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RESEARCH ARTICLE

A financial stability index for Colombia

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Abstract The imbalances of the financial systems have showed the vast economic and social costs generated by financial instability. As a consequence, the development of stress indexes has spread as an alternative to assess the soundness of financial systems. The aim of this paper is to construct a continuous and quantifiable index with the capacity of establishing the stress level of the Colombian financial system as a function of profitability, liquidity and probability of default. Results show that the index determines effectively the stress level of the system. In addition, we performed forecasts of the financial stability index using macroeconomics variables.

Keywords Financial stress index · Financial institutions · Early warning systems · Financial fragility · Monitoring

JEL Classification E44 · G21 · C25

1 Introduction

The financial systems' imbalances during the current crisis and the late nineties have showed the vast economic and social costs generated by these periods of financial instability. Therefore, central banks and regulatory agencies have focused a good portion of their efforts to study the development of potential early warning indicators, stress testing exercises (e.g. Čihák 2004; Boss et al. 2004) and research about the actual situation of financial sector. With this kind of studies, these institutions try to gauge

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the fragility of the system and understand how it reacts to macroeconomic shocks and to changes in the regulatory framework.

The absence of a wide spread theoretical and empirical definition of financial stability, has generated some troubles in the monitoring and comparison of financial systems across countries and throughout time. In comparison of the definition of price stability, there is a general assent and quantitative analysis in terms of monetary aggregates, interest and inflation rates that provide some tools to reach the price stabilities goals.

Therefore, the main obstacle to develop a good measure of financial stability is the non-existence of a consensus about its definition, so it is difficult to forecast the performance of financial systems. Likewise, most of financial stability reviews are descriptive and backward-looking, whereas the prices stability reviews are more forward-looking. Many financial stability studies have been based on the analysis of historic crisis episodes around the world, looking for common antecedent factors in the attempt to examine what factors may cause instability. Some examples of this approach are the papers developed by Kaminsky and Reinhart (1996), Demirgüç-Kunt and Detragiache (1998), Berg (1999), Logan (2000) and Disyatat (2001). In spite of the fact that this approach helps to improve the diagnosis of crisis events, the disadvantage is that the definition of a crisis is entirely subjective. Additionally, the relationship between the events before the crisis and the crisis phenomena in itself is likely to be subject to the Lucas critique, in the sense that identification of prior regularities will change the behavior of financial agents.

Initially, literature on financial crisis and financial stress did little to arrive to a contemporary measurement of the current state of a system. In fact, crises usually were classified and measured with simple binary variables, and treated specifically as banking and/or exchange market phenomena, with an indication as to whether or not a crisis had occurred. In contrast, a financial stress indicator represents a continuous state, one that describes the conditions of the sector throughout time, generating a current vision of the contemporary stress level, which is crucial to monitor the system. Among the studies that have developed a metric for assessing financial stability, the papers of Illing and Liu (2003), and Hanschel and Monnin (2005) can be highlighted. The problem is that in both cases the variables in their financial stress index are not derived from any structural model.

From another perspective, Aspachs et al. (2006) develop a metric of financial stability based on a general equilibrium model that introduces a financial system in the economy with heterogeneous agents and endogenous default. The main contribution of this paper is that it defines a financial stability situation in terms of variables related with the performance of banks in an endogenous way: profitability and probability of default.

Additionally, Aspachs et al. (2007) propose a measure of financial fragility that is based on economic welfare (GDP as a proxy of welfare) in a general equilibrium model calibrated against UK data. The authors define financial fragility as a combination of high probability of default and low bank profitability and address the impact of monetary and regulatory policy, credit and capital shocks in the real and financial sectors. Finally, they investigate whether data support their claim that banking sector's distress induces welfare losses. Using a Panel VAR model, they show that shocks to bank's probability of default and equity values have a impact on output.

For the Colombian case, there is not a metric or indicator that describes the situation of the financial system period by period. Then, there is not a clear measure of the stress level inherent in the system, making monitoring really hard. Therefore, there exist an interest to develop an indicator that can allow the monitoring of the Colombian financial stress throughout time.

The financial stability index (FSI) described in this paper is a continuous and quantifiable measurement that can be used to determine the stress level in the Colombian financial system. It is a monthly indicator that features considerations developed in Aspachs et al. (2006) with respect to profitability and probability of default. To that end, we used capital, liquidity, credit risk and return ratios for various types of financial institutions in Colombia, such as commercial banks (CB), mortgage banks (BECH in Spanish), commercial financial companies (CFC) and financial cooperatives (Coop). The aim is reached by generating and combining information obtained from different indicators through econometric techniques. One of the main contributions of this document is that we develop a stress indicator by type of institution. This fact has an enormous relevance in banking supervision and monitoring.

The selected variables took into account the systemic relevance, the ability of the variables to reflect the performance of financial institutions, previous studies about the Colombian financial system, the frequency of data and the criteria that the international literature suggests. Finally, the index is constructed by aggregating the variables.

This article is divided into five sections, including this introduction: in Sect. 2 we present the antecedents and methodologies used to build financial stress indexes. In Sect. 3 we describe the selected variables and we develop the methodology to build the index. In the fourth section we analyze the results obtained for the financial system and replicate the methodology for different types of institutions. In Sect. 4, the forecasts of the indexes are reported. Finally, in the sixth section we incorporate some comments and conclusions about the main results of this paper.

2 Literature review

Most of the empirical research about the stress level of financial systems has been developed in the last decade. The crisis of the eighties and the south-east Asiatic crisis of late nineties have stimulated a significant body of empirical research on potential leading indicators of financial stress. The first approaches studied the financial vulnerability level from the analysis of the main factors associated with banking system failures. Demirgüç-Kunt and Detragiache (1998) use a multinomial logit model to analyze the factors associated with the emergence of systemic banking crisis for a sample of developed and developing countries between 1980 and 1994; the results show that a crisis tends to generate when the macroeconomic environment is weak, particularly when the economic growth is low and the inflation rate is high. Additionally, they analyze the relationship between financial liberalization and system vulnerability. Their results suggest that liberalization increases the banking failure probability, but it does in a lesser way when the macroeconomic environment is solid.

Kaminsky (1998) develops a study for currency crises. The results show that most crises have been generated in fragile economies with signs of stress emanating from various sectors of the economy. This makes the degree of vulnerability of economy a useful leading indicator of currency crises. The author constructs early warning systems (EWS) based on empirical regularities observed in a sample of twenty countries from 1970 to 1995. The author proposes four different composite leading indicators and evaluates them in terms of forecasting accuracy and calibration. The indicators are tested out of sample for the Asian crisis and the results show that Asian economies were in bad conditions, with clear signs of distress surfacing as early as eighteen months before the currency collapse. From that it could be inferred that the crisis could be predicted.

González-Hermosillo (1999) contributes to the literature of systemic banking crises by analyzing the role of macroeconomic and microeconomic factors of bank failures. She develops a simple model: bank failures based on credit, market and liquidity risk, where the failure probability for each bank is estimated using a logit model for panel data. The author finds that low levels of capital equity and reserve coverage of risky loans ratio are a leading indicator of bank distress. Using a similar methodology, Demirgüç-Kunt and Detragiache (1999) explore how statistical analysis of past systemic banking crisis may be used to construct monitoring tools that could be implemented in the development of qualitative measures for determining banking sector weaknesses. The study suggests EWS that will issue a signal in case that the probability of crisis excedes certain threshold, in the framework of a multivariate logit model.

Bell and Pain (2000) review the results of a selection of recent empirical studies and assess the practical usefulness of these leading indicator models. The paper points out that there are two approaches in literature for the analysis of the crisis and financial distress: the first one relies on macroeconomic indicators as key explanatory variables of banking crises; the second one uses models that assess how microeconomic factors (i.e. bank-specific characteristics) may have contributed to that crisis. The article identifies two methodological approaches to develop the financial stress indicators: signalling approach and qualitative response models. The former compares the information generated by indicators in the calm periods with that of crisis periods, analyzing the generated type I and II errors. The latter employs regression techniques to estimate the relationship between potential indicators and identifies a discrete outcome, for example a banking failure or a financial crisis.

In recent years financial stress indexes have been developed widely as an alternative to evaluate the quality of financial systems in some countries. Some examples of those indexes are the constructed for Canada, Switzerland and United States by Illing and Liu (2003), Hanschel and Monnin (2005), and Puddu (2008), respectively. For the Canadian case, the authors develop an index that provides an ordinal measure of financial stress level. This index was built using several techniques, including factor analysis, econometric benchmarking, and generalized autoregressive conditional heteroscedasticity (GARCH) modeling. An internal Bank of Canada survey is used to condition the choice of variables. Similarly, Hanschel and Monnin (2005) propose a stress index that summarizes the current condition of the Swiss banking sector in one single measure. The authors develop forecast exercises for the index with macroeconomic information. One of the main results of the paper is that macroeconomic imbalances have the potential to influence the condition of the banking sector in the medium-run. Additionally, results suggest that macroeconomic imbalances usually appear with some anticipation to the increase of financial stress level.

Puddu (2008) develops a variety of indexes using different methodologies for the US case; among the methodologies employed, the author uses indexes based on the signalling approach and based on estimations from count data models. The paper contrasts the previous results with indexes based on the variance-equal weight method (VEW) and principal factor analysis (PF). The main difference among the results of each method is that financial stress level differs but the cycle and shape of indexes are very similar. In general, the variables used to build the index are financial ratios of profitability and credit risk. Puddu (2008) also develops forecasts for the indexes using regression methods that take into account macroeconomic variables.

3 Methodology

The aim of this paper is to develop a continuous and quantifiable measurement that can be used to determine the stress level in the Colombian financial system. Two important conditions are needed to reach this goal: first, appropriate selection of variables and second the weights that each variable takes in the index. The following subsections explain the variables and data set used, as well as the different approaches to determine the weights.

3.1 The data

Monthly data ranging from January 1995 to November 2008 is employed (167 periods), that includes data from several fases of the economic and credit cycle. The data set covers 170 financial institutions that existed during the period of sample classified as commercial banks (CB), mortgage banks (BECH[1] in Spanish), commercial financial companies (CFC) and financial cooperatives (Coop). The sample is not homogenous during the observation period because the financial crisis that took place during the late 1990s led to several bank failures, mergers and acquisitions as well as to the entry of new institutions.

The variables used to build the index are the following: return on assets (ROA), return on equity (ROE), ratio of non-performing loans to total portfolio (NP),[2] ratio of net loan losses to total loan portfolio (LP),[3] intermediation spread (IS),[4] ratio of liquid liabilities to liquid assets (LL), ratio of interbank funds to liquid assets (IF), uncovered liabilities ratio (ULR) and the number of financial institutions with high stress level (Stress)[5] per period. Table 1 presents a summary of the data.

[1] These type of institutions took an important role in the Colombian financial crisis in late nineties. Nowadays this classification not exist but some institutions that conformed the BECH still exist.

[2] Non-performing loans comprises loans that are overdue 30 days or more.

[3] Loans that do not generate financial income to credit institution.

[4] The intermediation spread is calculated as the difference between the implicit lending rate and the implicit deposit rate.

[5] This variable is specified later. See Appendix A.

Table 1 Summary of the dataset

Variable	Obs	Average	Standard Deviation	Max	Min
ROA	167	0.014	0.022	0.040	−0.035
ROE	167	0.114	0.182	0.329	−0.313
NP	167	0.073	0.034	0.163	0.026
LP	167	0.056	0.031	0.134	0.017
IS	167	0.085	0.010	0.111	0.064
LL	167	0.261	0.111	0.707	0.051
IF	167	0.087	0.043	0.202	0.018
ULR	167	−0.154	0.088	0.001	−0.311
STRESS	167	11.934	12.841	44	0

ROA refers to the profitability of institutions relative to total assets. This ratio gives an idea of the efficiency of using the assets to generate profits. Similarly, the ROE is a ratio that shows information about the profitability taking into account equity; in other words, this ratio shows how efficient is the entity when it uses the investors' resources. The intermediation spread (IS) is an approximation for profits of financial institutions. Basically, it is the difference between the interest rate payed by borrowers and the interest rate payed to depositors. The rest of the variables summarize the vulnerability of financial institutions: non-performing loans to total portfolio (NP) and the ratio of net loan losses to total loan portfolio (LP) are credit risk indicators. While the ratio of liquid liabilities to liquid assets (LL), the ratio of interbank funds to liquid assets (IF) and the uncovered liabilities ratio (ULR) are liquidity risk indicators.

It is important to mention that measures of future predictability are needed in order to construct a single metric for financial stability as the theoretical literature argues. This also explains why we include some leader indicator variables for stress episodes as IS, LP, IF, and ULR; these indicators change their behavior with some anticipation to the stress events.

The other variables that we include are historical measures that varies around the stress events (ROA, ROE, CV and CI). In spite of this fact, we consider these variables because they have not only a contemporaneous, but a dynamic relation with the stress level of financial system, so we can infer that the behavior of these variables in period t determines the probability to observe stress events in period $t+1$. Another criterium to include these indicators is that according to Aspachs et al. (2006), a measure of financial fragility should consider two key variables: profitability and probability of default.[6]

In general, the variables that make up the indicator have been selected based on those suggested by international literature and previous analysis for the Colombian financial system, the systemic relevance of those variables, and on the frequency and availability of data.

[6] They develop a two-variable definition of financial fragility, that is a combination of low profitability and default probability.

3.2 Combining the variables into a single index

The most difficult aspect is to determine how the variables are weighted to arrive to a measurement, as this determines the impact each variable will have on the stress index. The difficulty in weighing the variables hinges on the absence of a reference indicator that makes it possible to verify the precision of weights and to perform tests with them. A wide variety of methods are used to weigh variables. In this case, we use the variance-equal weight approach, principal components and count data models: zero inflated poisson and zero-inflated binomial negative regressions.[7] The techniques based on the signalling approach were not taken into account because in the analysis period there was only one financial crisis, so there is insufficient information to establish thresholds to evaluate the variables that determine the imbalances and this forbids the development of a good study for the Colombian case.

The index is determined by the selected variables' weights. Equation 1 presents ω_i that shows the weight that each variable has in the composition of the index. At the end, the FSI is composed by the addition of the weighted variables.

$$\begin{aligned} \mathrm{FSI}_t &= \omega_1\mathrm{ROA} + \omega_2\mathrm{ROE} + \omega_3\mathrm{NP} + \omega_4\mathrm{LP} + \omega_5\mathrm{IS} \\ &\quad + \omega_6\mathrm{LL} + \omega_7\mathrm{IF} + \omega_8\mathrm{ULR}. \end{aligned} \tag{1}$$

3.2.1 Variance-equal weight method

This method is the most commonly used in the literature of stress indexes due to the fact that it is easier. This technique standardizes the variables so they can be expressed in the same unit and then adds using identical weights. The index formula is presented in Eq. 2.

$$I_t = \sum_{i=1}^{k} \omega_i \frac{X_{i,t} - \bar{X}_i}{\sigma_i}, \tag{2}$$

where k is the number of variables that compose the index, $\bar{X}_i$ is the average of the variable X_i, σ_i its standard deviation and ω_i is the weight on each variable. We also standardize the final index to express it in terms of deviations from its mean.

A primary drawback of this approach is that it generates the same weight for all standardized variables that compose the index. This assumption could be untrue because there could exist variables with higher incidence on the financial stress level than others, depending of system vulnerabilities and the strength of the institutions. For example, the incidence of a variable in a period of credit risk could differ from a episode of liquidity risk. Additionally, under this approach the variables are supposed to be normally distributed. This is a strong assumption that may be an additional limitation.

[7] Puddu (2008) develops different qualitative approaches, where he highlights the Zero Inflated Poisson (ZIP) and Zero Inflated Binomial Negative (ZINB) regressions.

In spite of mentioned above, the variance-equal approach is the most commonly used technique to build financial stress indexes, because it is easy to estimate and it has a better goodness of fit when is compared with another more complex methodologies. Illing and Liu (2003), Hanschel and Monnin (2005), and Puddu (2008)) use this methodology as a starting point to develop their indexes.

3.2.2 *Principal components*

In contrast to the variance-equal approach, the principal components method identifies patterns on data, showing their similitude and differences. The main idea behind this methodology is to obtain a series, in our case the index, from combining the selected variables, in such a way that the majority of the total variance generated by the variables is taken into account by the combination. The principal component analysis (PC) uses the correlations between the variables to develop a small set of components that empirically summarize the correlation between variables.

PC method is comparable with principal factors analysis (PF). This last method is widely used to compose stress indexes. The difference between the two techniques is that PC assumes that all the variability generated by the set of indicators must be considered, while PF only takes into account the variability that is in common between the selected variables.

For the Colombian case, it is possible to use this kind of approximation because the variables that have been selected have a similar cycle and a similar behavior. This fact allows this method to get a better goodness of fit. Additionally, in our analysis, the PC approach works well out of sample, because the weights obtained by this method keeps stable around the different samples.[8] This result is consistent with an approach based on an equilibrium model, where, in a steady-state the weights should maintain constant.

3.2.3 *Qualitative response approach*

Opposite to the methods described previously, this methodology is based on econometric estimations in order to model the relation between the stress variables and the dependent variable, defined as the number of bank failures or bank crisis. We assume that the same variables that have incidence on banking crisis have incidence on the financial stress level as well. Finally, from the regression results, we infer the weight that each explanatory variable has on the index.

The dependent variable has been constructed from the qualitative information that arises from financial crisis episodes. In most cases that variable has a discrete outcome and it is assumed to be drawn from a continuous probability function; this is conditioned on the features of the dependent variable.

Many empirical works have developed diverse econometric methodologies, in which the number of bank crisis are modeled as a function of some explanatory variables. Then the regression results are used to generate the variable weights. We

[8] We calculate the weights for six different samples and we obtain that the weights present small variations, actually, they keep stable for the different periods of sample.

assume that there exists a positive and monotonic relationship between the unobservable banking stress level and the number of banking failures so this implies, that by studying the impact of financial indicators on the number of banking failures it is possible to infer the relationship between the indicators and the stress level. As a consequence, regression results based on the number of entities with high stress levels are used to infer the existing relation between variables and the index.

Equation 3, models the financial stress level (y_t) as a function of the number of entities with high stress levels (X_{it}) plus a error term (ε_t). By estimating this model[9] the coefficients that allows us to generate the weights[10] that each variable obtains in the indicator, in such a way that the most relevant variables obtain the highest weigh in the index.

$$y_t = F(X_{it}) + \varepsilon_t \tag{3}$$

Dependent variable. For the Colombian case, we have to build a dependent variable that is able to represent the quantity of financial entities that have showed a critical situation. Then, we construct a matrix that evaluates each entity over time, taking into account profitability, liquidity and credit risk criteria. The strategy was to create a matrix that recognizes the entities that were under certain financial stability threshold defined *ad hoc*,[11] considering the extreme faced by the financial ratios on the end of nineties, in the context of the financial crisis in Colombia. At the end, a variable that represents the quantity of entities with high stress levels by period is defined[12] (see Fig. 1a).

Analyzing Fig. 1b we find that the distribution of financial entities with stress levels does not behave as a normal distribution. In fact, the data is clustered on the left side of the distribution; in other words the data is positive skew. Additionally, if we analyze the distribution's frequency, it is possible to see the high frequency that the zeros outcomes have, this is explained by the long periods of financial stability that the system faces because the crisis periods are inusual. Therefore a lot of periods with not entities with high levels of stress are registered.

Count data model estimation. Given the nature of the dependent variable, the methods that assume normality like OLS[13] are inappropriate. A more appropriate distribution to consider is, for instance, the *Poisson* distribution where the main assumption is that the model mean and variance are equal. If this is not the case, the data set is

[9] Puddu (2008) suggests some count data models (Poisson and Negative Binomial regressions) to build the financial stress index.

[10] In order to determine the weights of the explanatory variables, we focused in the incidence rate ratio (IRR) discounted by the precision of the estimators. So, we can generate a vector of optimal weights.

[11] In order to test the sensibility of the distressed entities to the *ad hoc* assumptions of thresholds, we perform little variations to the thresholds, and compared the conclusions in each scenario. At the end, we find that the number of entities classified in distress are robust to several values of the thresholds. In addition, the selected thresholds replicate in a proper way the high level of financial stress presented during the crisis of the end of nineties.

[12] A further explanation about the definition of the distressed entities is provided in Appendix A.

[13] Ordinary Least Squares.

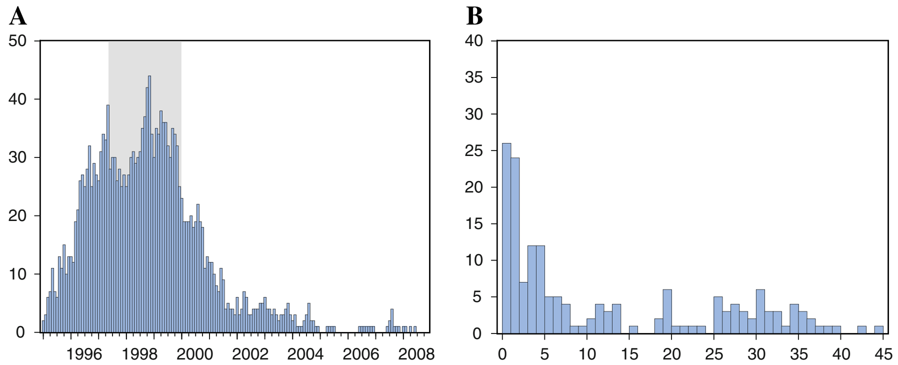

Fig. 1 Dependent variable: **a** entities with stress levels, **b** histogram

over-dispersed with respect the Poisson model (Table 1), perhaps due to as a consequence of an excessive number of zero outcomes.

On the other side, the *Negative Binomial* distribution represents a possible solution to this problem, because it can be used as an alternative to the Poisson distribution when the model variance exceeds the model mean. In general, given the excess zeros in data set, the best manner to model the data is by using the *Zero Inflated Poisson* (ZIP) or *Zero Inflated Binomial Negative* (ZIBN) methodologies. Both take into account the high quantity of zeros in the distribution, making these models more appropriate for this kind of analysis.

Both approaches develop the estimation under two separate regimes and later combine them. The first stage is necessary to define the elements that characterize observations equal to zero (inflated part), whereas the second specification defines variables that affect the part of the dependent variable that takes values different to zero (not inflated part). Equation 4 specifies the two regimes:

$$y_t = \begin{cases} G(Z_{it}) + \varepsilon_t & \text{if } y_t = 0, \\ F(X_{it}) + \eta_t & \text{if } y_t > 0 \end{cases} \tag{4}$$

where the dependent variable (y_t) is the number of financial entities with high stress level, $G(.)$ and $F(.)$ are functions that relate the explanatory variable vector with the dependent variable; Z is a vector of variables conformed by the returns on assets (ROA) and the uncovered liabilities ratio (ULR) in each time period. Finally, X is a vector of variables that include the return on equity (ROE), ratio of non-performing loans to total portfolio (NP), ratio of net loan losses to total loan portfolio (LP), intermediation spread (IS), ratio of liquid liabilities to liquid assets (LL) and finally the ratio of interbank funds to liquid assets (IF).

There is not exist a clear criterium to specify the variables that are in each vector Z and X in the model showed in Eq. 4. In this methodology, in order to construct the vector Z, we analyze the variables with high relevance on financial stability periods and variables that could generate multicollinearity problems in the same specification.[14] All the independent variables are lagged one period in order to avoid endogeneity problems.

[14] There is a high correlation between ROE and ROA, additionally between the ULR and IF.

Table 2 Estimations from count data models

	ZIP		ZINB	
	$y = 0$	$y > 0$	$y = 0$	$y > 0$
ROA	4.182 (1.086)***		5.800 (2.076)***	
ROE		−0.013 (0.004)***		−0.002 (0.007)
NP		0.234 (0.062)***		0.496 (0.147)***
LP		−0.428 (0.057)***		−0.584 (0.127)***
IS		0.784 (0.046)***		0.858 (0.091)***
LL		0.013 (0.002)***		0.0135 (0.006)**
IF		0.022 (0.008)***		0.033 (0.018)***
ULR	0.118 (0.043)***		0.140 (0.062)**	
Constant	−11.581 (2.937)***	−4.114 (0.328)***	−16.824 (6.072)***	−6.221 (0.730)***
Lnalpha			−1.594 (0.196)***	
Vuong Test	4.2***		2.42***	
Obs, $y = 0$	26		26	
Obs, $y > 0$	140		140	
Total Obs	166		166	

ZIP zero inflated poisson, *ZINB* zero inflated negative binomial
***Significance at a 1% level, **significance at a 5% level

For the *inflated* part, a Probit model is estimated to characterize the excess number of zeros. For the other specification (*no inflated* part), the ZIP and ZINB estimations are based on Poisson or Binomial Negative regressions respectively. As mentioned, this specification is necessary to define the elements that characterize this part of the model that is not affected by the excess number of zeros in the dependent variable.

The results from ZIP and ZIPN estimations are reported in Table 2. The sign of each estimated coefficient was equal in both approaches. For the ROA, in the *inflated* part ($y = 0$), the sign is positive, which is consistent with what is expected: a larger ROA implies a higher probability to present low levels of financial stress. For the case of ULR[15] the estimated sign is not intuitive because it infers that an increase[16] in ULR increases the probability of financial stability.

Analyzing the signs of the estimated coefficients from the *no inflated* part ($y > 0$), we found that the coefficient associated to ROE shows a negative sign. This indicates that the probability to get financial entities with high stress levels in period t decreases if the ROE had a high level in period $t-1$.[17] With respect to the ratio of non-performing

[15] For more information about the ULR calculation, see *Financial Stability Report 2008*. Banco de la República Colombia.

[16] The uncovered liabilities ratio ULR indicates a better liquidity situation when its value is small, when it tends to negative values.

[17] As mentioned previously, we assume that ROE and ROA have not only a contemporaneous, but a dynamic relation with the stress level of financial system; in spite of fact that these variables vary around the stress events and they are not the better measures of future predictability, they allow us to obtain the contemporaneous stress level.

loans to total portfolio (NP), the estimated sign shows a positive relation between this variable and the probability to find entities with high stress levels. On the other hand, the sign of the ratio of net loan losses to total loan portfolio (LP) is not the expected because suggest that an increase in this ratio generates a smaller probability of finding entities with high stress level.

For the intermediation spread (IS) the expected sign is not clear. First, we know that this profitability indicator is high when the financial system has a high level of profits and a low stress level. Likewise, the IS can be an indicator of the competitiveness of the banking sector: a low IS level could implicate a strong competition among banks; then higher competition levels pressures banks to relax their exigences when granting credit, so the stress level may increase in the future. These two arguments imply an inverse relation between the IS and the banking stress level; however, these arguments can be refuted; the IS can be affected by the capital requirements that are supervised by the monetary authorities, so the exigent regulatory measures can reduce IS but at the same time makes financial system safer and robust to face futures banking crisis. Taking into account the last argument, a low IS level does not necessarily implicate a higher stress level. In the end, the expected sign is ambiguous but the model estimates a positive relation between the IS and the probability.

Another possible case is the presented for Colombia. Perez Reyna et al. (2008) analyze the effects of an increase in reserve requirements increases on financial stability using a DSGE[18] model. The results suggest that in Colombia, after a transitory increase in reserve requirements, the intermediation spread rises in the next trimester, and that causes an increment on banks' profits. However, after the measure, these entities present a lower credit supply that causes a rise in the active interest rate; thus this effect increases the house financial burden. As a consequence, after the second trimester, the profits of banks decrease until the tenth trimester, when they reach their long-run level.

As a consequence of a rise in the IS during the financial crisis period in the nineties and the positive sign estimated by the model, in this paper we assume a direct relation between the IS and the probability to find entities with high stress levels in period t. In other words, we assume that when the IS increases, probability increases as well.

The ratio of liquid liabilities to liquid assets (LL) and the ratio of interbank funds to liquid assets (IF) have a direct relation with financial stress level. The signs that present the estimate coefficients are positive, which is consistent with the expected. When this ratios have a high value, this indicates that there are less liquids assets to support the most urgent obligations, representing a lower liquidity. Both models, as ZIP as ZINB suggest that an increase in the liquidity ratios rise the probability of having entities with high levels of stress.

Finally, we perform the Vuong (1989) test, that allows us to compare the ZIP and ZINB models with the standard *poisson* and *binomial negative* regressions, respectively. As the z value is positive and significant, the *Vuong* test shows that the *Zero-Inflated* model has a better fit than the standard model (*Poisson o Binomial negative*).

[18] Dynamic stochastic general equilibrium model.

On the other hand, the standard count data models assume conditional independence on realizations; thereby lots of critics arise when this type of models are used to model time series data (see Gurmu and Trívedi 1994). There are other types of models that can be used to approach the banking crisis determinants without facing the limitation mentioned before. For the Colombian case, Gomez-Gonzalez and Kiefer (2009) developed a *duration model* to explain the banking failures through specific determinants of banks. In that paper, the authors identified the bank-specific determinants of bank failure during the financial crisis in Colombia. Results suggest that the capitalization ratio, profitability and credit risk have a high incidence. The coefficient signs obtained in that paper are similar to the obtained in this one.

Weights based on the incidence rate ratios (*IRR*) The methodology mentioned above implies that the estimated coefficients cannot be interpreted directly as the marginal effects of the explanatory variables on the independent one. In order to find the impact generated on the independent variable, we calculate the incidence rate ratio (IRR) for each explanatory variable of the *not inflated* part. Equation 5 shows the IRR. This ratio is define as the exponential of the estimated coefficient (see Appendix B).

$$\mathrm{IRR} \equiv e^{(\beta_i)} \tag{5}$$

The IRR represents the expected number of entities with stress levels in period $i = n + 1$ and $i = n$, keeping the rest of variables constant. In other words, it measures in relative terms how the dependent variable changes given a unit of change in the explanatory variable i, holding all other factors fixed. This ratio is used for the Poisson or Binomial negative part, depending on case. On the other hand for the Probit part it is necessary to transform the estimated coefficients, as we need to obtain comparable values with the IRR. We can reach that defining a variable ρ (see Appendix B). At the end, those indicators allow us to generate the weights for each associated variable.

After obtaining the IRR and ρ of the parameters associated with the explanatory variables, we develop a ratio that takes into account the indicators mentioned before with their precision. Then, we use the standard deviation associated to each ratio in order to generate a weighing that considers the magnitude of IRR, ρ and their precision. The precision of the incidence ratios, measured as the standard deviation, is a function of the estimated coefficient.[19] In order to calculate that deviations it is necessary to employ the *delta method*.[20]

$$\varphi_i = \begin{cases} \frac{\mathrm{IRR}(\hat{\beta}_i)}{1+se(\mathrm{IRR}(\hat{\beta}_i))} & \text{Poisson or Binomial Negative Model,} \\ \frac{\rho(\hat{\beta}_i)}{1+se(\rho(\hat{\beta}_i))} & \text{Probit Model.} \end{cases} \tag{6}$$

where φ_i converges to IRR or ρ when the standard error tends to zero.

[19] For the IRR and the ρ, the standard deviation is defined as $se(IRR(\hat{\beta}_i))$ and $se(\rho(\hat{\beta}_i))$ respectively.

[20] Basically with the delta method is possible to expand the function of a random variable around its mean. The approach that is usually used is the first order Taylor expansion then is possible to find the variance.

Table 3 Weighings of each variable in the the index

	Variance-equal weight (%)	Principal Components (%)	ZINB (%)
ROA	12.50	17.53	7.65
ROE	12.50	17.79	11.75
NP	12.50	18.01	15.69
LP	12.50	15.81	6.17
IS	12.50	12.79	23.03
LL	12.50	6.55	11.95
IF	12.50	7.41	12.03
ULR	12.50	4.12	11.73

The next step consists in finding the explanatory variables' weights. In order to reach that goal, we aggregate all our incidences rate ratios and our scaled coefficients estimated by the Probit model because with this aggregation we can calculate the weight that generates each IRR and ρ in the total.

We define τ as the sum of the absolute values of the variable φ_i:

$$\tau = \sum_{i=1}^{p} |\varphi_i| \tag{7}$$

Finally, we calculate the individual weights w_i as the ratio between φ_i and τ. The vector of weights generated is reported in Table 3, where the weights are compared with the methodologies mentioned in previous subsections.

$$\omega_i = \frac{|\varphi_i|}{\tau} \tag{8}$$

This model allows us to build the optimal weights from the variables that are included in the index. The optimal weights are reached transforming the associated coefficients of the regression with the equations developed before.[21] At the end, with these three different methodologies (variance-equal approach, principal components and the zero-inflated binomial negative regressions), we generate the weights to construct the index. Additionally, the development of these three methodologies allows us to reduce the shortcomings that would entail if we used only one methodology.

In short, we built the indexes with three different methodologies, and we obtained that these indexes presented a similar behavior. Particulary for the principal components and count data models (ZINB) case, the indexes gave a high weight to the profitability and credit risk ratios. In Table 3, we present the weights estimated by

[21] The limitations for the Colombian case lie on the fact that in this methodology the selected variables present some degree of multicolineality. Thus the inference from the estimators may be wrong, but the estimators still are unbiased and consistent. However we make some exercises deleting some variables that probably could cause the multicolineality and the results suggested an index with similar behavior in comparison with the index that we present in this document but with important differences in the stress level.

the variance-equal weight method, principal components and zero-inflated binomial negative regression.[22]

4 Financial stability index (FSI)

From the previous section, we obtained different weighings vectors that are going to be used to construct the index. With the vector of weights, the last step is to define the sign that each variable has to take in order to construct the index.

For that purpose we base on economic intuition. In this way, the ROA and ROE are weighted with a negative sign due to their inverse relation with stress episodes (less profitability, higher stress level). The other variables are weighted with a positive sign, considering their direct relation with such episodes. For example, when credit risk indicators (NP and LP) increase, the expected result is an increase in financial stress level, the same happens when liquidity ratios (LL, IF and ULR) rise. With respect to the intermediation spread (IS), its incidence is ambiguous on the stress level; in the Colombian case we assume that there exists a positive relation between this variable and the stress level, as mentioned above.

The information generated by the FSI is easy to interpret because each variable has been standardized. The stress level for the current period can be compared to the historic one in terms of deviation from the mean. Index values above zero are equivalent to periods of above-average financial stress, while negative values indicate periods of below-average stability. Likewise, increases in the index during a particular period also provide useful information on the evolution of the stress level on a given period of time.

The different methods used to generate the weights made the development of three different indexes possible. These indexes present a quasi identical behavior, but they differ slightly on the stress level. In general, all the indexes allow to infer the same conclusions about the financial stress level. On the other side, it is important to mention that assessing the accuracy of an index is a very hard issue, because stress levels are an unknown variable. Thus international literature suggests to compare the stress level defined by the index with the historic evaluations of financial crisis. It is expected that when a financial crisis[23] occurs, the index presents high stress levels.

Figure 2 shows how the financial stability index for Colombia evolved from 1995 to 2008.[24] As mentioned before, index values above zero are equivalent to periods of above-average financial stress, while negative values indicate periods of below-average stability. The index is expressed in units that represents the standard deviations with respect the mean.

One important feature that the index must have is the capacity to detect the main event. For the Colombian case, the economic crisis at the end of the nineties is detected

[22] The ZIP model results are not presented because they are very similar to those presented for the ZINB model.

[23] There is not a generalized consensus about what constitutes a systemic financial crisis. Many researchers tend to trust on the criterium generated by the experts in banking systems. See Bell and Pain (2000).

[24] Data from January 1995 to November 2008.

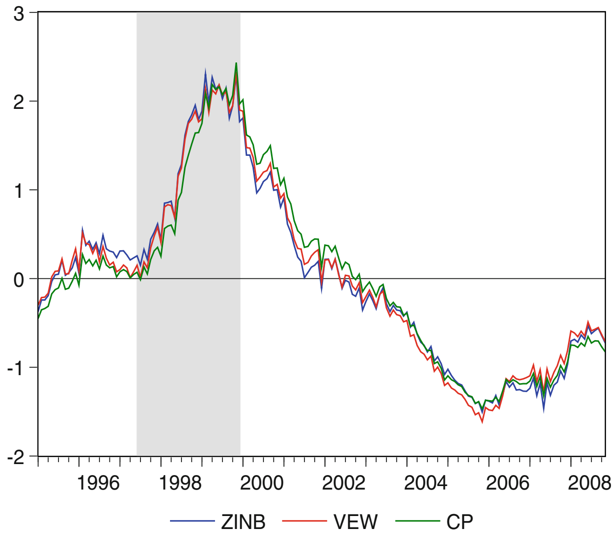

Fig. 2 Financial stability index

well in advance by the FSI. As the Fig. 2 illustrates, the financial stress level suggested by the index adopted an increasingly upward course as of late 1997 and peaked at the end of 1999. For the recent years the index also identifies times with low stress levels; namely, 2005 and 2006. It is important to mention that during the final years of the period in question, the tendency of the index turned positive and inclined, suggesting the stress level has begun to increase. Accordingly, one can conclude that the system has become more vulnerable. However, it is important to point out that the indicator has not yet suggested the existence of a high stress level, compared to its historic mean.

The FSI, by definition, identifies the contemporary level of stress in the system and, as such, it cannot be expected to predict future periods of stress or crisis. Hence, for policy purposes, it is extremely helpful in producing models that can be used to forecast the stress level. In this case, the FSI could be used as a dependent variable and could be modeled on the basis of macroeconomic variables.

4.1 Stress index (FSI) by type of institution

One of the main differences between this work and existing literature is that it manages to develop a stress index per type of institution and per institution, thanks to the availability of data for Colombia. The methods used for this analysis were the variance equal approach and principal components. The count data models were not considered in this case.[25] In the end, an index was developed for commercial banks

[25] The count data models were not used in this case because we do not consider a variable with the number of entities over high stress level by type of entity.

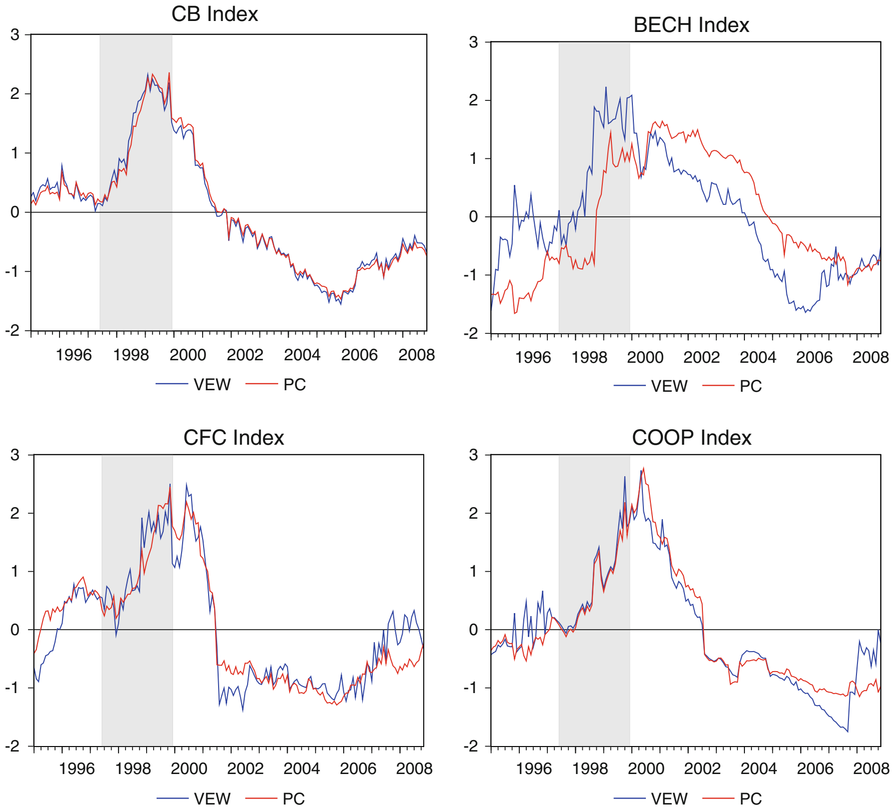

Fig. 3 Financial stress index by type of institution

(CB), mortgage banks (BECH), commercial financial companies (CFC) and financial cooperatives (Coop).

In general, one can see that the trend in the behavior of the index, per type of institution, is similar to that of the system index. However, because of this breakdown, it is possible to determine what types of institutions have the highest stress level. Figure 3 shows the four indicators for each type of institutions. One sees accelerated growth in the CFC and COOP indicators during the last few months, which suggests a rapid increase in their stress level. In the case of CFC, the indicator reached a point above average, which denotes a moderate stress level. For BC and BECH, the increase in stress level has been accelerated as well, but to a lesser degree.

In terms of policy and regulation it is important to monitor the financial system as a whole as well as each institutions that pertains to it. Thus the necessity to develop a stress index for each type of institution because it allows to obtain a more specific and detailed overview of the financial system situation. From the perspective of a global index, sometimes it is hard to observe the stress level of some types of entities since they have a small share of the financial assets, but might generate contagion problems affecting the financial system as a whole. If this is the case, the stress level cannot be observed from a global perspective just because the small proportion that these entities have in the total assets, however this financial stress could be observed in the financial index by entity.

For example, when we analyze the global FSI, the financial stress level for the last year in the sample reached a point below average, but when we analyze the index of the CFC, we observe that one of the indicators reached a stress level above average.

5 Forecasting

As mentioned before, the financial stability index (FSI) generates a contemporaneous measure of the stress level that the Colombian financial system presents for each period. For policy and banking supervision an important issue is to forecast the future level of financial stress, in order to anticipate the crisis episodes and to develop regulatory measures in order to prevent system vulnerabilities.

This section presents some possible models used to forecast the index; likewise, we show the results, strengths and limitations of our method. In general, the international literature suggests to use macroeconomic variables in order to develop the forecasts for the stress index. Hanschel and Monnin (2005) forecasted the Swiss financial index running a regression using as explanatory variables the gaps[26] of some macroeconomic variables, as the share price index, housing price index, the GDP, the credit to GDP ratio and the investment to GDP ratio. For the United State, Puddu (2008) follows the methodology of the early warning system (EWS) based on a macroeconomic approach. The selected variables were the inflation rate, GDP growth, credit to GDP ratio and the median sales prices of new homes sold in United States. The author employs a regression with the first and fourth lag of each explanatory variable in order to forecast the stress index.

We develop the forecasts under two different methodologies. The first focuses on an autoregressive analysis. This approach assumes that the history of the stress index contains the necessary information to explain the future behavior of the index under normal conditions; thus we estimate an ARIMA[27] model. The second methodology uses macroeconomics variables that we have considered relevant and that present a significative relation with the index when we perform causality tests. In this part of the study, we employ a VECM[28] model. From this last perspective we assume that the macroeconomic environment has an important influence on stress levels, because this level do not only depend on the vulnerabilities of the system but, also on the state of the economy as well.

5.1 ARIMA

From the univariate perspective, we developed an autoregressive model where the dependent variable in moment t is explained by its past. Taking into account that the

[26] This is the difference between the original series and the trend.

[27] Autoregressive Integrate Moving Average.

[28] Vector error correction model.

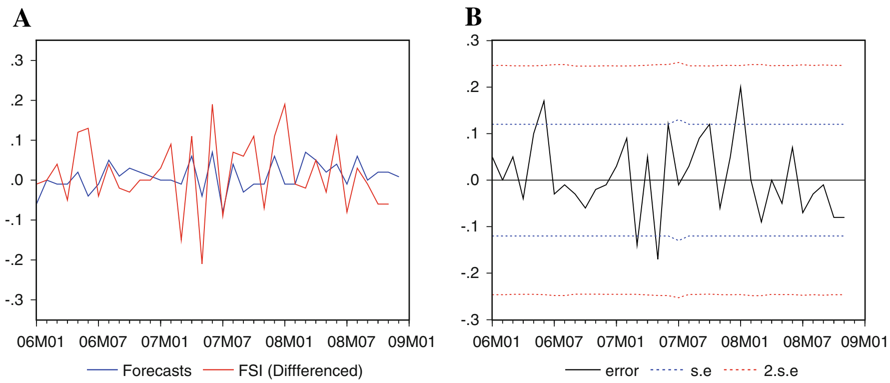

Fig. 4 Forecasting (1-L)FSI in-sample: **a** forecasting using ARIMA, **b** forecasting errors

FSI index is an integrated serie of order one $I(1)$[29] we employ an *ARIMA(p,r,q)* model. After analyzing the information criterions of Akaike, Hannan-Quinn and Schwarz, and the correlograms graphs, the most parsimonious model was an *ARIMA(2,1,1)*:

$$\begin{aligned}(1-L)\mathrm{FSI}_t &= 0.00037 + 0.5058(1-L)\mathrm{FSI}_{t-1} + 0.3979(1-L)\mathrm{FSI}_{t-2} \\ &\quad + \epsilon_t + 0.7487\epsilon_{t-1},\end{aligned} \tag{9}$$

where FSI_t is the stress index, L is the lag operator, and ϵ is the error term.

Using this model we forecasted the index. We started by performing in-sample forecast, so we estimated the model until December of 2005 and later we perform one-step-ahead forecasts until November of 2008. Figure 4a shows the observed values of the differences of index and the forecasting estimated for the model. Figure 4b shows the error term behavior.

Figure 5 illustrates the forecasts extrapolated on the index level. Under this approach, the forecast seems to underestimate the observed values but it does captures the trends, which is important for the stress financial analysis.

The forecasting in-sample results obtained from the ARIMA model have a goodfit if we compare then with the observed values of the index in first differences, but underestimate the values in levels. In the end, the forecasts can model the trend that the index will take in the future when *one-step ahead* forecasts are performed. Figure 6 presents the forecasts out-of-sample using the *recursive forecasts method*; where each forecasted value is replaced in the estimated model in order to generate forecasts periods ahead.

5.2 VECM: vector error correction model

From this perspective, we perform forecast for the FSI index taking into account the behavior of some macroeconomics variables. The variables that have been considered

29 We perform unit root tests that are not presented in this version but can be send upon request.

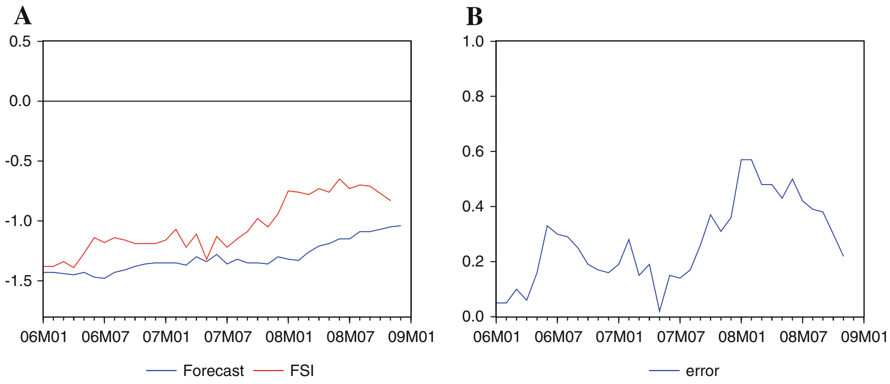

Fig. 5 Forecasting FSI in-sample: **a** forecasting using ARIMA, **b** forecasting errors

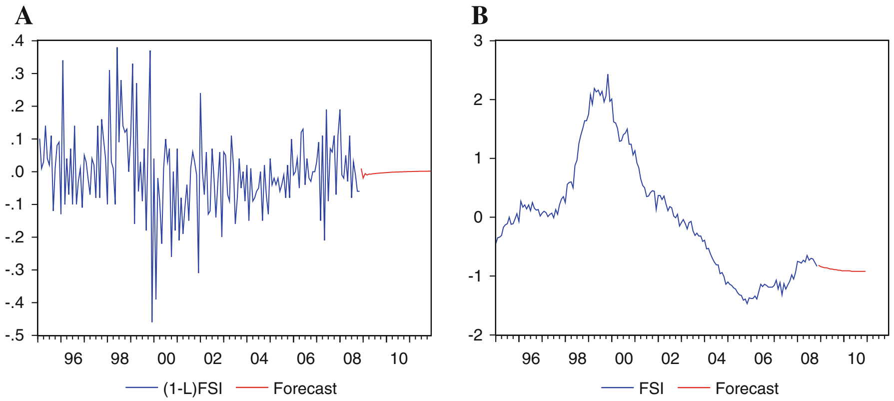

Fig. 6 Forecasting FSI out-sample: **a** (1-L)FSI forecasts, **b** FSI forecasts

are the inflation rate and unemployment rate, the Colombian monthly economic activity index (IMACO), and the new home price index (IPVN).[30] These variables were selected following the international literature and because there exist an available data set. Another important criterium to choose the variables is the causality relations between the macroeconomics variables and the index.[31]

High inflation rates have harmful effects on households' wealth and on optimal investment decisions. Likewise, a high positive variation on prices incentives rises on the interest rates in an inflation targeting framework. All the mentioned above cause a lower credit demand and given the rise on interest rates, the solvency ratios can diminish, in the sense that the rises on interest rates cause losses on bond portfolio value of financial institutions. Additionally they cause a higher household financial burden levels that could generate a higher quantity of assets weighted by risk given the rise in credit risk.

[30] IMACO and IPVN for their Spanish abbreviations.

[31] At the end, this causality relations were defined by the Granger (1969) causality test.

Thereby, we expect a direct relation between inflation and the financial stress index. In turn, unemployment rate has a positive relation with the index as well; with a higher unemployment rate a higher unpaid rate for the granted loans may be expected causing an increase on non-performing loans and high levels of financial stress.

A leading economic activity indicator was considered too. The IMACO index is used in order to take into account a variable related with production. It is expected that this variable presents a negative relation with the financial index, in the sense that a lower economic growth generates a higher ratio of non-performing loans to the total loan portfolio, besides from a lower profitability of financial institutions. Finally, the new home price index (IPVN) is taken as an approximation of household wealth, because real state represents one of the most important assets of Colombian households; this fact implies that a higher IPVN level increases the household debt capacity, given that the home can be used as a collateral. Then, it a negative relation between IPVN and the stress level is expected.

The selected variables are not stationary. On the contrary they are first order integrated $I(1)$. If there exists a long-run relationship between the variables, one possible approach to model the data set is through a vector error correction model (VECM). The Johansen cointegration test is used in order to find out the long-run relations of the series. The results suggests that there are two cointegrating vectors.[32] After estimating the model, we performed forecasts of the financial stability index (FSI), using the forecasts of the macroeconomic variables (see Fig. 7).

The results suggest that if the economy registers a lower inflation rate or a lower unemployment rate, additional to a high growth of new homes prices accompanied by a less negatives economic activity growth rates, then the financial stress level presented for the next eighteen months will be lower than the presented at the end of 2008 (Fig. 7).

6 Final comments

For policy makers and financial regulators, a measurement that can monitor the financial system on the time, and that generates a quality indicator of system period by period is a useful tool that gives a clear overview of the system vulnerabilities. Additionally, this measure helps to take timely and appropriate regulatory decisions in order to diminish the harmful effects caused by the crises and instability periods.

Considering that fact, in this paper we calculated a financial stability index that can be used to determine the stress level of the Colombian financial system. To that end, we used capital, liquidity, credit risk and return ratios for the various types of financial institutions. The index was constructed weighting the most relevant financial ratios through different methodologies suggested by international literature. The approaches used were the variance-equal approach, the principal components method and count data models. We constructed an index that presented a similar behavior under the three different methodologies and that, in general, gave a high weight to the profitability and credit risk ratios.

[32] The estimated model and test are not presented in the document, but can be send upon request.

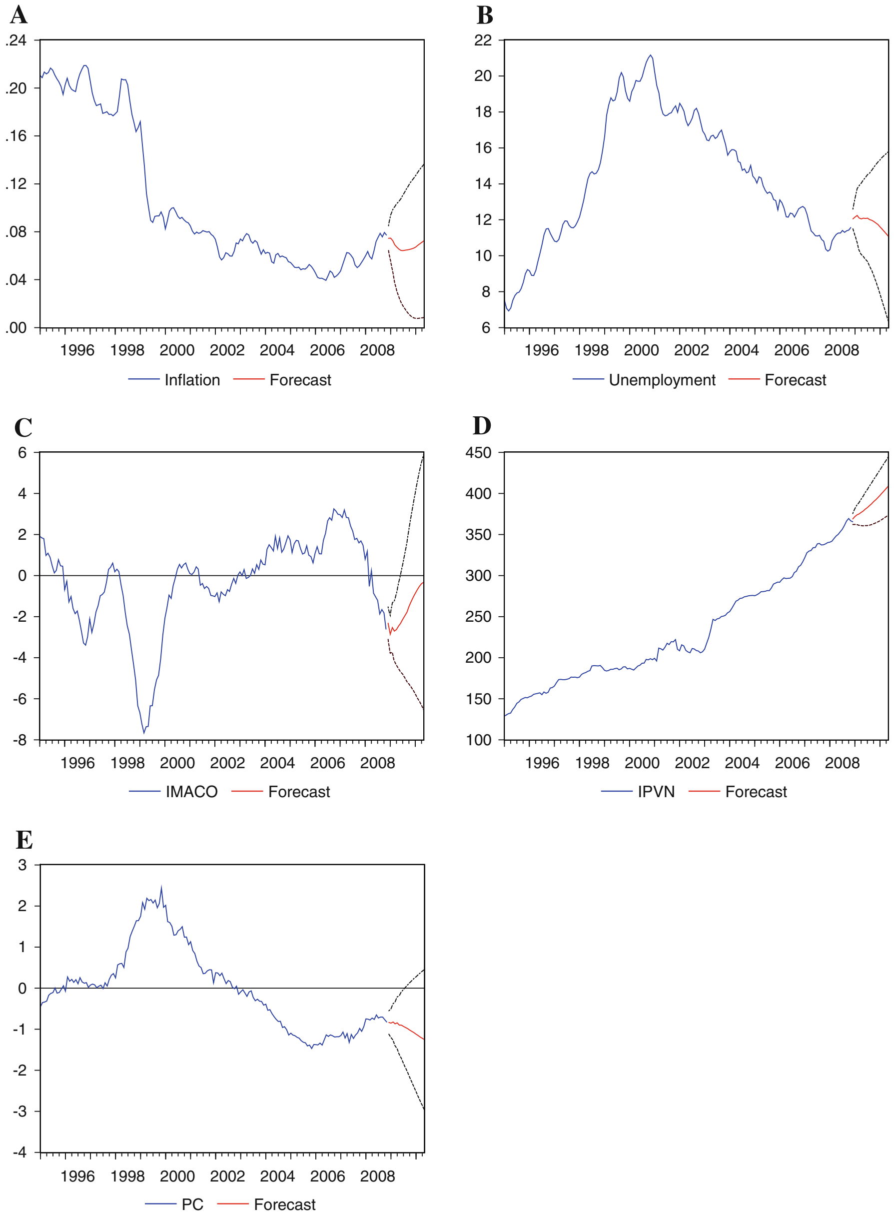

Fig. 7 Macroeconomics variables: **a** inflation, **b** unemployment, **c** IMACO, **d** IPVN, **e** FSI

Some methodologies used to construct the index present certain limitations that have to be overcome in studies that follow. The way in which that we established the thresholds in order to determine the dependent variable (Stress) was *ad hoc*, so it could be improved in the next studies. Additionally, the search for new methodologies that allows to generate accurate weights in order to complete the methodologies employed in this study will be necessary.

Regardless of the existent limitations in the methods used, the behavior of the index is accurate enough, and has a good fit if we evaluate the index with the historic crises and low financial stress periods. Actually, the indicator anticipates the Colombian financial crisis some months in advance, during which the index showed an accelerated growth in the stress level. Another attribute of the indicator is that it is a continuous and quantifiable measurement with a monthly periodicity, that allows an exhaustive monitoring plus it is easy to interpret and to express. Besides, one of the main contribution of this study to literature is that it generates stress financial indicators at an aggregate level and by type of institution, in order to have a detailed overview about the financial system situation.

As an additional exercise, we perform some forecasts of the financial stress index, with the purpose of having an intuition about the future behavior of stress level. For that, we develop two separate models: first, we estimate an autoregressive model (ARIMA) assuming that all the necessary information to forecast the future values is found in the indicator history; then we estimate a multivariate model (VECM) using macroeconomic variables as suggested by the international literature review.

This paper is a starting point for the development of early warning systems (EWS) and a financial stress index for Colombia. Likewise, we expect that the FSI can be used as a reference for future financial stability analysis, considering that the index is a continuous measure that could generate more information in the construction of EWS than a binomial model in which we define if we are in crisis or not.

Acknowledgments For helpful comments, we thank Dimitrios Tsomocos, Stefano Puddu, David Pérez, Javier Gutiérrez, Adriana Corredor, Juan Carlos Mendoza, the staff of the Financial Stability Department of Banco de la República and Alexandra Heredia. The opinions contained herein are those of the authors and do not necessarily represent those of the Banco de la República or of its Board of Directors.

Appendix A: Defining the dependent variable for the ZIP and ZINB Models

In order to perform the count data model we constructed a variable that quantify the failure entities or the number of entities with high stress level during each period. For the Colombian index, we constructed a variable that represents the quantity of entities that face some stress levels throughout time for a monthly periodicity. We made a statistical analysis for each entity during the period between 1994 and 2008 with the purpose of construct the dependent variable (Stress). The idea behind this was to determine the financial ratios of all the entities and evaluate it with respect a threshold, so we could define if the institution evaluated present financial stress or not.

Table 4 shows the thresholds used for the first selection criteria. These thresholds were assigned arbitrarily, but took into account a moderate level of financial stress. The method used consisted in analyze the balance sheet of each financial entity observed in period t, and then elaborated different ratios that were used to construct the index; these were the ROA, ROE, NP, LP, IS, LL, IF and ULR. With these ratios, we determined

Table 4 Established thresholds

Variable	Thresholds (%)	First criterium
ROA	3.00	$>Xi, t$
ROE	5.00	$>Xi, t$
NP	25.00	$<Xi, t$
LP	10.00	$<Xi, t$
LL	40.00	$<Xi, t$
IF	60.00	$<Xi, t$
ULR	0.00	$<Xi, t$
IS	15.00	$<Xi, t$

The thresholds were established *ad hoc*

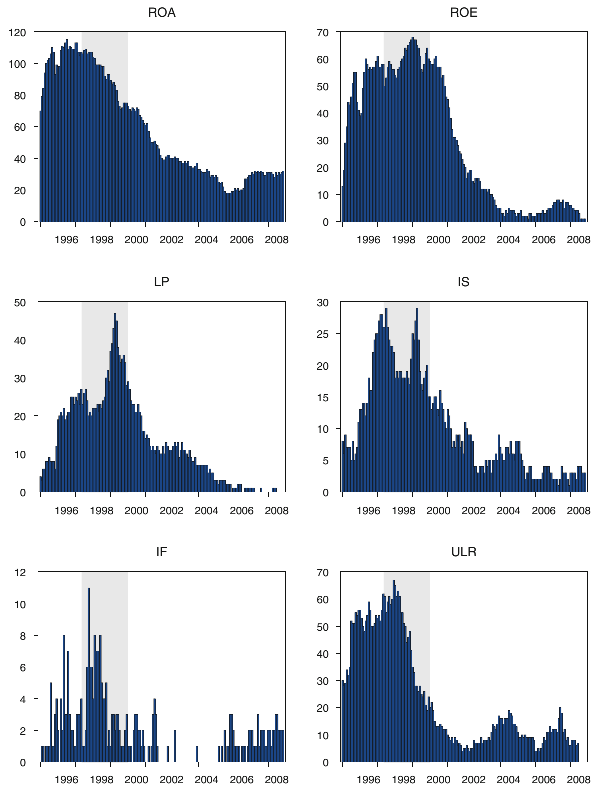

Fig. 8 Entities above certain threshold

the quantity of entities that were above or below the threshold, depending on case.[33] From this first analysis, the quantity of entities that fail some criterion are shown in Fig. 8.

[33] For example, when the ROA is analyzed, the Table 4 define a threshold of 3%, then an $entity_i$ fail this criterion if presents a ROA lower on period t.

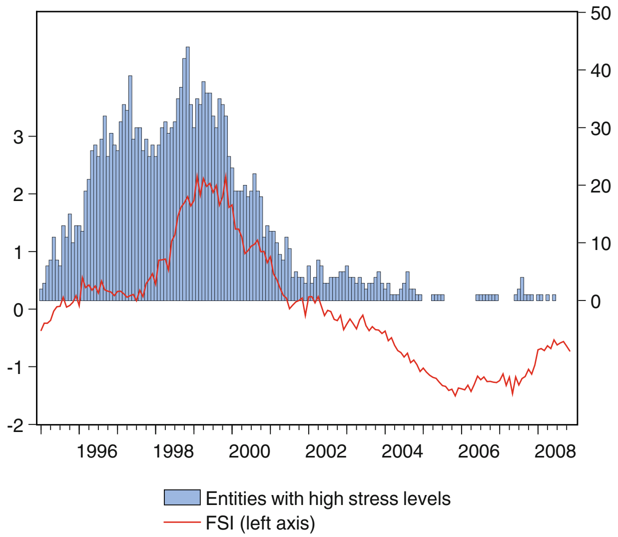

Fig. 9 Entities with high stress levels and FSI

After identifying the entities that did not satisfy the criteria defined previously, we defined the entities with weaknesses in their balance sheet on that period, taking those that failed more than three criterions in the same period t.

Figure 9 illustrates the number of entities with stress levels according to exposed criterions. It is possible to observe that in the crisis periods, the maximum is reached with a total of 44 entities, whereas for the 2005 and 2006 year, there are some months in which we did not find entities with high financial stress levels. This variable was used as the dependent variable in order to perform the estimations of the count data models. The explanatory variables were the financial ratios described above.

Figure 9 also compares the *Stress* variable with the system financial stability index (FSI); the index has a similar behavior to the presented by the variable *Stress*, this fact confirms the fit that the FSI with respect the stress level. Considering all the criterions explained above, during periods with a high number of entities with financial stress levels the index reach its maximum, while on periods when there are not entities with high stress levels, the index reaches its minimums.

Appendix B: Incidence rate ratio (IRR)

Coefficients associated to the no inflated part

The estimated coefficient of an explanatory variable i obtained by a Poisson[34] regression can be interpreted as the logarithm of the ratio of the expected values for the entities with high stress level evaluated on $i = n + 1$ and $i = n$ keeping the rest of variables constant. Equation 10.

[34] For the *Binomial negative* regression applies a similar analysis.

$$\beta_i = log\left(\frac{\mu_{i=n+1}}{\mu_{i=n}}\right), \tag{10}$$

where β_i is the regression coefficient and μ is the expected number of entities with high stress level. In this case, subscript indicates one unit change on the estimated variable. We can interpret the results as the logarithm of the quotient of expected events. Using exponential in both sides we obtain:

$$e^{(\beta_i)} = \frac{\mu_{i=n+1}}{\mu_{i=n}} = \mathrm{IRR}_i \tag{11}$$

The incidence rate ratio (IRR) is defined as the exponential of the regression coefficient; this IRR represents in expected relative terms how changes the dependent variable when the explanatory variables changes in one unit.

Coefficients associated to the inflated part

The regression coefficients estimated in this regime with a Probit model have to be re-scaled in order to make it comparable with the IRR.

Assuming a probit model:

$$y = x\beta + \epsilon \tag{12}$$

where,

$$y = \begin{cases} = 1 & \text{if } y* > 0, \\ = 0 & \text{if } y* = 0 \end{cases} \tag{13}$$

Given the explanatory variables, the probability to obtain $y = 0$ is showed in the following equation:

$$P(y = 0|x) \equiv 1 - \Phi(x\beta) \tag{14}$$

where $\Phi(x\beta)$ is the cumulative distribution function of the error term ϵ evaluated in $x\beta$. If we assume an explanatory variable, for example ULR, and a constant $\hat{\alpha}$ and we define ρ as the quotient between $P(y = 0|x)$ when ULR $=1$ and the same probability when ULR $=0$ then we have:

$$\rho \equiv \frac{P(y = 0|\mathrm{ULR} = 1)}{P(y = 0|\mathrm{ULR} = 0)} \tag{15}$$

The ratio ρ is defined as a function of the parametrization and the estimated coefficient β_{ULR} and $\hat{\alpha}$. We interpret that coefficient as follows: with an one unit increase on the explanatory variable then the probability to obtain $y = 0$ rises in ρ.

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