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Up for count? Central bank words and financial stress[◊]

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Abstract

While knowing there is a financial distress 'when you see it' might be true, it is not particularly helpful. Indeed, central banks have an interest in understanding more systematically how their communication affects the markets, not least in order to avoid unnecessary volatility; the markets for their part have an interest in better deciphering the message of central banks, especially of course with regard to the conduct of future monetary policy. In this paper we use a novel approach rooted in textual analysis to begin to address these issues. Building on previous work from textual analysis, we are able to use quantitative methods to help identify and measure financial stress. We apply the techniques to the European Central Bank's Monthly Bulletin and show that the results give a much more complete and nuanced picture of market distress than those based only on market data and may help improve how the Central Bank's communication is designed and understood.

Keywords: Financial stress, central bank communication, textual analysis, logit distribution.

JEL codes: E50, E58, G10

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Introduction

In this paper we exploit the information contained in central bank communication to measure the level of stress in financial markets. Since stress is not a well-defined concept, there are some conceptual as well as methodological issues to confront. It is important to note that financial stress is related to – but is not identical to – market volatility. For example, there can be a lot of volatility in the market when new, unexpected information arrives but this need not imply that there is stress in the market.

We take a pragmatic approach and use quantitative techniques to design a measure that is easy to use and interpret. Our starting point is research in finance on qualitative information and central bank communication, such as in Loughran and McDonald (2011), Ehrmann and Fratzscher (2009), Lucca and Trebbi (2009) and Sturm and de Haan (2009). Qualitative variables have also been used in related contexts to help explain stock market prices as well as to predict firms' accounting earnings and stock returns (see, for example, Tetlock (2007)).

We apply these methods in a novel way to measure and interpret financial stress (or distress) in the markets. Our focus is on the euro area and we draw on communication contained in the European Central Bank's (ECB) Monthly Bulletins. Our measure of stress – a financial stress indicator (FSI) – is related to the literature on financial (currency and banking) crises and the literature on early warning signals. One of its advantages is that it is based on real-time, high-frequency data, and another is that it incorporates a much richer set of nuances than possible with conventional methods, e.g. those based only on market price data.

The layout of the paper is as follows. Section 1 briefly reviews related research on qualitative information as well as on stress/crisis indicators. In Section 2 we describe the rationale for the FSI and how we construct it by aggregating market-based variables and extracting information from the ECB Monthly Bulletins. Section 3 discusses the features of the FSI and Section 4 its robustness properties. Section 5 concludes.

1. Related research

How can the information contained in texts be converted to quantitative form? There is of course a multitude of ways to do this, depending on the particular focus. In textual analysis, one of the more common methods is a word categorization, i.e. the transformation of unstructured text into a representation able to capture aspects of that text, for example the degree to which it conveys positive or negative information. Authors, such as Tetlock (2007) and Loughran and McDonald (2010), commonly focus on a “bag of words” derived from existing lists such as ‘Harvard’s General Inquirer’ or construct a glossary as in Rosa and Verga (2008), who found that central bank communication has a significant impact on longer-dated interest rates. Lucca and Trebbi (2009) instead use an automated scoring technique to help measure the content of central bank communication about future interest rate decisions based on information from the Internet and news sources. Li (2006) and Davis, Piger and Sedor (2006) analyse the tone of qualitative information using word counts from corporate annual reports and earnings press releases, respectively, whereas Tetlock (2007) links the Wall Street Journal’s column “Abreast of the Market” with subsequent stock returns and trading volumes and found that high levels of pessimistic words help to predict earnings and stock returns. Our study is related to such studies as we use a word categorization method based on an algorithm of word count. We divide our “bag of words” into two categories – negative and positive words – and measure their relative frequency in each Monthly Bulletin. All in all, we have more than 130 ECB Monthly Bulletins spanning a period of more than ten years (July 1999 to June 2010).

We use the information from the word categorization method to help define periods of financial stress in the euro area. By assigning a value of one to periods of stress and zero to non-stress periods, we construct the dependent variable of a logit model. The independent variables are derived from individual financial variables that together cover a relatively broad spectrum of issues related to financial stress. The FSI is then derived as the fitted probability of the logit model.

The choice of the logit model and a measure of stress in the form of an indicator makes our model close to models largely used in the literature about banking and currency crisis, or more generally, financial crisis. We share with these studies not only the basic model but also the fuzziness of the definition of (financial) stress. However, although the literature does not provide a precise definition of financial stress, in general, stress is the product of vulnerable markets and shocks. For the purposes of this paper, we can think of the *level* of stress as being determined by the interaction between financial vulnerabilities and the size of shocks. The more fragile financial conditions are, i.e. the more vulnerable markets are, the more likely a shock is to result in stress. In extreme cases, either when the shock is very large or when financial conditions are very weak, a shock can result in a crisis and extreme stress.

In addition, because of the lack of an agreed-upon definition of financial stress, dating financial stress periods is also not straightforward as the literature provides several methods to date financial crises but not stress. One method of dating is provided in Illing and Liu (2006). Another approach is provided in Bussière and Fratzscher (2006), who also take into account post-crisis periods, so that the crisis variable takes the value of zero in tranquil periods, one before and during the crisis, and two in the post-crisis period. Lestano, Jacobs and Kuper (2003) distinguish between currency crisis, banking crisis and debt crisis. For currency crises, they use a variety of determinants, while they identify banking and debt crisis with the help of IMF reports and central banks publications. Goldstein, Kaminsky and

Reinhart (2000) use a qualitative approach to identify banking crises which focuses on events, for example the occurrence of bank runs. To identify events they rely on existing studies of banking crises and on historical narratives.

2. Constructing the Financial Stress Indicator (FSI)

2.1 Using words to identify stressful periods

Since there is no commonly agreed list of stressful periods in the euro area, one way to proceed is to create a list that matches well-defined criteria. In order to do so, and inspired by research on textual analysis, we use one of the more common word categorization methods based on a word-count. The idea is that the frequency of words tends to be correlated with market conditions. Thus, if negative words are overrepresented in a certain period then that period is likely to be a "negative" period, i.e. a period of increased stress. We construct and run an algorithm to count pre-selected negative and positive words from the entire text in each ECB Monthly Bulletins.

The text in the Monthly Bulletin of course reflects market developments and would – if represented as simultaneous equations in an econometric model – contain tricky identification issues. However, just as econometric identification only is a problem insofar as parameters of interest cannot be uniquely determined without further assumptions, it does not pose a problem for us. For our purposes, we are not interested in the parameters of the model, only in the fitted model and the goodness of fit.

More practically, Lucca and Trebbi (2009), Bligh and Hess (2009) and de Haan and Sturm (2009) show that the flow of information from central banks is indeed relevant for the movements and the volatility of financial markets (see also de Haan and Berger (2010) and

Berger, de Haan and Sturm (2010)).[1] In addition, Rosa and Verga (2008) have shown that the Monthly Bulletins contain complementary information to that of the markets that has a value in its own right. Ultimately the performance of the FSI should be measured on how well it extracts information and how much it helps us to clarify the often conflicting signals from different sources.

The Monthly Bulletins have another advantage as well. It is true that some other sources can provide information at higher frequency, such as weekly or daily data. Unfortunately, the higher the frequency the stronger the noise tends to be. And even when noise can be efficiently filtered away, filters contain their own set of problems. Overall, monthly frequency provides a good balance between the need for timely information and the potential risk of overreacting to noise.

The word-count or textual analysis in the ECB's Monthly Bulletins was conducted as follows.[2] Table 1 shows the complete list of selected words.[3] We have selected negative words whose meaning is commonly associated with stress, tension, vulnerability or general weakness in the financial markets as well as in the overall economy. We have also included words with positive meaning, such as "recovery", "robust" and "favourable". To capture

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[1] In particular, Lucca and Trebbi (2009) attempt to measure central bank communication about future interest rate decisions based on information from the Internet and news sources while trying to control for "semantic orientation", i.e. the intensity and the direction of meaning. They apply the methodology to the statements released by the Federal Open Market Committee (FOMC) after its policy meetings. Bligh and Hess (2009) try to establish the impact of Greenspan's speeches, testimonies and FOMC statements on financial market variables by applying computerised content analysis. de Haan and Sturm (2009) show that, by adding an indicator of communication to a simple Taylor rule, the predictability of the ECB's actions is significantly improved.

[2] Word–count and textual analysis are not synonyms as the word-count is only a part of the much broader textual analysis. However we will use the two as interchangeable through the paper, for the sake of simplicity.

3 We run a pre-selection on a larger pool of words. One of the pre-selection criteria is that selected words appear at least once in the Monthly Bulletins for each year. In addition, in case of synonyms, we choose the word that appears more often. One alternative would have been to use Harvard's General Inquirer, however this is not specific to the financial discipline. In addition, Loughran and McDonald (2010) have shown that word lists developed for other disciplines significantly misclassify common words in financial text.

variations of the chosen words, we use a wildcard in the search algorithm, which in Table 1 is denoted by a "*".

The list of positive words including inflections consists of 15 words and therefore fewer words than in the negative word list (33 words). The greater prevalence of negative words over positive words is in part a reflection of the text. In addition, there tends to be fewer positive words that are unambiguously positive compared to negative words. For example, the noun *risk*, depending on the context, could have a positive nuance if *risks were lower* or negative if *risks were higher*. Nonetheless, when the word *risk* appears it means that *there are risks* and therefore there is (at least some) stress in the economy. While it is certainly possible to write about negative developments with words such as *favourable*, *optimistic*, *upturn*, *recovery* it often becomes convoluted or overly categorical ("no evidence for an upturn"; "recovery not in sight"). For this reason we do not account for negation.[4]

Table 1 illustrates the results of the textual analysis for the year 2007, when the global financial crisis started. To set a benchmark for the stress signal, we first count the number of negative (positive) words for each month, and then compute the monthly average of negative (positive) words. To obtain efficient information, the raw word count needs to be adjusted (Jurafsky and Martin (2009)). There are several weighting schemes at hand in the literature (see Manning and Schütze 2003).[5] We chose a weighting scheme based on the frequency of the words adjusted by the commonality of the words, similar to Loughran and McDonald (2010). We define the weighted word count as:

[4] Negation of negative words (*there are no risks*) to express positive meaning is not appealing as well.

[5] Weighting schemes are added to address three issues: the importance of a word in the document (measured by the log of the frequency), normalisation for the document length and the importance of the word in the sample of documents or *corpus* (measured by the inverse of document frequency).

$$W_{\mathrm{i,j}} = \begin{cases} \dfrac{\left(1+\log\left(tf_{i,j}\right)\right)}{\left(1+\log\left(a_j\right)\right)} * log\dfrac{S}{df_i} * \left(\dfrac{N_-}{N_+}\right) & if\ tf_{i,j}\ \geq 1\ and\ w_{i,j}\ is\ positive, \\ \dfrac{\left(1+\log\left(tf_{i,j}\right)\right)}{\left(1+\log\left(a_j\right)\right)} * log\dfrac{S}{df_i} & if\ tf_{i,j}\ \geq 1\ and\ w_{i,j}\ is\ negative, \\ 0 & otherwise \end{cases} \quad (1)$$

where *i* is the ith word and *j* is the jth document, $tf_{i,j}$ is the raw count, a_j is the sum of the word count in the document and S is the total number of Monthly Bulletins in our collection (132), df_i the number of Monthly Bulletins containing at least one occurrence of the of the ith word, N_+ and N_- are the number of positive and negative words included in the list respectively, $w_{i,j}$ is the unadjusted ith word in the jth document.[6] The first term dampens the impact of high frequency words by a simple log transformation. For example, 1+log3 better reflects the importance of a word with three occurrences than the count 3 itself. The document is somewhat more important than a document with only one occurrence but not three times as important. The second term - $log\frac{N}{df_i}$ adjusts the impact of a word by its commonality. Words that occur only in one document would have full weight whereas words that occur in all documents would be given zero weight. Finally, the multiplicative factor $\left(\frac{N_-}{N_+}\right)$, i.e., the ratio between the number of negative and positive words (including inflections) in the list, is a simple adjustment factor to set the more frequent negative words on an equal footing with the positive words.

In order to decide in which months the signal from the Monthly Bulletins is positive (no-stress) or negative (stress), we look at the sum of the adjusted word count for each month, as reported at the bottom of the table. In Table 1, if the sum for positive adjusted words is

[6] This weighting scheme is sometimes criticised as ad-hoc because it is not directly derived from a mathematical model of term distribution or relevancy. However, this scheme has proved to be effective in practice and to work robustly in a broad range of applications see (Loughran and McDonald (2011)).

larger than the negative words then the signal is positive and vice-versa, resulting in a binary value.

Insert Table 1 approximately here

Not surprisingly, as can be seen from Table 1 tensions were clearly higher in the markets from the summer 2007 until the end of the year. These are also the months during which the signal from negative words is strong (words of negative meaning are above the threshold) whereas the signal from positive words is somewhat weaker. For example, the sum of negative words at the bottom of the table is relatively higher in the third and fourth quarter of 2007 and reaches record high in November mirrored by the sum of words of positive meaning that reaches the lowest levels in November (as well as in September).

Table 2 shows the results of the word-count for the year 2000, i.e. the year when the dot.com bubble burst. The months from March to June are the months during which the frequency of negative words is higher. However, the positive words also score relatively high.

Insert Table 2 approximately here

These results are consistent with anecdotal evidence. Notably, the effects from the sharp decline in the NASDAQ composite index from its peak in March were beginning to be more widely felt on the European markets only from mid-spring. In fact, despite the sharp decline in the NASDAQ, the mood on the European markets remained fairly positive. For example, The Economist (2000a), in referring to the dot.com bubble, focuses on the M&As activities of several European stock exchanges. The editorial of the March Monthly Bulletin in 2000 (last paragraph on page 6) reports that:

> "In conclusion, economic conditions and prospects for the euro area appear to be better at present than at any time in the past decade. Growth is strong, employment is expected to increase further and the still high level of unemployment should continue to fall. Remaining vigilant to counter upside risks to price stability and pursuing structural reform are the foundation for a sustained period of strong economic expansion and a lasting process of job creation."

In April after stating that there were risks to price stability, the editorial of the Monthly Bulletin (page 5) reports that:

> "...both consumer and industrial confidence have now reached levels which are at or close to the highest since the start of these series in the mid-1980s. This picture of continuing strong domestic demand supports the favourable outlook for economic growth in the euro area as shown in recent forecasts."

But even after Black Friday (14th April) when the NASDAQ lost 34% compared to only one month earlier, in accounts from the financial press …"most bulls remained …bullish" (The Economist (2000b)) – even though market uncertainty was increasing with great speed.

Such patterns are also shown in the Chart 1 where the left panel shows the sum of the words with negative and positive meaning for 2007 and the right panel the sum for 2000 as taken from Tables 1 and 2.

Insert Chart 1 approximately here

It is now uncontroversial that the crisis 2007-2009 was the most severe crisis in decades. Moreover, it was for the most part unexpected as can be seen from Chart 1. On the left panel of Chart 1, while the sum for negative (adjusted) words begins increasing in May 2007, the sum of positive (adjusted) words drops from September 2007 and remains lower the remaining months of that year. It is also noteworthy that for the dot.com bubble, on the right panel of Chart 1, the sum of negative (adjusted) words increases around the months the bubble burst and, correspondingly, the sum of the positive (adjusted) words declines, but the overall picture is less clear-cut than in 2007.

To capture the information in our full sample, we repeated the word-count for each month of each year between July 1999 and June 2010.[7] The results of this count are displayed in Chart 2, where on the left panel we plot for each month the sum of appearances for each word of negative meaning adjusted by the term weighting as in equation 1. Symmetrically, on the right panel, we plot the sum of the adjusted positive words. Clearly, there are years in which stress was high and years where it was lower. As per construction, these years coincide with the years in which the sum of negative (positive) words is high. Notably, for the years 2000-2003, the signal that there was stress in financial market is arguably weaker than at other points, i.e. 2007- 2010.

Insert Chart 2 approximately here

2.2 Comparing the word-count to other sources

To have a reference for comparison and to evaluate the economic relevance of the results of our textual analysis, we consider two other sources. First, we consider the €coin index. The €coin index is a good candidate because it is fairly well known and its updates are published at a relatively high frequency, i.e. every month. While it is not constructed to measure financial stress, indirectly it can be associated with changes in financial conditions. Thus, the comparison with the €coin serves a double purpose: both as a reference to something that is well known and also as a measuring rod of how much better our method performs.

The comparison is carried out as follows. In Chart 3 we see the turning points from the €coin that mark the beginning (and end) of periods of contraction (and expansion) and, without making a statement on the causality of these relationships, they tend to reflect an

[7] Tables of the word-count similar to Tables 2 and 3 are available on request.

easing (or worsening) of general economic conditions. For example, in the period around the burst of the dot.com bubble, the index steeply declines as it also does during the crisis 2007-2009. But it also decreased around the time of Worldcom and during the summer 2004, even if to a lesser extent. The general pattern of the index therefore coincides fairly well with the episodes of stress we have identified in the previous section. To make our comparison more precise we identify periods of stress for the €coin index as those between the peak and the trough.[8]

Insert Chart 3 approximately here

As can be seen from Chart 3, starting in 1999, there are few stress periods, i.e. the period between March 2000 and November 2001, the period between July 2002 and April 2003, the period between February 2004 and July 2005, the period from March 2007 to February 2009 and finally the period from April 2010 to the last observation - July 2010.

Turning to the other source, i.e. anecdotal evidence from The Financial Times, The Economist as well as academic papers such as Dungey, et al. (2010), Cardarelli, Elekdag and Lall (2009), Chulia, et al. (2009) and Leigh, Wolfers and Zitzewitz (2003), we identify several periods of stress. To do this we use a simple content analysis. By running a search on the websites of our sources – The Financial Times and The Economist – with pre-selected key (negative) words, e.g. *risk* and *crisis*, we are able to select a large number of articles and news. We then read the material and assign a value of 1 if the reference is to a stressful event or 0 if the opposite is the case. We check the results, where possible, with sources from academic literature as well as central bank publications, such as the editorial of the ECB's Monthly Bulletins. The results are shown in Table 3, while appendix 1 describes a timeline of

[8] The peak is not included in the stress period.

relevant events from 1999 to 2010, mostly selected from The Financial Times and The Economist.[9]

Insert Table 3 approximately here

Chart 4 below shows the periods of financial stress that are identified by textual analysis, the €coin anecdotal evidence.

Insert Chart 4 approximately here

When comparing the results from textual analysis with those based on anecdotal evidence as well as the €coin some differences emerge, as shown in Chart 4. In general, the periods selected through textual analysis are somewhat shorter than in the other methods. This is not very surprising given the different nature of the selection approaches as well as, and especially concerning the anecdotal approach, their different degree of subjectiveness. Therefore we would not expect the periods to overlap perfectly, but, for our purposes, it suffices that periods identified with textual analysis are in line with those based on anecdotal evidence as well as measures of general economic conditions.

2.3 Selecting individual variables

In the previous section we discussed the identification and dating of financial stress periods. In this section we describe the selection of the underlying financial variables which are at the core of our FSI.

We select 16 market-based individual variables as basic financial measures (Table 4). We choose data that are of high quality, are available at daily frequency, have economic relevance and are able to reflect agents' behaviour. Although this is somewhat restrictive and some information might be omitted, the underlying variables together cover a relatively broad

[9] We are indebted to Tracey Green for collecting articles and news from several sources.

spectrum of issues related to financial stress. Specifically, the variables reflect vulnerabilities in the corporate bond, government bond, banking, equity and money markets. We also included several measures that are commonly thought of as being a gauge of the financial markets' mood and a fairly reliable measure of agents' risk attitudes, such as the implied stock volatility. Vulnerability in the household sector is implicitly reflected in the behaviour of agents in these other markets. Table 4 below lists the variables by market segment.

The choice of the variables reflects to some extent the choice of variables in related studies, including Kaminsky (1999) and Illing and Liu (2006). The corporate bond yield spreads are used as measures of stress for the corporate sector (Illing and Liu (2006)). They are computed as the difference in yield between the corporate bond and government bond indices with equivalent maturity. They can widen if expectations of future losses increase and/or uncertainty about their magnitude increases. In our sample we use corporate spreads related to three different rating classes: AA, BBB and High Yield.

For the sovereign bond markets we use the spreads between euro area countries' long term bonds (10 years) vis-à-vis Germany's long-term (10 years) bond.[10] In the literature, sovereign spreads are often related to *fundamentals*, i.e. liquidity and credit risk premiums, as well as to market uncertainty. While liquidity and country creditworthiness usually play a role, market uncertainty is commonly found to play a non-trivial role, especially at times of stress when market uncertainty increases.

For the banking sector, we use bank share prices to proxy for banking market stress. Similar to the literature on stock market bubbles, an increase in bank share prices may be indicative of the build-up of imbalances (bubbles) and therefore might be interpreted as a signal of *impending* stress, while a sudden and protracted decrease in bank share prices

[10] The long-term German bond, Bund, is commonly used as the benchmark, as it features both low liquidity and credit risk premiums.

(crash) is interpreted as a sign of stress. In addition, euro area major banks and financial institutions, which represent most of the financial institutions assets, fall under AA and A+ rating classes. Therefore, AA corporate bond spreads can be interpreted as a proxy of banking sector risk spread.

For the equity markets we use share prices, actual earnings per share and equity risk premium to proxy for stress. High equity risk premiums are (often) indicative of stress. A decline in earnings per share (EPS) may signify trouble and is often interpreted as a sign of stress.

We use the spreads between the Euribor and EONIA rates at different maturities as measures of liquidity-premium which may contain information about stress in the money markets. In addition, we include the spread between the main refinancing rate and the 2-year bond yield. This spread is indicative of monetary liquidity a decrease suggests a worsening of liquidity (Nelson and Perli (2006)).

Finally, we use several measures of risk aversion like the implied stock volatility, which is computed through option prices and therefore contains information about expectations. We also include in our dataset several measures of uncertainty about the future level of interest rates, which may also reflect expectations about future monetary policy. An increase in such measures is often associated with stress.

Insert Table 4 approximately here

2.4 Computing the FSI

Following Nelson and Perli (2006), the information contained in these basic individual measures is conveniently summarised into three summary indices that capture their *level*, *rate* *of change* and *co-movement*. Together these three indices contain much of what characterises periods of stress that each one on their own might not detect.

The first index, the *level index*, is a simple arithmetic average of the values of the individual variables. The individual variables have been weighted by the inverse of their variances so that higher values of the index are associated with greater market stress.

The *speed* with which the underlying market variables change may also give valuable information. For example, one would expect that when liquidity premiums, risk spreads and measures of uncertainty move higher, markets are becoming more vulnerable and stress is building up. Conversely when they move down rapidly, this might indicate that the period of (most) acute stress may be passed even if the index remains at elevated levels. In order to capture this feature, we construct the second index, the *rate of change* of the level index computed over a rolling window.[11]

Finally, one would expect that periods of acute financial stress are the periods in which underlying individual financial variables would be highly correlated. In order to express this feature we compute a *co-movement index* as captured by the percentage of the total variation of the individual variables explained by a common component as extracted from a principal component analysis over a rolling window.

The information contained in all three indices is combined into a FSI obtained by using a logit-model to extract the information contained in the indices in an efficient way. Specifically, the FSI is constructed by including the three indices on the right-hand side and a binary variable (i.e., S_t=0 or 1) on the left-hand side of the regression. The binary variable S_t

[11] Results are robust to various window lengths, see appendix 2.

identifies periods of financial stress, as we identified in section 2.2 by using textual analysis and translated to weekly frequency by simple interpolation:[12]

$$S_t \;=\; L(\,\beta_0 + \beta_1\lambda_t + \beta_2\delta_t + \beta_3\rho_t\,) \qquad (2)$$

where λ is the level index, δ the rate of change, ρ the co-movement index, β_i (i= 1,..,3) are the coefficients and L denotes the Logit probability distribution function. The model is estimated using weekly data from January 1999 to June 2010. The fitted probability from the estimation of equation 1 is the FSI.

3. The FSI: a contingent indicator.

The model in equation 1 is a model of a contingent indicator, and therefore the FSI gives information about vulnerabilities and stress in the economy and their magnitude *as they transpire*.

Chart 5 shows the FSI, i.e. the fitted probability of being in a period of stress at each point in time as computed in equation 2 in the chosen sample period. The shaded areas represent the stressful periods as described in section 2. As can be seen from the chart, the indicator captures reasonably well well-known periods of financial stress.

Insert Chart 5 approximately here

Not surprisingly, the period of August 2007 onwards emerges as the most acute episode of financial stress of recent history. Interestingly, the indicator also captures the switch in sentiment that the market experienced during the turmoil. For example, at times when major central banks temporarily succeeded in calming the markets by injections of liquidity the indicator decreases, only to increase again soon afterwards. The indicator mirrors well the

[12] By interpolating the dependent variable we increased its dependence and therefore standard errors may be incorrect. In order to address such a problem, we use a robust HAC covariance matrix. Berg and Coke (2004) have shown that an HAC correction largely solves the problem of dependency in the dependent variable.

mood of the markets both on the ups and the downs when at the end of 2009 financial stress began to ease as well as when a new wave of stress in the early spring 2010 due to worries and uncertainties about the sustainability of public finances in a number of euro area countries.

Notably, the indicator also shows an increase in the probability of stress at other, much less memorable, points in time. For example, there is an increase in 2000 in the wake of the dot.com bubble and in September 2001 and the subsequent months following the 9/11-terrorist attack. In 2002, financial markets experienced uneasiness originating from a string of defaults from large companies in telecommunications accompanied by the Worldcom implosion and the Enron and Vivendi-Universal accounting irregularities.[13]

3.1 Comparing the FSI to the VSTOXX

In the previous section, we showed how the financial stress indicator could capture what, we now know, were instances of financial stress rather well and thus be in line with the anecdotal evidence. In this section, we instead ask how the indicator is systematically related to more general financial market conditions. Though the indicator is able to measure and detect times of stress, it is useful to see this as measuring rod against other well-known indices of relatively high frequency.

In Chart 6 we show the FSI and the VSTOXX which represents the implied volatility of the Euro Stoxx 50 index.[14] While the VSTOXX index is based on equity prices it is designed to reflect market expectations of near-term volatility and, given its forward-looking character, to be a more general measure of agents' perception of market uncertainty. The larger the value of the VSTOXX index the larger the market uncertainty. Here we see that

[13] Among others, for example, Adelphia, one of the largest US broadcasting companies, defaulted. In Europe, ABB, a Swedish-Swiss engineering firm, and Elan, a biotech Irish firm, were also caught in a string of severe accounting irregularities.

[14] The VSTOXX Index is based on Dow Jones EURO STOXX 50 real time option prices.

while financial stress is related to market volatility, it is certainly not the same. For example, there can be a lot of volatility in the market when new, unexpected information arrives but this need not imply that there is stress in the market. On the other end, with high spreads signifying something amiss, for example that no trade is taking place, the volatility might be very low but stress very high. So while the VSTOXX measure is useful, these shortcomings imply that its role as an indicator is somewhat limited. Notably, the VSTOXX would have missed the onset of the financial crisis well into 2008.

Insert Chart 6 approximately here

3.2 The FSI's noise/signal content

Another way to assess the signal/noise content of the FSI is to consider the number of false signals, positive or negative. One particularly simple way to do this is to consider a threshold level when the markets go from signalling a tranquil period to a period of stress. The critical threshold level is calculated so as to strike a balance between "bad" and "good" signals. A "bad" signal is a signal not followed by an actual period of stress within a certain horizon and a "good" signal is one followed by an actual period of stress within the chosen horizon, similar to Kaminsky, Lizondo and Reinhart (1998). We choose the current one-week period as horizon.

There are four possible cases to consider. A first possible outcome is that a signal is followed by a stress period in the current one-week period.[15] A second possible outcome is that the signal is not followed by a stress period in the current one-week period. A third is that the signal has not been issued but a stress period occurs within the chosen window. The final possible outcome is that a signal was not issued and stress did not occur. Following

[15] Results are robust to different lengths of the "chosen horizon".

Kaminsky, Lizondo and Reinhart (1998), this information can be summarised in the following matrix (Table 5):

Insert Table 5 approximately here

where A is the number of periods that a good signal was issued, B is the number of periods that a bad signal was issued, C the number of periods that a signal should have been issued (a *missing* signal) and D is the number of periods that a signal was, rightly, not issued. The ratio C/(A+C) represents the share of missed periods of stress when stress occurred (A+C). It can also be interpreted as the share of type I errors. Similarly, the ratio B/(B+D) represents the share of false alarms when stress did not occur (B+D) and therefore it also can be thought of as the share of type II errors.

Following Alessi and Detken (2009), the critical threshold is calculated so as to optimise a loss function of an agent, for example a policy maker, that takes into account her relative preferences regarding error type I and error type II. The loss function is defined as:

$$\text{Loss} = \theta(C/(A+C)) + (1-\theta)(B+/(B+D)), \qquad (3)$$

The loss then can be interpreted as the preference weighted sum of type I and II errors. For values of θ lower than 0.5, the agent is increasingly less averse to missing stress than a false alarm. Correspondingly, for values of θ higher than 0.5, the agent is more averse to missing stress than to receiving a false signal. Table 6 shows the loss function values associated with different thresholds when the agent has balanced preferences, i.e. θ=0.5.[16]

Insert Table 6 approximately here

[16] Alessi and Detken (2009) argue that while values of θ lower than 0.5 may have been somewhat realistic *prior* to the global financial crisis (2007-2009), it is more likely in the wake of the crisis that preferences have shifted towards a higher θ. In Appendix 4 we show the values of the loss function for different θ at different threshold levels.

The first column shows the threshold values, while column 2 shows the number of weeks the FSI was above the threshold within a tranquil period (false signal). Column 3 shows the number of weeks the FSI was below the threshold within a stress period (missing signal). Columns 4 and 5 show the right signal, when the FSI is above the threshold within a stress period and when it is below within a tranquil period, respectively. The last column shows the Loss function value. The minimum value of the Loss function (0.19) is associated with a threshold value of 0.5. Thus, we choose this as the critical threshold value.

As table 7 shows, at this critical threshold (0.5) the FSI signal is right most of the time (83%). To interpret this percentage number correctly, it is useful to compare it to the percentage of right signals that would be obtained by chance, i.e. by a naïve model. A naïve model assigns the same probability to all alternatives in the sample (see Maddala (1983)). It then obtains a percentage of "correct" signals that is equal to the actual outcome for that alternative. The success ratio for a naïve model is 0.41 and thus it performs significantly worse than our model. [17]

Insert Table 7 approximately here

4. Robustness checks

In this section we check the robustness of the FSI by looking at its out-of-sample performance. In order to do this, we estimate the parameters of the FSI up to July 2006, i.e. well before the financial crisis began in the summer 2007. Consequently, these estimates use

[17] The success ratio is computed here as the number of right (false) signals over the total number of periods when a right (false) signal should have been issued. In Appendix 6 we report the success ratio for different threshold levels of T.

neither information on the 2007-2009 financial crisis nor on the European debt crisis 2010. We then estimate the FSI out-of-sample based on the estimated parameters.[18]

Chart 7 shows the resulting estimates in-sample, the red continuous line, and out-of-sample, the dotted blue line. The red line is the FSI as estimated in the previous section and it can be thought as the "actual" FSI, while the blue dotted line is the (out-of-sample) fitted FSI.

It can be seen that the out-of-sample FSI mirror the "actual" FSI well; it picks up the surge in stress around August 2007 and remains at elevated levels throughout the entire 2007-2009 crisis period and up to the European debt crisis in 2010.[19]

Insert Chart 7 approximately here

The performance of the FSI can be also measured by more formal tests such as the Root Mean Squared Error test reported in Table 8. The Root Mean Squared Error (RMSE), i.e. the root of sum of the squared differences between the out-of-sample estimates (*FX*) and the in-sample values (*X*) (*forecast errors*) divided by the number of periods in the out-of-sample period, can be written as:

$$RMSE = \sqrt{\frac{\sum e_t^2}{h}} \quad , \qquad (4)$$

where e_t^2 are the squared forecast errors in period t, i.e. $e_t^2 = (FX\text{-}X)^2_t$, and h is the number of out-of-sample periods. The RMSE is one of the most common statistics used to evaluate forecast performance between different models and it can be usefully applied to also evaluate the performance of the FSI – the lower the value the better the model fit. As can be seen from Table 8, its value is rather good at 0.35 and it performs considerably well compared to both an alternative model in which the dependent variable is regressed on a constant (Alternative 1)

[18] This is not a "true" forecast exercise. We perform a conditional out-of-sample forecast based on the observed value for the out-of-sample period of the independent variables.

[19] The results are robust to different starting points of the out-of-sample period.

and a model in which the dependent variable is regressed on a constant and its own lagged values (Alternative 2). Further evidence of good performance is provided by Theil's inequality coefficient decomposition (Theil-U), which is based on RMSE but is scaled in such a way that it will always fall between 0 and 1, just like a probability. It can be written as:

$$Theil-U = \frac{RMSE}{\sqrt{\frac{\sum FX_t^2}{h}} + \sqrt{\frac{\sum X_t^2}{h}}} \quad , \qquad (5)$$

As a rule of thumb, a value of the Theil-U < 0.5 indicates a good model fit, where Theil-U=0, i.e. when $FX_t=X_t$ for all t, indicates that the model is a perfect fit and conversely if U=1 then all other models would be better (see Pyndyck and Rubinfeld (1991) and Brooks (2008)).

As shown in Table 8, the FSI also performs relatively well in terms of the Theil-U measure.

Insert Table 8 approximately here

5. Conclusions

We have investigated the extent to which the language used in central bank communication provides information about the level of stress in financial markets. In order to quantify the qualitative aspects of central bank communication we have applied a word categorization method that is based on a word-count of negative and positive words. The logic of this method is that the higher the frequency a word appears in a text – up to a point – the higher is the impact of that word in defining the tone of the text and therefore the text's overall negativity or positivity.

We find that the application of such a method to the ECB's Monthly Bulletins can effectively identify periods of financial stress in the euro area.

We have shown that such information together with the information derived from individual, market-based, basic financial variables is helpful in the construction of an indicator of financial stress (FSI) that is able to detect stress in the euro area financial markets in a timely fashion while having few false positives.

The FSI is also robust in several dimensions including an out-of–sample performance test and surpasses other measures such as the VSTOOX in terms of performance.

The indicator presented in this paper, while belonging to a small group of financial stress indicators constructed for developed countries, is the first to systematically exploit the nuances in central bank communication to help measure and detect financial stress in the euro area. In addition, it has the valuable advantage of being based on an objective and easy-to-replicate methodology.

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Appendix 1. Timeline of events from July 1999 to June 2010

Appendix 1. Timeline of events from July 1999 to June 2010

July 1999–Dec 1999

Financial markets were relatively volatile both within and outside the euro area, due in part to the perception by financial market participants of operational risks in connection with Y2K. Concerns start to rapidly decline from the second half of December 1999, after the successful completion of a series of year 2000 tests which enhanced the perception of a smooth transition to the year 2000.

March 2000

March 2000 was dominated by news about the bursting of the dotcom bubble. In 2000, the Nasdaq Composite index declined by close to 20% between the end of February and mid-April. However, in the United States the positive outlook for future corporate earnings and the strength in the pace of economic activity continued. The Standard and Poor's 500 index recorded a 7% increase.

In the euro area, the ECB Monthly Bulletin reports that broad indices of euro area stock prices declined in March. This was due mainly to the correction in telecommunications- and technology-related stock prices as well as the strong growth registered by these stocks in the previous months. The decline was partly compensated by increases in the stock prices of both the financial and energy sectors.

April 2000-December 2000

In this period, the spill-over effects from the bursting of the dotcom bubble to other sectors of the stock market were more widely felt. In the euro area, the volatility of stock prices increased and remained high. In addition, the perception of an increasing deterioration of the broad economic outlook increased. Stock markets remained highly volatile for most of 2000 as this excerpt from the December Monthly Bulletin (page 25) clearly states: “Continuing a pattern which has been evident for much of this year, conditions in the major stock markets were volatile in the course of November and early December. This mainly reflected heightened uncertainty on the part of market participants about the prospects for corporate profitability amid indications of a slowdown in the pace of global economic activity.”

Jan 2001

The year start was marked by a substantial decline in long-term yields. The decline was mainly due to the uncertainty of market participants about future economic activity in the US as well as in the euro area.

March 2001

The uncertainty that characterised the previous months continues to weigh on the euro area developments. Although there were very few signs that the slowdown in the US was having significant impact or that there were lasting spill-over effects on the euro area.

One noteworthy observation is that inflation was higher than the 2% target and was not expected to decline in the coming months.

April 2001

The macroeconomic outlook continues to deteriorate both in the US and in the euro area. Although according to Monthly Bulletin, the moderation in growth in the euro area is not regarded as having an impact on its overall economic strength. However, market participants revised their corporate earnings expectations downwards for euro area firms. The Dow Jones EURO STOXX index fell by close to 9% between the end of January and the end of February. In addition, euro area stock prices appeared to be affected by spill-over from global stock market developments.

May 2001

Real GDP growth in the euro area continued to decline while inflation was on the rise. It was during this month the outbreak of the foot-and-mouth disease was confirmed. Moreover, producer prices were increasing noticeably driven by lagged and indirect effects from rises in oil prices and the depreciation of the euro.

Sept 2001

Financial market developments were dominated by the terrorist attacks in the United States on "9-11". It is important to note that, in the euro area, this did not cause but added to the deteriorating outlook for economic growth that financial markets had been experiencing for some months. Interest rates and bond yields (especially short-medium maturities) declined and volatility surged. However, already towards the end of September and in early October, global financial markets stabilised somewhat and implied volatilities declined.

Oct 2001-early Nov 2001

While the stock market recovered in October with a decrease in investors' risk aversion, economic activity remained weak and there was a substantial decline in bond yields.

Nov 2001

In November there was a general recovery in financial markets.

June 2002-Aug 2002

In the wake of the Enron scandal, Worldcom scandal and Vivaldi-U scandal, markets showed increasing stress, in part reflecting increasing concerns about the reliability of financial accounting information but also weaker-than-expected corporate earnings. Bond yields as well as stock markets in the euro area and in the United States recorded sharp falls which reinforced the continued downward trend.

Sept 2002-Oct 2002

The outlook for the global economy was increasingly uncertain due to the substantial increase in geopolitical tensions. As a result, concerns about the possible impact on oil prices as well as stock market developments were also increasing.

Jan 2003-Mar 2003

The Iraq war was declared in March (see FT, 19 March 2003), but the impact of the threat of war on the macroeconomic outlook had already been felt for weeks, if not months. While investors' risk aversion was increasing, consumer confidence was diminishing substantially. Oil markets were volatile and economic activity remained generally subdued.

March 2004

This was the month of the terrorist attacks in Madrid (11 March). It contributed to the surge in short-term uncertainty which added to the not-so-bright outlook in an environment of mixed macroeconomic data, an appreciating euro and declining bond yields.

April 2005-June 2005

Prospects for global growth were perceived as highly uncertain. However, the perception of the relative strength of the euro area did not change much.

Oct 2005-Nov 2005

The outlook for economic activity remained clouded by downward risks. As in the previous months, these were related mainly to oil prices. Consumer confidence was low.

Sources: ECB Monthly Bulletins,The Economist, and The Financial Times

Appendix 2: Logit model estimation.

The dependent variable S_t in equation 1 is a binary variable where 0=no stress and 1=stress.

Following the usual notation in a logit model, it is assumed that S_t is an indirect observation of the continuous latent variable S_t^*, where

$$S_t^* = \alpha + \beta' X_t + \varepsilon_t \quad ,$$

t= 1,…T and X_t is the set of explanatory variables. Under the logistic distribution for ε_t, the probability of being in stress can be written:

$$P\langle S_t = 1 | X_t, \alpha, \beta \rangle = \frac{\exp(\alpha + \beta' X_t)}{1 + \exp(\alpha + \beta' X_t)}$$

$$P\langle S_t = 0 | X_t, \alpha, \beta \rangle = \frac{1}{1 + \exp(\alpha + \beta' X_t)} \quad .$$

In the text the set of variables X consist of the *level*, the *rate of change* and the *co-movement* indicators. The estimation results are presented in the following table:

Insert Table A1. approximately here

Appendix 3. Loss function values and Success Ratio

Table A2. approximately here

Table A3. approximately here

Tables and Figures

Table 1. Count-words: list of words and results for 2007

	Jan-07	Feb-07	Mar-07	Apr-07	May-07	Jun-07	Jul-07	Aug-07	Sep-07	Oct-07	Nov-07	Dec-07
slowdown*	0	0	0	0	0	0	0	0	0	0	0	0
uncertainty*	2	2	2	2	2	2	2	2	2	2	2	2
weak*	0	0	0	0	0	0	0	0	0	0	0	0
decelerate*	53	75	48	74	51	77	75	61	76	85	70	28
adverse*	13	21	19	13	0	0	31	32	28	12	36	29
risk*	0	0	0	0	0	0	0	0	0	0	0	0
deteriorate*	49	0	44	0	0	0	0	0	43	28	65	73
difficult*	0	49	67	30	31	0	31	0	72	115	109	80
tension*	57	0	0	54	0	74	55	76	138	160	145	164
imbalances	26	25	26	23	28	27	23	27	26	23	23	33
downturn	0	0	37	25	0	47	25	0	23	24	23	34
contraction*	0	0	25	61	0	0	0	25	0	25	25	36
turmoil	0	0	155	164	0	163	88	188	217	172	257	253
stabilise*	11	8	11	4	8	10	10	11	11	8	9	10
improvement*	6	6	8	6	5	6	7	6	4	3	3	5
easing*	42	67	49	17	73	42	18	72	51	69	33	55
expansion*	0	0	0	0	0	0	0	0	0	0	0	0
sound	25	15	33	15	24	14	15	23	32	23	37	56
robust	26	25	24	24	24	25	23	21	20	20	19	21
favourable	9	9	11	10	9	11	9	9	10	8	8	8
recovery*	13	5	8	0	0	7	5	11	9	0	4	6
upturn	54	0	0	65	33	49	66	49	0	31	0	0
optimistic*	35	34	63	0	53	50	68	51	0	32	31	29
sum negative	**199**	**172**	**423**	**445**	**111**	**390**	**331**	**409**	**624**	**646**	**755**	**733**
sum positive	**220**	**169**	**207**	**141**	**229**	**214**	**221**	**253**	**138**	**192**	**143**	**190**

Note: The entries in Table 1 are weighted according to equation 1 in the main text.

Table 2. Count-words: list of words and results for 2000

	Jan-00	Feb-00	Mar-00	Apr-00	May-00	Jun-00	Jul-00	Aug-00	Sep-00	Oct-00	Nov-00	Dec-00
slowdown*	0	0	0	0	0	0	0	0	0	0	0	0
uncertainty*	1	1	2	2	2	2	0	2	2	2	2	2
weak*	0	0	0	0	0	0	0	0	0	0	0	0
decelerate*	0	0	0	0	0	0	0	0	0	0	0	63
adverse*	0	0	0	0	26	22	0	0	0	36	17	38
risk*	0	0	0	0	0	0	0	0	0	0	0	0
deteriorate*	0	0	0	0	0	0	0	0	0	0	0	0
difficult*	0	0	52	36	0	75	0	0	0	0	39	30
tension*	0	0	0	0	0	0	0	0	0	0	70	0
imbalances	0	0	10	0	18	9	0	0	0	0	11	20
downturn	30	0	0	30	50	0	0	0	0	0	0	0
contraction*	0	0	45	0	0	0	0	0	28	0	54	26
turmoil	0	0	0	0	0	0	0	0	0	0	0	54
stabilise*	0	5	4	5	0	7	9	5	10	14	5	9
improvement	5	4	6	6	5	6	8	6	6	4	5	3
easing	0	0	0	21	0	0	0	23	0	0	0	17
expansion	0	0	0	0	0	0	0	0	0	0	0	0
sound	0	0	16	0	0	32	33	0	0	21	20	15
robust	12	18	8	9	15	16	11	17	18	18	10	15
favourable	0	8	7	7	0	7	5	7	10	6	7	7
recovery	20	18	17	14	6	18	14	16	17	0	6	12
upturn	111	67	82	0	83	55	72	0	71	45	0	0
optimistic	94	43	109	0	0	57	73	0	84	46	0	0
sum negative	**32**	**1**	**109**	**68**	**96**	**109**	**0**	**2**	**30**	**38**	**193**	**234**
sum positive	**242**	**163**	**249**	**61**	**108**	**196**	**225**	**75**	**216**	**154**	**53**	**80**

Note: The entries in Table 2 are weighted according to equation 1 in the main text.

Table 3. Periods of stress

Y2K	Jul 99 - Jan 00
dot.com	Mar 00 - Dec 00
9/11	Sep 01 - Nov 01
Corporate scandals	Jun 02 - Aug 02
Iraq war	Mar 03 - May 03
Heightened uncertainty/Oil prices increases	Jun 04 - Dec 04
Global financial crisis	Aug 07 - Jun 09
European debt crisis	March10 -

Table 4. List of financial variables, weekly data from 1999 to June 2010

- AA risk spreads
- BBB risk spreads
- High-yield risk spreads
- Sovereign bond spreads (Austria, Belgium, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal, Spain *versus* Germany)

- DJ EUROSTOXX
- DJ EUROSTOXX Financial

- Equity risk premium
- Actual earnings per share (EPS)

- 1-mo Euribor-EONIA spread
- 3-mo Euribor-EONIA spread
- Main refinancing rate – 2-yr bond yield

- Long implied bond volatility
- Implied stock volatility
- Euribor futures implied volatility
- 1-year forward 1-year swaption implied volatility (euro vs Euribor).
- 1-year forward 10-year swaption implied volatility (euro vs Euribor).

Table 5. Matrix of signals and no-signals

	Stress	No Stress
Signal	A	B
No Signal	C	D

Table 6. Loss function values for different thresholds

T	**False Alarm**	**Missing Stress**	**Right Signal Stress**	**Right Signal no-stress**	**Number Obs**	**LOSS θ=0.5**
0.1	227	8	229	111	575	0.281
0.2	136	26	211	202	575	0.239
0.3	104	33	204	234	575	0.212
0.4	76	53	184	262	575	0.210
0.5	28	72	165	310	**575**	**0.190**
0.6	2	92	145	336	575	0.197
0.7	0	103	134	338	575	0-217
0.8	0	116	121	338	575	0.245
0.9	0	133	104	338	575	0.281

Table 7. The FSI Success Table

T=0.5;θ=0.5

	S=0	S=1
number right signals	310	72
number false signals	28	165
number of right signals		475
percentage of right signals		0.83
naive model percentage of right signals		0.41

Table 8. Evaluation of Fit

	FSI	**Alternative 1**	**Alternative 2**
Root Mean Squared Error	0.351486	0.680463	0.828539
Theil-U	0.229066	0.628195	0.919761

Note: Alternative 1 refers to a model in which the dependent variable is regressed on a constant; Alternative 2 refers to a model in which the dependent variable is regressed on a constant and its own one lagged value.

Table A1. Logit model estimation

	FSI	FSI	FSI
Level	**6.89**	**6.79**	**6.65**
Change 8 periods			**-0.08**
Change 12 periods		**-0.08**	
Change 18 periods	**-0.06**		
Comovement	**0.02**	**0.02**	**0.02**
McFadden R-squared	0,41	0,42	0,41

Note: Figures in bold are significant at least at 5% significance

Table A2. FSI Loss Function for different θ and T

T	θ=0.3	θ =0.4	θ =0.5	θ =0.6	θ =0.7	θ =0.8
0.1	0.480	0.416	0.353	0.289	0.225	0.161
0.2	0.315	0.285	0.256	0.227	0.198	0.168
0.3	0.257	0.240	0.223	0.207	0.190	0.173
0.4	0.224	0.224	0.224	0.224	**0.224**	0.224
0.5	0.149	**0.171**	**0.193**	**0.215**	0.238	0.260
0.6	**0.121**	0.159	0.197	0.235	0.274	0.312
0.7	0.130	0.174	0.217	0.261	0.304	0.348
0.8	0.147	0.196	0.245	0.294	0.343	0.392
0.9	0.168	0.224	0.281	0.337	0.393	0.449

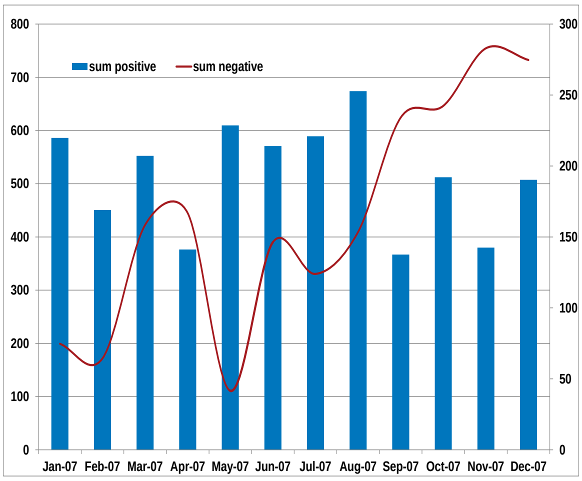
Note: In bold the minimum values of the Loss Function

Table A3. FSI Success Ratio for different T (θ=0.5)

	right signal		false signal	
T	**S=0**	**S=1**	**S=0**	**S=1**
0.1	33%	97%	67%	3%
0.2	60%	89%	40%	11%
0.3	69%	86%	31%	14%
0.4	78%	78%	22%	22%
0.5	92%	70%	8%	30%
0.6	99%	61%	1%	39%
0.7	100%	57%	0%	43%
0.8	100%	51%	0%	49%
0.9	100%	44%	0%	56%

Chart 1. Sum of negative and positive words, 2007 and 2000[20]

2007



2000

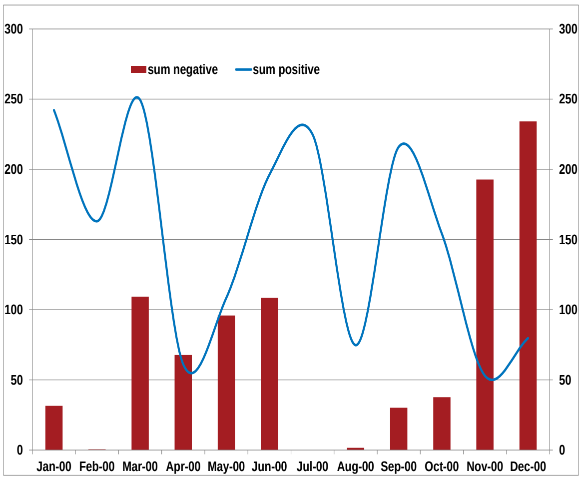
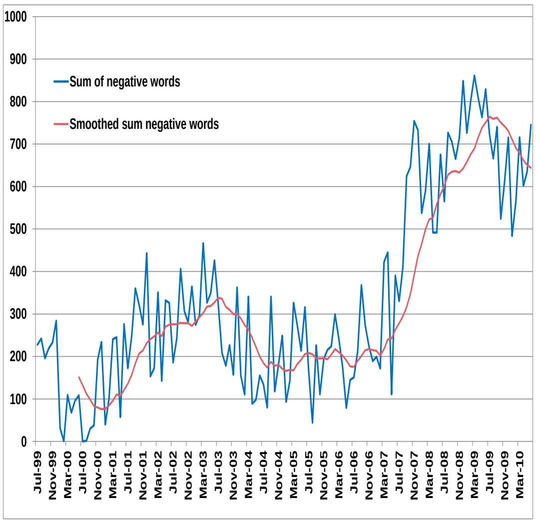
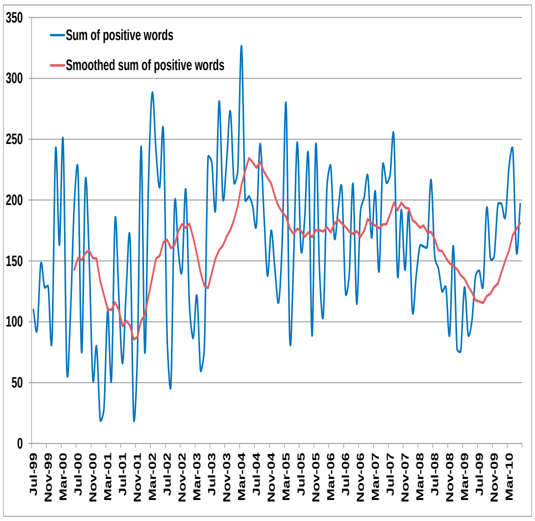


Chart 2. Negative and Positive words, 1999- 2010, (*monthly sum*)[21]

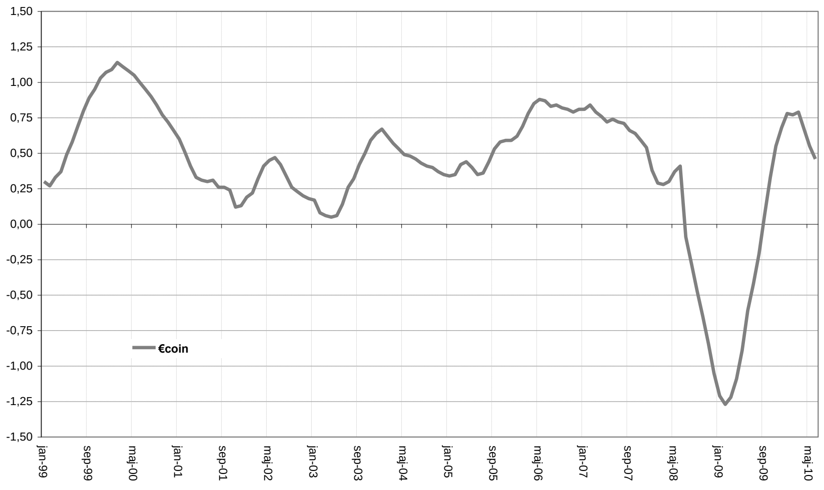




[20] Negative words are on the left axis, positive words on the right axis.

[21] Monthly scores (blue lines) are plotted together with (12-month) moving averages (red lines).

Chart 3. The €coin[22]



[22] Source CEPR , http://eurocoin.bancaditalia.it/.

Chart 4. Periods of stress as identified through textual analysis. the €coin and anecdotal evidence

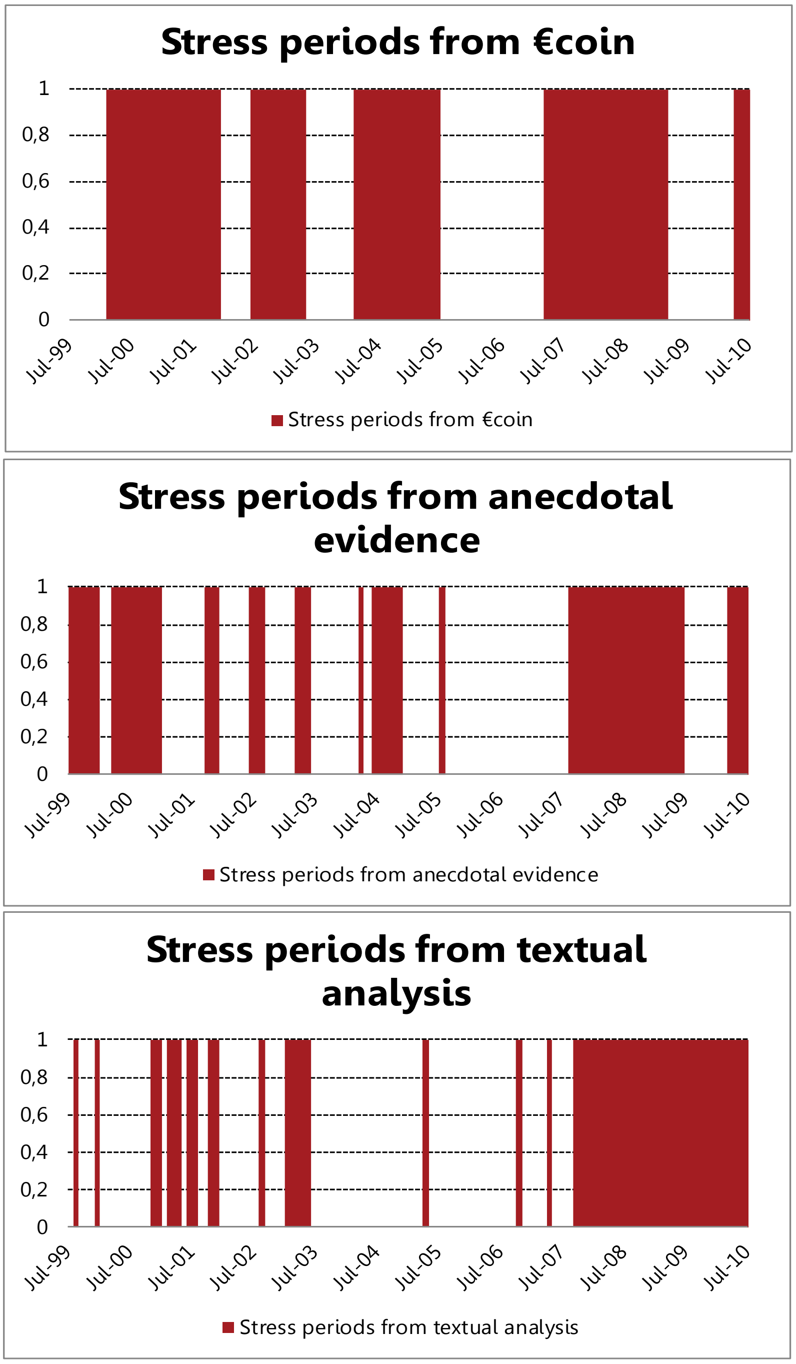


Chart 5. FSI and Periods of Financial Stress

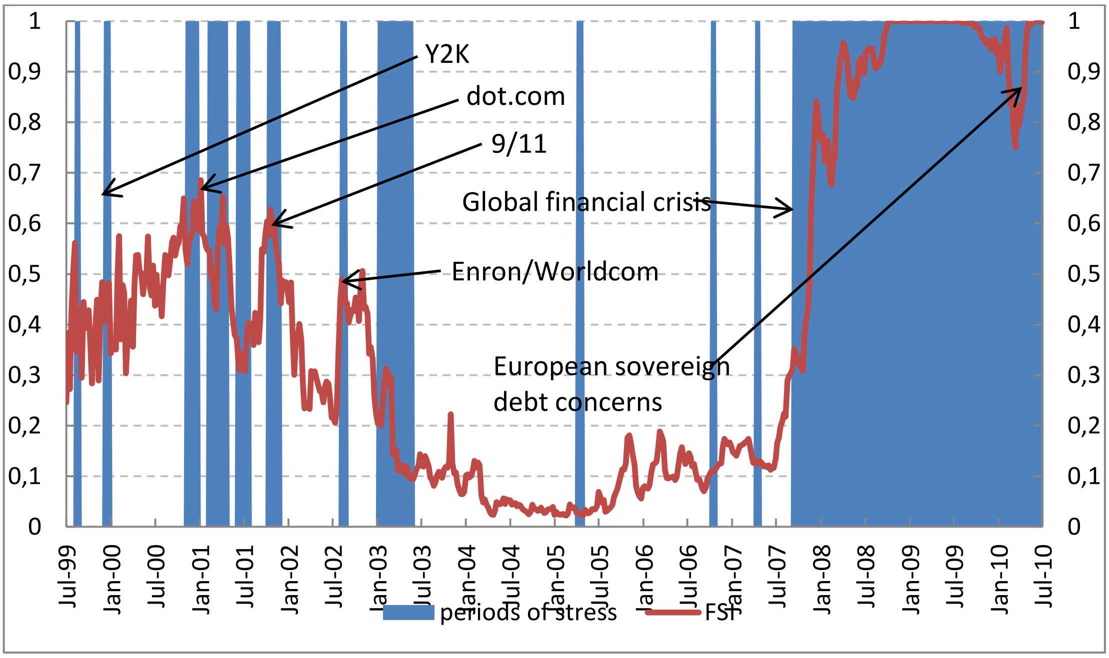


Chart 6. FSI and the VSTOXX index

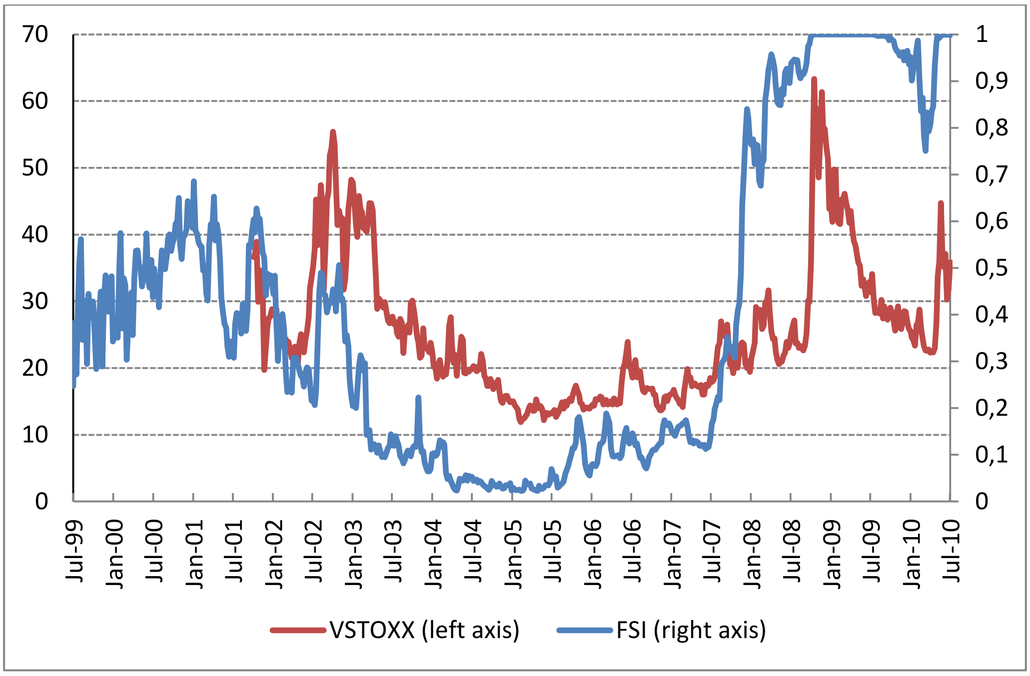
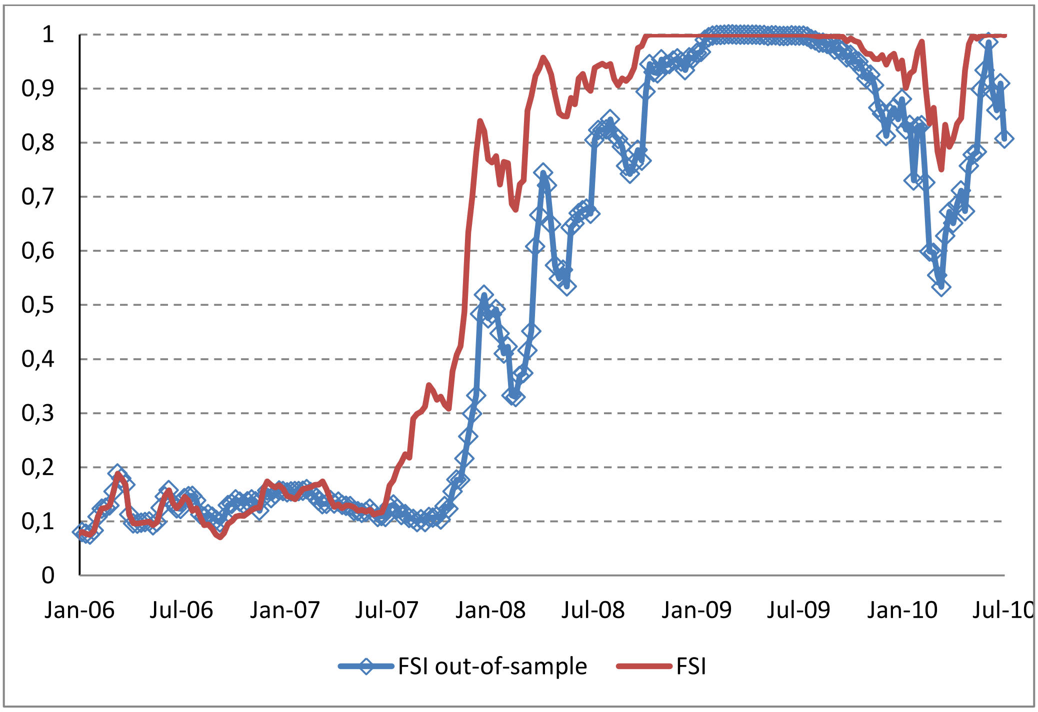


Chart 7: Out-of-sample estimation



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