. Thus, the distribution of working/discussion papers we observe is not dominated by a particular country or institution. This result additionally corroborates that our sample of papers allows for sufficient international variation in the contributions on financial stability, making it representative.

[9] PCA applies to develop financial stress indices both at the national level in the major economies (Kliesen et al., 2012) and globally (Monin, 2019).

[10] We implement an R package ***nsprcomp*** to conduct sparse PCA (https://cran.r-project.org/web/packages/nsprcomp/nsprcomp.pdf).

[11] This scenario involves a 40-percent semiannual shrinkage in global stock market indices, e.g. the MSCI world index.

[12] Since our indicators are not necessarily I(0) series, we implement the Toda-Yamamoto correction to estimate the VAR models (Toda and Yamamoto, 1995). According to it, a VAR(p) model should be set up in levels, irrespective of the orders of integration of the data. An appropriate lag length for the variables in the VAR model is based on the Akaike information criteria. The model is also tested for overall stability and the absence of serial correlation in the residuals. If the maximum order of integration of the variables is m, then the preferred VAR model should be extended to include these m additional lags as exogenous parameters. For example, if the maximum order of integration is I=1 and the optimal model is VAR(2), the specification that ensures the validity of Granger causality test will be VAR(3).

in each variable in total yield unity.

To capture potential nonlinear causalities, we extract residuals from the VAR models and apply to them a nonparametric multivariate Granger (no) causality test proposed by Diks and Wolski (2016). This test extends the bivariate nonparametric Granger (no) causality test introduced by Diks and Panchenko (2006) by applying so called data sharpening to minimize the bias of the bivariate test statistic in a high-dimensional setting. The extended test assumes the first-order VAR process in the residuals obtained after conducting Granger (no) causality tests in the linear framework.[13]

If the s-GFS index appears to fare well relative to the competing measures, it should Granger cause at least some of them, while being cushioned from any significant causal feedback in the linear and nonlinear setting.

2.3. *Estimating lead-lag relationships between the s-GFS index, the global financial cycle proxy and real economic activity*

Miranda-Agrippino and Rey (2020) demonstrate that there is a significant co-movement in international asset and commodity prices, credit and capital flows, attributing it to the global financial cycle (GFC). They also show that the GFC is conditional on global volatility and risk aversion, i.e. the VIX index. Thus, the financial stress indices, both sentiment-based and building on hard data, may be covariates of the GFC.

Besides, Miranda-Agrippino and Rey (2020) report that the dynamics of the GFC has real effects, i.e. during the contractionary phases of the GFC real economic activity diminishes. The adverse impact of traditional financial stress indices on economic activity is extensively studied in the literature, e.g. Mallick and Sousa (2013), Mittnik and Semmler (2013), Chen and Semmler (2018). As regards the sentiment-based measures, Püttmann (2018) examines the effect of NpFSI on US GDP and industrial production, finding that it lasts for about two years.

In this light, we test for lead-lag relationships between our s-GFS index, the GFC proxy, and world industrial production. The GFC proxy is a dynamic factor derived by Miranda-Agrippino and Rey (2020) from over one thousand asset and commodity price series and explaining about 20 % of their dynamics. The data on world industrial production index (WIP) comes from the CPB Netherlands Bureau for Economic Policy Analysis. Similar to the techniques described in Section 2.2, we first specify a VAR model to conduct conventional Granger (no) causality tests along with the FEVD and then apply the Diks-Wolski (2016) test to the residuals from the VAR model to dissect causalities in the nonlinear setting. The estimation period is between January 2004 and April 2019 for this VAR model given the length of the GFC proxy series.

2.4. *Assessing the macrofinancial interaction between the s-GFS index and major economies*

We seek to extend the analysis described in Section 2.3 by studying the interaction between the s-GFS index and macrofinancial indicators of the major economic centers in the world, i.e. the USA, China and the Eurozone.

We adhere to our econometric methodology which allows to uncover causal linkages in the linear and nonlinear setting. For each economy, we estimate the relationships between the s-GFS index, national financial stress index (FSI) and industrial production. To make our estimations comparable, we adopt uniform measures of financial stress and real economic activity. The FSI series are retrieved from the Asia Regional Integration Center of the Asian Development Bank and are based on the study by Park and Mercado (2014). These data series measure the degree of financial stress in four segments of the financial system, i.e. banks, foreign exchange, equity and bonds. The data on national industrial production indices comes from the OECD statistical database. The estimation period in this empirical exercise spans from January 2004 to December 2020.

2.5. *Estimating lead-lag relationships between the s-GFS index and central bank digital currency sentiment*

Given the rising importance of the debate on digital currencies in general and central bank digital currencies (CBDC) in particular, we assess the interaction between the s-GFS index and two recently proposed measures of CBDC sentiment, CBDC uncertainty index (CBDCUI) and CBDC attention index (CBDCAI). These indices are introduced by Lucey et al. (2021) and Wang et al. (2022), capturing trends and variations in the CBDC media coverage based on the LexisNexis News & Business digital database. In this analysis, we transform the original weekly CBDCUI and CBDCAI series into monthly ones by taking their 4-week average values and again resort to our baseline methodology for the estimation period between January 2015 and December 2020.

2.6. *Assessing the interaction between the s-GFS index and the occurrence of financial crisis waves*

Finally, we examine if the s-GFS index has any predictive power for the occurrence of financial crises. In contrast to Correa et al. (2021) who tackle this issue in the panel data framework by specifying a probit model, our analysis is again carried out from the time series perspective. Using the data on the starting dates of banking, sovereign debt and currency crises from Laeven and Valencia

[13] We are grateful to Dr. Marcin Wolski for sharing the code for a trivariate case of the test https://marcinwolski.org/download/code/dp3_gaussian.c) and giving advice for its practical implementation.

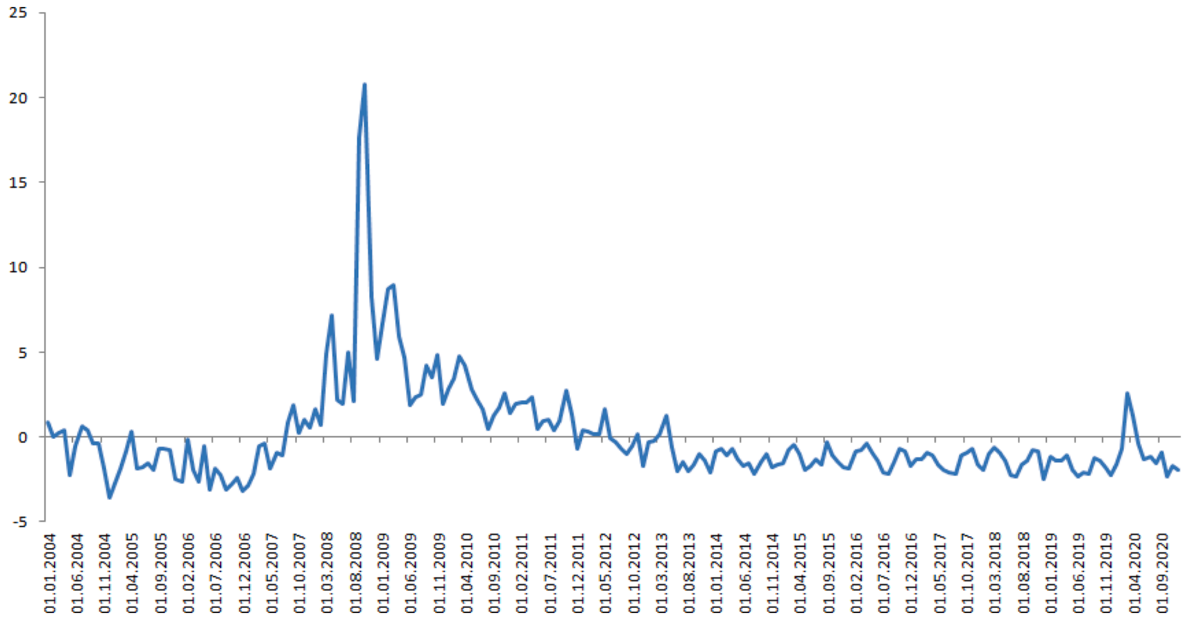

Fig. 3. The s-GFS index dynamics, January 2004-December 2020.

(2020), we sum up the number of crisis outbreaks across the globe for each month during January 2004-December 2017. Thus, the series which capture the changing frequency of each crisis type are obtained. By running our baseline causality tests, we seek to test for lead-lag relationships between the s-GFS index and these waves of financial crises.[14] In a similar vein, we assess the interaction between our index and the IMAPP index (Alam et al., 2019), which accounts for macroprudential policy tightening as a response to the occurrence of financial crises.

3. Results and discussion

3.1. Features of the s-GFS index

Fig. 3 displays the evolution of the s-GFS index between January 2004 and December 2020.

The index captures the major crisis episodes during the observation period. It starts to rise in the early 2007, reaching its maximum after the outbreak of the global financial crisis (GFC), i.e. in October 2008. Then it gradually decreases, exhibiting local peaks, which capture the most acute phases of the European financial crisis, e.g. in September 2011, when international concerns about the severity of the crisis substantially intensify, or in May 2012, when the political crisis in Greece unfolds, thereby elevating the risk of the Eurozone disintegration. However, based on the s-GFS index, since the middle of the year 2013 onwards the worldwide financial stress returns to the pre-GFC level and remains largely stable until the onset of the COVID-19 pandemic.

Based on the sparse PCA, we identify 79 terms and word collocations out of 128 items included in our dictionary and conveying negative sentiment about global financial stability. They shape the dynamics of the s-GFS index, having non-zero component loadings (Table 1), while the complete dictionary is available in the Appendix, Table A1.

Table 1 indicates that the dynamics of the s-GFS index is primarily driven by the intensity of cross-country search for the terms and word collocations describing disruptions in the banking sector, e.g. “credit crisis”, “banking crisis”, “bank failure”, “credit bubble”. Due to the intrinsic roots of the GFC, the list contains a number of items related to mortgage lending, e.g. “subprime crisis”, “foreclosure crisis”, “mortgage loss”, etc. However, such legacy of the GFC does not exert predominant influence over the dictionary composition: the fraction of the items explicitly related to the subprime origins of the GFC is 7.6 % of the whole list. There are also terms and word collocations underlying the s-GFS index which refer to the impaired activity of other parts in the financial system, e.g. the exchange rate market (“currency collapse”, “currency crisis”, “currency mismatch”), residential real estate market (“housing bust”, “housing bubble”), debt markets (“sovereign default”, “overborrowing”, “external debt”) and asset markets (“asset bubble”, “investment fund risk”). There are also items in the dictionary gauging negative phenomena which can affect all the mentioned segments, e.g. “illiquidity”, “speculative bubble”, “risk transmission”, etc. Besides, not only commonly used terms and word collocations are characterized by non-negligible component loadings. Some professional items like “bank run” and “counterparty risk” significantly impacting

[14] Since we test for these relationships in the bivariate setting, we implement the Diks-Panchenko (2006) nonparametric Granger (no) causality test to the residuals extracted from the VAR models. The test runs in both directions for lags from 1 to 10 and for the bandwidth equal to 1.5, taking into account our time series length.

Table 1
Terms and word collocations determining the s-GFS index dynamics.

Term/word collocation	Component loading	Term/word collocation	Component loading
credit crisis	0.30	panic	0.06
credit crunch	0.29	recession risk	0.06
subprime crisis	0.27	exchange rate risk	0.05
Great Depression	0.25	currency collapse	0.05
banking crisis	0.24	currency crisis	0.05
bank failure	0.22	liquidity risk	0.05
financial turmoil	0.21	contagion	0.05
foreclosure crisis	0.21	overborrowing	0.04
mortgage loss	0.20	external debt	0.04
mortgage default	0.19	financial vulnerability	0.04
turmoil	0.18	risk transmission	0.04
bankruptcy	0.18	banking distress	0.04
bank run	0.17	loan forbearance	0.04
global financial crisis	0.16	moral hazard	0.03
failed bank	0.16	financial pressure	0.03
loss	0.15	risk connectivity	0.03
default risk	0.13	asset bubble	0.03
sovereign default	0.13	liquidity shock	0.02
credit bubble	0.13	market turmoil	0.02
insolvency	0.12	currency mismatch	0.02
counterparty risk	0.12	volatility spillover	0.02
bank risk	0.11	credit contraction	0.02
bubble	0.11	credit loss	0.02
market vulnerability	0.11	market stress	0.02
market collapse	0.10	fire sales	0.02
liquidity crunch	0.10	credit risk	0.01
loan default	0.10	risk spillover	0.01
illiquidity	0.09	debt overhang	0.01
illiquid assets	0.09	asset price bubble	0.01
liquidity shortage	0.09	sovereign debt crisis	0.01
speculative bubble	0.08	housing price bubble	0.01
systemic risk	0.08	European debt crisis	0.01
systemic crisis	0.08	herd behavior	0.01
financial panic	0.07	financial stress	0.01
distressed bank	0.07	bank distress	0.01
risk	0.07	investment fund risk	0.01
liquidity crisis	0.07	coordination failure	0.01
financial instability	0.07	global risk	0.01
housing bust	0.06	volatility in financial markets	0.01

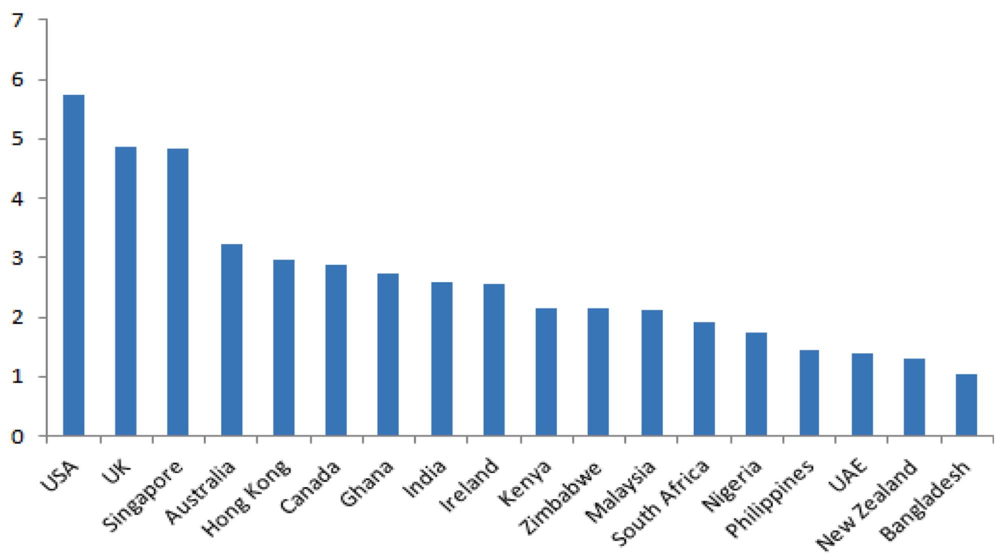

Fig. 4. Most important countries by search intensity for all the items underlying the s-GFS index with non-zero component loadings.

Table 2
Correlation coefficients between the s-GFS index and alternative measures of financial stress.

Financial Stress indicators	Correlation with the s_GFS index
SRISK	0.32***
VIX	0.77***
OFR FSI	0.82***
NpFSI (Püttmann, 2018)	0.79***
FSS index (Londono et al., 2021)	0.64***

*** - denotes statistical significance at the 1% level.

Table 3
Results of parametric and non-parametric Granger (no) causality tests for the VAR(2) model including the s-GFS index and global financial stress measures based on hard data.

Null hypotheses	Conventional Granger causality tests, χ^2	Nonparametric multivariate Granger causality tests, *T*-statistic
OFR FSI FSI → s − GFS	0.03	1.20
SRISK → s − GFS	0.54	−0.48
VIX → s − GFS	0.25	0.90
s − GFS → OFR FSI	23.22***	1.90***
SRISK → OFR FSI	0.72	0.56
VIX → OFR FSI	0.00	2.47
OFR FSI → SRISK	4.41	0.99
s − GFS → SRISK	1.48	−1.62
VIX → SRISK	0.57	−0.36
OFR FSI → VIX	0.55	1.73
s − GFS → VIX	35.54***	1.80***
SRISK → VIX	0.11	0.33

*** - denotes statistical significance at the 1% level.

the s-GFS index appear in the top-25 of terms and word collocations by the value of component loadings.

The Google *Trends* app allows to investigate through its mapping add-on where this or that term or word collocation is most actively searched for. After obtaining country rankings based on search intensity for each of the items with non-zero component loadings, we weigh all the countries' values in each ranking by the respective component loading. Then, we sum up the values across the countries and the items, and compute each country's share in the resultant indicator, thereby capturing the geographical distribution of search intensity underlying the s-GFS index. Although we consider only English terms and word collocations, the shares of the USA and the UK leading in the geographical distribution of search intensity appear quite moderate, hardly totaling altogether 10 %. Meanwhile, the list of top 18 countries with the shares in the geographical distribution of search intensity exceeding 1 % includes Malaysia, the United Arabic Emirates and Bangladesh, where English is neither national, nor an official language (Fig. 4).

Using the full list of countries and territories covered by the *Google Trends* mapping add-on, we calculate the Herfindahl-Hirschman index (HHI) based on their shares, obtaining the value of 175.7. This is a low estimate of concentration, indicating a substantial cross-country dispersion in the search intensity with respect to the terms and word collocations conveying negative sentiment about financial stability. The finding provides further evidence that searches only in English are unlikely to undermine the informativeness of the s-GFS index.

3.2. Lead-lag relationships between the s-GFS index and alternative measures of global financial stress

Table 2 below indicates that the contemporaneous linkages between the s-GFS index and the alternative indicators of financial stress are positive, i.e. consistent with theoretical expectations. The biggest correlation ratios are observed between the s-GFS index and the OFR FSI as well as the NpFSI. However, even in case of the SRISK the moderate absolute value of correlation is significant at the 1 % level.

In order to examine if the s-GFS index bears more information about global financial stress compared to the contenders, we now investigate lead-lag relationships between the former and two sets of competing measures: SRISK, the VIX index, OFR FSI, which are based on hard data, and the NpFSI along with the FSS index, which are sentiment-based.

We begin this empirical horse race by estimating vector autoregressions (VAR) for the two sets of indicators, including the s-GFS

Table 4
Results of parametric and non-parametric Granger (no) causality tests for the VAR(3) model including the s-GFS index and global financial stress measures based on sentiment data.

Null hypotheses	Conventional Granger causality tests, χ^2	Nonparametric multivariate Granger causality tests, *T*-statistic
NpFSI $\rightarrow$ s−GFS	2.39	−1.03
FSS $\rightarrow$ s−GFS	3.48	1.03
s−GFS $\rightarrow$ NpFSI	1.91	0.94
FSS $\rightarrow$ NpFSI	0.59	1.51*
s−GFS $\rightarrow$ FSS	4.72*	1.00
NpFSI $\rightarrow$ FSS	0.26	−1.10

Note: *- denotes statistical significance at the 10% level.

index itself. Before specifying the VAR models, we run the augmented Dickey-Fuller unit root (ADF) tests to examine the data series for stationarity. Based on the ADF tests, the s-GFS index, SRISK, the VIX index, OFR FSI and the FSS index have unit root, i.e. they are I(1) series, while the NpFSI is I(0).[15] Keeping the ADF test results in mind, we set up the VAR models in levels by applying the Toda-Yamamoto (1995) correction to preserve information embedded in the raw data. In case of the s-GFS index and the indicators based on hard data, the best specification based on the Akaike criteria which also ensures model stability and no serial correlation in the residuals is VAR(2). For the s-GFS index and sentiment-based measures the optimal model specification is VAR(3).

Table 3 reports the results of Granger (no) causality tests for the s-GFS index and the first set of indicators, while Table 4 does the same for the second set. The statistically significant relationships involving the s-GFS index are in bold.

Both analyses indicate that the s-GFS index Granger causes the VIX index and OFR FSI. This relationship is unidirectional, being significant at the 1 % level in the linear framework and at the 5 % level in the nonlinear one. Meanwhile, we do not document any linkage between the s-GFS index and SRISK. The FEVD analysis reveals that the s-GFS index on impact explains 8.3 and 13.4 % of the VIX index and OFR FSI variance, while at the horizon of 12 periods the proportions reach 37.7 and 37.9 %, respectively. Meanwhile, the VIX index and OFR FSI only account for 9.7 and 18.5 % of our index variance at the one-year horizon.[16] All in all, based on the in-sample estimation of lead-lag relationships, our sentiment-based index appears to be more informative than the two well-known metrics, the VIX index and OFR FSI.

We document scarce evidence for causal relationships within the set of sentiment-based measures (Table 4). There is a single linkage running from the s-GFS index to the FSS index in the linear setting, and also one relationship directed from the FSS index to NpFSI in the nonlinear framework. However, both of them are marginally significant at the 10 % level. Given the diverse methodologies underpinning the sentiment-based indices, it is unsurprising that there is a limited number of causal linkages among them. The FEVD analysis confirms the weak effects exerted by the sentiment-based measures on each other. For instance, irrespective of the significant causality running from the s-GFS index to the FSS index, the former accounts for the scanty 0.4 % of the latter on impact, and 3.2 % at the horizon of 12 periods. Against this backdrop, the s-GFS index at least appears cushioned from any causal impact by its competing measures.

3.3. Lead-lag relationships between the s-GFS index, the proxy of global financial cycle and world industrial production

The correlation ratios between the contemporaneous values of the s-GFS index, the GFC index and WIP are equal to −0.32 and −0.27, both significant at the 1 % level, i.e. increases in our sentiment-based index are associated with a decline in asset and commodity prices, retrenchment in capital and credit flows as well as with a decrease in the world industrial production index. In the realm of causal analysis, we find that the s-GFS index drives the global financial cycle (GFC) proxy developed by Miranda-Agrippino and Rey (2020) in the linear and nonlinear settings without any causal feedback (Tables 5). Based on FEVD, s-GFS index on impact explains 9.4 and 24.2 % of the GFC proxy variance in a year, which is an economically sizeable proportion. There is also a bi-directional relationship between the s-GFS index and world industrial production.

Thus, the sentiment about financial instability embedded in the s-GFS index is an important driver of the co-movement in international asset and commodity prices as well as in global credit and capital flows. The findings suggest that our index anticipates the dynamics of the global financial cycle. Besides, the dynamics of the s-GFS index and global real economic activity appear to feed each other. The results matter for policymakers, corroborating that the s-GFS index can be used as an indicator aimed at monitoring and/or stress testing global financial conditions. Similar indicators or even their dashboards are developed by national central banks and international regulatory bodies, e.g. the IMF (Huang et al., 2019). Furthermore, the statistically significant interaction with world industrial production reinforces the potential value added of the s-GFS index inclusion into these monitoring systems.

[15] The detailed results of the ADF test for this and other lead-lag analyses in the paper are available from the authors upon request.
[16] For space reasons we do not report generalized impulse response functions (GIRFs) related to our FEVD analysis. However, the GIRFs are available from the authors upon request.

Table 5
Results of parametric and non-parametric Granger (no) causality tests for the VAR(6) model including the s-GFS index, the GFC proxy and WIP.

Null hypotheses	Conventional Granger causality tests, χ^2	Nonparametric multivariate Granger causality tests, *T*-statistic
WIP → s − GFS	15.91**	0.07
GFC → s − GFS	5.70	0.82
s − GFS → GFC	22.28***	3.08***
WIP → GFC	9.17	1.32*
s − GFS → WIP	22.73***	0.76
GFC → WIP	28.66***	0.79

*** - denotes statistical significance at the 1% level.
** - at the 5% level.
* - at the 10% level.

Table 6
Results of parametric and non-parametric Granger (no) causality tests for the VAR models including the s-GFS index, industrial production index and the FSI for the USA (VAR(7)), Euro area (VAR(2)) and China (VAR(3)).

Null hypotheses	Conventional Granger causality tests, χ^2	Nonparametric multivariate Granger causality tests, *T*-statistic
USA		
IP_US → s − GFS	6.82	1.12
FSI_US → s − GFS	4.92	1.27
s − GFS → FSI_US	31.39***	1.65*
IP_US → FSI_US	12.24*	0.10
s − GFS → IP_US	6.21	1.80**
FSI_US → IP_US	31.61***	2.72***
Euro area		
IP_Euro → s − GFS	0.22	1.17
FSI_Euro → s − GFS	0.05	1.87**
s − GFS → FSI_Euro	17.13***	1.89**
IP_Euro → FSI_Euro	11.82***	1.74
s − GFS → IP_Euro	5.80**	1.57*
FSI_Euro → IP_Euro	0.00	0.27
China		
IP_China → s − GFS	1.46	1.12
FSI_China → s − GFS	1.02	1.42*
s − GFS → FSI_China	37.51***	1.65*
IP_China → FSI_China	16.37***	0.39
s − GFS → IP_China	1.91	2.02**
FSI_China → IP_China	2.16	0.52

*** - denotes statistical significance at the 1% level.
** - at the 5% level.
* - at the 10% level.

3.4. The relationship between the s-GFS index and macrofinancial indicators of the major economic centers

The s-GFS index also plays a notable role in the macrofinancial linkages in case of the major economic centers in the world (Table 6). The index unidirectionally leads the US FSI, while exhibiting bi-directional linkages with the financial stress indices for China and the Eurozone.[17] The s-GFS index Granger causes industrial production in the USA, the Eurozone and China. Its causal impact

[17] In unreported results which involve an alternative financial stress measure, the composite indicator of systemic stress (CISS) introduced by Holló et al. (2012) and published under the auspices of the ECB, the s-GFS index appears to Granger cause this index for all the three major economic centers. However, since the CISS series for China are somewhat shorter than for the USA and the Eurozone, in the baseline estimations we adopt the FSI series provided by the Asia Regional Integration Center which are fully uniform in length.

Table 7
Results of parametric and non-parametric Granger (no) causality tests for the VAR(3) model including the s-GFS index, CBDCUI and CBDCAI indices.

Null hypotheses	Conventional Granger causality tests, χ^2	Nonparametric multivariate Granger causality tests, *T*-statistic
$s - GFS \rightarrow CBDCUI$	1.65	0.44
$CBDCUI \rightarrow s - GFS$	3.33	0.13
$s - GFS \rightarrow CBDCAI$	0.85	0.06
$CBDCAI \rightarrow s - GFS$	2.99	0.33

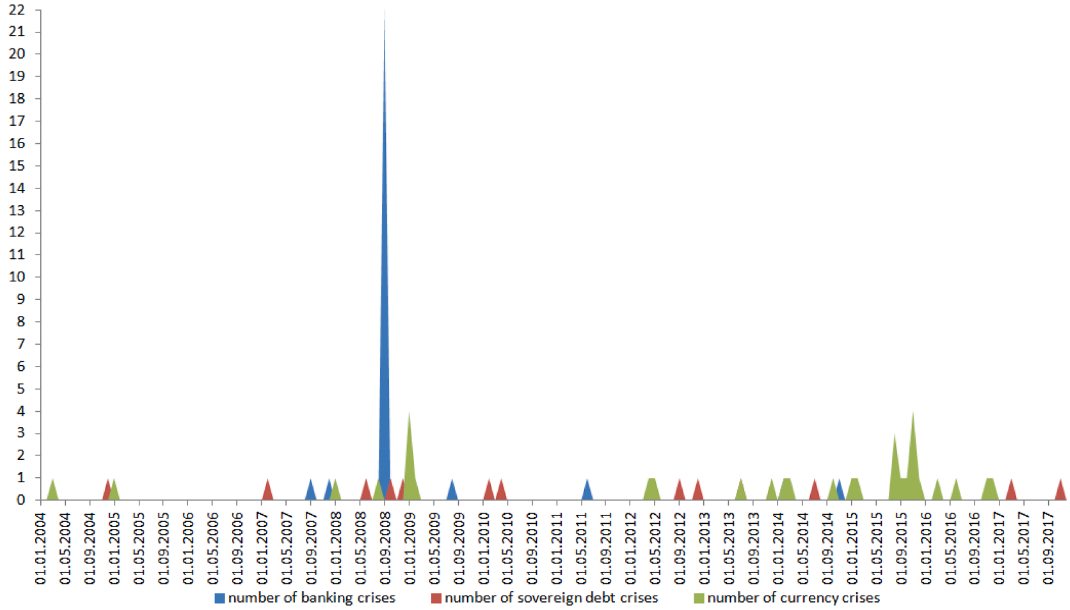

Fig. 5. Worldwide waves of banking, sovereign debt and currency crises, January 2004-December 2017.
Source: Laeven and Valencia (2020)

on industrial production is unilateral, being especially pronounced in the nonlinear setting.

Based on FEVD, we find that our index accounts for 44.7 % of the US FSI variance, while the latter explains 4.7 % of the s-GFS index at the horizon of 12 months. Regarding the magnitude of the impact produced by our index on industrial production, the USA outperforms other central economies. Namely, the proportion accounted for by the innovations in s-GFS index reaches 25.8 % of the variance in the US industrial production in a year, whereas in case of the Eurozone and China the indicator is equal to 17 and 4.9 %, respectively.

However, the effects of the s-GFS index documented above may not be confined to the central economies under consideration. In the literature there is compelling evidence that the USA, the Eurozone and China tend to spread their domestic shocks, both financial and real ones, to the rest of the world, e.g. Beutel et al. (2020), Fadejeva et al. (2017), Fu et al. (2019), Metiu et al. (2016). Hence, the effects of the s-GFS index on financial stress and industrial production in the central economies can be spread to the rest of the world and potentially amplified through these macrofinancial spillovers. This mechanism provides a plausible rationale for the causal linkages between the s-GFS index, the global financial cycle and world industrial production reported in Section 3.3.

3.5. The interaction between the s-GFS index and central bank digital currency sentiment

Table 7 indicates that the s-GFS index and central bank digital currency sentiment do not exhibit any lead-lad relationships, i.e. there are no causal linkages between our index and the CBDCUI/CBDCAI indices in the linear and non-linear settings. Thus, fears about global financial stress do not appear important for uncertainty in central bank digital finance, and vice versa.

3.6. The interaction between the s-GFS index and the occurrence of financial crisis waves

Fig. 5 visualizes the changing frequencies of banking, sovereign debt and currency crises, suggesting that they tend to occur in waves.

Table 8
Correlation coefficients between the s-GFS index and the frequency of banking, sovereign debt and currency crises.

Frequency of financial crises	Correlation with the s_GFS index
Banking	0.43***
Sovereign debt	0.12
Currency	0.01

*** - denotes statistical significance at the 1% level.

Table 9
Results of Granger (no) causality tests for the bivariate VAR models including the s-GFS index and the frequency of banking, sovereign debt and currency crises.

Null hypothesis	χ^2
$s-GFS \rightarrow$ CURRENCY	42.00***
CURRENCY $\rightarrow s-GFS$	6.01
$s-GFS \rightarrow$ BANKING	48.73***
BANKING $\rightarrow s-GFS$	51.02***
$s-GFS \rightarrow$ SOVEREIGN	19.49***
SOVEREIGN $\rightarrow s-GFS$	9.33

*** - denotes statistical significance at the 1% level.

The contemporaneous correlations between the waves of financial crises and the s-GFS index are close to zero, except for the coefficient involving the frequency of banking crises, which is positive and significant at the 1 % level (Table 8). Thus, our index exhibits the signs of being a coincident indicator for the global waves of banking crises during the observation period.

In order to examine if the s-GFS index can be a leading indicator for these waves of crises, we specify bivariate VAR models and run conventional and nonlinear Granger (no) causality tests. In case of banking and currency crises, the optimal VAR order is eight, while for sovereign debt crises the preferred specification is VAR(6). Tables 9-10 report the results of Granger (no) causality tests.

The analyses indicate that there is a bi-directional relationship between the frequencies of banking and sovereign debt crises worldwide and the s-GFS index, i.e. a rise in the negative sentiment among Google users about financial stability tends to increase the number of these crises, but their occurrence itself leads to the deterioration (increase) in the s-GFS index, as the users start to search more actively for the terms and word collocations with a negative connotation. This evidence suggests that the s-GFS index has no predictive power for the frequencies of these crisis waves. Nonetheless, the estimations show that our index can be a leading indicator for the frequency of currency crises, as it Granger causes their total number worldwide.

The conclusion that the s-GFS index is a leading indicator for the frequency of currency crises and a coincident one for the wave of banking crises meshes well with the literature studying interlinkages between different types of financial crises. Namely, Glick and Hutchison (2000) are the first to find that banking crises tend to precede currency ones. Similar evidence is provided by Eijffinger and Karatas (2020) as well as by Laeven and Valencia (2020). Hence, a coincident indicator for banking crises can be a leading one for currency crises in the meantime. Overall, our findings are generally in line with Huang et al. (2019) who find that sentiment-based indicators have certain potential to predict financial crises.

The occurrence of financial crises involves an increase in the number of macroprudential measures implemented worldwide. Since the s-GFS index is a coincident indicator for the waves of banking crises and leads currency ones, it is feasible to examine if a surge in our index can be a precursor of macroprudential policy tightening. In order to figure it out, we estimate a bivariate relationship between the s-GFS index and a dummy-type index measuring the worldwide stance of macroprudential policy based on Alam et al. (2019). This index (IMAPP) is a sum of introduced and canceled macroprudential measures coded with +/− 1 respectively for 134 countries covered by Alam et al. (2019). The absence of changes in macroprudential policy with respect to this or that measure relative to the previous month is coded with zero and does not affect the overall value of the IMAPP index. This index is available for the period January 2004-January 2019.

The results reported in Tables 11 and 12 indicate that the s-GFS index indeed tends to anticipate the increase in the number of macroprudential measures implemented worldwide. However, this relationship is significant at the 5 % level and is only found in the linear setting. Thus, the s-GFS index can weakly signal about an upcoming macroprudential policy tightening worldwide. Yet, we treat the result with caution and are far from asserting that policymakers in standalone countries need to adopt our index to introduce or

Table 10
Results of nonparametric multivariate Granger (no) causality tests for the VAR models including the s-GFS index and the frequency of crises.

lag	**$s - GFS \rightarrow CURRENCY$ *T*-statistic**	**$CURRENCY \rightarrow s - GFS$ *T*-statistic**	**$s - GFS \rightarrow BANKING$ *T*-statistic**	**$BANKING \rightarrow s - GFS$ *T*-statistic**	**s −GFSvSOVEREIGN *T*-statistic**	**SOVEREIGNvs −GFS *T*-statistic**
1	−1.29	0.51	1.28	1.91**	1.10	0.48
2	−0.43	1.18	1.98**	1.60*	0.75	0.44
3	0.10	1.21	1.97**	1.85**	0.74	0.81
4	0.39	0.76	2.01**	2.00**	0.18	0.49
5	0.15	−0.02	2.75***	1.70**	0.37	0.09
6	−0.24	−0.88	2.78***	1.79**	−0.24	0.93
7	0.34	−1.08	2.72***	1.65*	−0.25	1.37*
8	−0.28	−1.47	2.58**	1.75**	0.03	1.16
9	−0.81	−1.53	2.00**	1.68*	0.09	1.17
10	−0.13	−1.40	2.55**	1.58*	−0.06	0.88

*** - denotes statistical significance at the 1% level.
** - at the 5% level.
* - at the 10% level.

Table 11
Results of conventional Granger (no) causality tests for the bivariate VAR(2) model including the s-GFS index and the IMAPP index.

Null hypotheses	χ^2
IMAPP → s −GFS	0.17
s −GFS → IMAPP	3.86**

** - denotes statistical significance at the 5% level.

Table 12
Results of nonparametric bivariate Granger (no) causality tests for the VAR(2) model including the s-GFS index and the IMAPP index.

lag	**IMAPP → s − GFS*T*-statistic**	**s − GFS → IMAPP*T*-statistic**
1	−2.67	−1.39
2	−2.87	−2.17
3	−2.92	−2.49
4	−2.42	−2.63
5	−2.65	−2.77
6	−2.80	−2.89
7	−3.01	−2.83
8	−3.10	−2.73
9	−2.98	−2.70
10	−2.80	−2.70

cancel their national macroprudential measures or replace conventional indicators used to calibrate and implement such measures, e.g. credit-to-GDP gaps, with the s-GFS index.

In general, we qualify the findings in this Section as largely tentative. In our time series framework, we cannot assess the effect of our index on the likelihood of these crises by means of a probit/logit model. Besides, we have data only on the starting dates of the crises and are therefore unable to control for their duration.[18] Also, the crisis sample we use contains relatively few episodes, and most of them are clustered around the years of the global financial crisis. All this can potentially bias our findings, emphasizing the need for additional tests for the predictive power of the s-GFS index with respect to various types of financial crises.

4. Robustness check

We conduct a threefold check to examine the robustness of the s-GFS index. First, we alter the econometric methodology and apply structural VAR analysis to the lead-lag relationships involving more than two variables, i.e. reported in Sections 3.2-3.5. To this end, we specify structural VAR models of order equal to one, adopting the Cholesky identification. Based on the impulse response functions (IRF) derived from the SVAR models, the results appear qualitatively close to the baseline estimations. The s-GFS leads the VIX and OFR FSI. We also find that the s-GFS index unilaterally leads the global financial cycle proxy as well as financial stress indices in the USA, Eurozone and China. As for the sentiment-based contenders of the s-GFS index (the NpFSI by Püttmann (2018) and the FSS index by Correa et al. (2021)), there are no any significant lead-lag relationships among them and our index. The results of the IRF analysis are represented in the Appendix, Figs. A1-A6. We also test for such relationships between the s-GFS index and recently developed CBDC uncertainty and CBDC attention indices in order to capture potential linkages between global financial stress and the central bank digital currency sentiment. Similar to our baseline approach, the IRF analysis does not reveal any significant linkages among the three indicators (Fig. A7 in the Appendix).

Second, we invite three independent readers with relevant expertise[19] to validate our dictionary on financial instability. Based on the same set of research papers, they suggest replacing seven items from the dictionary with alternative terms and word collocations coming from the raw list of 327 items which, according to our reading, do not bear clear-cut negative connotation with respect to financial stability. The suggested changes are summarized in Table 13.

We follow the suggestions and re-construct our index based on the modified dictionary. The alternative index, s-GFS_alt, mimics the dynamics of our baseline index having a correlation ratio with it equal to 0.97 (Fig. 6).

Third, we construct another alternative version of the s-GFS index, building on the items which come from the working/discussion papers in the BIS repository published by major world central banks (the Fed, ECB, Bank of England, Bank of Japan). This approach to

[18] As far as we know, only the European financial crisis database (Lo Duca et al., 2017) provides information on the duration of crisis episodes, i.e. not only on the starting, but also on the so called “end of crisis management” dates. However, given the length of our observation period and the geographical scope of the database, we doubt that it is representative enough.

[19] Two of them represent the Monetary Policy Division of the Central Bank of Russia and the third reader is affiliated with the Department of Economics at the University of Konstanz.

Table 13
Changes in the dictionary on financial instability suggested by independent readers.

Items to be added	Items to be removed
stress test	shock
restructured loan	risk
flight to liquidity	financial frictions
regulatory intervention	bank distress
shadow banking	liquidity shock
flight to safety	herd behavior
capital injection	liquidity mismatch

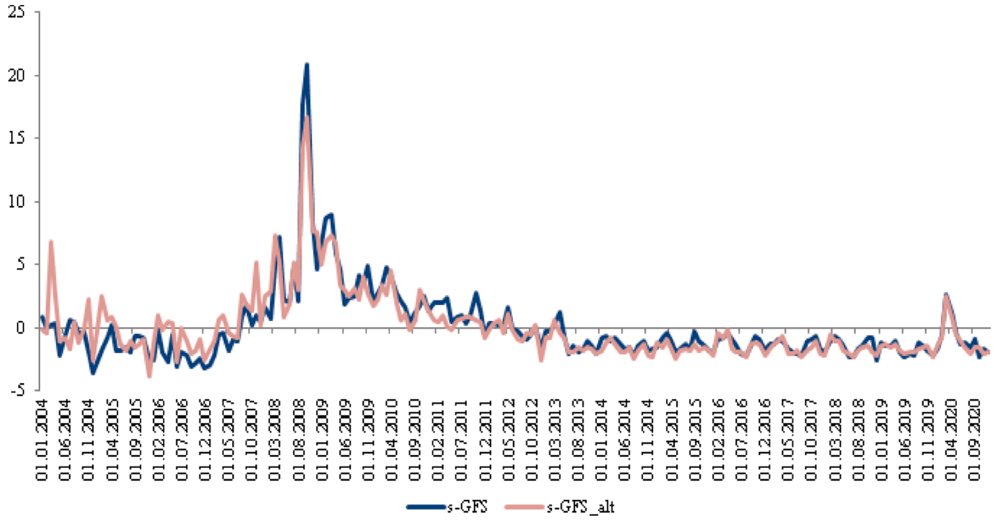

Fig. 6. Dynamics of the baseline s-GFS index vs s-GFS_alt, January 2004-December 2020.

Fig. 7. Dynamics of the baseline s-GFS index vs s-GFS_reduced, January 2004-December 2020.

the s-GFS index construction leads to a decrease in the number of terms and world collocations in our dictionary from 128 to 87. The number of items with non-zero component loadings totals 39. This reduced s-GFS index still appears strongly correlated with the baseline, with the correlation ratio equal to 0.97 (Fig. 7).

We next apply our standard econometric methodology to test for a lead-lag relationship between the s-GFS and its alternative versions, the s-GFS_alt and s-GFS_reduced (Tables 14-15).

Although no Granger causality is found in the linear setting, the Diks-Panchenko test indicates that our baseline index leads the s-

Table 14
Results of Granger (no) causality tests for the bivariate VAR (4) model including the s-GFS and the s-GFS_alt indices and the VAR(5) model including the s-GFS index and its reduced version (Fed, ECB, BOE, BOJ).

Null hypotheses	χ^2
s −GFS → s −GFS_alt	2.60
s −GFS_alt → s −GFS	1.02
s −GFS → s −GFS_reduced	1.85
s*v*GFS_reduced → s −GFS	3.65*

* - denotes statistical significance at the 10% level.

Table 15
Results of nonparametric bivariate Granger (no) causality tests for the VAR(4) model including the s-GFS and the s-GFS_alt indices and the VAR(5) model including the s-GFS index and its reduced version (Fed, ECB, BOE, BOJ).

lag	s −GFS_alt → s_GFS *T*-statistic	s −GFS → s −GFS_alt *T*-statistic	s −GFS → s −GFS_reduced *T*-statistic	s −GFS_reduced → s −GFS *T*-statistic
1	0.66	0.98	1.34*	1.37*
2	0.36	1.55	1.99**	1.44*
3	0.51	1.50	1.92**	1.18
4	−0.06	1.54	2.09**	1.31*
5	0.56	1.82**	1.92**	1.62*
6	−0.06	1.92**	1.94**	1.36*
7	−0.39	2.12**	1.99**	1.45*
8	0.71	2.08**	1.98**	1.31*
9	0.07	1.65*	1.60	1.34*
10	0.13	1.56	1.57	1.05

** - denotes statistical significance at the 5% level.
* - at the 10% level.

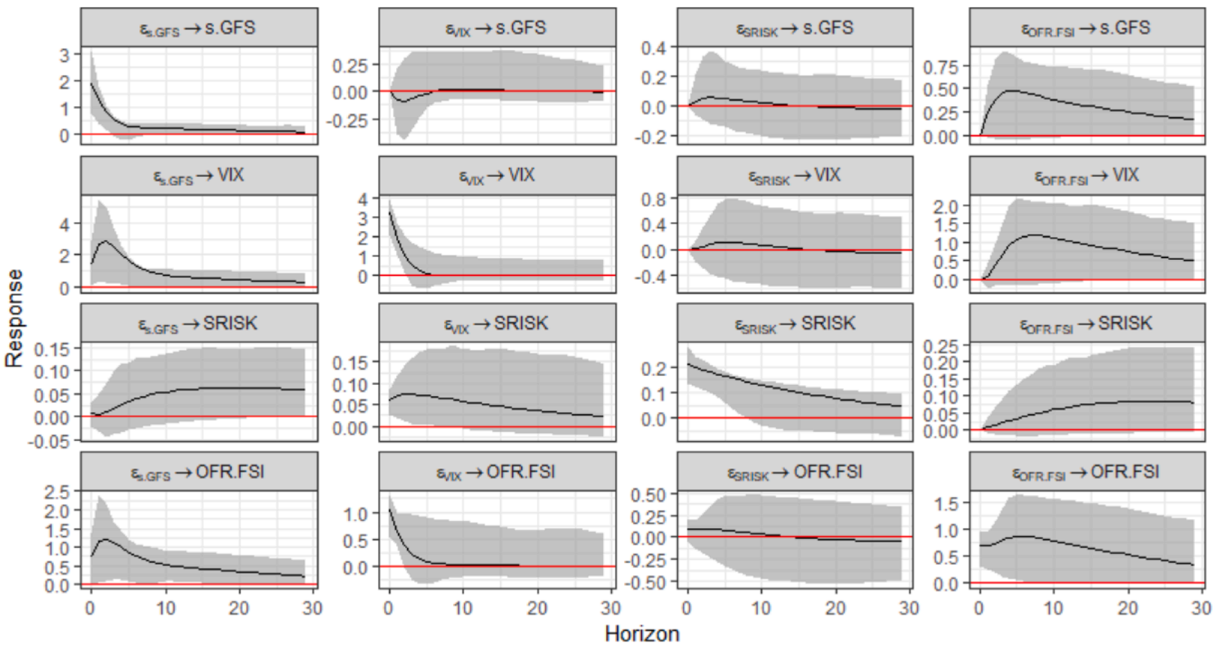

Fig. A1. Impulse response functions from the SVAR model, including the s-GFS index, VIX, SRISK and OFR FSI.

GFS_alt index. Thus, our initial index appears superior to the version incorporating the changes in the dictionary suggested by the independent experts.

Moreover, the baseline s-GFS index leads its reduced version in the nonlinear framework, whereas in the linear setting there are no causal linkages between them at the conventional significance level.

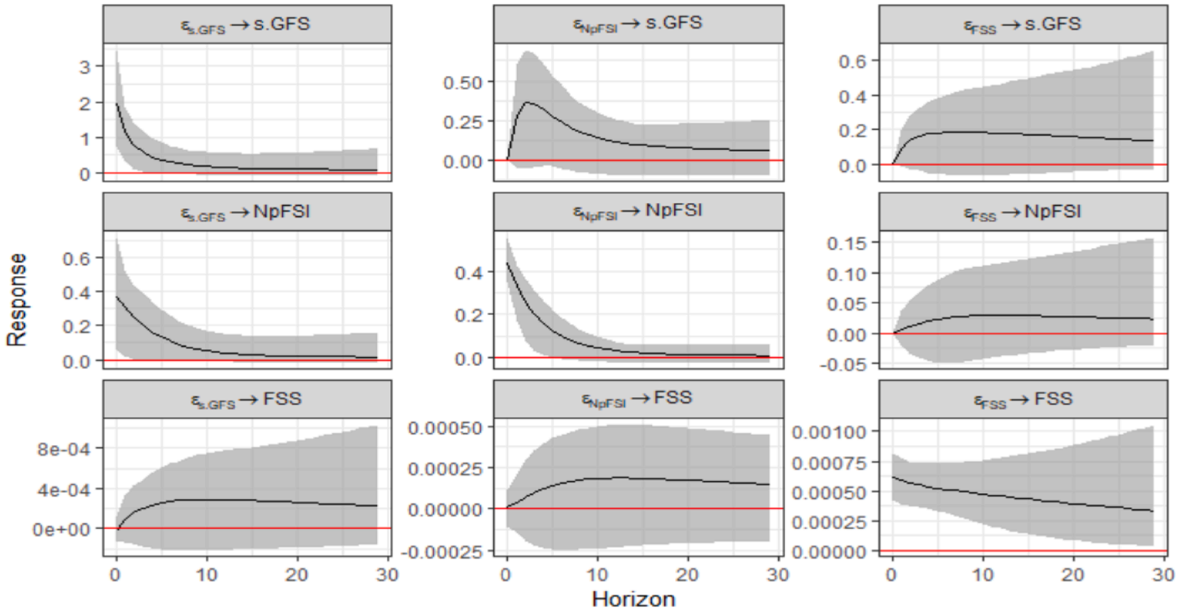

Fig. A2. Impulse response functions from the SVAR model, including the s-GFS, NpFSI, FSS indices.

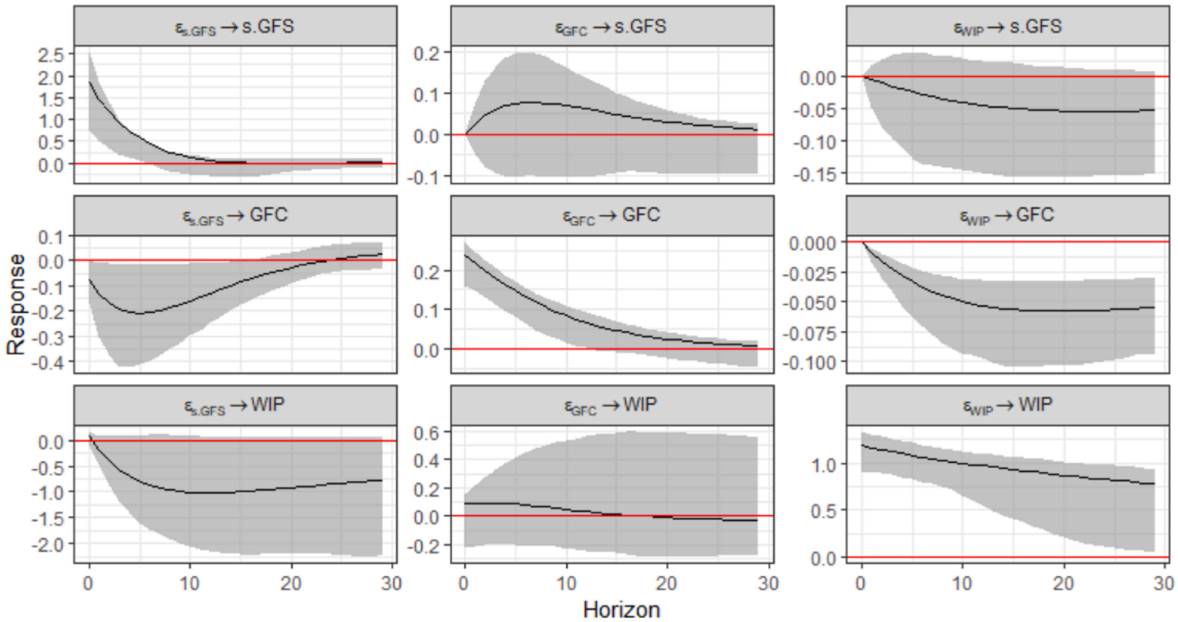

Fig. A3. Impulse response functions from the SVAR model, including the s-GFS, GFC, WIP indices.

Thus, the Google search for terms and word collocations related to global financial stress and based only on the research conducted in leading central banks appears less informative in comparison with the search involving all the regulators which upload research on financial stability to the BIS repository. The superiority of the baseline s-GFS index in this robustness exercise meshes well with the finding reported in Section 2.1, showcasing the low concentration of research on financial stability in terms of the reporting countries' shares.

5. Conclusion

The objective of this study is to construct a sentiment index of global financial stress based on the intensity of Google searches for specific terms and word collocations capturing the negative perception of worldwide financial stability stance. We select these terms

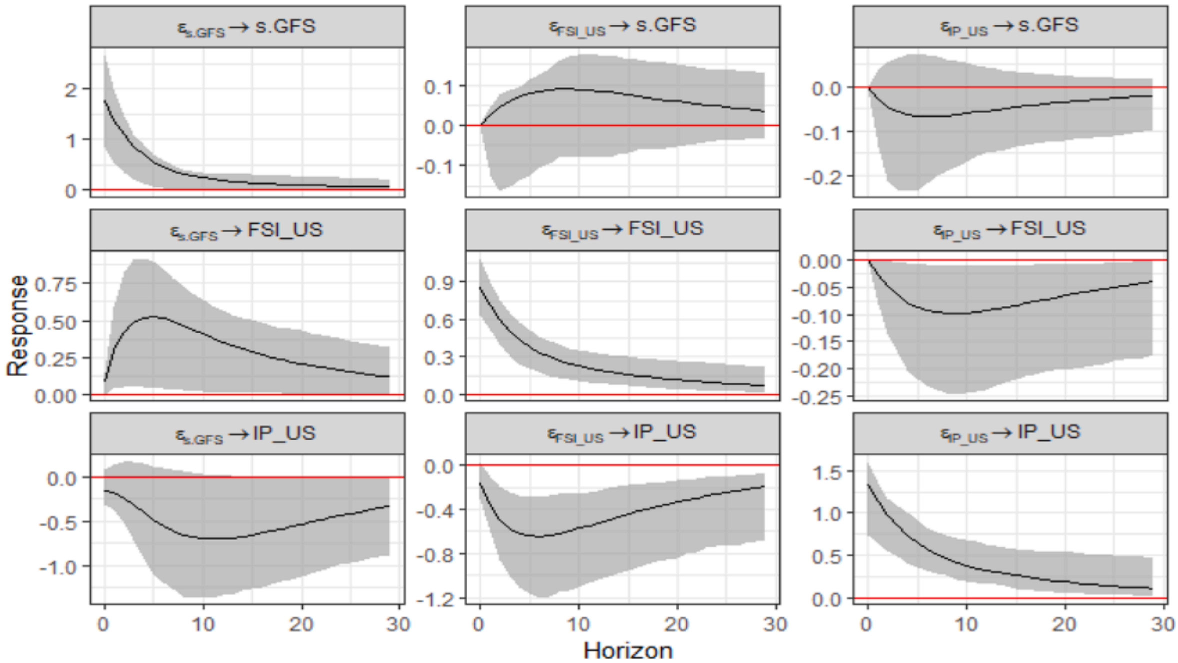

Fig. A4. Impulse response functions from the SVAR model, including the s-GFS, US FSI and US IP indices.

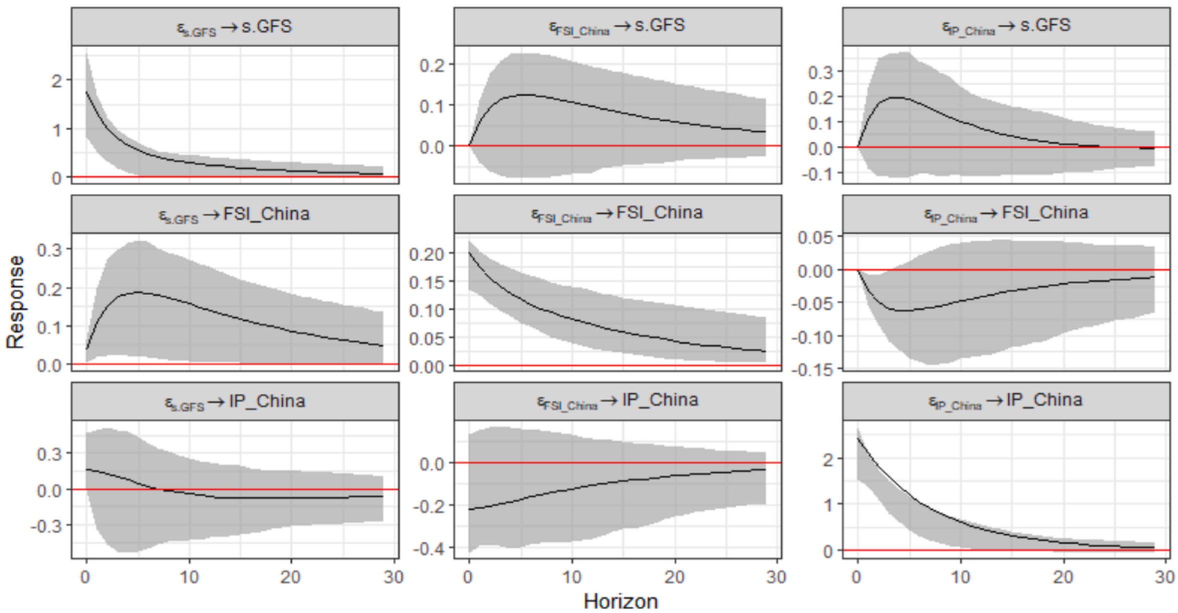

Fig. A5. Impulse response functions from the SVAR model, including the s-GFS, FSI and IP indices for China.

and word collocations based on the titles and abstracts of the working/discussion papers covering different dimensions of financial stability and posted on the BIS Central Bank Research Hub. Using *Google Trends,* we obtain search intensity indices for each of the items from our dictionary specific to financial instability for the period January 2004-December 2020. By adopting sparse principal component analysis we derive a composite measure, which is our sentiment index of global financial stress (s-GFS index).

The index captures the most severe episodes of financial stress during the observation period. As for its informational contents, the s-GFS index is largely underpinned by the terms and word collocations describing the impaired functioning of the banking sector. Although we select only the terms and word collocations in English, the index is likely to be robust, as even leading countries (the USA, the UK) which are on the top of the geographical distribution by search intensity account for less than 6 % each of total searches. The s-GFS index performs reasonably well compared to the alternative measures of global financial instability. Namely, it Granger causes the

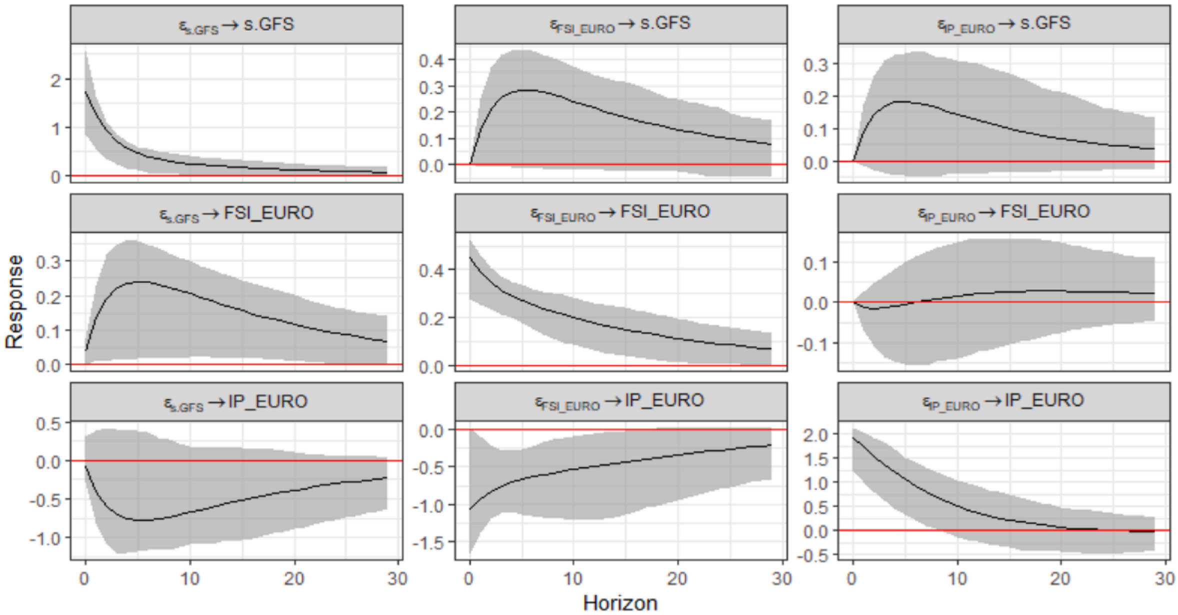

Fig. A6. Impulse response functions from the SVAR model, including the s-GFS and FSI and IP indices for the Eurozone.

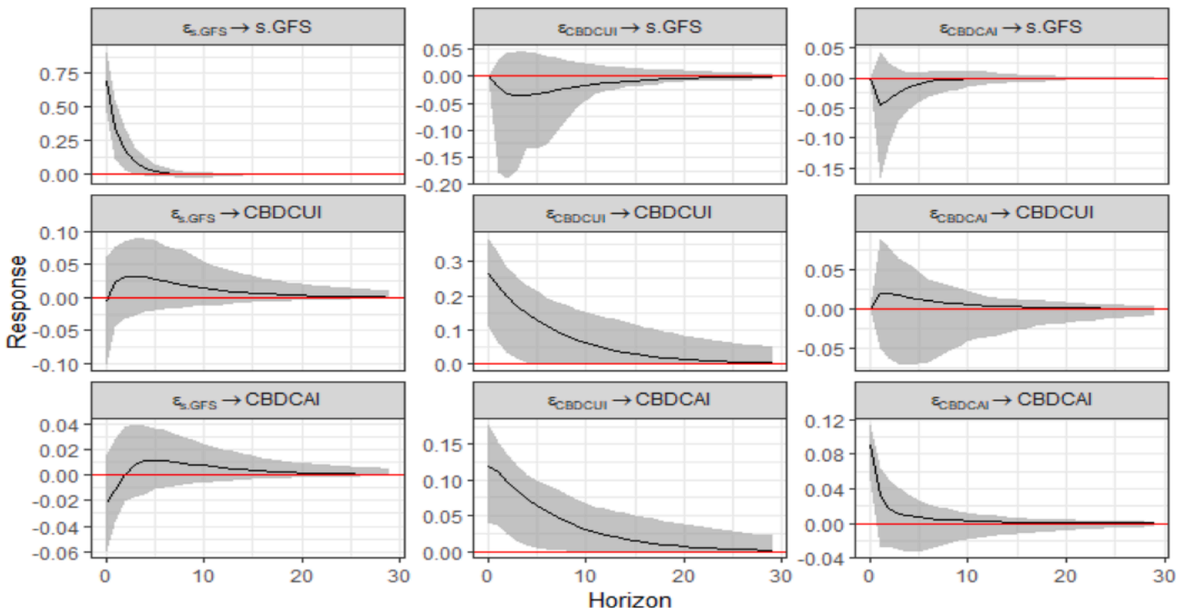

Fig. A7. Impulse response functions from the SVAR model, including s-GFS, CBDCUI and CBDCAI.

VIX index and OFR FSI among the indicators based on hard data. Within the set of sentiment-based metrics the s-GFS index weakly leads the financial stability sentiment index by Correa et al. (2021). In general, in this framework the number of causal linkages is very limited, but at least our index is not driven by any competing measures. Since global financial stress measures can be viewed as the covariates of the global financial cycle and can influence real economic activity, we examine if the s-GFS index has lead-lag relationships with these variables. The relationship runs from the s-GFS index to the global financial cycle proxy by Miranda-Agrippino and Rey (2020). Furthermore, based on forecast error variance decomposition, our index accounts for nearly 25 % of the variance in the GFC proxy, which is an economically sizeable proportion. There is also a bi-directional causal linkage between our index and world industrial production. Our index plays a pivotal role in the macrofinancial linkages assessed for leading economic centers in the world, the USA, the Eurozone and China. It leads the financial stress index for the USA, exhibiting a bi-directional relationship with the European and Chinese indices. Besides, the s-GFS index Granger causes industrial production in all the three economic centers. Such

Table A1
Dictionary of terms and word collocations conveying negative sentiment about global financial stability.

currency crisis, shock, banking crisis, risk, sovereign credit risk, bank run, twin crisis, volatility spillover, financial vulnerability, financial stress, moral hazard, financial frictions, credit crunch, credit rationing, REPO run, financial imbalances, default risk, debt overhang, banking panic, tail risk, asset price bubble, credit constraints, bank distress, fire sales, liquidity crisis, loan forbearance, global risk, stress event, systemic crisis, systemic risk, global financial crisis, mortgage default, exchange rate risk, financial disruption, downside risk, external imbalances, non performing loans, risky loans, volatility in financial markets, market stress, counterparty risk, bubble, financial instability, financial pressure, banking distress, credit risk, currency attack, financial distress, bankruptcy, balance of payment crisis, stock market crash, speculative bubble, financial turmoil, panic, contagion, market collapse, risk spillover, central counterparty risk, bank risk, credit crisis, stock market contagion, turmoil, sudden stops, asset bubble, subprime crisis, currency collapse, liquidity shock, housing price bubble, financial market shock, loan default, bank failure, liquidity risk, risk connectivity, foreclosure crisis, European debt crisis, loss, credit loss, Great Recession, external shock, credit bubble, shock propagation, failed bank, external debt, domestic debt, mortgage loss, housing bubble, rollover risk, crisis severity, flash crash, recession risk, illiquidity, Great Depression, currency depreciation, herd behavior, insolvency, systemic stress, bad balance sheet, overborrowing, risk transmission, liquidity crunch, bank closure, default correlation, debt burden, currency mismatch, market turmoil, coordination failure, exchange market pressure, market vulnerability, financial panic, sovereign debt crisis, mortgage arrears, liquidity mismatch, credit contraction, housing bust, stressed bank, distressed bank, bank misconduct, currency devaluation, liquidity shortage, asset encumbrance, overleveraging, capital flight, financial tsunami, illiquid assets, capital constraints, sovereign default, redemption risk, investment fund risk

Table A2
Descriptive statistics.

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p-value
S_GFS	0.49	−0.57	20.80	−3.21	3.33	2.96	15.93	1214.36	0.00
SRISK	2.61	2.87	4.37	0.85	0.98	−0.63	2.16	13.58	0.00
VIX	19.40	16.50	62.67	10.82	9.06	2.39	9.99	430.51	0.00
OFR FSI	0.44	−0.88	24.75	−4.99	5.26	2.24	9.18	350.37	0.00
NpFSI	100.85	100.63	105.89	99.54	0.98	2.09	9.21	336.72	0.00
FSS	0.00	0.00	0.01	−0.01	0.01	0.40	2.60	4.80	0.09
GFC	0.64	0.50	2.85	−2.69	1.13	−0.14	2.95	0.47	0.79
WIP	102.39	103.83	118.64	83.36	9.34	−0.43	2.21	8.24	0.02
FSI_US	−0.11	−0.82	10.02	−3.28	2.66	2.29	8.34	297.25	0.00
IP_US	0.55	2.22	8.52	−15.29	4.82	−1.72	5.84	119.63	0.00
FSI_EURO	−0.11	−0.57	4.79	−2.14	1.45	1.43	4.72	66.66	0.00
IP_EURO	0.51	1.78	9.34	−21.25	5.77	−1.81	6.65	158.32	0.00
FSI_CHINA	−0.38	−0.69	3.54	−1.45	0.97	2.46	8.98	359.78	0.00
IP_CHINA	12.03	12.35	21.30	5.40	4.41	0.15	1.83	8.71	0.01
CBDCUI	99.76	99.60	101.68	99.21	0.55	1.86	6.50	65.41	0.00
CBDCAI	99.76	99.67	100.79	99.47	0.29	1.49	5.07	32.97	0.00
BANKING	0.19	0.00	22.00	0.00	1.84	11.67	138.66	113687.60	0.00
SOVEREIGN	0.08	0.00	1.00	0.00	0.27	3.19	11.17	645.01	0.00
CURRENCY	0.22	0.00	4.00	0.00	0.62	4.15	23.34	2895.32	0.00
IMAPP	16.75	7	219	−3	36.98	3.86	18.45	745.22	0.00

paramount role of the s-GFS index in these macrofinancial linkages helps explain why the index matters for the global financial cycle and global real economic activity. We also provide tentative evidence for the s-GFS index to be a leading indicator for the frequency of currency crises and a coincident one for the frequency of banking crises. Besides, the index appears a precursor of worldwide macroprudential policy tightening. Nonetheless, our index has no significant lead-lag relationships with central bank digital currency uncertainty and attention indices, which suggests that fears about global financial stress do not affect uncertainty related to central bank digital finance, and vice versa.

The s-GFS index withstands a threefold robustness check. Its first ingredient involves applying an alternative econometric methodology – structural VAR models instead of the conventional VAR models. The second ingredient consists in inviting three external experts to validate the dictionary on financial instability. Largely supportive of out dictionary, the experts still suggest introducing minor changes, and we construct an alternative version of the s-GFS index following their recommendations. Finally, we construct a reduced s-GFS version, building only on the terms and word collocations present in the working/discussion papers released by the major world central banks, i.e. the Fed, ECB, Bank of England and Bank of Japan. However, all the alterations do not affect the baseline trends in the index dynamics or the statistically significant causalities uncovered in our main estimations.

Overall, our s-GFS index can be of interest for policymakers. It tracks the buildup of global and US financial stress with a certain lead time compared to the alternative measures. Thus, the index can be included into the systems of indicators aimed at monitoring and/or stress testing global financial conditions.

However, all the promising results regarding the s-GFS index reported in the paper rest on the in-sample estimations. A natural extension of our research would therefore consist in validating the s-GFS index as an out-of-sample predictor of various financial and macroeconomic variables, in particular, those which are used by regulators to calibrate and implement policy measures, e.g. credit-to-GDP gaps, debt service ratios, etc. Besides, further research should be conducted to investigate if this index can be useful in predicting various types of financial crises at the national, regional and international levels. In contrast to our preliminary analysis building on the global waves of financial crises in the time series dimension, future studies should focus on the interaction between the s-GFS index and the occurrence of financial crises in the panel data and country-level framework. The outcome of such research will elucidate if the s-

GFS index is worth becoming a constituent of early warning systems of indicators.

Another plausible extension of our study lies in using our dictionary to construct sentiment sub-indices aimed at capturing stress in the specific segments of the global financial system, e.g. the banking sector, exchange rate market, etc. This can be performed by grouping the terms and word collocations from our dictionary that are undoubtedly associated with this or that segment and applying the sparse PCA to them. One can conjecture that such sentiment sub-indices may be even more useful than the s-GFS index to capture sector-specific financial vulnerabilities or stress events.

Finally, we also view certain potential in constructing national sentiment-based indices of financial stress. They can build on our dictionary and Google search confined to a particular country. This approach is mostly feasible in case of the countries where English is either a national or official language. Direct translation of the terms and word collocations from our dictionary is possible to build such indices for the countries where English plays a less significant role, but we would treat this strategy with caution. For example, Du et al. (2022) show that the translations of the Loughran and McDonald (2011) finance-specific dictionary into Chinese yield poor results in terms of sentiment analysis, as this approach does not account for cultural, societal and regulatory subtleties among languages.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

None.

Appendix

See Figs. A1-A6 and Table A1 and Table A2.

References

Alam, Z., Alter, A., Eiseman, J., Gelos, R.G., Kang, H., Narita, M., Nier, E., Wang, N., 2019. Digging deeper – evidence on the effects of macroprudential policies from a new database, *IMF Working paper* № 19/66.

Algaba, A., Ardia, D., Bluteau, K., Borms, S., Boudt, K., 2020. Econometrics Meets Sentiment: An Overview of Methodology and Applications. J. Econ. Surv. 34 (3), 512–547.

Ardia, D., Bluteau, K., Boudt, K., 2019. Questioning the News about Economic Growth: Sparse Forecasting Using Thousands of News-based Sentiment Values. Int. J. Forecast. 35 (4), 1370–1386.

Armelius, H., Bertsch, C., Hull, I., Zhang, X., 2020. Spread the Word: International Spillovers from Central Bank Communication. J. Int. Money Finance 103, 102116.

Baker, S., Bloom, N., Davis, S., 2016. Measuring Economic Policy Uncertainty. Q. J. Econ. 131 (4), 1593–1636.

Beutel, J., Emter, L., Metiu, N., Prieto, E., Schüler, Y., 2020. Dilemma in Mean, Trilemma in Tail: The Global Financial Cycle and Macroeconomic Tail Risk. Mimeo. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3623953.

Beutel, J., Metiu, N., Stockerl, V., 2021. Toothless Tiger with Claws? Financial Stability Communication, Expectations, and Risk-taking. *J. Monet. Econ.* 120, 53–69.

Bholat, D., Broughton, N., Ter Meer, J., Walczak, E., 2019. Enhancing Central Bank Communications Using Simple and Relatable Information. J. Monet. Econ. 108, 1–15.

Blix Grimaldi, M., 2011. Up for Count? Central Bank Words and Financial Stress, *Sveriges Riksbank (Central Bank of Sweden) Working Paper* № 252.

Born, B., Ehrmann, M., Fratzscher, M., 2014. Central Bank Communication on Financial Stability. Econ. J. 124 (577), 701–734.

Borovkova, S., Garmaev, E., Lammers, P., Rustige, J., 2017. SenSR: A Sentiment-based Systemic Risk Indicator, *DNB Working Paper* № 553.

Brownlees, C., Engle, R.F., 2017. SRISK: A conditional capital shortfall measure of systemic risk. Rev. Financ. Stud. 30 (1), 48–79.

Chen, M., Deininger, M., Lee, S.J., Sicilian, M., 2020. Identifying Financial Crises Using Machine Learning on Textual Data. Mimeo.

Chen, P., Semmler, W., 2018. Financial Stress, Regime Switching and Spillover Effects: Evidence from a Multi-regime Global VAR Model. J. Econ. Dyn. Control 91 (C), 318–348.

Choi, H., Varian, H., 2012. Predicting the Present with Google Trends. Economic Record 88 (s1), 2–9.

Čihák, M., Sharifuddin, S.T., Tintchev, K., Jahjah, S., Muñoz, S., 2012. Financial Stability Reports: What Are They Good For? *IMF Working Paper* № 2012/001.

Comelli, F., Ogawa, S., 2021. What Can We Learn from Financial Stability Reports? *IMF Working Paper* № 21/200.

Correa, R., Garud, K., Londono, J., Mislang, N., 2017. Constructing a Dictionary for Financial Stability, *IFDP Notes*. Board of Governors of the Federal Reserve System, Washington, D.C.

Correa, R., Garud, K., Londono, J., Mislang, N., 2021. Sentiment in Central Banks' Financial Stability Reports. Eur. Finan. Rev. 25 (1), 85–120.

Diks, C., Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. J. Econ. Dyn. Control 30, 1647–1669.

Diks, C., Wolski, M., 2016. Nonlinear Granger Causality: Guidelines for Multivariate Analysis. J. Appl. Economet. 31 (7), 1333–1351.

Dim, C., Koerner, K., Wolski, M., Zwart, S., 2021. News-implied Sovereign Default Risk, Mimeo. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3955052.

Du, Z., Huang, A.G., Wermers, R., Wu, W., 2022. Language and Domain Specificity: A Chinese Financial Sentiment Dictionary. Eur. Finan. Rev. 26 (3), 673–719.

Ehrmann, M., Wabitsch, A., 2021. Central Bank Communication with Non-experts: A Road to Nowhere? *ECB Working Paper* № 2594.

Eijffinger, S., Karatas, B., 2020. Together or Apart? The Relationship between Currency and Banking Crises. J. Bank. Financ. 119, 105631.

Ellingsen, J., Larsen, V., Thorsrud, L., 2022. News Media versus FRED-MD for Macroeconomic Forecasting. J. Appl. Economet. 37 (1), 63–81.

Fadejeva, L., Feldkircher, M., Reininger, T., 2017. International Spillovers from Euro Area and US Credit and Demand Shocks: A Focus on Emerging Europe. J. Int. Money Financ. 70, 1–25.
Fernandez, R., Guizar, B.P., Rho, C., 2021. A Sentiment-based Risk Indicator for the Mexican Financial Sector. Latin American J. Central Banking 2 (3), 100036.
Fu, R., Lawson, J., Martinez, C., Watt, A., 2019. Chinese Financial Conditions and their Spillovers to the Global Economy and Markets, *CEPR Discussion Paper* № 14065.
Gao, Z., Ren, H., Zhang, B., 2020. Googling Investor Sentiment around the World. J. Financ. Quant. Anal. 55 (2), 549–580.
Gentzkow, M., Kelly, B., Taddy, M., 2019. Text as Data. J. Econ. Lit. 57 (3), 535–574.
Glick, R., Hutchison, M., 2000. Banking and Currency Crises: How Common are the Twins? Hong Kong Institute for Monetary Research Working Paper no 12000.
Harris, R., Karadotchev, V., Sowerbutts, R., Stoja, E., 2019. Have FSRs Got News for You? Evidence from the Impact of Financial Stability Reports on Market Activity, *Bank of England Staff Working Paper* № 792.
Holló, D., Kremer, M., Lo Duca, M., 2012. CISS – A Composite Indicator of Systemic Stress in the Financial Sector, *ECB Working Paper* № 1426.
Huang, C., Simpson, S., Ulybina, D., Roitman, A., 2019. News-based Sentiment Indicators, *IMF Working Paper* № 19/273.
Istrefi, K., Odendahl, F., Sestieri, G., 2021. Fed Communication on Financial Stability Concerns and Monetary Policy Decisions: Revelations from Speeches, *Banco de España Working Paper* № 2110.
Jun, S.-P., Yoo, H.S., Choi, S., 2018. Ten Years of Research Change Using Google Trends: From the Perspective of Big Data Utilizations and Applications. Technol. Forecast. Soc. Chang. 130, 69–87.
Kalamara, E., Turrell, A., Redl, C., Kapetanios, G., Kapadia, S., 2022. Making Text Count: Economic Forecasting Using Newspaper Text. J. Appl. Economet. 37 (5), 896–919.
Kliesen, K., Owyang, M., Vermann, E., 2012. Disentangling Diverse Measures: A Survey of Financial Stress Indexes. Federal Reserve Bank of St. Louis Econ. Rev. 369–397.
Laeven, L., Valencia, F., 2020. Systemic Banking Crisis Database II. IMF Economic Review 68 (2), 307–361.
Lanne, M., Nyberg, H., 2016. Generalized Forecast Error Variance Decomposition for Linear and Nonlinear Multivariate Models. Oxf. Bull. Econ. Stat. 78 (4), 595–603.
Larsen, V., Thorsrud, L., 2019. The Value of News for Economic Developments. J. Econ. 210 (1), 203–218.
Lo Duca, M., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., Lang, J., Detken, C., Peltonen, T., 2017. A New Database for Financial Crises in European Countries. European Systemic Risk Board Occas. Pap. 13.
Loughran, T., McDonald, B., 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. J. Financ. 66, 35–65.
Loughran, T., McDonald, B., 2016. Textual Analysis in Accounting and Finance: A Survey. J. Account. Res. 54 (4), 1187–1230.
Loughran, T., McDonald, B., 2020. Textual Analysis in Finance. Annu. Rev. Financ. Econ. 12, 357–375.
Lucey, B., Vigne, S., Yarovaya, L., Wang, Y., 2021. The Cryptocurrency Uncertainty Index. Financ. Res. Lett. 102147.
Mallick, S., Sousa, R., 2013. The Real Effects of Financial Stress in the Eurozone. Int. Rev. Financ. Anal. 30 (C), 1–17.
Manela, A., Moreira, A., 2017. News Implied Volatility and Disaster Concerns. J. Financ. Econ. 123 (1), 137–162.
Metiu, N., Hilberg, B., Grill, M., 2016. Credit Constraints and the International Propagation of US Financial Shocks. J. Bank. Financ. 72, 67–80.
Miranda-Agrippino, S., Rey, H., 2020. US monetary policy and the global financial cycle. Rev. Econ. Stud. 87 (6), 2754–2776.
Mittnik, S., Semmler, W., 2013. The Real Consequences of Financial Stress. J. Econ. Dyn. Control 37 (8), 1479–1499.
Monin, P., 2019. The OFR financial stress index. *Risks* 7 (1), 25.
Moreno, A.I., González Pedraz, C., 2020. Sentiment Analysis of the Spanish Financial Stability Report, *Bank of Spain Working Paper* № 2011.
Munday, T., Brookes, J., 2021. Mark My Words: the Transmission of Central Bank Communication to the General Public via the Print Media. Bank of England Staff Working Paper No 944.
Oosterloo, S., de Haan, J., Jong-A-Pin, R., 2007. Financial Stability Reports: A First Empirical Analysis. J. Financ. Stab. 2 (4), 337–355.
Park, C.-Y., Mercado, R., 2014. Determinants of Financial Stress in Emerging Market Economies. J. Bank. Financ. 45, 199–224.
Preis, T., Moat, H., Stanley, H.E., 2013. Quantifying Trading Behavior in Financial Markets Using Google Trends. Nat. Sci. Rep. 3.
Püttmann, L., 2018. Patterns of Panic: Financial Crisis Language in Historical Newspapers, Mimeo. Available at SSRN: https://ssrn.com/abstract=3156287.
Shapiro, A., Sudhof, M., Wilson, D., 2022. Measuring News Sentiment. J. Econ. 228 (2), 221–243.
Toda, H.Y., Yamamoto, T., 1995. Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. J. Econ. 66 (1–2), 225–250.
Wang, Y., Lucey, B., Vigne, S., Yarovaya, L., 2022. The Effects of Central Bank Digital Currency News on Financial Markets. Technol. Forecast. Soc. Chang. 180, 121715.
Wischnewsky, A., Jansen, D.-J., Neuekirch, M., 2021. Financial Stability and the Fed: Evidence from Congressional Hearings. Econ. Inq. 59 (3), 1192–1214.
Woloszko, N., 2020. Tracking Activity in Real Time with Google Trends, *OECD Economics Department Working Paper* № 1634.