Sentiment in Central Banks’ Financial Stability Reports*

Ricardo Correa¹, Keshav Garud², Juan M. Londono†, and Nathan Mislang³

¹Federal Reserve Board
²University of Michigan
³Cornell University

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Abstract

We use the text of financial stability reports (FSRs) published by central banks to analyze the relation between the sentiment they convey and the financial cycle. We construct a dictionary tailored specifically to a financial stability context, which classifies words as positive or negative based on the sentiment they convey in FSRs. With this dictionary, we construct financial stability sentiment (FSS) indexes for 30 countries between 2005 and 2017. We find that central banks’ financial stability communications are mostly driven by developments in the banking sector. Moreover, the sentiment captured by the FSS index explains movements in financial cycle indicators related to credit, asset prices, systemic risk, and monetary policy rates. Finally, our results show that the sentiment in central banks’ communications is a useful predictor of banking crises—a 1 percentage point increase in FSS is followed by a 29 percentage point increase in the probability of a crisis.

JEL Classification: G15, G28.

Keywords: Financial stability, Central bank communications, Text analysis, Dictionary, Sentiment index.

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†Corresponding author. E-mail: juan.m.londono@frb.gov

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1. Introduction

After the Global Financial Crisis (GFC), policymakers around the world embarked on a series of reforms to enhance the resilience of the financial system. As a result, many central banks were tasked with monitoring financial stability and some were assigned a financial stability mandate. Similarly, some central banks added financial stability to their monetary policy decision making process and financial stability communication became an additional tool to curtail financial vulnerabilities. In this new environment, announcements related to financial stability may reveal information about the condition of the financial system or about the reaction function of central banks to financial developments. However, little is known about the information and sentiment conveyed through central banks’ communications of financial stability and whether this information translates into changes in financial cycle indicators or is reflected in monetary policy decisions.

To fill this gap in the literature, we analyze the sentiment in financial stability reports (FSRs), one of the main tools used by central banks to disseminate their views on financial stability developments. We propose and validate a financial stability text analysis dictionary that captures the sentiment conveyed by words typically used in financial stability communications. We use this dictionary to calculate financial stability sentiment (FSS) indexes using the text from FSRs published by central banks and multilateral organizations. We explore how financial information is incorporated into FSS indexes and test whether central bank communications, as captured by these indexes, are related to future movements in financial cycle indicators, especially extreme events or turning points in the cycle.

FSRs have become an increasingly popular communication tool among central banks in the past 20 years. These reports are used to convey to the public the most salient risks and vulnerabilities in the financial system and are also meant to increase central bank transparency. The Bank of England is, as far as we are aware, the first central bank to have published an FSR in 1996. By 2005, 35 institutions were publishing versions of their FSRs in English.

We construct our financial stability dictionary using words from the FSRs published in English by central banks in 63 countries, the European Central Bank (ECB), the U.S. Financial Stability Oversight Council (FSOC), and the International Monetary Fund (IMF) between 2000 and 2017. This dictionary is a refinement of general dictionaries proposed in the literature, such as Harvard’s General Inquirer, and of finance-specific dictionaries, such as that in Loughran and McDonald (2011) (LM hereafter), as words can have a different connotation in a financial stability context—30 percent of the words in our dictionary are not classified in the LM dictionary.

We use the financial stability dictionary to compute FSS indexes for all FSRs in our sample. After some preprocessing of the FSR, we calculate the FSS index as the relative proportion of negative to positive words in these financial stability documents. We find that the cross-country average FSS index increases considerably around the peak of the GFC and then again around the peak of the euro-area sovereign debt crisis in 2011. Because sentiment is an unobservable characteristic of FSRs that could be mismeasured, we conduct a set of robustness tests to assess the stability of our index and our dictionary. In particular,
we calculate confidence intervals for the sensitivity of the FSS index to the words in the dictionary and find that relatively small variations in the dictionary have minimal effects on the dynamics of FSS indexes.

We validate our dictionary and test the informational content in central banks’ communications by following a three-step strategy using the FSS indexes of the 30 countries with at least one FSR published each year between 2005 and 2017. First, we analyze central banks’ focus on particular sectors or topics to understand the information set used to determine their overall financial stability communication strategy. For this purpose, we calculate a set of topic-specific sentiment indexes using a subset of sentences in FSRs that relate to one of the following topics: banking, asset valuations, households, real estate, the corporate sector, the external sector, and the sovereign sector. We find that most topic-specific indexes significantly drive the time variation in the FSS index, but concerns about the banking sector are the main driver of the overall FSS index. In particular, a one-standard deviation increase in the banking subindex is followed by a 0.42 standard deviation increase in the total FSS index, compared with a 0.19 standard deviation increase following a one-standard deviation change in the household subindex, the second main driver of the total FSS index. We also investigate how information from financial indicators drives these topic indexes, which provides evidence on the reaction function of central banks to financial developments. We find that information in topic-specific quantitative indicators is incorporated into topic-specific sentiment indexes. For instance, a deterioration in bank resilience indicators, such as credit default swaps (CDS), are followed by a significant deterioration in central banks’ financial stability sentiment related to banking.

Second, we study the contemporaneous and lead-lag relations between central banks’ overall sentiment about financial stability and financial cycle variables related to credit, asset prices, systemic risk, and monetary policy rates. We find that financial cycle characteristics and central banks’ sentiment jointly influence each other. In particular, a deterioration of financial cycle indicators is accompanied by a deterioration in financial stability sentiment. However, a deterioration in central bank sentiment, while significantly related to credit growth, does not appear to be significantly related to one-year-ahead changes in market-based financial cycle indicators such as asset valuation metrics. Interestingly, we find that an increase in monetary policy rates is followed by a deterioration in financial stability sentiment and, in turn, a deterioration in sentiment is followed by a significant reduction in monetary policy rates. This finding provides some evidence that monetary policy is reactive to financial stability developments in our sample of countries.

To account for the endogeneity between central bank sentiment and the financial cycle, we estimate a panel vector autoregressive (VAR) model in which the dependent variables are the FSS index and a set of variables characterizing the financial cycle. We find that a deterioration in sentiment about financial stability is followed by a significant deterioration of most financial cycle indicators for horizons between one and four quarters. In particular, an increase in the FSS index is followed by a significant increase in the debt service ratio, a drop in asset prices, an increase in systemic risk indicators, and a decrease in monetary policy rates. These results imply that central banks are able to incorporate information from financial developments into their communication products, and, at the same time, they are able to foresee future developments in those financial indicators.

More than analyzing regular developments in the financial cycle, central banks should
be prepared to determine turning points in the financial cycle, especially those that end in crisis episodes. In the last step, we use a probit model to investigate whether central banks are able to assess and communicate the vulnerabilities surrounding turning points in the financial cycle. We find evidence that the sentiment communicated in FSRs is a significant predictor of banking crises as defined by [Laeven and Valencia, 2013], at least at the one-quarter horizon. The predictive power of the FSS index for banking crises is economically meaningful, as a 1 percentage point increase in the demeaned FSS index, which corresponds to 1.3 times the average standard deviation of the FSS index across countries, is followed by a one-quarter-ahead increase of 29 percentage points in the probability of a banking crisis. Interestingly, however, for longer horizons, the coefficient associated with FSS becomes negative and significant, which would suggest that central banks that communicate deteriorations in financial vulnerabilities in advance of crisis episodes are able to decrease the likelihood of such events occurring. In particular, a one-standard deviation increase in the demeaned FSS index is followed by a 23 percentage point drop in the four-quarter-ahead probability of a crises. Thus, communications through FSRs may be useful to reduce the probability of extreme events, but only if they are delivered with a considerable lead.

The predictive power of the FSS index for banking crises is additional to that of several predictors previously used in the literature. Moreover, the predictive power of domestic FSS indexes is additional to that of the IMF FSS index, which we use as a proxy for global financial stability sentiment. Interestingly, after controlling for the IMF FSS index, an increase in FSS is followed by a significant drop in the probability of a crisis for horizons of three and four quarters, but the one-month horizon coefficient, although still positive, becomes insignificant.

Because our short sample includes very few crisis episodes, and most of these episodes in our sample took place during the GFC, we also consider a measure of turning points in the credit-to-GDP gap, which strengthens our results for the predictive power of the FSS index. The FSS index becomes a useful predictor for this alternative measure of turning points in the financial cycle for horizons of up to four quarters. In this case, a 1 percentage point increase in the demeaned FSS index is followed by an increase of 23 percentage points in the probability of a turning point at the one-quarter horizon.

The predictive power of the FSS index provides evidence that central banks are aware and are able to communicate that financial vulnerabilities are increasing and that the economy is close to a turning point in the financial cycle. This financial stability strategy is accompanied by a monetary policy reaction in the form of lower rates, which may allow the central bank to ameliorate the potential effect of financial stress on real activity. Although it is difficult to assess a counterfactual without these communications, our findings are suggestive that these FSR communications are able to significantly reduce financial vulnerabilities in the system for horizons of one year. In this context, our evidence suggests that central banks may use these communication tools, in combination with macroprudential and microprudential instruments, to reduce financial vulnerabilities. In the long run, as participants in the financial system become more familiar with these communications and the reaction function of central banks to financial vulnerabilities, the potency of financial stability communication may become stronger.

The rest of the paper is organized as follows. Section 2 describes the contribution of our paper to the extant literature. Section 3 introduces the financial stability dictionary and
Section 4 explains the methodology used to construct the FSS index. Section 5 explores the relation between the FSS index and the financial cycle, while Section 6 concludes.

2. Related Literature

Our paper mainly contributes to the literatures on central bank communications and textual analysis. Text analysis, or natural language processing, techniques have been extensively used in finance to capture how the sentiment of texts impacts firm and market behavior. A survey of these methods and finance applications can be found in Kearney and Liu (2014).

Within the textual analysis literature, general-purpose dictionaries, such as those found in Harvard’s General Inquirer and Diction, have been used extensively to analyze word tonality. However, these dictionaries might not be suitable to assess the sentiment conveyed by documents in more topic-specific contexts. Henry and Leone (2016) compare the Harvard and Diction dictionaries with that developed by Henry (2006, 2008), which is designed specifically for financial disclosure. They find that context-specific dictionaries yield scores that are more closely related to financial market reactions to news. Also, Loughran and McDonald (2011, 2016) find that general dictionaries do not provide sufficient accuracy for tonality in finance contexts.\footnote{Li (2010) also compares several dictionaries using a machine-learning approach.}

LM create a dictionary tailored to the context of 10-K reports and find that almost three-fourths of the words in the Harvard dictionary have a different connotation in finance. In this paper, we introduce a dictionary tailored to financial stability communications and show that a large portion of words have different connotations in a financial stability context compared to a general or even to a finance context.

The literature on central bank communications has mostly focused on announcements related to monetary policy (see, for instance, Blinder et al., 2008; Ericsson, 2016; and Stekler and Symington, 2016). Recent studies in this strand of the literature have used text analysis techniques to determine the effect of central banks’ monetary policy communications on asset prices and real variables (Hansen and McMahon, 2016; Hubert and Labondance, 2017). However, central banks’ communications on financial stability have garnered less attention. Cihak et al. (2012) and Cihak (2006) do a qualitative assessment of FSRs. Osterloo, de Haan, and Jong-A-Pin (2007) explore the effect of the publication of FSRs on a set of business and financial cycle characteristics.

The closest paper to our study is Born, Ehrmann, and Fratzscher (2014), which analyzes the effect of central banks’ financial stability communications on stock returns. They extract the sentiment conveyed by the executive summaries of FSRs and news articles describing interviews and speeches by central bank officials to test whether the tonality of these communications has an effect on equity prices. They find mixed results, with “optimistic” FSRs having the most significant effect on abnormal stock returns. Our paper differs from Born, Ehrmann, and Fratzscher (2014) in two key aspects. First, our study develops a new financial-stability-specific dictionary to capture the positive or negative sentiment expressed in communications focused on that topic. In contrast, Born, Ehrmann, and Fratzscher (2014) relies on Diction, a general-purpose text analysis tool that classifies words as optimistic or pessimistic, which may not accurately capture the sentiment of very specific topics, such as financial stability. Second, the aim of Born, Ehrmann, and Fratzscher (2014) is to analyze
the immediate effect of financial stability communications on stock returns, while our aim is to test whether changes in financial vulnerabilities affect the sentiment conveyed by FSRs or, conversely, whether central bank communication through FSRs affects the medium- and long-term path of financial vulnerabilities. This analysis provides additional information on the role of FSRs as a central bank communication tool.

Lastly, our paper also contributes to a broader strand of the literature that attempts to measure the buildup in vulnerabilities and systemic risks in the financial system and to predict turning points in the financial cycle. Drehmann and Tsatsaronis (2014) and Drehmann et al. (2015) find that the credit-to-GDP gap and the debt service ratio contain useful information to predict financial crises for a large set of countries. Econometric-based measures of the level of interconnectedness of financial systems have also been shown to increase around financial crises. Billio et al. (2012) and Diebold and Yilmaz (2014) provide evidence of the relation between connectedness and financial crises for the U.S., and Demirer et al. (2018) propose a global measure of financial connectedness. Other econometric-based measures, such as those in Brownlees and Engle (2017) and Adrian and Brunnermeier (2016), provide information about systemic risk; in particular, about connectedness conditional on market downturns. Cesare and Picco (2018) provide a survey of systemic risk measures. We show that the FSS index might contain information that is additional to that of other measures commonly used in the literature to predict financial crises and turning points in the financial cycle.

3. A Dictionary for Financial Stability Analysis

In this section, we introduce a dictionary tailored to the financial stability context. Our dictionary is created using words from the FSRs prepared by 63 countries’ central banks, the ECB, the FSOC, and the IMF. First, we discuss the availability and general structure of FSRs and then we explain in detail the method used to create our financial stability dictionary.

3.1 Financial Stability Reports

Our dictionary is created using words from FSRs either originally written in or translated into English for a sample spanning between 2000 and 2017. Table 1 summarizes the availability of these FSRs. FSRs for all countries in our sample are available online through the website of each institution publishing the report. Over half of the 66 institutions publishing FSRs do so on a biannual frequency, while the rest publish reports annually. Publishers are located predominantly in Europe, with an even mix of advanced and emerging-market economies in our sample. Although the central banks of England, Sweden, and Norway started publishing FSRs as early as 1996 (Born, Ehrmann, and Fratzscher, 2014), regular publication started in these countries between 1999 and 2000. Other early publishers of FSRs include the IMF (2002), Austria (2001), Belgium (2002), Brazil (2002), Canada (2002), Denmark (2002),

3Prior to 2018, the Federal Reserve Board did not publish an FSR. The only FSR available for the United States in our sample period was produced by the Financial Stability Oversight Council (FSOC), of which the Federal Reserve Board is a voting member.
Hungary (2000), and Spain (2002). By 2005, 35 institutions were publishing FSRs. Most other institutions began publishing reports around the GFC.

Following these criteria, our sample of FSR is composed of 1,082 documents. Reports in our sample have a mean length of 94 pages, with the 90 percent interval around the mean spanning from 38 to 184 pages. The contents of FSRs are heterogeneous across the sample, but most of their sections can be classified into the following categories: executive summary, domestic sector, global sector, financial sector, special topics, and payment systems. We filter out the text from special topics and payment system sections, as they are often theoretical in nature or unrelated to the financial stability outlook. We do not consider FSRs that focus on special topics, such as those published by the Bank of France.

All FSRs are available in PDF format. To analyze the text, we first preprocess the PDF documents using the PDFMiner package available for Python, which converts the programmatic rendering of text in PDF documents into plain text or other formats. We convert the text in FSRs into html format because this format includes tagging that allows us to ignore text in titles, footnotes, and boxes.

3.2 Methodology for Creating the Dictionary

As suggested by LM and Henry and Leone (2016), words might have different connotations depending on the context they are being used, which implies that applying a general dictionary to a specialized context can cause substantial errors in a sentiment index. We find that a considerable portion of words used in FSRs have a different connotation compared to a general context or even to a finance context, such as the texts in financial disclosures (e.g., 10-K reports in the United States). There are three main reasons why connotations in financial stability can differ from those in existing general or finance-specific dictionaries. First, words often convey a different sentiment in a financial stability context. For instance, the word “confined” is classified as having a negative connotation in other dictionaries, but almost always conveys a positive sentiment in a financial stability context, as it refers to limiting negative spillovers. Second, words that have a positive or negative connotation in other dictionaries might be used mostly as part of technical terms in a financial stability context, as it refers to limiting negative spillovers. Second, words that have a positive or negative connotation in other dictionaries might be used mostly as part of technical terms in a financial stability context, as it refers to limiting negative spillovers. Second, words that have a positive or negative connotation in other dictionaries might be used mostly as part of technical terms in a financial stability context, as is the case for words such as “default” (“credit default spreads”) or “delinquency” (“delinquency rates”). By themselves, however, “default” and “delinquency” rarely drive sentiment in a financial stability context. The third reason our financial stability dictionary is distinct from its predecessors is because we exclude some common words used in other dictionaries that mostly describe historical events rather than sentiment. An example of a word in this category, and widely used in FSRs in our sample, is “crisis,” which is classified as negative in previous dictionaries but is mostly used to refer to the 2008 global financial crisis.

To create our financial stability dictionary, we process the text from FSRs and extract individual words. To do so, we first strip the financial stability texts of all punctuation. Next, we delete stop words, such as “and,” “the,” and “of.” We then select the top 98 percent of the most frequent remaining words across all FSRs in our sample, which amounts to 7,388 words. We then remove words that obviously convey no sentiment, such as “vehicle” and

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4 See Cihak et al. (2012) for more background and a broader qualitative assessment of FSRs.

5 The remaining 2 percent of words by frequency amount to 34,579 words, of which 27,219 words are used
“study.” The remaining 1,484 words are classified into categories of either positive, negative, or neutral connotation.

To determine each word’s connotation, we randomly choose 25 sentences that include each word from across all FSRs. Each word with its respective sentences is then independently classified by two readers. Any disagreement in the classification of words between these readers is then discussed. If disagreement persists, the words are examined by an additional team formed by two other readers.

Table 2 reports the distribution of words in our financial stability dictionary. The iterative word classification process results in 96 positive and 295 negative words. Positive and negative words combined account for 5.38 percent of all distinct words in FSRs, and, in terms of frequency of use, they account for 1.45 and 2.56 percent, respectively. Another interesting conclusion from our classification process results from comparing the words in our dictionary with those in LM’s dictionary. We find that, while there are similarities between the two dictionaries (270 words are classified in both dictionaries), almost 31 percent of all positive or negative words (121 words in total) are unique to the financial stability dictionary. The uniquely financial stability words represent 1.67 of all distinct words in FSRs and 0.73 percent of the frequency of use across all FSRs. Some examples of these uniquely financial stability words are: “contagion” (negative connotation), “resilient” (positive), and “spillovers” (negative).

4. A Sentiment Index for Financial Stability

In this section, we introduce the FSS index. In the first part, we explain the method used to calculate the index using the dictionary described in section 3. In the second part, we explore the sensitivity of the FSS index to the classification of the words in the dictionary.

4.1 The FSS Index

For each FSR, the FSS index is calculated as follows:

\[
FSS \text{ index}_{country, period} = \frac{\#Negative \text{ words} - \#Positive \text{ words}}{\#Total \text{ words}}, \tag{1}
\]

where the negative or positive connotation of words is obtained from the financial stability dictionary introduced in section 3. The number of total words corresponds to all words in each FSR after removing stop words. Our index does not apply any weighting to the words included in the index because FSRs are typically long, which implies that most words in the dictionary are used in each report. Traditional weighting schemes for textual analysis, such as the term frequency-inverse document frequency (tf-idf), are useful for large samples of short documents.

five or fewer times in all 1,082 reports. Thus, the lowest 2 percent of words corresponds to very specific (often regional) uses of language or are only found in few reports, making them impractical to apply to a broader financial stability context.

Our financial stability dictionary can be found in Juan M. Londono’s website: [Link to dictionary](https://ssrn.com/abstract=3091943)
Similar to LM, we negate positive words within three words of “not,” “no,” “nobody,” “none,” “never,” “neither,” and “cannot.” However, we do not turn negative words in the vicinity of “not,” “no,” “nobody,” “none,” “never,” “neither,” and “cannot” into positive expressions, as double negations do not necessarily convey positive sentiment. Thus, double negations are considered neutral. According to Equation (1), an increasing FSS index indicates a deterioration in sentiment.

Table 3 shows a set of summary statistics for the FSS indexes for all countries in our sample, and figure 1 shows their demeaned time series. Although we calculate individual FSS indexes across all countries and periods in our dataset, for the remainder of the paper, we focus on the FSS indexes for the 30 countries in our sample with FSRs available at least once each year between 2005 and 2017 (see table 1). This reduced sample of countries allows us to compare the indexes for a homogeneous time period. Moreover, restricting the sample to countries with FSRs available for at least 13 years increases the reliability of the empirical exercise described later in the paper, because most countries not included in this sample began publishing FSRs around the GFC. Nevertheless, we also use an unbalanced panel for all countries publishing FSRs in English since 2000 to assess the robustness of our main empirical results.

The information in table 3 shows that all countries have a positive mean FSS index, except for Argentina. This implies that negative words are used more often than positive words for most countries. FSS indexes display considerable time variation, with standard deviations ranging from 0.49 (Iceland) to 1.17 (Denmark). In particular, as can be seen in figure 1, all countries’ FSS indexes increased (more negative sentiment) in the period around the failure of Lehman Brothers in September of 2008. In fact, for 21 countries, the maximum FSS index realization occurred within one year after this event. Interestingly, for Germany (November 2007), Chile (December 2007), and the United Kingdom (April 2008), the maximum FSS index occurs within one year prior to the collapse of Lehman Brothers. All FSS indexes also increased before the approval of the second EU-IMF bailout for Greece in the first quarter of 2012. Five of the European countries in our sample and the IMF experienced their highest FSS index within one year of this event.

4.2 Sensitivity to the Dictionary

The methodology used to create a sentiment dictionary is subject to classification errors, as discussed by Correa et al. (2017). After all, each word’s connotation is defined by individuals using isolated sentences. Moreover, some words might transmit a different connotation depending on the context or their connotation may vary over time. We now investigate the sensitivity of the FSS index to the set of words in the financial stability dictionary. To do so, we calculate confidence intervals for the FSS index by randomly removing words from the financial stability dictionary at two levels: 5 and 20 percent. We then calculate each FSS index with the remaining words in the dictionary and repeat the process of randomly removing words from the dictionary and calculating the FSS index 1,000 times. Each time, the indexes are multiplied by a correction factor so that the levels are of comparable magnitude. This correction factor is necessary because removing words from the dictionary reduces the

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7The monthly time series for the FSS indexes for all countries with FSRs published in English can be found in Juan M. Londono’s website: Link to FSS time series.
value of the numerator of the FSS index (see Equation (1)), essentially watering down the
index. Our methodology of randomly removing words is similar to that used in Jegadeesh
and Wu (2013) to assess the effect of an incomplete dictionary.
To get an idea of the width of the confidence intervals for the FSS index after removing
words from the dictionary, we show in figure 2 the 90 percent confidence interval for a selected
set of countries or regions. The figure shows that, even if one out of every five words in the
dictionary are misclassified, the contours of FSS indexes are largely preserved. This evidence
is robust across countries and suggests that relatively small choices and disagreement in
the dictionary formation process have a minimal effect on the dynamics of FSS indexes.
Moreover, this evidence suggests that a dictionary does not have to be comprehensive to be
complete and reliable. In unreported results, we find that, for all countries in our sample,
indexes and their confidence intervals vary enough to pass a simple test of time variation.
Specifically, in no country can a horizontal line be drawn that is contained in the 90 percent
confidence interval of the FSS indexes, even if 20 percent of words are removed from the
dictionary.8
In unreported results, we also address the heterogeneity in word use frequency across
time. To do so, we split our word corpus into three buckets: Early (before 2008), middle
(2008-2012), and late (after 2012), and we ran an algorithm that iteratively let each bucket
vote in their favorite word and form three mutually exclusive sub-dictionaries, which are
used to calculate new FSS subindexes. The correlations with the benchmark FSS index
are: 0.78, 0.83, and 0.73 for the early, middle, and late FSS subindexes, respectively. These
correlations are particularly high given that subindexes are formed from mutually exclusive
sets of words, and they fall within the 90th confidence interval derived from calculating 1,000
FSS subindexes from randomly formed word buckets. Thus, our evidence suggests that the
FSS index is very robust to researcher decisions related to the words in the dictionary.

5. The Informational Content of the FSS Index

In this section, we investigate the informational content of the sentiment conveyed by central
banks through FSRs. First, we assess the sectors and topics that drive financial stability
sentiment and how quantitative information is incorporated into the sentiment related to
these topics. Then, we analyze the relation between the FSS index and the financial cycle
and whether the FSS index is a useful predictor of banking crises.

5.1 Topics Driving Financial Sentiment

Although the FSS index is an overall measure of the sentiment conveyed in FSRs, the index
does not identify which topics drive the changes in sentiment. The structure and topics
of FSRs vary greatly across countries and over time, which makes it difficult to manually
categorize sections within FSRs. In this subsection, we analyze central banks’ focus on

8 The main difference between our method and that in Jegadeesh and Wu (2013) is that their method
removes words from the dictionary controlling for frequency of use. In unreported results, we have calculated
confidence intervals by dropping 50 percent of words using the method in Jegadeesh and Wu (2013). Our
main results that the contours of FSS indexes are preserved remain unchanged.
particular sectors or topics to understand how central banks use information to determine their financial stability communication strategy.

As a first step to gain intuition and to understand the focus of FSRs on different topics, we plot in figure 3 a word cloud with the most frequently used words in these reports for the following years: 2004, 2008, 2012, and 2016. In the figure, the size of the words indicates the relative frequency of use across all FSRs; that is, larger words have a larger count in a particular period. The top right quadrant shows the most frequently used words in 2004, a period that could be considered to have low financial stress for most countries in our sample. This stress level is reflected in the sparsity of words used, with no fundamental topic driving the narrative in the FSRs. In contrast, FSRs published during the GFC in 2008 have a defined focus around the words “credit,” “financial,” “losses,” “market(s),” and “turmoil.” All these words clearly reflect the areas most affected by the crisis, which was initially centered around the housing market in the United States and later spread to global financial markets. A similar pattern is observed in 2012, around the European sovereign debt crisis, but with the emphasis shifting to the banking and sovereign sectors. In the lower right quadrant, which shows the most frequently used words in 2016, the intensity of word use decreases, as in 2004, but discussions in FSRs are focused on monetary and regulatory policies and their effect on different sectors, as well as on the oil and commodity markets. The evolution of the narratives adopted in FSRs is crucial for understanding the topics and sectors driving the FSS index and the underlying vulnerabilities in each country.

To formally analyze the patterns suggested by the word cloud, we calculate a set of topic-specific FSS indexes. The topics selected are based on a review of the literature on early-warning indicators used by central banks and multilateral organizations to assess financial vulnerabilities (see, for instance, IMF 2010). To identify these topics, we also follow closely the general structure of FSRs, which typically covers most of these topics in dedicated sections. Each topic index is calculated using only those sentences in FSRs containing terms that are related to a specific topic. Table 4 shows the terms used to identify each topic, which in most cases align with sectors in the economy. These terms are selected taking into account the frequency in which they are included in FSRs as well as a manual analysis of the context in which they are mentioned. For each country and topic, the index is calculated as in Equation (1) using only the portions of FSRs that contain sentences with the terms in table 4.

To explore the drivers of financial sentiment, we estimate the following panel-data regression for the overall FSS index as a contemporaneous function of the topic indexes:

\[ FSS_{i,t} = u_i + \sum_{j=1}^{S} B_j FSS^j_{i,t} + \sum_{j=1}^{S} C_j Freq^j_{i,t} + e_{i,t}, \]  

where \( FSS_i \) represents each country’s FSS index and \( FSS^j_i \) is the FSS index for topic \( j \) for country \( i \). We control for the frequency at which each topic’s words are used in each report \( (Freq^j_i) \), as movements in topic indexes might be partially explained by the density of words

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\[9\] In unreported results, we explore alternative ways of defining topics, including the Latent Dirichlet Allocation (LDA) algorithm (see, for instance, Jegadeesh and Wu 2013) and the construction of bigrams and trigrams. However, these methods proved to be limited in identifying key topics in FSRs.

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Electronic copy available at: https://ssrn.com/abstract=3091943
from the financial stability dictionary used within those sentences. To estimate the panel-data regression, we use quarterly data, and the quarter assigned to each FSR corresponds to the quarter in which the report was made available. Because FSRs are published at a biannual or annual frequency, we assume a step function to interpolate between any two dates when reports are available. The coefficients are estimated using pooled ordinary least squares in which the coefficients associated with the topic indexes and their frequency are restricted to be homogeneous across countries. We standardize the indexes to compare the magnitude of the estimated coefficients across topics.

The estimates of the coefficients associated with the topic indexes in Equation (2) are shown in table 5. All topic indexes are significant in explaining the time variation in the overall FSS index, at least at the 10 percent confidence level. The banking topic, with an estimated coefficient of 0.42, drives most of the time variation in the overall index, followed by household (0.19), external (0.16), corporate (0.15), asset valuation indicators (0.15), real estate (0.13), and sovereign (0.06).

We now investigate how information from quantitative indicators is incorporated into the FSS topic indexes. To do so, we propose the following panel-data regression setting in which topic-specific quantitative indicators explain the time variation in each topic index:

\[
FSS_{i,t}^j = u_i + \beta X_{i,t-h}^j + e_{i,t},
\]

where \(X_{i,t}^j\) is each one of the topic-specific variables defined in table 6. The results are summarized in table 7.

Overall, the evidence suggests that FSS subindexes incorporate information from topic specific indicators. In particular, all bank-related indicators are contemporaneously and positively correlated with the banking FSS index and this relation remains positive when the quantitative indicators are lagged by one year. The contemporaneous and lagged relation between the household FSS index and the debt service ratio for households is positive and significant at the 1 percent level. For the stock valuation topic, an increase in volatility or a reduction in stock market prices relative to either book values or dividends paid is related to a deterioration in sentiment. The contemporaneous and lagged relation between the corporate FSS index and the debt service ratio for private nonfinancial corporations is positive and significant at the 1 percent confidence level. For the external sector topic, the contemporaneous relation is positive and significant for currency volatility and the ratio of external debt to GDP. For the real estate sector, a reduction in real and nominal property prices or an increase in house prices relative to rent is accompanied by a significant deterioration of sentiment related to this topic. Finally, for the sovereign sector, an increase in sovereign CDS spreads or the ratio of government debt to GDP is accompanied by a deterioration of sentiment related to this sector.

5.2 Financial Stability Sentiment and the Financial Cycle

We now explore the relation between sentiment communicated in FSRs and the financial cycle. To characterize each country’s financial cycle, we use variables related to credit growth, asset valuations, and systemic risk. Ng (2011) and Hatzis et al. (2010) provide a survey of financial cycle measures.
FSS index and monetary policy rates. The variables considered are explained in detail in table 6. In the first step, we use a panel regression to investigate the contemporaneous and lead-lag relations between the FSS index and each one of the variables characterizing the financial cycle. In the second step, we consider a panel VAR to account for the endogeneity between financial cycle variables and the FSS index. In the final step, we investigate the predictive power of the FSS index for turning points in the financial cycle, including extreme events such as banking crises.

5.2.1 Contemporaneous and lead-lag relations

We explore the contemporaneous and lead-lag relations between the FSS index and each one of the financial cycle characteristics. To explore how information from financial cycle indicators is incorporated into the FSS index, we use a panel-data setting similar to that in Equation (3),

$$FSS_{i,t} = u_i + \beta X_{i,t-h} + \gamma FSS_{i,t-h} + e_{i,t}.$$  

We also consider the reverse causality, in which the FSS index has predictive power for financial cycle indicators, as in

$$X_{i,t} = u_i + \beta FSS_{i,t-h} + \gamma X_{i,t-h} + e_{i,t}.$$  

The results for the contemporaneous ($h = 0$) and lead-lag ($h = 4$) analysis are summarized in table 8. Contemporaneously, the FSS index is significantly correlated, at any standard confidence level, with all financial cycle characteristics, but not with interest rates. In particular, an increase in the FSS index, which corresponds to a deterioration in sentiment, is accompanied by a contemporaneous increase in the credit-to-GDP gap and the debt service ratio; a drop in stock and house prices; and an increase in SRISK, CDS spreads, and stock return volatility.

Our results for the lead-lag relation suggest that buoyant financial cycle conditions related to credit growth are followed by a significant deterioration in financial stability sentiment. This evidence suggests that information in credit indicators is incorporated in financial stability communications. However, a deterioration in sentiment is followed by a decrease in the debt-service ratio, but this relation is not significant for the credit-to-GDP gap.

The long-term relation between FSS and market-based financial cycle indicators related to asset valuations or systemic risk is less clear than that between FSS and slow-moving characteristics of the cycle, such as credit growth. In particular, asset valuation measures and market-based systemic risk measures are not significantly related to financial stability sentiment at the four-quarter horizon. If anything, our evidence suggests that an increase in stock market volatility is followed by a significant deterioration in financial stability sentiment.

We also explore the lead-lag relation between financial stability sentiment and monetary policy rates. This exploration allows us to assess the relation between central banks’ financial stability communications and monetary policy; that is, whether these communications incorporate information about previous changes in monetary policy rates and whether these communications are associated with future changes in policy rates. The evidence suggests that rising interest rates are followed by a significant deterioration of financial stability senti-
ment. In contrast, a deterioration in sentiment is followed by a reduction in monetary policy rates. The latter evidence favors the hypothesis that growing financial stability concerns are followed by accommodative monetary policy, which might actually prevent a sharp turning point in the financial cycle.

In table 9, we assess the robustness of our contemporaneous and lead-lag analysis along several dimensions. First, we consider an unbalanced panel with all FSRs available between 2000 and 2017. Second, we assess the robustness of our results outside of the GFC. Specifically, we calculate the coefficients associated with the financial cycle indicators and the FSS index for a sample that excludes the third and fourth quarters of 2008 and the first quarter of 2009. Third, we consider an alternative specification of the FSS index calculated using only text from the executive summaries of financial stability reports, whenever they are available. Central banks carefully consider the message communicated through the executive summaries, so these indexes may better represent the intended message of the FSR. Last, we include an FSS index calculated based on the text published in the IMF’s Global Financial Stability Report. This allows us to control for global factors that may influence domestic financial stability conditions.  

We find that the relation between credit indicators and the one-year ahead FSS index is mostly robust to the alternative samples, indexes, and controls. However, the effect of communications on the evolution of credit indicators is more sensitive to the sample or to the index considered. In particular, the relation is not significant when we use the full sample or the alternative FSS index. Interestingly, our evidence suggests that, outside of the GFC, a deterioration in financial stability sentiment is followed by a further deterioration of credit indicators. This finding may lend credence to the notion that central banks are able to foresee a deterioration in financial vulnerabilities during normal times, but they are not able to curtail a deterioration of these financial stability indicators. Our main results remain robust when we control for the IMF FSS index.

The results for the robustness tests also suggest that excluding the GFC period unmasks some of the relations between the FSS index and market-based financial cycle indicators. In particular, outside of the GFC, a deterioration of financial stability sentiment is followed by a further deterioration of market-based financial cycle indicators: a significant drop in stock prices relative to their book values, an increase in SRISK-to-GDP ratios, and an increase in bank CDS spreads.

The relation between the FSS index and future monetary policy rates remains robust across the four alternative specifications. However, the association between changes in monetary policy rates and future financial stability communications is more sensitive to the sample or the index being considered. In particular, changes in monetary policy rates are only significantly associated with one-year ahead financial stability sentiment if we consider the sample with all FSRs or if we include the IMF FSS index with our original sample. The coefficients for the non-GFC sample and the FSS index based on executive summaries point in the same direction, but are slightly smaller and not significant.

\footnote{Table A.1. in the online appendix shows the results for a multivariate setting including both the IMF and the ECB FSS indexes. This setting yields insignificant coefficients associated with the ECB FSS index.}
5.2.2 Panel VAR

The lead-lag patterns documented in tables 8 and 9 suggest that financial cycle variables and financial sentiment might be endogenously determined. This finding is not surprising, as financial cycles are relatively long and central bank communications are unlikely to change drastically in the different phases of the cycle. We account for this potential endogeneity by estimating the following panel VAR:

\[ Y_{i,t} = u_i + \sum_{l=1}^{L} Y_{i,t-l} A_l + e_{i,t}, \]  

where \( i \) and \( t \) denote, respectively, the country and time dimension of the panel data. \( Y_{i,t} \) is a vector of dependent variables, which includes the FSS index and a financial cycle measure, \( u_i \) is a vector of country fixed effects, and \( e_{i,t} \) is a vector of idiosyncratic errors, with zero mean and serially uncorrelated. \( L \) is the number of lags in the VAR, which we assume is equal to 1, given the relatively short length of our sample. The matrices \( A_l \) are estimated using the GMM procedure in Abrigo and Love (2015).

Figure 4 (Figure 5) shows the response functions following changes in the FSS index (the financial cycle variables) for the panel VAR system in Equation (4) for horizons between one and four quarters. The results in figure 4 suggest that changes in the FSS index are followed by an increase in both the credit-to-GDP gap (panel (a)) and the debt service ratio (panel (b)), although the effect is significant only for the latter for up to three quarters—a one-standard deviation increase in FSS is followed by an increase of the debt service ratio between 1 and 3.5 percent. Changes in the FSS index are also followed by a significant reduction in asset prices. In particular, changes in the FSS index are followed by a significant reduction in bank stock prices relative to market values for up to four quarters (panel (c)) and relative to paid dividends for up to two quarters (panel (d)). Variations in the FSS index are also followed by a significant reduction of real property prices for up to four quarters (panel (e)). Changes in the FSS index are followed by a significant deterioration of the systemic risk characteristics of the financial cycle: a significant increase in the SRISK-to-GDP ratio, bank CDS spreads, and stock market volatility (panels (f) to (h), respectively). Finally, a deterioration in financial stability sentiment is followed by a drop in monetary policy rates, although the effect is only significant if we assume that policy rates are not bounded at zero (panel (j)) for the one-quarter horizon.

The results in figure 5 are in line with those reported in table 8 and figure 4. In particular, an increase in any of the financial cycle characteristics, except for the change on real property prices, is followed by a significant (borderline in the case of the debt service ratio) deterioration in financial stability sentiment.

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12 In the VAR estimation, FSS is ordered first, as financial stability sentiment assigned to each quarter corresponds to FSRs published throughout the previous quarter or year, depending on the frequency of publication, while financial cycle characteristics correspond to end-of-the-quarter indicators.

13 Figure A.1. in the online appendix shows the IRFs when we control for the IMF FSS index as a proxy for global sentiment.
5.2.3 Financial Stability Sentiment and Financial Crises

In the previous section, we showed that changes in central banks’ sentiment are significantly related to changes in the path of indicators that characterize the financial cycle, including monetary policy rates. However, financial stability monitoring and more aggressive communication about financial stability concerns are more likely to be clustered around turning points in the financial cycle, such as at the starting point of banking crises. We investigate further the relation between financial sentiment and the financial cycle by assessing whether the sentiment conveyed by central banks in FSRs is a useful predictor of banking crises. To do so, we estimate the following probit model:

\[ Pr[C_{i,t} = 1] = \Phi[X_{i,t-h}/\beta], \]

where \( C_{i,t} \) is a dummy variable that takes on the value of 1 when a banking crisis occurs in country \( i \) at time \( t \) and 0 otherwise. The banking crisis dummies are calculated based on [Laeven and Valencia (2013)]. The vector \( X \) includes the demeaned FSS index as the main regressor. We use demeaned FSS indexes as the probit model does not allow for fixed effects. The CDF of a standard normal distribution is denoted by \( \Phi \) and \( h \) denotes the number of lags of the regressors.

The results for the probit model are summarized in panel A of table 10 and suggest that the FSS index is a near-term predictor of banking crises. The coefficient associated with the one-quarter lagged FSS index is significant at the 10 percent level. The estimated coefficient is also economically significant—a 1 percentage point increase in the demeaned FSS index, which corresponds to 1.28 times its average standard deviation across countries, is followed by an increase of 29 percentage points in the probability of a banking crisis.

However, we also find that at longer horizons, such as four quarters, the coefficient turns negative and significant. This may provide some evidence that central banks can reduce the likelihood of a banking crisis if they are able to communicate in advance that vulnerabilities are becoming more salient. This is a relevant finding, as it suggests that communications may be an important tool to limit these financial stability events.

As can be seen in the rest of the panel, our results for the predictive power of the FSS index for banking crisis are robust to considering the full sample of FSRs, but not the FSS based on the executive summaries of FSRs. For this latter measure, we still find that early communications about the rise in financial vulnerabilities may be associated with a significantly lower likelihood of these events materializing.

The predictive relation of the FSS index is also robust to an alternative characterization for turning points in the financial cycle. In particular, we consider turning points in the credit-to-GDP gap that are followed by a decrease in the gap over at least the next four quarters. This alternative definition of a turning point in the credit cycle allows us to overcome statistical limitations related to the small number of banking crises in our sample and the clustering of these episodes around the GFC. Using this alternative dependent variable, the FSS index becomes a useful predictor of turning points in the credit-to-GDP gap for up to three quarters—a 1 percentage point increase in the FSS index is followed by an increase of 23 percentage points in the probability of a turning point in credit-to-GDP gap at the one-quarter horizon. Interestingly, for turning points, early (one-quarter before) communication
does not seem to be associated with a lower probability of a turning point in the financial cycle.

In panel B of table 10, we add additional controls to the probit setting, some which are commonly used in the literature (see Drehmann et al., 2015) to predict financial crisis. Each row in the table names the specific control added and the coefficients represent those of the FSS index at different lags. Two of the most relevant controls are the credit-to-GDP gap and the debt-service ratio, which have been shown to be good predictors for banking crisis. We find that the predictive power of the FSS index for banking crises is additional to that of the credit-to-GDP gap or the debt service ratio. In unreported results, we show that the coefficient associated with these two variables is not statistically significant at any standard confidence level for our sample. We also find that early communication of the buildup of vulnerabilities continues to be negatively associated with the likelihood of a banking crisis, irrespective of the control variable considered.

Panel C compares the coefficients for the country-specific FSS indexes and the index based on the IMF’s global financial stability report. We make this comparison for the same specifications reported in panel A. Interestingly, the IMF FSS index is positively associated with the likelihood of banking crises at all horizons. That is, the negative sentiment conveyed in the IMF FSS is a very good predictor of these financial stability events. Interestingly, in this setting, the FSS index based on the central banks’ FSRs has a negative and significant coefficient at the three- and four-quarter horizons. That is, central banks with stronger financial stability communications are able to limit the possibility of extreme stress episodes after controlling for overall global conditions, as captured by the IMF FSS. For less extreme events, such as turning points in the credit cycle, FSS indexes are significantly better predictors at the one- and two-quarter horizons, with positive and significant coefficients associated with FSS.

The results for the probit setting suggest that central banks appear to be able to foresee the starting point of banking crises or, at least, intensify their communications around these episodes. However, the predictive power of the FSS index is borderline significant unless we consider a broader definition of turning points in the financial cycle. We also find evidence that central banks that communicate that there is a buildup in vulnerabilities earlier in the credit cycle may be able to reduce the likelihood of a banking crisis. These divergent results are a sign that there is a degree of heterogeneity in terms of the communication strategies of central banks. Some institutions are either more cautious about the outlook or they could decide to focus on communicating the degree of resilience of the financial sector instead of the risks identified. Other institutions may be more aggressive in communicating early on that financial conditions are too loose. These strategies may depend on the prudential instruments at the disposal of the central banks and on the macroprudential governance structure in the country. Exploring this heterogeneity is a potential avenue for future research in this area.

\[14\text{The IMF index is highly correlated with country-level FSS indexes (0.45, on average), which could cause partial multicollinearity.}\]
6. Conclusion

Text analysis techniques have been used extensively to analyze central banks’ communications focused on monetary policy. Although financial stability has gained prominence beyond monetary policy in central banks’ operations after the global financial crisis and the European sovereign debt crisis, communications on this topic have garnered less attention in the literature.

We propose a dictionary tailored specifically to the financial stability context, as we find that a large portion of words in FSRs, one of central banks’ communication tools on financial stability, convey a different connotation compared to that assigned in previous general or finance-specific dictionaries. We use this dictionary to construct the FSS index, which summarizes the sentiment in financial stability communications.

We show that our index is useful for financial stability analysis. In particular, we find that a set of indicators commonly used in the literature on early-warning systems explains the time variation in the FSS index, with concerns about the banking sector being the main driver of the index’s dynamics. We also show that central banks incorporate developments in the financial cycle in their financial stability communications. In addition, using a panel VAR that controls for endogeneity between the FSS index and financial cycle indicators, we find that an increase in the FSS index, which signals a deterioration in sentiment, is followed by a further deterioration of financial cycle indicators and by a drop in monetary policy rates. We interpret these results as preliminary evidence that, although central banks are able to identify and communicate financial stability risks, communications through FSRs alone are not sufficient to alleviate a deterioration in financial vulnerabilities. Finally, we analyze whether central banks are able to predict and communicate turning points in the financial cycle. Using a probit model, we show that the FSS index is a useful predictor of banking crises in the near term, even after controlling for commonly used predictors of these events. The predictive power of the FSS index is stronger when we consider an alternative characterization of financial crisis as turning points in credit-to-GDP gap. We also find that central banks that are more pro-active and forward looking in communicating the buildup of vulnerabilities in the financial system, are able to decrease the likelihood of banking crises. These findings provide evidence that central banks change the sentiment in their communications prior to crises, although they are only able to prevent them if they flag the risks of such an event with a considerable lead.

An important caveat in our analysis is that our estimation strategy does not take into account the specific financial stability governance framework in each country, which could explain the difference in the short- and long-term predictability of the FSS index for financial crises. For example, we do not take into account whether or not central banks have a direct supervisory role or regulatory powers. Different governance frameworks may lead central banks to be more aggressive (or passive) in communicating financial stability developments. We leave for future research the study of the interaction between communication strategies and central banks’ financial stability tools and governance frameworks.
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Table 1: Financial stability reports, availability

This table summarizes the availability of FSRs written in or translated into English. Frequency denotes the number of times in a year an FSR is released, on average. Occasionally, central banks release reports with a different frequency in a given year, and there are missing reports for particular countries for certain years. We account for these differences in our empirical exercise in section 5. The ECB report aggregates information for all euro-area countries, while the IMF report aggregates global information. Brazil did not publish financial stability reports in English between 2011 and 2016.

| Publisher          | Institution                                      | Availability | Frequency |
|--------------------|--------------------------------------------------|---------------|-----------|
| Albania            | Bank of Albania                                  | 2008-2017     | 2         |
| Argentina          | Central Bank of Argentina                        | 2004-2017     | 2         |
| Australia          | Reserve Bank of Australia                        | 2004-2017     | 2         |
| Austria            | Oesterreichische Nationalbank                    | 2001-2017     | 2         |
| Bangladesh         | Bangladesh Bank                                  | 2011-2016     | 1         |
| Belgium            | National Bank of Belgium                         | 2002-2017     | 1         |
| Brazil             | Banco Central do Brasil                          | 2002-2017*    | 2         |
| Canada             | Bank of Canada                                   | 2002-2017     | 2         |
| Chile              | Banco Central de Chile                           | 2004-2017     | 2         |
| China              | People’s Bank of China                           | 2011-2016     | 1         |
| Colombia           | Banco de la Republica Colombia                  | 2005-2014     | 2         |
| Croatia            | Croatian National Bank                           | 2008-2017     | 2         |
| Cyprus             | Central Bank of Cyprus                           | 2015-2016     | 1         |
| Czech Republic     | Czech National Bank                              | 2004-2017     | 1         |
| Denmark            | Danmarks Nationalbank                            | 2002-2016     | 2         |
| Estonia            | Bank of Estonia                                  | 2003-2017     | 2         |
| Germany            | Deutsche Bundesbank                               | 2004-2017     | 1         |
| Greece             | Bank of Greece                                   | 2009-2010     | 1         |
| Hong Kong          | Hong Kong Monetary Authority                     | 2003-2017     | 2         |
| Hungary            | Magyar Nemzeti Bank                              | 2000-2017     | 2         |
| Iceland            | Central Bank of Iceland                          | 2005-2015     | 1         |
| India              | Reserve Bank of India                            | 2010-2017     | 2         |
| Indonesia          | Bank Indonesia                                   | 2003-2017     | 2         |
| Ireland            | Central Bank of Ireland                          | 2012-2017     | 2         |
| Israel             | Bank of Israel                                   | 2014-2017     | 2         |
| Italy              | Banca d’Italia                                   | 2010-2017     | 1         |
| Jamaica            | Bank of Jamaica                                  | 2006-2017     | 1         |
| Japan              | Bank of Japan                                    | 2006-2017     | 2         |
| Korea              | Bank of Korea                                    | 2005-2017     | 2         |
| Kyrgyzstan         | National Bank of Kyrgyz Rep.                    | 2005-2016     | 2         |
| Latvia             | Latvijas Banka                                   | 2003-2017     | 1         |
Table 1: Financial stability reports, availability, continued

| Publisher     | Institution                        | Availability | Frequency |
|---------------|------------------------------------|--------------|-----------|
| Lithuania     | Bank of Lithuania                  | 2007-2017    | 1         |
| Macedonia     | National Bank of Macedonia         | 2007-2016    | 1         |
| Malawi        | Reserve Bank of Malawi             | 2012-2017    | 2         |
| Malaysia      | Bank Negara Malaysia               | 2007-2017    | 1         |
| Malta         | Central Bank of Malta              | 2009-2017    | 1         |
| Namibia       | Bank of Namibia                    | 2008-2017    | 2         |
| Nepal         | Nepal Rastra Bank                  | 2012-2016    | 2         |
| Netherlands   | De Nederlandsche Bank              | 2004-2017    | 2         |
| New Zealand   | Reserve Bank of New Zealand        | 2004-2017    | 2         |
| Nigeria       | Central Bank of Nigeria            | 2010-2016    | 2         |
| Norway        | Norges Bank                        | 2000-2017    | 1         |
| Poland        | National Bank of Poland            | 2003-2017    | 2         |
| Portugal      | Banco de Portugal                  | 2005-2017    | 2         |
| Romania       | National Bank of Romania           | 2006-2015    | 1         |
| Russia        | Bank of Russia                     | 2012-2017    | 2         |
| Saudi Arabia  | Saudi Arabian Monetary Agency      | 2015-2017    | 1         |
| Singapore     | Monetary Authority of Singapore    | 2004-2017    | 1         |
| Slovakia      | Narodna Banka Slovenska            | 2005-2017    | 2         |
| Slovenia      | Banka Slovenije                    | 2004-2017    | 1         |
| South Africa  | South African Reserve Bank         | 2004-2017    | 2         |
| Spain         | Banco de Espana                    | 2002-2017    | 2         |
| Sri Lanka     | Central Bank of Sri Lanka          | 2009-2013    | 1         |
| Suriname      | Centrale Bank Van Suriname         | 2016         | 1         |
| Sweden        | Sveriges Riksbank                  | 1999-2017    | 2         |
| Switzerland   | Schweizerische Nationalbank        | 2003-2017    | 1         |
| Taiwan        | Central Bank of Taiwan             | 2008-2017    | 1         |
| Thailand      | Bank of Thailand                   | 2013-2017    | 1         |
| Trinidad      | Central Bank of Trinidad           | 2009-2016    | 2         |
| Turkey        | Central Bank of Turkey             | 2005-2017    | 2         |
| U.A.E         | Central Bank of the U.A.E          | 2012-2017    | 1         |
| Uganda        | Bank of Uganda                     | 2010-2016    | 1         |
| United Kingdom| Bank of England                    | 1999-2017    | 2         |
| USA           | Financial Stability Oversight Council| 2011-2017    | 1         |
| IMF           | International Monetary Fund        | 2002-2017    | 2         |
| ECB           | European Central Bank              | 2004-2017    | 2         |

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Table 2: Financial stability dictionary, word distribution and frequency

This table shows the distribution of positive and negative words in our financial stability dictionary introduced in section 3. The word distribution shows the number of dictionary words as a percentage of all distinct words (after removing stop words) across all FSRs used in our sample (see table 1). The word frequency is the number of times words occur across all FSRs divided by the sum of all words across all FSRs. We also report a comparison between the words in our dictionary and the dictionary in LM. Uniquely financial stability words are those words not classified in LM’s dictionary. The complete financial stability dictionary can be found in Juan M. Londono’s website: Link to dictionary.

| Number of words | Word distribution (percent) | Word frequency (percent) |
|-----------------|-----------------------------|--------------------------|
| Total financial stability | 391 | 5.38 | 4.01 |
| Positive words | 96 | 1.32 | 1.45 |
| Negative words | 295 | 4.06 | 2.56 |
| Overlap with LM | 270 | 3.72 | 3.28 |
| Uniquely financial stability words | 121 | 1.67 | 0.73 |
Table 3: FSS index, summary statistics

This table shows a set of summary statistics for the FSS indexes for the 30 countries with FSRs available at least once a year between 2005 and 2017. The minimum and maximum dates are the dates when the FSS index takes on its lowest and highest values, respectively. N is the total number of reports between January 2005 and December 2017. Standard deviation is abbreviated as SD.

| Country         | N  | Mean | SD  | Kurtosis | Skewness | Min. Date | Max. Date |
|-----------------|----|------|-----|----------|----------|-----------|-----------|
| Argentina       | 24 | -0.43| 0.70| 2.37     | 0.22     | Apr-05    | Apr-09    |
| Australia       | 28 | 1.22 | 0.64| 2.48     | 0.20     | Sep-04    | Sep-08    |
| Austria         | 34 | 0.69 | 0.72| 2.29     | 0.32     | Dec-17    | Jun-09    |
| Belgium         | 16 | 0.95 | 0.54| 2.55     | 0.48     | Jun-05    | Jun-09    |
| Canada          | 31 | 2.19 | 1.02| 2.55     | -0.70    | Jun-04    | Dec-08    |
| Chile           | 27 | 0.64 | 0.81| 3.30     | -0.53    | Dec-04    | Dec-07    |
| Czech Republic  | 11 | 1.27 | 0.69| 1.95     | 0.26     | May-06    | May-09    |
| Denmark         | 20 | 1.39 | 1.17| 3.83     | 1.18     | Dec-13    | Dec-08    |
| Estonia         | 27 | 0.48 | 0.57| 2.09     | -0.16    | Nov-05    | Oct-11    |
| Germany         | 13 | 1.35 | 0.58| 1.67     | -0.17    | Nov-04    | Nov-07    |
| Hong Kong       | 28 | 0.54 | 0.95| 2.21     | 0.41     | Sep-17    | Dec-08    |
| Hungary         | 34 | 1.17 | 0.80| 2.33     | 0.63     | Feb-01    | Nov-11    |
| Iceland         | 16 | 0.90 | 0.49| 2.22     | -0.23    | Oct-15    | Oct-09    |
| Indonesia       | 27 | 0.31 | 0.72| 3.54     | -0.32    | Sep-10    | Mar-09    |
| Korea           | 25 | 1.40 | 1.08| 2.72     | 0.50     | Apr-10    | Apr-09    |
| Latvia          | 18 | 0.51 | 0.78| 4.21     | 1.05     | Jan-04    | Jan-09    |
| Netherlands     | 26 | 1.98 | 0.89| 2.77     | 0.17     | Oct-17    | May-09    |
| New Zealand     | 27 | 1.27 | 0.73| 3.01     | 0.67     | May-10    | Nov-08    |
| Norway          | 31 | 1.36 | 0.85| 2.09     | -0.24    | Nov-04    | Oct-14    |
| Poland          | 28 | 0.79 | 0.57| 2.00     | 0.06     | Dec-03    | Jun-09    |
| Portugal        | 17 | 0.89 | 0.68| 2.81     | 0.88     | May-15    | May-09    |
| Singapore       | 16 | 1.08 | 1.06| 2.95     | 0.79     | Jun-06    | Dec-08    |
| Slovakia        | 23 | 1.07 | 0.70| 2.47     | -0.02    | May-04    | May-09    |
| Slovenia        | 14 | 0.93 | 0.74| 1.63     | -0.35    | May-06    | May-12    |
| South Africa    | 28 | 2.00 | 0.68| 4.36     | 1.22     | Sep-04    | Mar-09    |
| Spain           | 31 | 0.65 | 1.01| 2.08     | -0.02    | May-06    | Nov-11    |
| Sweden          | 38 | 1.38 | 0.83| 2.35     | 0.29     | Jun-04    | Nov-08    |
| Switzerland     | 15 | 1.50 | 1.05| 2.21     | 0.21     | Jun-06    | Jun-09    |
| Turkey          | 24 | 0.45 | 0.63| 2.96     | 0.12     | May-17    | Nov-11    |
| United Kingdom  | 36 | 1.83 | 0.66| 3.21     | 0.95     | Jun-14    | Apr-08    |
Table 4: Terms defining topics

This table shows the terms used to identify sentences that refer to a particular topic. These words are used to calculate the topic indexes introduced in section 5.1. We only report the singular form of each word, although, to calculate the topic indexes, we also use their plural forms. We identify words that relate to real estate separately from words that relate to the rest of the household sector.

| Topic       | Terms associated                                                                 |
|-------------|----------------------------------------------------------------------------------|
| Banking     | Bank, financial/depository institution, financial service, lending standard       |
|             | interbank, nonperforming loan/exposure (NPL and NPE)                               |
| Valuation   | Financial/capital/commodity market, equity/bond/stock return, derivative,          |
|             | risky/riskier/financial asset, bond yield, debt spread, corporate bond            |
| Household   | Credit card, personal/private/auto/vehicle loan, private consumption,            |
|             | consumer credit, auto/vehicle debt                                               |
| Real estate | Real estate, residential, property/house price, housing, property market          |
|             | home purchase, mortgage                                                          |
| Corporate   | Firm, SME, nonfinancial company/business/private/corporation,                     |
|             | corporate sector                                                                  |
| External    | Current account, reserves, external debt/imbalance, balance of payments,          |
|             | foreign currency, exports, imports, emerging markets, international,              |
|             | EME, advanced economies, global, foreign                                          |
| Sovereign   | Government debt, fiscal, fiscal debt/balance                                      |
Table 5: Topics driving financial stability sentiment

This table shows the estimates of the coefficients associated with the topic indexes in the following panel-data regression:

\[ FSS_{i,t} = u_i + \sum_{j=1}^{S} B_j FSS^j_{i,t} + \sum_{j=1}^{S} C_j Freq^j_{i,t} + e_{i,t}, \]

where \( FSS_i \) represents each country’s FSS index, \( FSS^j_i \) is the FSS index for topic \( j \) for country \( i \) (see table 4 and section 5.1), and \( Freq^j_i \) is the frequency at which topic \( j \) words are used in each report. Sentiment indexes are standardized to facilitate sorting the coefficients according to their relevance at explaining the time variation in the overall FSS index. The coefficients associated with the frequency of topic words are omitted to save space. Standard errors are corrected using [Driscoll and Kraay (1998)] standard deviations, and are reported in parentheses. \*, \**, and \*** represent the usual 10\%, 5\%, and 1\% significance levels.

| Topic     | \( B_j \)   |
|-----------|-------------|
| Banking   | 0.42***     |
|           | (0.04)      |
| Household | 0.19***     |
|           | (0.03)      |
| External  | 0.16***     |
|           | (0.03)      |
| Corporate | 0.15***     |
|           | (0.03)      |
| Valuation | 0.15***     |
|           | (0.03)      |
| Real estate | 0.13***   |
|           | (0.02)      |
| Sovereign | 0.06*       |
|           | (0.03)      |

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| Variable | Description | Source | Units |
|----------|-------------|--------|-------|
| SRISK to GDP | SRISK to GDP ratio. SRISK is the systemic risk measure in Brownlees and Engle (2017): Capital shortfall of the banking system conditional on a severe market decline. SRISK is aggregated at the country level and divided by nominal GDP. | V-Lab, NYU Stern | Percent |
| Bank CDS | Value-weighted average of the 5-year unsecured CDS spreads of a group of representative financial institutions. | Markit, Federal Reserve Board | Percent |
| Credit to GDP gap | Deviations of the credit to GDP ratio from its long-run trend (see Borio 2014). | BIS | Percent |
| DSR, private nonfinancial | Ratio of interest payments plus amortizations to income for private nonfinancial corporations (see Drehmann et al. 2015). | BIS | Percent |
| DSR, households | DSR ratio for households. | BIS | Percent |
| Stock volatility | Quarterly realized volatility of the headline stock index. Quarterly volatility is calculated as the square of the sum of squared daily returns for all days within the quarter. | Bloomberg | (annualized) |
| Market to Book | Value-weighted average of the market-to-book ratio for a group of representative financial institutions. Market value is calculated as the number of outstanding shares times the end-of-the-quarter market price. | Datastream | Ratio |
| Dividend yields | Dividends paid out to current price for the country’s representative stock market index. | Bloomberg | Percent |
| Nominal property price | Log change in the BIS nominal property price index from last year. | BIS | Percent |
| Real property price | Log change in the BIS real property price index from last year. | BIS | Percent |
| Price to rent | Nominal house prices to rent ratio. | OECD | Index (100 in 2010) |
| Currency volatility | Quarterly realized volatility of the exchange rate of the country’s currency with respect to the US dollar. Quarterly volatility is calculated as the square of the sum of squared daily appreciation rates for all days within the quarter. | Bloomberg | Percent |
| Current account to GDP | Current account to GDP ratio. | Haver analytics, IMF | Percent |
| External debt to GDP | External debt to GDP ratio. | World Bank | Percent |
| Sovereign CDS | Country’s 5-year Credit Default Swap spread. | Markit | Percent |
| Government debt to GDP | Government debt to GDP ratio. | OECD | Percent |
| Monetary policy rates | Monetary policy rate published by the country’s central bank. The shadow rate replaces monetary policy rate by Wu and Xia (2018)’s rate for countries at the zero-lower bound. | Central banks and Wu and Xia (2018) | Percent |
This table summarizes the results for the information incorporated into topic subindexes. The table shows the estimated coefficients for the following panel-data regression setting:

\[ FSS_{i,t}^j = u_i + \beta X_{i,t-h}^j + e_{i,t}, \]

where \( FSS_{i,t}^j \) represents the FSS index for topic \( j \) for country \( i \) (see table 4) and \( X_{i,t-h}^j \) is each one of the \( h \)-quarter lagged topic-specific variables defined in table 6. Some of these variables fall into multiple topic categories. We report the results for \( h = 0 \) (contemporaneous) and \( h = 4 \). Standard errors are corrected using Driscoll and Kraay (1998) standard deviations, and are reported in parentheses. *, **, and *** represent the usual 10%, 5%, and 1% significance levels. For each combination of subindex and topic-specific variables, we also report the total number of quarterly observations, \( N \).

| Subindex          | Variable                | \( h = 0 \)    | \( h = 4 \)    | \( N \) |
|-------------------|-------------------------|----------------|----------------|-------|
| Banking           | SRISK to GDP            | 0.12***        | 0.01           | 1,323 |
|                   |                         | (0.02)         | (0.02)         |       |
|                   | Bank CDS                | 0.26***        | 0.03           | 861   |
|                   |                         | (0.03)         | (0.06)         |       |
|                   | Credit to GDP gap       | 0.01***        | 0.01*          | 1,270 |
|                   |                         | (0.00)         | (0.00)         |       |
|                   | DSR, private nonfinancial| 0.12***        | 0.07*          | 1,018 |
|                   |                         | (0.01)         | (0.03)         |       |

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Table 7: Information in topic indexes, continued

| Subindex       | Variable                        | $h = 0$  | $h = 4$  | $N$  |
|----------------|--------------------------------|----------|----------|------|
| **Household**  | DSR, households                | 0.41***  | 0.47***  | 611  |
|                |                                | (0.05)   | (0.07)   |      |
| **Valuation**  | Stock volatility               | 0.04***  | 0.00     | 1,406|
|                |                                | (0.01)   | (0.01)   |      |
|                | Market to book                 | -0.74*** | 0.52     | 1,221|
|                |                                | (0.10)   | (0.37)   |      |
|                | Dividend yield                 | 0.59***  | -0.22    | 1,142|
|                |                                | (0.06)   | (0.17)   |      |
| **Corporate**  | DSR, private nonfinancial      | 0.23***  | 0.25***  | 1,018|
|                |                                | (0.03)   | (0.05)   |      |
| **External**   | Currency volatility            | 0.00***  | -0.00*   | 1,228|
|                |                                | (0.00)   | (0.00)   |      |
|                | Current account to GDP         | -0.01    | -0.03*   | 1,519|
|                |                                | (0.01)   | (0.01)   |      |
|                | External debt to GDP           | 0.00***  | 0.00***  | 1,507|
|                |                                | (0.00)   | (0.00)   |      |
| **Real estate**| Nominal property prices        | -0.03*** | 0.01     | 1,307|
|                |                                | (0.00)   | (0.01)   |      |
|                | Real property prices           | -0.03*** | 0.00     | 1,307|
|                |                                | (0.00)   | (0.01)   |      |
|                | Price to rent                  | 0.01**   | 0.02     | 771  |
|                |                                | (0.00)   | (0.01)   |      |
| **Sovereign**  | Sovereign CDS                  | 0.06***  | 0.02     | 1,423|
|                |                                | (0.02)   | (0.03)   |      |
|                | Government debt to GDP         | 0.00     | 0.00     | 1,512|
|                |                                | (0.00)   | (0.01)   |      |
Table 8: Lead-lag relations between financial cycle indicators and the FSS index

This table summarizes the results for the contemporaneous and 4-quarter lead-lag relations between each of the financial cycle indicators and the FSS index. We show the estimate of the coefficient associated with each financial stability indicator in the following regression:

\[ FSS_{i,t} = u_i + \beta X_{i,t-h} + \gamma FSS_{i,t-h} + \epsilon_{i,t}, \]

and the estimate of the coefficient associated with the FSS index in the regression:

\[ X_{i,t} = u_i + \beta FSS_{i,t-h} + \gamma X_{i,t-h} + \epsilon_{i,t}. \]

\( FSS_i \) represents each country’s FSS index and \( X_i \) is each of the financial cycle indicators considered. We classify these indicators into four categories. The first category, credit indicators, includes the credit-to-GDP gap and debt service ratios (DSRs) for private nonfinancial corporations. The second category, valuation indicators, includes the market-to-book ratio for banks, the dividend yield for each country’s representative stock index, and log changes in real property prices with respect to one year ago. The third category, systemic risk indicators, includes the SRISK-to-GDP ratio, the average CDS spread for banks, and the volatility of the representative stock market index. The fourth category, policy rates, includes the monetary policy rate and the shadow rate. Table 6 provides a detailed description of these financial cycle characteristics as well as their sources. Standard errors are reported in parentheses and are corrected using Driscoll and Kraay (1998) standard deviations. *, **, and *** represent the usual 10%, 5%, and 1% significance levels.

| Category      | Indicator                  | Contemporaneous     | \( X_{t-4} \)     | \( FSS_{t-4} \) |
|---------------|----------------------------|---------------------|-------------------|------------------|
| Credit        | Credit to GDP gap          | 0.01***             | 0.01***           | -0.77            |
|               |                            | (0.00)              | (0.00)            | (0.46)           |
|               | DSR, private nonfinancial  | 0.14***             | 0.08*             | -0.22*           |
|               |                            | (0.01)              | (0.03)            | (0.10)           |
| Valuations    | Market to book             | -0.56***            | 0.18              | -0.06            |
|               |                            | (0.04)              | (0.19)            | (0.06)           |
|               | Dividend yield             | 0.37***             | 0.04              | 0.13             |
|               |                            | (0.02)              | (0.08)            | (0.10)           |
|               | Real prop pr. ch.          | -0.04***            | 0.01              | -1.06            |
|               |                            | (0.00)              | (0.01)            | (0.75)           |
| Systemic risk | SRISK to GDP              | 0.13***             | 0.01              | 0.13             |
|               |                            | (0.01)              | -0.03             | (0.12)           |
|               | Bank CDS                  | 0.24***             | -0.03             | 0.08             |
|               |                            | (0.02)              | (0.07)            | (0.07)           |
|               | Stock volatility          | 0.03***             | 0.01*             | 0.39             |
|               |                            | (0.00)              | (0.00)            | (0.69)           |
| Policy rates  | Policy Rate               | -0.01               | 0.11*             | -0.53**          |
|               |                            | (0.01)              | (0.04)            | (0.16)           |
|               | Shadow Rate               | -0.01               | 0.08*             | -0.62***         |
|               |                            | (0.01)              | (0.04)            | (0.17)           |
Table 9: Lead-lag relations between financial cycle indicators and the FSS index, robustness tests

This table summarizes the results for the robustness tests for the contemporaneous and 4-quarter lead-lag relations between each of the financial cycle indicators and the FSS index (see table 8). We report the contemporaneous and lead-lag relations between FSS and each financial stability indicator for two additional samples: an unbalanced panel with all FSRs available and a sample outside of the GFC. To estimate the coefficients for the sample outside of the GFC, we construct a dummy variable that takes the value of 1 for Q3 and Q4 of 2008 and Q1 of 2009 and 0 otherwise. We have this dummy interact with either FSS or X and add these interactions to the lead-lag regression setting to control for the effects during the GFC. We also consider an alternative specification of the FSS index calculated using only text from executive summaries of FSRs. Finally, we consider a specification in which we control for the IMF FSS as a proxy for a global FSS index. Standard errors are reported in parentheses and are corrected using [Driscoll and Kraay (1998)] standard deviations. *, **, and *** represent the usual 10%, 5%, and 1% significance levels.

| Category                  | Indicator                      | Full Sample  | Outside the GFC | FSS Summary | Control for IMF FSS |
|---------------------------|--------------------------------|--------------|-----------------|-------------|--------------------|
|                           |                               | $X_{t-4}$    | FSS$_{t-4}$     | $X_{t-4}$   | FSS$_{t-4}$        | $X_{t-4}$ | FSS$_{t-4}$ |
| Credit                    | Credit to GDP gap              | 0.01***      | -0.41           | 0.01***     | 2.50*              | 0.02**    | -0.25      | 0.01*** | -1.00* |
|                           |                                | (0.00)       | (0.49)          | (0.00)      | (1.14)             | (0.01)    | (0.23)     | (0.00)  | (0.43) |
| DSR, private nonfinancial |                               | 0.06*        | -0.15           | 0.11**      | 0.55***            | 0.12*     | -0.04      | 0.04    | -0.25* |
|                           |                                | (0.02)       | (0.09)          | (0.03)      | (0.13)             | (0.05)    | (0.05)     | (0.02)  | (0.10) |
| Valuations                | Market to book                 | 0.03         | -0.17*          | -0.18       | -0.23**            | 0.21      | -0.03      | 0.26    | 0.01   |
|                           |                                | (0.04)       | (0.08)          | (0.15)      | (0.08)             | (0.26)    | (0.02)     | (0.13)  | (0.03) |
|                           | Dividend yield                 | 0.07         | 0.05            | 0.18**      | 0.17               | -0.01     | 0.04       | -0.05   | 0.04   |
|                           |                                | (0.06)       | (0.09)          | (0.07)      | (0.11)             | (0.11)    | (0.04)     | (0.07)  | (0.07) |
|                           | Real prop. pr. ch.             | 0.00         | -0.66           | -0.01*      | -1.73*             | 0.02*     | -0.41      | 0.01    | -0.34  |
|                           |                                | (0.00)       | (0.61)          | (0.00)      | (0.65)             | (0.01)    | (0.29)     | (0.01)  | (0.62) |
| Systemic risk             | SRISK to GDP                   | 0.00         | 0.03            | 0.05*       | 0.73***            | -0.02     | 0.06       | -0.03   | -0.11  |
|                           |                                | (0.02)       | (0.12)          | (0.02)      | (0.18)             | (0.03)    | (0.04)     | (0.02)  | (0.10) |
|                           | Bank CDS                       | -0.01        | 0.15            | 0.08        | 0.25*              | -0.13     | 0.04       | -0.1    | 0.02   |
|                           |                                | (0.03)       | (0.08)          | (0.05)      | (0.10)             | (0.16)    | (0.02)     | (0.06)  | (0.08) |
|                           | Stock volatility               | 0.01**       | 0.07            | 0.01**      | 0.5               | 0.01      | 0.23       | 0.01    | -0.66  |
|                           |                                | (0.00)       | (0.55)          | (0.00)      | (0.65)             | (0.01)    | (0.34)     | (0.00)  | (0.78) |
| Policy rates              | Policy Rate                    | 0.08*        | -0.48**         | 0.06        | -0.63*             | 0.10      | -0.25**    | 0.10**  | -0.34* |
|                           |                                | (0.03)       | (0.14)          | (0.05)      | (0.24)             | (0.07)    | (0.07)     | (0.03)  | (0.13) |
|                           | Shadow Rate                    | 0.06*        | -0.57***        | 0.04        | -0.76*             | 0.08      | -0.28***   | 0.08*   | -0.37**|
|                           |                                | (0.03)       | (0.16)          | (0.04)      | (0.30)             | (0.06)    | (0.07)     | (0.03)  | (0.13) |
Table 10: The predictive power of FSS for systemic banking crises

This table summarizes the results from a panel-data probit model for the predictive power of FSS indexes for country-level banking crises. We estimate the following model:

\[ Pr[C_{i,t} = 1] = \Phi[X_{i,t-h} \beta], \]

where \( X_{i,t-h} \) is a vector which includes each country’s demeaned FSS index and \( C_{i,t} \) is a dummy variable that takes the value of 1 when a banking crisis occurs in country \( i \) at time \( t \) and 0 otherwise. The banking crisis dummies are obtained from Laeven and Valencia (2013). We report the estimated coefficients associated with FSS as well as the standard deviations (in parentheses). *, **, and *** represent the usual 10%, 5%, and 1% significance levels. In panel A, we report the estimate of the coefficient associated with FSS for the benchmark 2005-2017 sample, for an unbalanced panel with all FSRs available, and the coefficient associated with the FSS index calculated using only the text in each FSR’s summary. The last two rows of this panel show the results for an alternative definition of the financial crisis dummy. The “turning points” dummy takes the value of 1 when there is a turning point in the credit-to-GDP gap that implies a reduction in the gap for at least 4 quarters. In panel B, we report the coefficient associated with the FSS index after controlling for a large set of predictors (individually, see table 6). In panel C, we report the coefficient associated with the FSS index after controlling for the IMF FSS index as a proxy for global sentiment.

### A. Alternative measures and samples

|                | \( h = 1 \) | \( h = 2 \) | \( h = 3 \) | \( h = 4 \) |
|----------------|------------|------------|------------|------------|
| FSS            | 0.298*     | 0.107      | -0.096     | -0.235*    |
|                | (0.120)    | (0.106)    | (0.107)    | (0.099)    |
| Full sample    | 0.328**    | 0.120      | -0.106     | -0.265*    |
|                | (0.126)    | (0.114)    | (0.119)    | (0.111)    |
| FSS summary    | 0.120      | -0.106     | -0.076     | -0.130*    |
|                | (0.067)    | (0.061)    | (0.067)    | (0.060)    |
| Turning points | 0.231****  | 0.261***   | 0.243**    | 0.172      |
|                | (0.068)    | (0.071)    | (0.081)    | (0.009)    |

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Table 10: The predictive power of FSS for systemic banking crises, continued

| B. Country-specific control variables | $h = 1$  | $h = 2$  | $h = 3$  | $h = 4$  |
|--------------------------------------|---------|---------|---------|---------|
| Credit to GDP gap                    | 0.308** | 0.091   | -0.134  | -0.272* |
|                                      | (0.117) | (0.112) | (0.122) | (0.109) |
| DSR, private nonfinancial             | 0.325** | 0.114   | -0.101  | -0.249* |
|                                      | (0.122) | (0.114) | (0.119) | (0.106) |
| Market to book                       | 0.398***| 0.218   | 0.023   | -0.097  |
|                                      | (0.119) | (0.114) | (0.118) | (0.103) |
| Dividend yield                       | 0.356** | 0.175   | -0.022  | -0.157  |
|                                      | (0.124) | (0.117) | (0.120) | (0.103) |
| Real prop pr. ch.                    | 0.287   | 0.146   | -0.043  | -0.165  |
|                                      | (0.151) | (0.143) | (0.148) | (0.137) |
| SRISK to GDP                         | 0.315** | 0.109   | -0.107  | -0.243**|
|                                      | (0.101) | (0.095) | (0.100) | (0.092) |
| Bank CDS                             | 0.466** | 0.318*  | 0.149   | 0.326   |
|                                      | (0.147) | (0.146) | (0.147) | (0.179) |
| Stock volatility                     | 0.354** | 0.173   | -0.032  | -0.126  |
|                                      | (0.114) | (0.110) | (0.115) | (0.110) |
| Policy Rate                          | 0.317*  | 0.109   | -0.111  | -0.266* |
|                                      | (0.136) | (0.117) | (0.116) | (0.104) |
| Shadow Rate                          | 0.317*  | 0.111   | -0.106  | -0.262* |
|                                      | (0.135) | (0.116) | (0.115) | (0.103) |

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Table 10: The predictive power of FSS for systemic banking crises, continued

### C. Global control variables

|                  | $h = 1$     | $h = 2$     | $h = 3$     | $h = 4$     |
|------------------|-------------|-------------|-------------|-------------|
| FSS              | 0.117       | -0.136      | -0.320*     | -0.467***   |
|                  | (0.132)     | (0.126)     | (0.127)     | (0.123)     |
| IMF FSS          | 0.870***    | 0.930***    | 0.480***    | 0.420***    |
|                  | (0.130)     | (0.160)     | (0.050)     | (0.060)     |
| FSS (full sample)| 0.223       | -0.025      | -0.258      | -0.425**    |
|                  | (0.136)     | (0.130)     | (0.137)     | (0.132)     |
| IMF FSS          | 0.800***    | 0.820***    | 0.400***    | 0.350***    |
|                  | (0.100)     | (0.120)     | (0.050)     | (0.060)     |
| FSS summary      | 0.024       | -0.100      | -0.189*     | -0.232**    |
|                  | (0.080)     | (0.072)     | (0.079)     | (0.073)     |
| IMF FSS          | 0.870***    | 0.930***    | 0.480***    | 0.400***    |
|                  | (0.130)     | (0.160)     | (0.060)     | (0.070)     |
| FSS (for turning points) | 0.214**   | 0.230**     | 0.229**     | 0.133       |
|                  | (0.082)     | (0.086)     | (0.085)     | (0.097)     |
| IMF FSS          | 0.030       | 0.060       | 0.030       | 0.080       |
|                  | (0.050)     | (0.040)     | (0.040)     | (0.040)     |
The figure shows the equally-weighted average of all countries’ demeaned FSS indexes (the bold line). We also show the range of demeaned FSS indexes for all countries in our sample (the shaded area). To calculate the quarterly average and range, for each country, we assume a step function to interpolate between any two dates with FSRs available.
Figure 2: Confidence intervals for the FSS index for selected countries and regions

This figure summarizes the results for the sensitivity of FSS indexes to the words in the dictionary. The shaded areas show 90 percent confidence intervals calculated by randomly removing 5 (dark blue) and 20 (light blue) percent of the words in the dictionary for selected regions (IMF and ECB) and countries (Sweden and Korea). To calculate the intervals, the process of randomly removing words from the dictionary and recalculating FSS indexes is repeated 1,000 times.
This figure shows a word cloud constructed from all FSRs available for the following years: 2004, 2008, 2012, and 2016. The size of the words is determined by their relative frequency of use so larger words are more frequently used in each time period.

Figure 3: Word cloud
Figure 4: Impulse response functions from a panel VAR, response of financial cycle measures to shocks in the FSS index

This figure shows the orthogonalized IRFs of a shock to the FSS index to each financial cycle measure. Specifically, panels (a) to (j) show the response of each one of the following financial cycle measures: the credit to GDP gap, debt service ratio for nonfinancial corporations, market-to-book ratio for banks, dividend yield for the representative stock index, log changes in real property prices with respect to one year ago, SRISK-to-GDP ratio, average bank CDS spread, stock return volatility, monetary policy rate, and monetary policy shadow rate to a one standard deviation shock in the FSS index. The panel VAR setting is the following:

\[ Y_{i,t} = u_i + \sum_{l=1}^{L} Y_{i,t-l} A_l + e_{i,t}, \]

where \( i \) and \( t \) denote, respectively, the country and time dimension of the panel data. \( Y_{i,t} \) is a vector of dependent variables, which includes the FSS index and each of the financial cycle measures (see table for more details on these measures). \( u_i \) is a vector of country fixed effects, and \( e_{i,t} \) is a vector of idiosyncratic errors, with zero mean and serially uncorrelated. \( L \) is the number of lags in the VAR, which we assume is equal to 1, given the relatively short length of our sample. The matrices \( A_l \) are estimated using the GMM procedure in Abrigo and Love (2015).
Figure 4: Impulse response functions from a panel VAR, response of financial cycle measures to shocks in the FSS index, continued
Figure 5: Impulse response functions from a panel VAR, response of the FSS index to shocks to financial cycle variables

This figure shows the orthogonalized IRFs of a shock to each one of the financial cycle measures in figure 4 to the FSS index. Specifically, panels (a) to (j) show the response of the FSS index to a one standard deviation shock in each one of the following financial cycle measures: the credit to GDP gap, debt service ratio for nonfinancial corporations, market-to-book ratio for banks, dividend yield for the representative stock index, log changes in real property prices with respect to one year ago, SRISK-to-GDP ratio, average bank CDS spread, stock return volatility, monetary policy rate, and monetary policy shadow rate. The panel VAR setting is the same as that in figure 4.
Figure 5: Impulse response functions from a panel VAR, response of the FSS index to shocks to financial cycle variables, continued
Figure A.1: Impulse response functions from a panel VAR, controlling for the IMF FSS index
This figure shows the orthogonalized IRFs from the following panel VAR setting:
\[ Y_{i,t} = u_i + \sum_{l=1}^{L} Y_{i,t-l} A_l + e_{i,t}, \]
where \( i \) and \( t \) denote, respectively, the country and time dimension of the panel data. \( Y_{i,t} \) is a vector of dependent variables, which includes the country-level FSS index, the IMF FSS index, and the financial cycle measures in figure 4. \( u_i \) is a vector of country fixed effects, and \( e_{i,t} \) is a vector of idiosyncratic errors, with zero mean and serially uncorrelated. \( L \) is the number of lags in the VAR, which we assume is equal to 1, given the relatively short length of our sample. The matrices \( A_l \) are estimated using the GMM procedure in Abrigo and Love (2015).
Figure A.1: Impulse response functions from a panel VAR, controlling for the IMF FSS index, continued
Internet Appendix

Table A.1: Lead-lag relations between financial cycle indicators and the FSS index, controlling for “global” FSS indexes

This table shows the results for the contemporaneous and 4-quarter lead-lag relations between each of the financial cycle indicators and the FSS index (see table 8) after controlling for the IMF and the ECB FSS indexes. Standard errors are reported in parentheses and are corrected using Driscoll and Kraay (1998) standard deviations. *, **, and *** represent the usual 10%, 5%, and 1% significance levels.

| A. Dependent variable: $FSS_{j,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|-----------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| $FSS_j$                           | 0.09| 0.13| 0.20*| 0.14| 0.14| 0.14| 0.19*| 0.13| 0.21*| 0.21*|
|                                  | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.08) | (0.08) | (0.08) |
| IMF FSS                          | 0.30**| 0.26**| 0.30***| 0.28**| 0.23**| 0.29**| 0.33**| 0.27**| 0.24**| 0.24**|
|                                  | (0.09) | (0.08) | (0.08) | (0.09) | (0.08) | (0.09) | (0.10) | (0.08) | (0.07) | (0.08) |
| ECB FSS                          | -0.03| 0.00| 0.01| 0.02| 0.04| 0.04| 0.01| 0.00| -0.04| -0.03|
|                                  | (0.13) | (0.13) | (0.12) | (0.14) | (0.12) | (0.14) | (0.13) | (0.12) | (0.08) | (0.08) |
| Credit to GDP gap                | 0.01***|   |   |   |   |   |   |   |   |   |
|                                  | (0.00) |   |   |   |   |   |   |   |   |   |
| DSR, private nonfinancial        | 0.04|   |   |   |   |   |   |   |   |   |
|                                  | (0.02) |   |   |   |   |   |   |   |   |   |
| Market to book                   | 0.27|   |   |   |   |   |   |   |   |   |
|                                  | (0.14) |   |   |   |   |   |   |   |   |   |
| Dividend yield                   | -0.07|   |   |   |   |   |   |   |   |   |
|                                  | (0.08) |   |   |   |   |   |   |   |   |   |
| Real prop pr. ch.                | 0.01|   |   |   |   |   |   |   |   |   |
|                                  | (0.01) |   |   |   |   |   |   |   |   |   |
| SRIK to GDP                      | -0.03|   |   |   |   |   |   |   |   |   |
|                                  | (0.03) |   |   |   |   |   |   |   |   |   |
| Bank CDS                         | -0.1|   |   |   |   |   |   |   |   |   |
|                                  | (0.06) |   |   |   |   |   |   |   |   |   |
| Stock volatility                 | 0.01|   |   |   |   |   |   |   |   |   |
|                                  | (0.00) |   |   |   |   |   |   |   |   |   |
| Policy Rate                      | 0.11**|   |   |   |   |   |   |   |   |   |
|                                  | (0.03) |   |   |   |   |   |   |   |   |   |
| Shadow Rate                      | 0.08**|   |   |   |   |   |   |   |   |   |
|                                  | (0.03) |   |   |   |   |   |   |   |   |   |
Table A.1: Lead-lag relations between financial cycle indicators and the FSS index, controlling for “global” FSS indexes, continued

| B. Dependent variable: $X_{j,t}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|----------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| FSS$_{j}$                        | -1.21** | -0.18* | 0 | 0.09 | -0.1 | -0.01 | 0.1 | -1.31 | -0.18** | -0.22** |
|                                  | (0.37) | (0.09) | (0.02) | (0.06) | (0.57) | (0.09) | (0.08) | (0.73) | (0.06) | (0.07) |
| IMF FSS                         | 0.43 | 0.14 | -0.14* | 0.27 | -1.21 | 0.61** | 0.19 | 1.41 | -0.22 | -0.36* |
|                                  | (0.51) | (0.09) | (0.06) | (0.14) | (0.80) | (0.21) | (0.12) | (2.07) | (0.12) | (0.14) |
| ECB FSS                         | 0.45 | -0.23** | 0.04 | -0.19 | -1.24 | -0.29 | -0.22 | 1.84 | -0.5 | -0.47 |
|                                  | (0.67) | (0.08) | (0.07) | (0.14) | (1.32) | (0.17) | (0.12) | (1.25) | (0.29) | (0.30) |
| Credit to GDP gap                | 0.94*** |      |      |      |      |      |      |      |      |      |
|                                  | (0.05) |      |      |      |      |      |      |      |      |      |
| DSR, private nonfinancial        | 0.87*** |      |      |      |      |      |      |      |      |      |
|                                  | (0.06) |      |      |      |      |      |      |      |      |      |
| Market to book                   |      |      |      |      |      |      |      |      | 0.56*** |      |
|                                  |      |      |      |      |      |      |      |      | (0.06) |      |
| Dividend yield                   |      |      |      |      |      |      |      |      | 0.06 | (0.13) |
|                                  |      |      |      |      |      |      |      |      | (0.15) |      |
| Real prop pr. ch.                |      |      |      |      |      |      |      |      | 0.13 | (0.07) |
|                                  |      |      |      |      |      |      |      |      | (0.07) |      |
| SRISK to GDP                     |      |      |      |      |      |      |      |      | 0.50*** |      |
|                                  |      |      |      |      |      |      |      |      | (0.10) |      |
| Bank CDS                         |      |      |      |      |      |      |      |      | 0.38** |      |
|                                  |      |      |      |      |      |      |      |      | (0.12) |      |
| Stock volatility                 |      |      |      |      |      |      |      |      | 0.03 | (0.07) |
|                                  |      |      |      |      |      |      |      |      | (0.07) |      |
| Policy Rate                      |      |      |      |      |      |      |      |      | 0.74*** |      |
|                                  |      |      |      |      |      |      |      |      | (0.11) |      |
| Shadow Rate                      |      |      |      |      |      |      |      |      | 0.73*** |      |
|                                  |      |      |      |      |      |      |      |      | (0.10) |      |