Sentiment in central banks' financial stability reports*

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Abstract

We use the text of financial stability reports (FSRs) published by central banks to analyze the relation between the financial cycle and the sentiment conveyed in these official communications. To do so, we construct a dictionary tailored specifically to a financial stability context, which classifies words into positive and negative based on the sentiment these words 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 future 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 deteriorates prior to turning points in the financial cycle.

JEL Classification: G15, G28.
Keywords: Financial stability, Central bank communications, Text analysis, Dictionary, Sentiment index.

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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 sector. As a result, many central banks were tasked with monitoring financial stability developments and were assigned a financial stability mandate. Consequently, some central banks added financial stability to their monetary policy decision making process (Jeanneau, 2014) and financial stability communication became an additional tool for central banks to curtail financial vulnerabilities (Born et al., 2014). 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 sentiment 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 communicated in financial stability reports (FSRs), one of the main tools used by central banks to disseminate their views on financial stability developments. We first propose a financial stability text analysis dictionary that captures the sentiment conveyed by words typically used in financial stability communications. We then use this dictionary to calculate financial stability sentiment (FSS) indexes based on the text from FSRs published by central banks and multilateral organizations. Finally, 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 of financial cycle indicators, especially extreme events or turning points in the cycle, including banking crises.

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 (see also Born et al., 2014 and Osterloo et al., 2011). 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 64 countries, the European Central Bank (ECB), 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). Our dictionary contains 391 words, of which 96 are positive and 295 are negative. Our word classification suggests that words can have a different connotation in a financial stability context. Specifically, we find that, although there is some overlap between the words in our dictionary and those in LM's, 30 percent of the positive or negative words in our dictionary are not classified in the LM dictionary.

We use the financial stability dictionary and our sample of FSRs to compute FSS indexes. The FSS index is calculated as the relative proportion of negative to positive words in these financial stability documents. Importantly, we preprocess the FSRs before calculating the FSS index, as there are several sections in these documents that are not used to communicate current vulnerabilities or risks in the financial system.[1] Those sections are excluded from the analysis.

After calculating the FSS index from the text in each FSR, 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. There are, however, important differences in the dynamics of the FSS indexes across countries. For instance, while the FSS index of some countries increases after crisis episodes, sentiment seems to deteriorate earlier for others. Because sentiment is an unobservable characteristic of FSRs

[1]Some FSRs publish summary pieces describing research products developed by the respective central bank's staff. Those sections typically do not convey any description of contemporary financial stability vulnerabilities or risks.

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 then proceed to formally test the patterns 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 the topics driving the FSS index and how information about specific sectors of the economy is incorporated into central banks' communications, as measured by the FSS index. Second, we study the financial cycle indicators that drive central banks' sentiment on financial stability and, conversely, whether central banks' communications lead to changes in future realizations of these financial cycle indicators. In this same vein, in the third step, we focus on assessing whether central banks are able to assess and communicate, through the sentiment conveyed in the FSRs, turning points in the financial cycle, including extreme events such as banking crises.

In the first step of our empirical analysis, we analyze central banks' focus on particular sectors or topics to understand the information set used by these institutions to determine their overall financial stability communication strategy. For this purpose, we calculate a set of topic-specific sentiment indexes. These indexes are produced 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, although most topic-specific indexes significantly drive the time variation in the FSS index, concerns about the banking sector are the main driver of the overall FSS index at the country level.

After analyzing the relative importance of topic-specific indexes for the overall financial stability assessment conducted by central banks, we investigate how information from financial indicators drives these topic indexes. This exercise provides evidence on the reaction function of central banks, at least on the communication front, to developments in financial indicators. Specifically, for each of the topic indexes, we assess the relation between the sentiment conveyed in the FSRs and quantitative indicators measuring different aspects of those sectors. We find that information in topic-specific quantitative indicators is incorporated into topic-specific sentiment indexes. For instance, a deterioration of financial indicators is, in general, followed by a significant deterioration in central banks' financial stability sentiment related to the banking sector.

In the second step of our analysis, 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. As with the topic indexes, we first test how information from financial cycle indicators is incorporated into the aggregate FSS index and, conversely, whether the communicated sentiment correlates with contemporaneous and future realizations of these financial cycle indicators. Although an analysis of the specific channels through which central bank communications affect the financial cycle is beyond the scope of this paper, we believe that testing for the significance of this relation supports the validity of our financial stability dictionary and is an important contribution to the literature on central banks' communications. We find that financial cycle characteristics and central banks' sentiment about financial stability jointly influence each other. In particular, a deterioration of financial cycle indicators related to credit growth, asset valuations, or systemic risk is accompanied by a deterioration in financial stability sentiment. The lead-lag analysis suggests that a deterioration of financial cycle indicators related to credit growth leads to a deterioration in the sentiment conveyed by central banks' communications. However, a deterioration in central bank sentiment does not appear to be significantly related to one-year-ahead changes in market-based financial cycle indicators related to asset valuations or systemic risk. Interestingly, we find that, while an increase in monetary policy rates is followed by a deterioration in financial stability sentiment, an increase (deterioration) in the FSS index 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 variables that characterize 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. The results from the panel VAR 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. We perform a comprehensive set of tests to assess the robustness of our lead-lag and panel VAR results.

More than analyzing regular developments in the financial cycle, central banks should be attuned and prepared to determine turning points in the financial cycle, especially those that end in crisis episodes. To explore this, in the third step of our analysis, 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, especially before banking crises as defined by Laeven and Valencia (2013). We find evidence that the sentiment communicated in FSRs is a useful predictor of banking crises. In particular, sentiment in FSRs deteriorates one quarter before the start of a banking crisis. Moreover, the predictive power of the FSS index for banking crises is additional to that of the credit-to-GDP gap and the debt service ratio, two commonly used predictors of banking crises (Drehmann et al., 2015).

Although the FSS index is a significant predictor of banking crises, it is just borderline significant for the one-quarter horizon, likely in part because our short sample includes very few crisis episodes. Moreover, most crises in our sample took place during the GFC, which reduces the power of the test. Therefore, we consider a measure of financial crises based on turning points in the credit-to-GDP gap, which strengthens our results for the predictive power of the FSS index. In particular, 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. The predictive power of a sentiment measure like the FSS index provides preliminary evidence that central banks are aware and communicate that financial stability concerns are increasing prior to a crisis.

1.1. Related literature

Our paper contributes to the literatures on central bank communications and textual analysis applied to financial stability. Text analysis 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).

The method we use to calculate the FSS index is a lexicon-based or dictionary approach to sentiment analysis. Lexicon-based approaches can be split into two categories: manual and automatic. In this study, we use the manual approach, as it allows us to restrict our dictionary to words that convey financial stability sentiment. Automatic approaches often rely on latent information that can be inferred through linguistic patterns.

Another approach to sentiment analysis commonly used in the literature uses machine learning algorithms to classify documents. This method requires an initial set of documents, known as the training sample, for the algorithm to determine the sentiment conveyed in all remaining documents. Because our sample contains 1,082 reports from 66 different sources across just over two decades, machine learning techniques would be inappropriate for our study.

While general-purpose dictionaries, such as those found in Harvard's General Inquirer and Diction, have been used extensively in the literature to analyze word tonality, 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.[2] 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 et al. (2011) 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 et al. (2014), which analyzes the effect of central banks' financial stability communications on stock returns. Born et al. (2014) 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 et al. (2014) in two key aspects. First, as noted before, our study develops a new financial-stability-specific dictionary to capture the positive or negative sentiment expressed

[2]Li (2010) also compares several dictionaries using a machine-learning approach.

in communications focused on that topic. In contrast, Born et al. (2014) relies on Diction, a general-purpose text analysis tool that classifies words as optimistic or pessimistic. As noted before, general dictionaries may not accurately capture the sentiment of very specific topics, such as financial stability. Second, the aim of Born et al. (2014) is to analyze the immediate effect of financial stability communications on stock returns. 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.

The rest of the paper is organized as follows. Section 2 introduces the financial stability dictionary. Section 3 explains the method used to construct the FSS index. Section 4 explores the relation between the FSS index and the financial cycle. Section 5 concludes.

2. 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 64 countries' central banks, the ECB, and the IMF.[3] In the first part of the section, we discuss the availability and general structure of FSRs. In the second part, we explain in detail the method used to create our financial stability dictionary. This dictionary is used to calculate the FSS index introduced in section 3.

2.1. 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

[3] As of 2018, the institution directly in charge of preparing a financial stability report in the United States is not the Federal Reserve System, the country's central bank, but the Financial Stability Oversight Council (FSOC).

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 a fairly 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 et al., 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), Hungary (2000), and Spain (2002). By 2005, 35 institutions were publishing FSRs. Most other institutions began publishing reports around the collapse of Lehman Brothers in September of 2008.

To create our dictionary, we have collected 1,082 FSRs published between 2000 and 2017. 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.[4] We filter out 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 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 with further processing.

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

2.2. Methodology for creating the dictionary

As suggested by LM and Henry and Leone (2016), words might have different connotations depending on what context they are being used in, which implies that applying a general dictionary to a specialized context can cause substantial errors in the 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 finance contexts, such as 10-K reports. 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 is the case of words such as "default," which is mostly used in a financial stability context for "credit default spreads," or "delinquency," which is usually used for "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 some words which traditionally have a connotation are used to describe historical events, not to convey 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 GFC, a use that refers to an event and does not contribute to sentiment.

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 most frequent remaining words across all FSRs in our sample, which amounts to

7,388 words.[5] We then remove words that obviously convey no sentiment, such as "vehicle" and "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. Words in disagreement between readers in this first classification are discussed in depth between the two initial readers. If disagreement remains, the words are examined by an additional team formed by two other readers.[6]

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.

3. 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 2. In the second part, we explore the sensitivity of the FSS index to the classification of the words in the dictionary.

[5]The remaining 2 percent of words by frequency amount to 34,579 words, of which 27,219 words are used 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.

[6]Correa, Garud, Londono, and Mislang (2017) provide a much more detailed explanation of the methodology used to create the financial stability dictionary, and our financial stability dictionary can be found in their online appendix.

3.1. The FSS index

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

$$FSS\ index_{country,period} = \frac{\#Negative\ words - \#Positive\ words}{\#Total\ words}, \tag{1}$$

where the negative or positive connotation of words is obtained from the financial stability dictionary introduced in section 2. The number of total words corresponds to all words in each FSR after removing stop words. The number of total words is related then to the total word frequency rather than to the number of distinct words in FSRs. Our index does not apply any weighting scheme because of the length of FSRs, 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 more useful for large samples of short documents. 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 that the number of negative words relative to the number of positive words increases, therefore increasing negative sentiment or reflecting 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 in section 4, especially because most countries not included in this sample began publishing FSRs around the 2008 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, except for Argentina, all countries' reports have a positive mean FSS index. This means that for most countries, negative words are used more often than positive words. 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 panel (a) of figure 1, all countries' FSS indexes became higher (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 the collapse of Lehman Brothers. Interestingly, for Germany (November 2007), Chile (December 2007), and the United Kingdom (April 2008), the maximum FSS index occurs within one year before the collapse of Lehman Brothers. All countries' indexes also became higher leading up to the second negotiation of the bailout of Greece's sovereign debt by euro-area authorities in the first quarter of 2012, and five of the European countries in our sample and the IMF experienced their highest FSS index within one year of this event.

3.2. Sensitivity to the dictionary

The methodology used to create a 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 might 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 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 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 FSS index confidence intervals after removing words from the dictionary, figure 3 shows the index's 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 were 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 FSS index's 90 percent confidence interval, even if 20 percent of words are removed from the dictionary.[7]

In this section we find that, although there are important differences in the dynamics of FSS indexes across countries, sentiment turns particularly negative in episodes of crisis. We also find that the method used to calculate the FSS index is robust to an incomplete dictionary in that the dynamics of the index are preserved even after removing a large portion of the words in the dictionary.

[7] The main difference between our method to assess the robustness of the dictionary 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.

4. The informational content of the FSS index

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

4.1. 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. To understand how central banks use information to determine their financial stability communication strategy, in this subsection, we analyze central banks' focus on particular sectors or topics.

As a first step to understand the focus of FSRs on different topics over time, in figure 2, we plot 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 word use, with no fundamental topic driving the narrative in the FSRs. In contrast, FSRs published during the GFC in 2008 have a defined focus centered 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, International Monetary Fund, 2010). 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 sector. 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:

$$FSS_{i,t} = u_i + \sum_{j=1}^{S} B_j FSS_{i,t}^j + \sum_{j=1}^{S} C_j Freq_{i,t}^j + e_{i,t}, \tag{2}$$

where FSS_i represents each country's FSS index and FSS_i^j 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 ($Freq_i^j$), as movements in topic indexes might be partially explained by the density of words 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:

$$FSS^j_{i,t} = u_i + \beta X^j_{i,t-h} + e_{i,t}, \tag{3}$$

where $X^j_{i,t}$ is each one of the topic-specific variables defined in table 6. The results are summarized in table 7.

We find that all bank-related indicators are contemporaneously correlated with the banking FSS index. In particular, a deterioration of these indicators—an increase in the SRISK-to-GDP ratio, bank CDS spreads, credit-to-GDP gap, and debt service ratio for private nonfinancial corporations—is accompanied by a deterioration of sentiment with respect to the banking sector. This relation between bank-related indicators and the FSS banking index remains positive when bank-related quantitative indicators are lagged by one year, although it becomes significant only for the credit to GDP gap and the debt service ratio. 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—a deterioration in the debt service ratio is accompanied and followed by a deterioration of sentiment related to the household sector. For the stock valuation topic, an increase in volatility or a reduction of stock market prices relative to either book values or dividends paid is related to a deterioration in sentiment but this relation becomes insignificant for the 1-year horizon. 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 1-year horizon, the relation remains positive and significant for the ratio of external debt and becomes negative and significant for currency volatility and the current-account-to-GDP ratio. 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, but the relation is not significant for the 1-year horizon for any of the indicators associated with the real-estate index. Finally, for the sovereign sector, a deterioration of sovereign CDS or the ratio of government debt to GDP is accompanied by a deterioration of sentiment related to this sector, although the relation is only significant for the former.

4.2. 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.[8] We also explore the relation between FSS and monetary policy rates. The variables considered are explained in detail in table 6. In the first step, we use a panel-regression setting 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

[8]Ng (2011) and Hatzius et al. (2010) provide a survey of financial cycle measures.

power of the FSS index for turning points in the financial cycle, including extreme events such as banking crises.

4.2.1. 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 a deterioration in financial cycle conditions related to credit growth is 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 borderline improvement 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 coherence of financial stability communications; that is, whether communication incorporates previous changes in monetary policy rates and is followed by changes in future rates. The evidence suggests that rising interest rates are followed by a significant deterioration of financial stability sentiment. 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 promote credit growth.

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.

We find that the contemporaneous relation between financial stability communications and financial cycle characteristics related to credit, asset valuations, and systemic risk remains unchanged when we consider the full sample, a sample outside of the GFC, and for the FSS summary index. Interestingly, the contemporaneous relation between FSS and interest rates becomes significant, at least at 5 percent confidence level, outside of the GFC. This evidence suggests that, removing the GFC period, an increase in financial stability concerns is accompanied by a significant drop in monetary policy rates.

The relation between credit indicators and the one-quarter ahead FSS index is robust to considering the full sample, a sample outside of the GFC, and for the FSS summary index. 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 becomes insignificant when we use the full sample unbalanced panel or the alternative FSS index. Interestingly, however, our evidence suggests that, outside of the GFC, a deterioration in financial stability sentiment is followed by a further deterioration of credit indicators.

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 relations between FSS and future monetary policy rates remain robust when we use the full sample, the sample outside of the GFC, and the alternative FSS summary index. However, how changes in monetary policy rates are incorporated in future financial stability communications is more sensitive to the sample or the index being considered. In particular, changes in monetary policy rates only have a significant effect on one-year ahead financial stability sentiment if we consider the sample with all FSRs available. This result, however, might be largely affected by the fact that many countries including in this sample starting writing financial stability reports around the beginning of the GFC.

4.2.2. 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:

$$\mathbf{Y}_{i,t} = u_i + \Sigma_{l=1}^{L} \mathbf{Y}_{i,t-l} \mathbf{A}_l + e_{i,t}, \tag{4}$$

where i and t denote, respectively, the country and time dimension of the panel data. $\mathbf{Y}_{i,t}$ 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).[9]

Figure 4 shows the impulse response functions (IRFs) between the FSS index and each one of the alternative financial cycle characteristics for the panel VAR system in Equation (4) for horizons between one and four quarters. The results from the panel VAR 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. 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

[9] 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.

(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.

In sum, our results for the panel VAR suggest that central banks not only incorporate the information from financial cycle indicators but also that an increase in the FSS index, which can be interpreted as a deterioration in sentiment, is followed by a significant deterioration of most financial cycle indicators and a drop in monetary policy rates beyond what is expected by the persistent nature of these measures.

4.2.3. 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:

$$C_{i,t} = u_i + \beta_{FSS} FSS_{i,t-h} + e_{i,t},$$

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 results for the probit model are summarized in table 10. Our results 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 FSS index, which corresponds to 1.28 times the average standard deviation of the FSS index across countries, is followed by an increase of 24 percentage points in the probability of a banking crisis.

As can be seen from the table, our results for the predictive power of FSS for banking crisis are robust to considering the full sample, the alternative FSS summary index, and to adding the credit-to-GDP gap and the debt-service ratio as control variables (see Drehmann et al., 2015). Thus, 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 fact, 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.

Finally, in the last two rows of the table, we consider an alternative characterization of financial crises. 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. Interestingly, the FSS index becomes a useful predictor of turning points in the credit-to-GDP gap for up to three quarters—a deterioration in financial stability sentiment is followed by a higher probability of a turning point in credit-to-GDP gap.

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. Central banks may ramp up their communication of the risks faced by the financial sector around these episodes, but not substantially compared to normal times. A reason for this pattern could be that central banks 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. The latter would weaken the predictive power of the FSS index. Nonetheless, for the episodes covered, we find that the FSS index does better at predicting banking crises than the alternative early-warning measures used in the literature. This result shows that, at least in relative terms, central banks' communications are a more useful predictor of crises than these other commonly used indicators.

5. Conclusion

Text analysis techniques have been used extensively to analyze central banks' communications on monetary policy. However, although financial stability has gained prominence beyond monetary policy 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, 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. These findings provide evidence that central banks change the sentiment in their communications prior to crises, although they are not able to prevent them.

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. 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 4. 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

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 2. 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.

	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.

	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
HongKong	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
NewZealand	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
SouthAfrica	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 4.1. 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:

$$FSS_{i,t} = u_i + \sum_{j=1}^{S} B_j FSS_{i,t}^{j} + \sum_{j=1}^{S} C_j Freq_{i,t}^{j} + e_{i,t},$$

where FSS_i represents each country's FSS index, FSS_i^j is the FSS index for topic j for country i (see table 4 and section 4.1), and $Freq_i^j$ 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
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)

Table 6: Topic variables and financial cycle indicators, data sources, and definitions

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	Percent (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 (annualized)
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 polity rate by Wu and Xia (2018)'s rate for countries at the zero-lower bound.	Central banks and Wu and Xia (2018)	Percent

Table 7: Information in topic indexes

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^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
		(0.10)	(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)	

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:

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

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

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

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. 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.

		Full Sample			Outside the GFC			FSS Summary		
Category	Indicator	Contemp.	X_{t-4}	FSS_{t-4}	Contemp.	X_{t-4}	FSS_{t-4}	Contemp.	X_{t-4}	FSS_{t-4}
Credit	Credit to GDP gap	0.01***	0.01***	-0.41	0.01***	0.01***	2.50*	0.03***	0.02**	-0.25
		(0.00)	(0.00)	(0.49)	(0.00)	(0.00)	(1.14)	(0.00)	(0.01)	(0.23)
	DSR, private nonfinancial	0.11***	0.06*	-0.15	0.11***	0.11**	0.55***	0.27***	0.12*	-0.04
		(0.01)	(0.02)	(0.09)	(0.01)	(0.03)	(0.13)	(0.02)	(0.05)	(0.05)
Valuations	Market to book	-0.13***	0.03	-0.17*	-0.48***	-0.18	-0.23**	-1.05***	0.21	-0.03
		(0.02)	(0.04)	(0.08)	(0.04)	(0.15)	(0.08)	(0.08)	(0.26)	(0.02)
	Dividend yield	0.28***	0.07	0.05	0.32***	0.18**	0.17	0.54***	-0.01	0.04
		(0.02)	(0.06)	(0.09)	(0.03)	(0.07)	(0.11)	(0.05)	(0.11)	(0.04)
	Real prop pr. ch.	-0.03***	0.00	-0.66	-0.03***	-0.01*	-1.73*	-0.06***	0.02*	-0.41
		(0.00)	(0.00)	(0.61)	(0.00)	(0.00)	(0.65)	(0.00)	(0.01)	(0.29)
Systemic risk	SRISK to GDP	0.10***	0.00	0.03	0.11***	0.05*	0.73***	0.15***	-0.02	0.06
		(0.01)	(0.02)	(0.12)	(0.01)	(0.02)	(0.18)	(0.02)	(0.03)	(0.04)
	Bank CDS	0.13***	-0.01	0.15	0.21***	0.08	0.25*	0.61***	-0.13	0.04
		(0.01)	(0.03)	(0.08)	(0.02)	(0.05)	(0.10)	(0.06)	(0.16)	(0.02)
	Stock volatility	0.02***	0.01**	0.07	0.03***	0.01**	0.5	0.03***	0.01	0.23
		(0.00)	(0.00)	(0.55)	(0.00)	(0.00)	(0.65)	(0.00)	(0.01)	(0.34)
Policy rates	Policy Rate	0.00	0.08*	-0.48**	-0.04**	0.06	-0.63*	-0.05*	0.10	-0.25**
		(0.01)	(0.03)	(0.14)	(0.01)	(0.05)	(0.24)	(0.02)	(0.07)	(0.07)
	Shadow Rate	0.00	0.06*	-0.57***	-0.04***	0.04	-0.76*	-0.05**	0.08	-0.28***
		(0.01)	(0.03)	(0.16)	(0.01)	(0.04)	(0.30)	(0.02)	(0.06)	(0.07)

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:

$$C_{i,t} = u_i + \beta_{FSS} FSS_{i,t-h} + e_{i,t},$$

where FSS_i represents each country's 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. 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. We also report the coefficient associated with FSS after controlling for the credit-to-GDP gap and the debt-to-service ratio for private nonfinancial corporations (see table 6). The last two rows of the table 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.

	$h = 1$	$h = 2$	$h = 3$	$h = 4$
FSS	0.24*	0.10	-0.04	-0.13
	(0.10)	(0.09)	(0.10)	(0.10)
Full sample	0.30**	0.17*	0.05	-0.00
	(0.10)	(0.09)	(0.09)	(0.09)
FSS summary	1.04*	0.35	-0.39	-0.78
	(0.61)	(0.57)	(0.62)	(0.59)
Adding control variables	0.25*	0.09	-0.08	-0.19
	(0.12)	(0.11)	(0.12)	(0.11)
Turning points	1.26*	1.46*	1.39*	0.94
	(0.61)	(0.63)	(0.66)	(0.72)

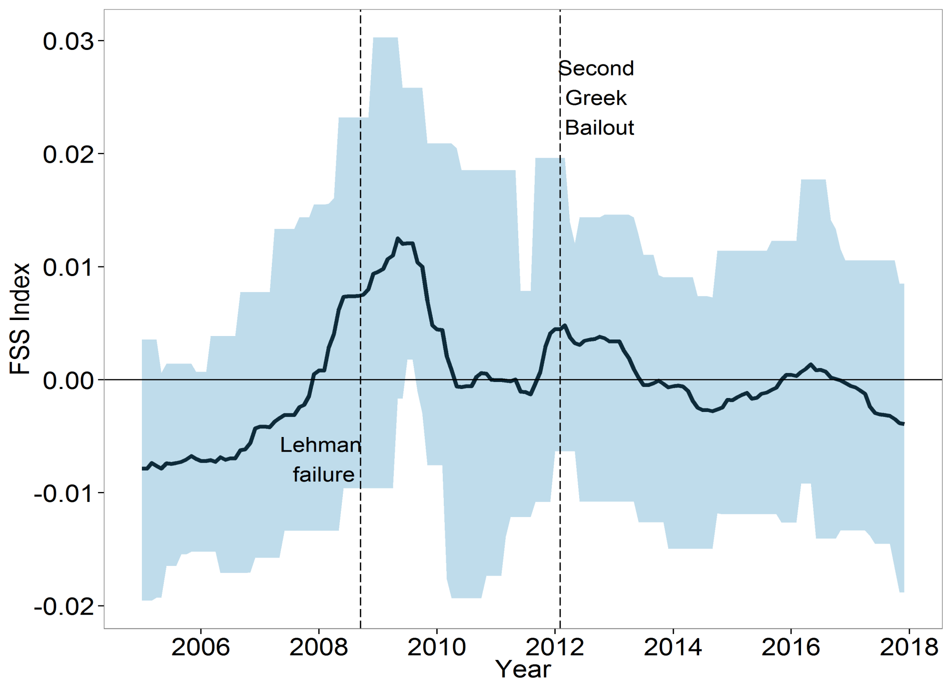


Figure 1: FSS indexes

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.

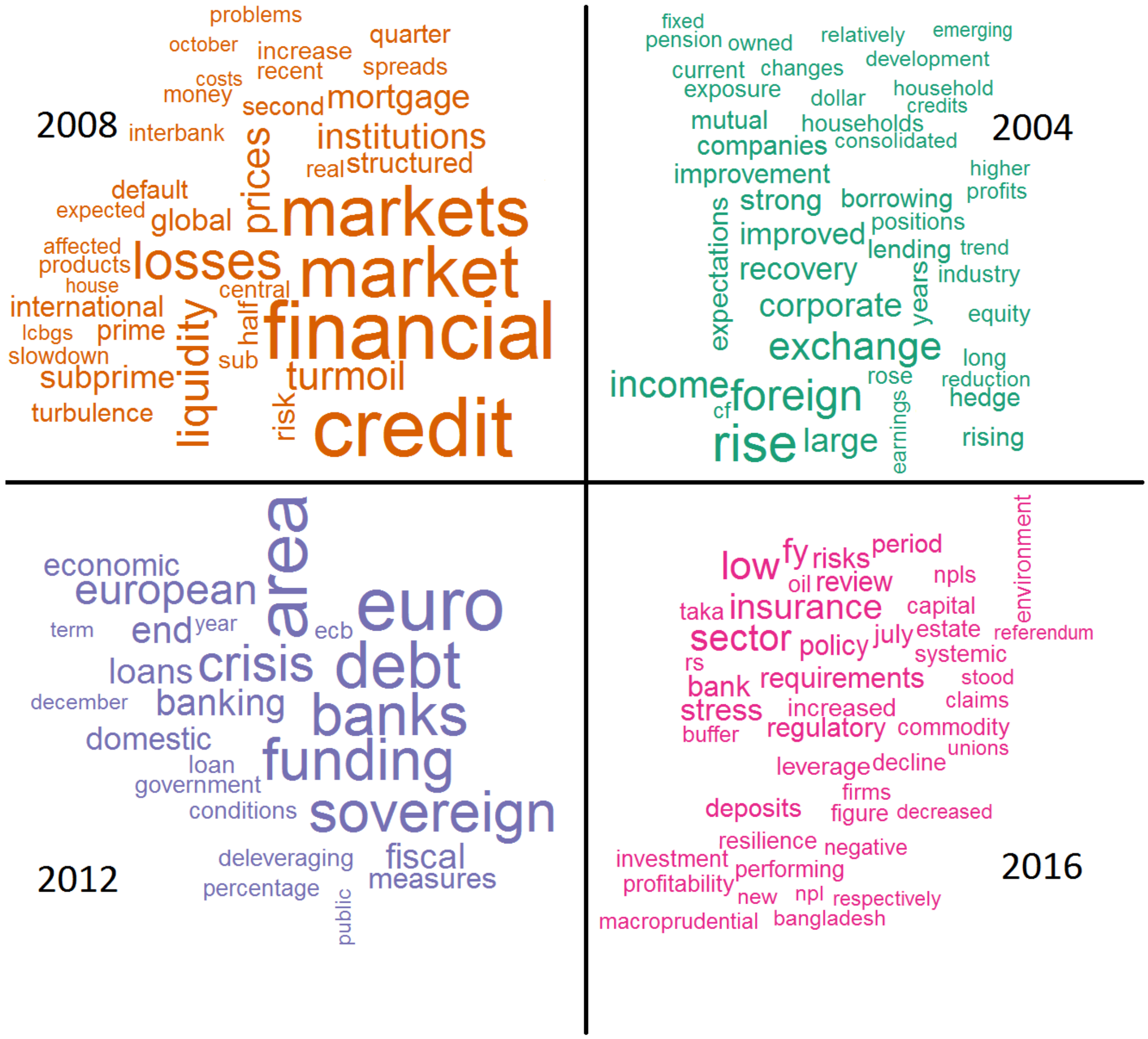
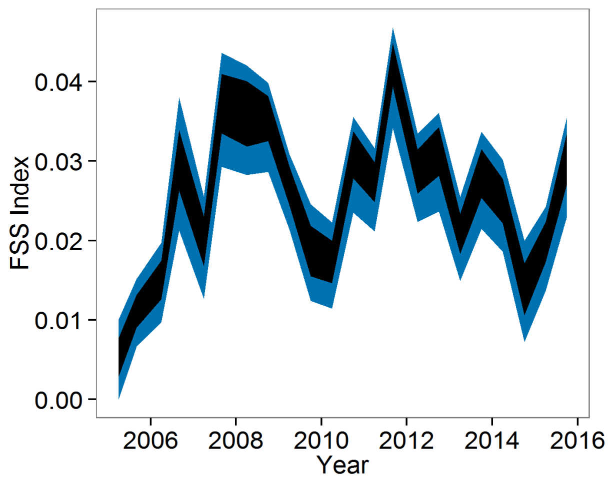
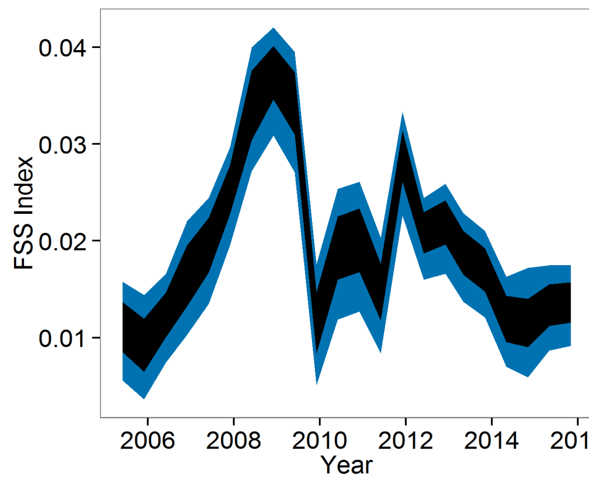


Figure 2: Word cloud

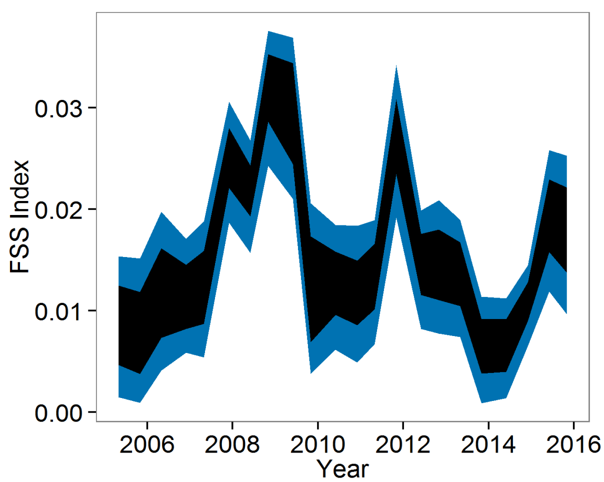
This figure shows a word cloud constructed from all FSRs available for the following years: 2004, 2008, 2012, and 2016. The size of the words is determined by their relative frequency of use, so larger words are more frequently used in each time period.



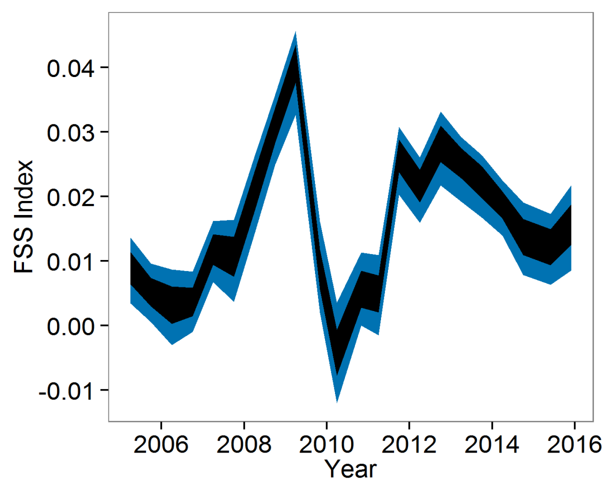
(a) IMF



(b) ECB



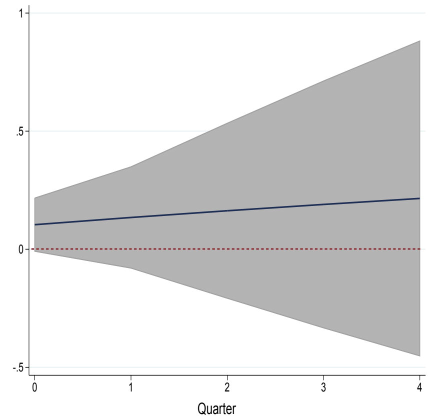
(c) Sweden



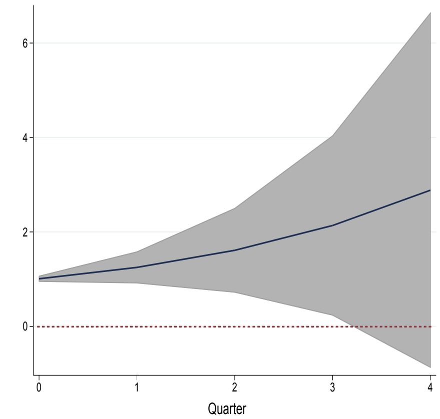
(d) Korea

Figure 3: Confidence intervals for the FSS index for selected countries and regions

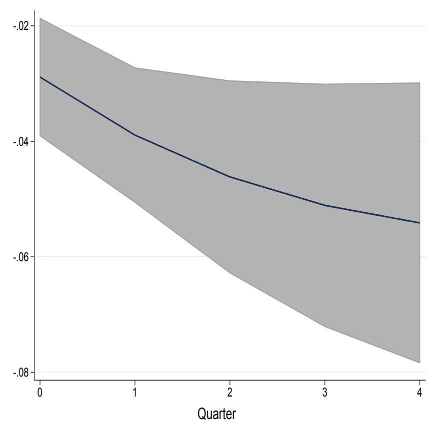
This figure summarizes the results for the sensitivity of FSS indexes to the words in the dictionary. The shaded areas show 90 percent confidence intervals calculated by randomly removing 5 (dark blue) and 20 (light blue) percent of the words in the dictionary for selected regions (IMF and ECB) and countries (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.



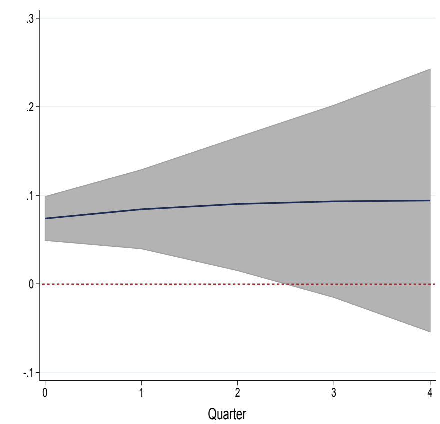
(a) Credit to GDP gap



(b) Debt service ratio



(c) Market-to-book ratio



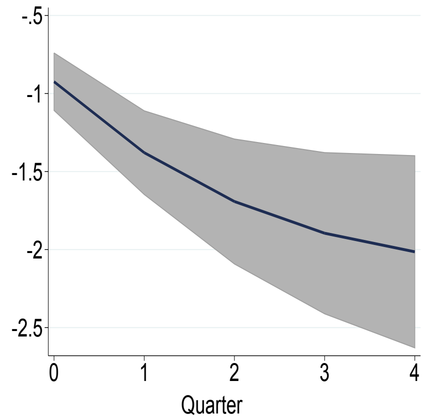
(d) Dividend yield

Figure 4: Impulse response functions from a panel VAR

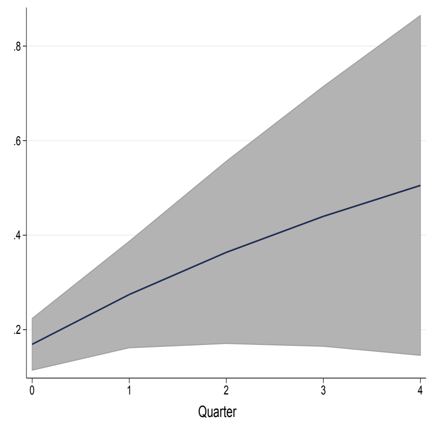
This figure shows the orthogonalized IRFs from the following panel VAR setting:

$$\mathbf{Y}_{i,t} = u_i + \Sigma_{l=1}^{L} \mathbf{Y}_{i,t-l} \mathbf{A}_l + e_{i,t},$$

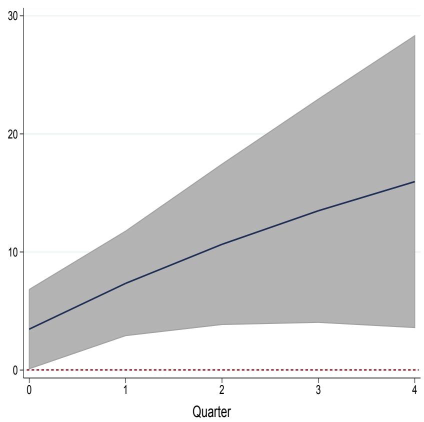
where i and t denote, respectively, the country and time dimension of the panel data. $\mathbf{Y}_{i,t}$ is a vector of dependent variables, which includes the FSS index and each of the following financial cycle measures: credit to GDP gap, debt service ratio for nonfinancial corporations, market-to-book 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 (see table 6), in panels (a) to (j), respectively. 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).



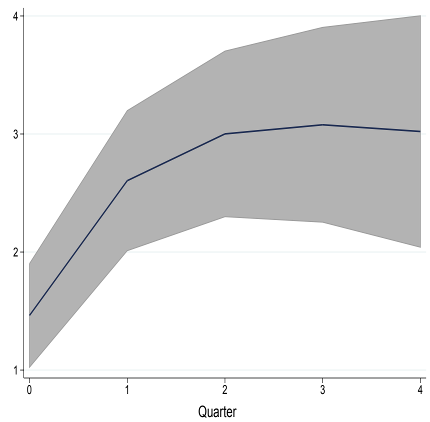
(e) Real property price



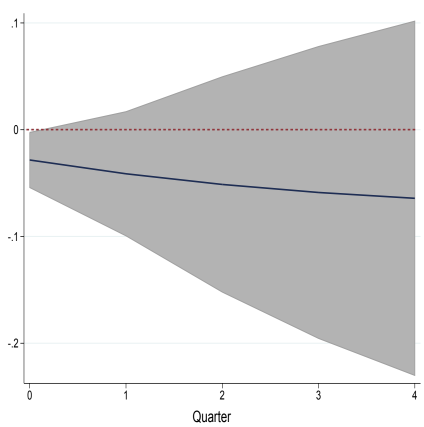
(f) SRISK-to-GDP ratio



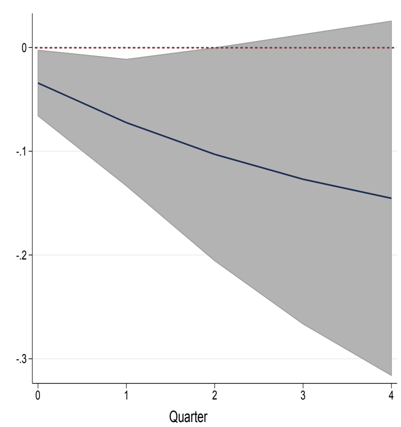
(g) Bank CDS



(h) Stock volatility



(i) Monetary policy rate



(j) Shadow rate

Figure 4: Impulse response functions from a panel VAR, continued