Exploring the Financial Conditions – Economic Conditions Nexus: Empirical Evidence from Developed and Developing Countries

Initial Draft – Please do not quote

Andreas Tsopanakis[#]

Abstract

Systemic financial crises can lead economies to major instabilities and, eventually, economic and financial losses. For this reason, there is a need for tools capable of indicating whether a financial catastrophe is on its way or not. This paper contributes to the relevant literature, by constructing a series of financial stress indices for 25 countries. The countries are grouped into three bundles (OECD, Asian, Latin American countries) and, apart from the national indexes, regional and a global index are being computed. In order to do this, a number of variables from the banking sector, financial and capital markets and the foreign exchange market of each country, have been used for the implementation of these indicators. The results are promising, showing that these indexes perform well, successfully capturing previous financial stress periods, while the financial turmoil of 2007-2009 is, without doubt, the most severe one. Also, empirical evidence is provided on the capability of these indices to work as successful predictors of the forthcoming macroeconomic conditions in the economies studied here. Finally, some propositions are made on how this kind of financial fragility tools can be improved and further research paths are also identified.

JEL Classifications: C43, G01, G15, F37

Keywords: Financial Fragility, Financial Stress Index, Monitoring, Forecasting

#University of Glasgow, Department of Economics, Adam Smith Building, G12 8RT, UK, tel: (+44) 0141 330 3323, email: a.tsopanakis.1@research.gla.ac.uk

1. Introduction

Financial crises are an integrated part of the function of the world economies. Their implications can be quite severe, leading to huge economic and financial losses, together with an unprecedented misallocation of income and resources in the economies. That is the main reason a lot of research effort has been focused to the study of these financial instability issues, the last two decades. A considerable number of papers have been published, dealing with this topic, suggesting and empirically applying a series of econometric techniques, mainly trying to offer useful tools for crises episodes' predictions. The results were interesting, but partial, in the sense that most of these models were dealing with specific types of financial upheavals (either balance of payments, banking or currency ones), while the modeling approaches employed could not offer a tool able to capture the current situation in the financial markets, in a timely manner and of a continuous nature.

The previously mentioned weaknesses of the crises models can, probably, be overcome by the implementation of a financial stress index (FSI henceforth), which is a composite indicator, consisting of a series of properly weighted financial variables, offering an overview of the financial markets health. This approach exhibits a number of advantages, like the easiness in the construction, together with the ability to offer a continuous, uninterrupted picture of the conditions in the financial markets. In this paper, we proceed to the construction of such indices for 25 countries, together with the computation of three regional ones, after grouping the countries in their respective bunch (OECD, Asian and Latin American countries). Moreover, we present a global financial stress index, which is the outcome of the aggregation of the three regional indexes. Additionally, an analytical exposition of the type (according to which market was the source of each episode, either banking, securities or foreign exchange-related) and the average duration of the financial distress experienced by each country and region, is being provided. As it will be made clear, these indices seem to perform quite well, for most of the regions and countries. It is by no surprise the fact that the current financial crisis, initiated on 2007, has been proved to be the most severe one for most of the countries, at least for the time period that reliable data are available. Hence, we believe that this piece of work contributes towards the creation of a more efficient financial stress index, where efficiency coincides with higher accuracy on signaling financially stressful periods. Finally, a forecasting exercise is materialized, aiming to provide empirical evidence on the relation between the financial conditions prevailing in an economy and the respective macroeconomic situation. It is shown that a model where our financial stress index is included can provide more accurate forecasts for each economy's future economic activity. In our knowledge, this is the first attempt to use such aggregate measures of financial risk and stability in such an empirical framework, for a such big and diverse group of economies.

This paper is organized in five sections, the contents of which are as follows. In section 2, an short review of the financial stress literature is offered. Section 3 provides a description of the data, together with an analytical presentation of the empirical approach implemented in the construction of our financial stress indices. Section 4 discusses the results of our financial stress indices' construction work, while the section 5 develops a model for testing the forecasting properties of a FSI-augmented model. Finally, section 6 concludes, together with a brief discussion of further research paths, able to improve these kinds of indices functionality and usefulness as forecasting tools.

2. Literature Review

The literature on financial stress (or, as some of the authors call them, financial fragility) indices (FSI), has mushroomed the last decade. It is a branch of the research developed as a continuation of the early warning indicators (EWI) literature, models that have been used in previous empirical work on, mainly, currency and banking crises episodes. As it will be made clear, these two approaches on modeling periods of financial crises look similar, although, they have quite distinctive characteristics. First of all, previous models were models analyzing country-specific or only specific types of crises episodes (either, currency, banking or balance of payments crises). The most recent periods of turmoil (especially, the sub-prime crisis beginning on 2007) showed that crises are systemic-wide and are not confined to a single market of the economy anymore. Also, exactly because of this nature of financial crises, there is a need to alter the modeling approach followed up to now, in order to be able to capture this special feature of modern financial abnormalities. Before, wide use of binary choice models (either probit or logit ones) has been made, predetermined in this way the outcome (being a choice between a crisis or non-crisis state) for each time period under consideration. With the FSI approach, a series with continuous values is provided, offering a timely illustration of the market conditions, thus, better monitoring of the financial system is possible. Moreover, most of the work done was focused on developing economies, something justifiable by the fact that these economies were the most vulnerable to periods of financial instability. Recent abnormal periods showed that new tools of monitoring the stability of the financial system are needed, able to anticipate the sources of financial stress and, most importantly, to be easily implementable and used as forecasting tools, in order to provide accurate and swift indication of forthcoming periods of instability. The relevant literature, discussed here, provides some answers to these complex and interesting issues.

In their work, Illing and Liu (2006) outbid for the creation of an FSI as a well-suited index of financial stress for developed economies, compared to other early warning indicators. According to their justification, such a stress index is more suitable because it is a continuous, high frequency reference variable, covering a range of markets (equity, bond, forex and banking ones), and hence, takes into consideration the complex issues of financial stability in advanced economies. The authors are mainly interested into three tasks here. First, they want to specify which time periods can be considered as stress periods for the Canadian economy, then which variables they should use to create their FSI and, finally, which one of the different FSI's they compute is the most efficient. For the first task, they conducted a survey within the Bank of Canada economists, collecting answers on a series of questions. Then, having specified the financially abnormal periods, they experiment with different methodologies and a series of variables, in order to develop a financial stress index for the Canadian economy. They construct three measures of financial stress. The first one is the standard measure, as they call it, where the variables used are those proposed by the relevant literature on the financial markets (and described afterwards), the second one, called the refined measure, contains only those variables that can be refined and, thus, potential extra information can be extracted and, finally, a measure based on GARCH techniques is constructed for the "price" variables (Canadian general and banking sector equity indices and the Can$/US$ exchange rate). In particular, the variables that were included to their index are the following: the beta of the Canadian banking equity index and the bank bond yield spread (from the long-term governmental bond yields), representing the situation in the banking sector of the country. For the foreign exchange market, they focus on the Canadian dollar volatility, using the CMAX calculation as a measure of it[1]. For the refined approach, they implement the following model, in order to gauge the exchange rate to its short-run fundamental value:

$$\begin{aligned}\Delta \ln\left(rfx\right)_t &= \alpha \ln\left(rfx\right)_{t-1} - \beta_0 - \beta_c \ln(comtot)_{t-1} - \beta_e \ln(enetot)_{t-1}{}^{2} \\ &\quad + \gamma \, intdif_{t-1} + \theta \Delta debtdif_{t-1} + \varepsilon_t \end{aligned} \qquad (1)$$

Then, regarding debt markets, they use the Canada-US covered interest differential and the corporate bond yield spread (from the long-term government bond yield) as indicators of the prevailing credit risk in the market, while, liquidity risk is captured here from three variables: the treasury bill bid-offer spread, the so-called TED spread, which is the difference of the commercial paper rate from the treasury bill rate and, finally, the inverted yield curve (long-term government bond yield – 90-day commercial paper rate). Trying to further refine their work, Illing and Liu (2006) apply different weighting scheme on their variables, so as to identify which one leads to the creation of a single FSI that outperform the rest of them and, consecutively, is the most efficient in capturing period of financial turmoil. They try four methodologies, factor analysis (which uses weighted linear combinations of the variables), credit weights (the contribution of each market to the total credit available in the Canadian economy is the important factor here), the variance-equal weights approach (by standardizing each variable by subtracting its mean and dividing the result by its standard deviation) and they also use the variables cumulative distribution functions to combine them (this scheme requires the transformation of each series into percentiles, based on its CDF and, then, average them using their arithmetic and geometric means). Based on the different indices' performance (in terms of Type-I and Type-II errors, as defined by their survey for extreme events in the Canadian economy and the capability of the indices to capture them), they conclude that the best financial stress index seem to be the credit-weighted one, although, in individual markets, some other indexes might perform quite well (for example, the GARCH measure for the stock market).

Recognizing that there is a gap on financial stress measuring for Colombia, Morales and Estrada (2010), seek to compute an FSI à la Aspachs et al. (2006). In this sense, they include banks' profitability and probabilities of default, as components of their indexes, together with a series of variables that sketch out the capital, liquidity and credit risk conditions in the country's financial markets. In order to improve the value of

[1] $CMAX_t = x_t/\max[x \in (x_{t-j} | \, j=0,1, .., T)]$, where x_t = value of canadian dollar vis-à-vis US dollar and T=one year time period.

[2] Here, rfx is the real exchange rate, comtot is an index of real non-energy commodity prices, enetot an index of real energy prices, intdif the Canada-US 90-day commercial paper rate differential and debtdif is the Canada-US debt/GDP differential.

their FSI, the authors construct one for each different type of financial institutions that operate in the Colombian market. These are commercial banks, mortgage banks, commercial financial companies and financial cooperatives. Their sample is comprised of 170 institutions, for the period 1995.1-2008.11, with data on monthly frequency to have been used. The variables that were invoked in their model were the following: returns on assets, returns on equity, non-performing loans/total portfolio, net loan losses/total loan portfolio, intermediation spread (lending rate – deposit rate), liquid liabilities/liquid assets, ration of interbank funds to liquid assets, uncovered liabilities ratio and the number of financial institutions with high stress level in each time period[3]. Additionally, they apply three different weighting schemes; the most commonly used variance-equal weighting, principal components analysis and count data modeling. According to this work, the FSI behavior, irrespective of the weights applied, is similar and accurately represents the financial instability period of the Colombian economy on late 90's. The same holds for the institutional indices as well. In the final part of this piece of work, the authors perform a forecasting exercise, checking whether it is possible to predict future values of the FSI. They use two models, an ARIMA one and a VECM. In the first case, the model seems to underestimate the observed values of the index, but captures the trend, while the VECM model, where four macroeconomic variables have also been included (inflation, unemployment, an economics activity index and a home price index), the forecasted FSI decline for the next 18 months.

Important research on financial stress has been conducted by the economists of IMF (2008). In their paper, they seek to create a FSI, able to accurately catch previous crisis episodes and analyze them for 17 advanced economies. Their approach is very similar to the one followed on the empirical part of this piece of work and embodies seven variables for the banking, securities and foreign exchange markets. These are the banking sector beta, the TED spread and the inverted term spread (for the banking sector), corporate spread (corporate bond yield – long-term government bond yield), stock decline[4] and time-varying stock volatility [representing by a GARCH(1,1) volatility model of general stock index] for the securities markets and the time-varying real effective exchange rate volatility (modeled as the stock volatility) for the foreign exchange market. In order to aggregate these constituents into a single index, they follow the equal-variance weight approach and, finally, they rebase it to range from 0 to 100. They identify periods of financial stress as those where the index is at least one standard deviation above its trend. Thus, they provide individual FSI's for these 17 economies, although they provide graphical evidence only for 6 of the countries, while they do not exert to provide any aggregate (in other words, a global) FSI. Additionally, they present an account of the number of episodes, for all the countries, in the last three decades, disaggregating them according to the source of each of these upheaval periods (whether they stemmed from the banking, securities of foreign exchange markets). Their index is able to capture 90 percent of the banking-led crises and more than 80 percent of the

[3] In order to determine this number, they set threshold values for all the aforementioned variables and, according to these thresholds, they could evaluate whether a financial institution was or not in stress in each time period.

[4] Stock index at t-1 minus stock index at t, divided by stock index at t-1.

currency crises. Finally, following a methodology developed by IMF[5], the authors distinguish the stress periods identified before which were followed by a recession. Thus, they infer that banking distress periods are more often followed by severe downturns, compared with foreign exchange or securities-borne crises periods and, also, that a financial crisis can be more protracted whenever the economy is characterized by increasing expansion of credit, a surge in house prices and expanding borrowing by households and firms.

Following a similar to the IMF (2008) empirical methodology, Melvin and Taylor (2009) narrate the repercussions of the subprime crisis to the foreign exchange market, while they proceed to the creation of an FSI which, according to the authors, might be successfully used as a predictor of any future excessive negative returns in the foreign exchange market. They do it for seventeen countries (the same as those used by the IMF), for the period December 1983 to October 2008. The distinctive feature of this piece of research is that they exclusively focus on the so-called global FSI, which was computed by simply averaging the national indices. According to established threshold of considering a period as a stressful one whenever the index is at least one standard deviation above its mean, they comport in favor of its performance. Especially for the current crisis, and for the situation sketched previously for the foreign exchange market, the authors believe that the index is quite effective to capture the foreign exchange market irregularities (mainly after the collapse of Lehman Brothers). Finally, the perform a simple prediction exercise, by employing a simple binary probit model, where the depended variable is a binary variable, representing periods of significant negative returns to an investment in the Deutsche Bank Carry Index and the FSI is the exogenous variable. The results are promising and provide an initial testimonial for the usefulness of such kind of indices as forecasting tools.

The questions of how severe the current financial crisis is for advanced and emerging economies, together with an investigation of whether some level of financial distress has been transmitted to emerging from the advanced economies, are provided with an answer to the paper by Balakrishnan et al. (2009). In order to do this, they first construct FSIs, using monthly data, for 26 countries, for a period from January 1997 to the latest available for each one. Their methodology is quite similar to the one used by Cardarelli et al. (2009), with two notable differences: the use of the sovereign debt spread[6] and the calculation of an exchange market pressure (EMPI) index for each of the countries. Thus, their FSIs consist of the following five variables: the banking sector beta, stock market returns, stock market volatility, sovereign debt spreads and the EMPI. Finally, these individual variables standardized values are aggregated, so that each country's FSI (EM-FSI) is created. Assuming that whenever the EM-FSI breaches the threshold of one and a half standard deviation above the mean is an indication of financial stress, the authors conclude that their indices perform quite well in capturing periods of intense financial upheavals. The next step in their research is the use of a fixed effects

[5] According to this methodology, an episode of financial stress is followed by a recession if a peak-to-trough business cycle begins within six quarters of the onset of the financial crisis.

[6] It is the difference between country's bond yield from the 10 year US Treasury yield, using JPMorgan Global spreads in the construction of this interest rate differential (or, whenever such data are not available, they used the 5 year CDS spreads).

panel model, in order to check if a co-movement factor of their EM-FSIs exists. Their model specification is: $EMFSI_{it} = \alpha_i + \sum_t \rho^t Month_t + \varepsilon_t$ (4)

in which α_i = country-specific fixed effect and $Month_t$ = dummy variable for month t. In this way, ρ^t represents the common time-varying element of each index. By estimating the model, Balakrishnan et al. (2009) found that, about, 50% of the EMFSI variation is explained by this common factor. Naturally, their interest was turned to the identification of the determinants of this common component (ρ^t). In doing so, they employed the following model: $\rho^t = \alpha + \beta AEFSI_t + \sum_g \gamma^g GF_t^g + \varepsilon_t$ (5)

in which AEFSI represents the advanced economies FSI (as taken by previous research from IMF) and GF are the so-called global factors[7]. From this model, they infer that 41 percent of the common component variation can be attributed to the AEFSI. Having established a relation between financial stress in emerging and developed economies, the authors proceed to further investigation of this relation, by using a two stage technique. This approach offers insights in the stress co-movement intensity (on stage 1), while stage 2 indicates cross-country variations in these co-movements. Thus, for the first stage, EMFSI is regressed on AEFSI, the global factors and EMFSI[8] with one lagged value, while they also take into account advanced economies regions (namely US/Canada, Western Europe and Japan/Australia). The model representation is the following:

$$
\begin{aligned}
EMFSI_{it} = \alpha_i + \sum_c \sum_{l=0,1} \left(\beta_i^{cl} AEFSI_{t-l}^c + \sum_{\tau=1,2} \beta_{\tau i}^{cl} D_\tau AEFSI_{t-l}^c\right) + \\
\sum_g \sum_{l=0,1} \gamma_i^{gl} GF_{t-l}^g + \sum_{l=0,1} \delta_i^l \overline{EMFSI_{it-l}} + \lambda_i EMFSI_{it-1} + \varepsilon_{it}
\end{aligned} \tag{6}
$$

Here, AEFSI can be, as the authors state, "an aggregate of 17 major advanced economies or three separate aggregates, indexed by c", for the three regions defined previously. Additionally, in the first brackets, dummy variables are included, in order to capture the effects of two (τ =1, 2) crisis episodes that could have affected the advanced economies[9]. Here, the estimation results are quite good, showing that financial stress transmission is strong enough (on average, 70% of it is transmitted from advanced to developing economies, while financial contagion from other emerging markets is also important. In most of the cases, it was found that only one to two months are needed for this transmission to happen, while the size and source of this spillover varies. Regarding the second stage of this analysis (examination of cross-country variations in these co-movements), the model used is the following:

$$\beta_{\tau i}^{c} = \alpha_i + \sum_\kappa \alpha_\kappa FL_{i\kappa}^{\tau c} + \alpha_l TL_i^{\tau c} + \sum_m \alpha_m X_{im}^{\tau c} + \varepsilon_{\tau i}^{c} \tag{7}$$

[7] Here, they are the year-over-year changes in world industrial production, commodity prices and the 3-month LIBOR.

[8] Excluding, in each regression, the country under investigation.

[9] The first one is for the period 1998-2003, covering LTCM crisis, dot-com bubble and Enron, Worldcom and Arthur-Andersen corporate scandals. The second episode in the sample is the sub-prime crisis.

in which the country-specific regional co-movement parameters are a function of the bank lending. Portfolio investment and direct investment to GDP ratio (FL), the total exports/GDP (TL), trade/financial openness (X). In this case, the financial linkages are proved to be more important than trade, while country-specific factors do not seem to be that crucial here. The final econometric exercise in this piece of research has to do with the potential relation of the FSI with country-specific variables. These estimations have been conducted in an annual frequency panel model, with the following form:

$$\begin{aligned} EMFSI_{it} &= \alpha_t + \beta AEFSI_t + \sum_j \xi^j X_{it-1}^j + \sum_j \theta^j AEFSI_t \times X_{it-1}^j + \\ &\quad \delta \overline{EMFSI}_{it} + \sum_g \gamma^g GF_t^g + \varepsilon_{it} \end{aligned} \tag{8}$$

where, the only extra variable is the interaction of the AEFSI with the country-specific variable X. The estimations results here provide evidence the β is highly significant, while δ is positive and larger than 1. The opposite effect is valid for the openness variables included in X (positive for the financial ones, negative for the trade ones). As a consequence of all this analysis, the authors suggest that emerging economies with low current account and fiscal deficits are more protected from financial stress transferred by advanced economies although, in cases of widespread crises, their effect is not that important.

A first attempt to construct an FSI for the Euro area has been made by Grimaldi (2010). Based on the indicators proposed by Nelson and Perli (2006), the author has a threefold intention: to specify the actual stress period for the Euro zone markets, to compute relevantly accurate indices and test whether her index can work as a leading indicator of stressful events. For the first goal, the author employs information contained in European Central Bank's communication (using ECB's Monthly Bulletins) to help her measuring financial market stress. In this way, she indicates periods that seem to reflect periods of financial upheaval[10]. In order to verify these findings, a financial fragility index is built, using sixteen variables from the bond, banking, equity and money markets. Specifically, the difference between each Euro zone's country long term bond yields from the German one represents the sovereign bond spreads. Then, for the banking sector, bank equity prices index and the AA-rated corporate bond spreads are used as proxies of the conditions prevailing in this sector. General equity index, actual earnings per share and equities risk premium were chosen for the equity market component of the indicator. Finally, regarding money markets, one and three month Euribor-EONIA rates spreads, together with the spread of the main refinancing rate and the two year bond yield were utilized. Moreover, a string of risk aversion measures have been included, like implied bond, stock and futures volatility. All these variables were then integrated into two indices, the first being the weighted (by the inverse of each variable's variance) average of them, while the second one is the rate of change. Finally, these two indexes were combined into a single indicator, with the help of a logit model, so that extraction of information on stressful periods to be more effective. The logit model is of the following form: $S_{t+h} = L\left(\beta_0 + \beta_1\lambda_t + \beta_2\delta_t\right), h \geq 0$ (9)

[10] This has been done by counting how many times specific words appear in the bank's bulletin.

where λ_t and δ_t are the weighted and the rate of change indices respectively, L is the logit probability distribution function, β's are the model's coefficients and S_{t+h} is a binary (0,1) variable, representing stress or tranquil periods. As it is obvious, whenever h is equal to zero, the model exhibit the contingent FSI, otherwise, the estimated model provides a forward indicator. Using weekly data for the period July 1999 to October 2009, the contingent financial stress index works well and captures crises periods of the last 10 years. Grimaldi confirms the good functionality of her FSI, comparing its performance with the VSTOXX index[11] and the signaling methodology, popularized by Kaminsky, Lizondo and Reinhart (1998). The last of the previously mentioned goals of this research (testing whether this index can be a leading indicator for stressful events) was accomplished by using the forward indicator version of the logit model, together with a slight transformation of the dependent variable of it. Now, the regressand has the following form: $$S_{t+h} = \begin{Bmatrix} 1 \text{ if } \exists h = 1,...k \ s.t. \ S_{t+h} = 1 \\ 0 \text{ otherwise} \end{Bmatrix} \quad (10)$$

, stating that the occurrence of a stress event can be at any point within a specific time frame. The author uses this model for a time window of 24 periods and figures out that it performs efficiently in this task as well.

A considerable effort is being made to introduce such policy tools in the central banks' financial monitoring ammunition, especially from economists of the US Federal Reserve System. A recent example of this is the work done by Hakkio and Keeton (2009), who introduced the Kansas City FED FSI (KCFSI). Their index consists of eleven variables. In more details, KCFSI consists of the following variables: the TED spread (3-month LIBOR – Treasury bill rate), the 2-years swap spread (which is the difference between a floating rate payment, based on LIBOR, from a fixed rate payment, which derives from the treasury bill rate, augmented by a premium), the yield differential of previously issued securities from the most recently issued one, of the same maturity (called as the off-the-run – on-the-run ten year treasury spread). Additionally, a number of bond spreads are also included in this index[12], together with the correlation of the stock returns with the two-year governmental bond yield, the implied volatility of the stock prices[13] and the idiosyncratic volatility of the bank stock prices (calculating as the standard deviation of the banks stock index daily returns from the S&P 500 index). Finally, the KCFSI is completed with the inclusion of the cross-sectional dispersion of bank stock returns (computed using the interquartile range of banks' stock returns). The authors have used principal components analysis to decide upon the weights of each of these variables, while they employed monthly data for the period February 1990 to March 2009. Inspecting the performance of KCFSI, they show that it works relatively well, with only two financial crises (the Mexican and the Asian ones) not being captured by the index (according to the authors, because of the limited spillover effects of these episodes to the US financial markets). In order to test for the effect of financial stress to real economic activity, the authors proceed to a comparison of the KCFSI values with the

[11] It is an implied volatility index, based on equity option prices.

[12] These are the Aaa – 10-year government bond spread, the Baa – Aaa bonds spread, high yield (i.e. junk) bond - Baa bonds spread and the difference between consumer ABS from 5-years Treasury bond.

[13] The authors use the well-known CBOE volatility index, mostly known as VIX index, representing the expected volatility in S&P 500 index in the options market.

SLOOS values (it is an index showing how tight credit standards are). Regressing SLOOS to lagged values of it and of KCFSI, they found out that KCFSI tends to lead changes in credit standards, while the same holds for the interrelation of KCFSI with CFNAI (Chicago FED's index of economic activity). Econometric estimations indicate that KCFSI helps predicting CFNAI values, showing that financial stress can lead to slower economic activity (also, the previously established relation of KCFSI with SLOOS implies such an adverse effect of financial conditions to the real economy, through the changes on the credit standards).

An investigation of the relation between financial conditions and economic activity, through the use of both single and composite financial indicators, has been accomplished by Hatzius et al. (2010). Apart from the empirical work, this paper provides an excellent theoretical account of the importance of the financial conditions for, both, the assessment of the monetary policy decisions effectiveness and the future economic activity. Their final target is the creation of a new FCI which overcomes the limitations of the previous ones. These are the limited time span, the exclusion of important financial conditions because of the aforementioned limitation and the lack of purification of previous indexes from the effects of the business cycle and of the monetary policy changes (as they are projected on the financial indicators incorporated to them). Thus, they decide to use 45 indicators for their new FCI, indicators representing interest rate spreads, asset prices, quantities and survey indicators. Two are the main criteria for the choice of variables, the wider time coverage, comparing to previous FCIs and the long data history, going back at least to 1970's. In order to construct this aggregate index, they use principal components analysis, but with some special characteristics (compared to previous cases): first, the authors allow for unbalanced panels (meaning that the data series do not cover the same time period, nor are they of the same frequency), second, they eliminate the variability of the included indicators which can be attributed to current and past influence of real economy variables and, finally, they use more than one principal components in the analysis. Their model has the following form:

$$X_{it} = \mathrm{A}_i(L)Y_t + v_{it} \quad (11)$$

$$v_{it} = \lambda_i F_t + u_{it} \quad (12)$$

where X_{it} = financial indicator i, Y_t = vector of macroeconomic indicators and v_{it} = error term uncorrelated with current and lagged valued of macroeconomic indicators. Hence, the error term represents the financial variables purified by the business cycle effects which, in turn, is decomposed to the F_t =kx1 vector of unobserved financial factors that capture the co-movement of the financial indicators. This vector should be estimated for the acquisition of the FCI. Based on the approximate dynamic factor models' literature, which suggests that least squares estimations of this vector are accurate for use in forecasting exercises, the authors consider this approach to obtain estimates of F_t. Inspecting the performance of the FCI, it is found that it behaves similarly to the previous indices, with the exception of the second half of 2009, where it shows a further worsening of the financial conditions. Proceeding to the evaluation of the forecasting accuracy of this and previous FCIs, the author firstly test the predictive ability of a number of single-variable financial indicators. These are the term spread (10-year Treasury note – federal funds rate), the real M2, the S&P500 stock index, the level of federal funds rate and the short-term credit spread (3-month commercial paper rate – 3-month Treasury bill rate). Using these indicators, they try to predict (in 2 and 4 quarters ahead) the growth rate of the following macroeconomic variables: real GDP, payroll employment, industrial production index and unemployment rate. They do it both in- and out-of-sample, while the regression specification is $y_{t+h} - y_t = \beta_0 + \sum_{i=1}^{p_y} \phi_i \Delta_{y_{t+1-i}} + \sum_{i=1}^{p_x} \gamma_i x_{t+1-i} + e_{t+i}$ (13)

with y_t representing the real activity indicator in each case, while x_t is the respective financial indicator. The number of lags, for both cases, was restrained to four. For the post-sample prediction, the authors use the same specification as previously, recursively estimated through the end of the sample period (fourth quarter of 2009). Here, lags for the explanatory variables were chosen according to the BIC criterion. The out of sample forecasts constructed for the period 1971Q1 onwards and they were compared with forecasts from an AR model (that is, excluding the financial indicator variable). For the in-sample forecast, it is found that the financial indicators are useful in explaining the variability in real economy variables, for both two and four quarters ahead. Apart from the stock market index, the rest of them present high instability, something that can be possibly attributed to changes in the financial structure of US economy through time. Regarding the out-of-sample prediction results, the models with financial indicators provide satisfactory results, only until the mid-80's. Additionally, they become in par with the simple AR model in the most recent period (last five years), while S&P500 and the credit spread did quite well the last decade. Checking the out-of-sample predictive performance of a number of FCIs[14], the improvement on the forecasting accuracy is general, especially at periods which are recognized as financially stressful ones. But, on average, they are not better than the stock market index, while the most noticeable improvement for the FCI model performance is during the last decade. Moreover, during the 90's, some of these financial conditions index are not better than the simple AR or the single indicators models. The results are rather mixed but this does hold for the authors' FCI, which performs better than the rest of the models (and the previous FCIs models) for the last five years, but not for the second half of the 1990's.

Brave and Butter (2011) use a dynamic factor model that allows the inclusion of unbalanced series in the index. In this way, they take into account one hundred financial indicators for the US economy, with different frequency and time coverage (47 of them are weekly, 29 monthly and 24 quarterly series, covering the period 1971-2010). This model is similar to the one discussed in the previous paragraph. Additionally, in order to capture the effects of the economic conditions (apart from the financial ones), they compute the so-called adjusted-FSI, by including the aforementioned CFNAI index and inflation in their estimation procedure. They do so by, first, regressing each individual financial indicator on current and lagged values of CFNAI and inflation and, second, the standardized residuals from these estimations are used in the construction of the adjusted-FSI. By inspecting these two indices, they conclude that both perform well, except a few cases where they do not (especially at the beginning of their sample in early 70's). Finally, the authors perform a forecasting exercise, similar to the one proposed by Hatzius et al. (2010) and, also, conducted here. Questioning whether FSI predicts any

[14] The authors do this using the same specification as in equation (13), but this time the individual financial indicator x is replaced by the FCI under consideration each time.

impacts of financial conditions to economic activity, they try to check whether the predictive ability of a model where the FSI is included, is superior to a simple AR model which includes only autoregressive lags of a number of macroeconomic variables. The model used for this forecasting exercise is

$$Y_{t+h} - Y_t = \alpha + \sum_{i=1}^{I} \beta_i \Delta Y_{t+1-i} + \sum_{j=1}^{J} \gamma_j CFNAI_{t+1-j} + \sum_{k=1}^{K} \delta_k FCI_{t+1-k} + \varepsilon_{t+h} \tag{16}$$

where, Y_t = logarithm of the macroeconomic variables[15]

CFNAI = 3-month moving average of CFNAI

FCI = 13-week moving average of adjusted FCI, FCI residual or adjusted FCI residual[16] (depending on specification). They recursively forecast for horizons of 1, 2, 4 and 6 quarters ahead, starting with data from 1973Q1 through 1984Q4. The evaluation is done through the calculation of the mean squared forecast error (RMSFE) ratio, which provides the ratio of the AR forecasts of the macroeconomic variables over the aforementioned model. If RMSFE <1, there is an improvement on predictive accuracy, when a version of the financial stress index is included in the model. According to the results, the inclusion of the FCI residual (together with the CFNAI) improves forecasts at every horizon and for every variable.

3. Data Description and Methodology

Our dataset is comprised of monthly data for three different groups of countries. The time span differs, not only between the groups but, sometimes, between the countries within the same group, due to problems of data unavailability. Countries' grouping has been done by taking into account the differentiation between advanced and emerging economies, but mostly, based on the regional economic links between them. Thus, we have a group of OECD economies, representing the most advanced economies in the world, a group of Asian countries[17] and, finally, a group of Latin American economies[18]. The methodology followed to construct the financial stress indexes presented in the following section, is the one proposed by IMF (2008).

The Financial Stress Index (FSI from now on) is a composite indicator, is constructed using seven variables for the following three economy sectors: the banking sector, the securities markets (stock and bond ones) and the foreign exchange market. The indicators for each one of these sectors are:

[15] These are GDP, Gross domestic purchases, Final sales, Nonfarm private inventories, residential investment, and nonresidential investment, PCE: durables, PCE: nondurables and PCE: services.

[16] FCI residual and adjusted FCI residual are the portion of the FCI and adjusted FCI that cannot be predicted from the index's historical dynamics. In other words, it corresponds with the error term from the transition function (12).

[17] In this group, we included Japan as well, even though this country could have been added to the advanced economies group. It is a matter of comparability (groups of countries from same continents, excluding the OECD group) and regionalism (ability to construct and discuss regional financial stress indices).

[18] OECD group consists of: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, UK, USA. Asian group: Japan, S. Korea, Malaysia, Philippines, Thailand. Latin American group: Argentina, Brazil, Mexico, Peru, Venezuela.

Banking Sector

1. Banking sector stocks' beta (calculated as the ratio of the moving covariance of the year-over-year percentage change of each country's banking sector equity index and the general equity index and the moving variance of the general stock index).
2. The TED spread (the difference between the 3-month LIBOR from the government short-term rate or the respective treasury bill rate)
3. Inverted Term Spread (treasury bill rate – government long-term bond yield)

Securities Market

4. Corporate Bond Spreads (the yield difference of the long-term corporate bonds from the governmental ones)
5. Stock market returns (the monthly percentage change of the general equity index performance)
6. Stock return volatility (calculated as a GARCH(1,1) model of the general equity index, modeled as an autoregressive process with 12 lags)

Foreign Exchange Market

7. Real effective exchange rate volatility (estimated on the same way as the stock return volatility)

This approach was materialized only for the OECD (and Japan) group of countries while, for the rest of them, the index was slightly reformed. This was deemed necessary because of data unavailability for the corporate bond series in Asian and Latin American countries. Instead of the corporate bond spreads, we use the so-called sovereign debt spreads, which are the government bond yields minus the 10-year United States Treasury yield. In any case, this does not degrade the usefulness and applicability of the index, for two main reasons. First, the corporate bond market is quite small in emerging economies, where most of the firms are still based on traditional sources of financing (like bank borrowing). Then, the fact that a large part of the private sector financing depends on national banks (which, most of them used to or are still under state control or mainly being refinanced with state money), designates that the use of sovereign debt spreads as a credit risk indicator is good enough for these economies.

Every part of the index is standardized. Each one of the index's components has an equal weight to the formation of it. As long as this has been done, the next step is the computation of the regional and global FSIs. The regional FSI's are the outcome of the average of the national indices for each group of countries (OECD, Asia, and Latin America), while the global one is the average of the regional indexes. Using these indices, we can check when and by how many standard deviations the FSI is above or below its value representing a "tranquil" period in the financial markets. Episodes of financial stress are identified when the index is, at least, one standard deviation above its mean. Finally, we are able to classify each episode of financial stress (i.e. whether it can be attributed to banking, securities or foreign exchange-related causes) by examining the change of FSI value prior to the start of the episode and the maximum value of it during the episode periods.

4. Discussion of Results

Graph 1 depicts the composite Global Financial Stress Index. Moreover, table 1 displays the number of stress episodes identified in each region, added up to produce the total number of them for the whole world, separated into three types (banking-related, securities-related and foreign exchange-related), according to the market each crisis episode was originated from. Additionally, the (average) duration of these episodes, measured in quarters, is being provided. In cases, where more than a single sector seems

Graph 1: Global Financial Stress Index

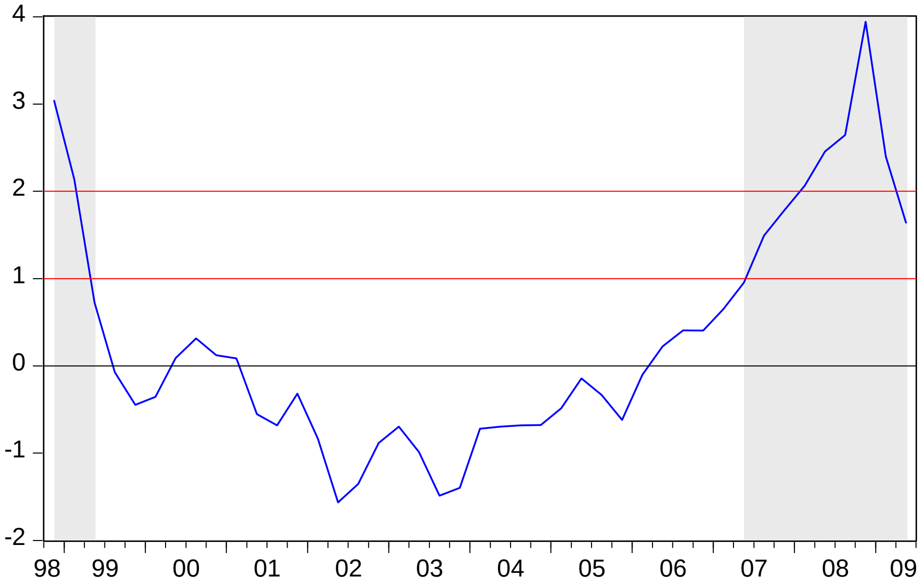


Table 1: Summary Statistics for Global and Regional FSI

Stress Types / Countries	*Banking*	*Securities*	*Foreign Exchange*	*Total*
OECD	54	68	25	147
Duration	*4*	*5*	*3*	*4*
Asia	8	10	2	20
Duration	*3*	*5*	*1*	*6*
Latin America	6	14	2	22
Duration	*2*	*4*	*0.5*	*3*
Global	68	92	29	189
Duration	*3*	*4.5*	*1.3*	*4*

Source: author's calculations. Duration of stress episodes in quarters

to contribute to the turmoil, adjudication is reached according to the market that has the highest attribution to this episode or, if this episode lasts for more than a quarter, according to the sector that appears to, most frequently, lead it. Stress periods are denoted by the grey areas in this graph as, of course, in all graphs used here.

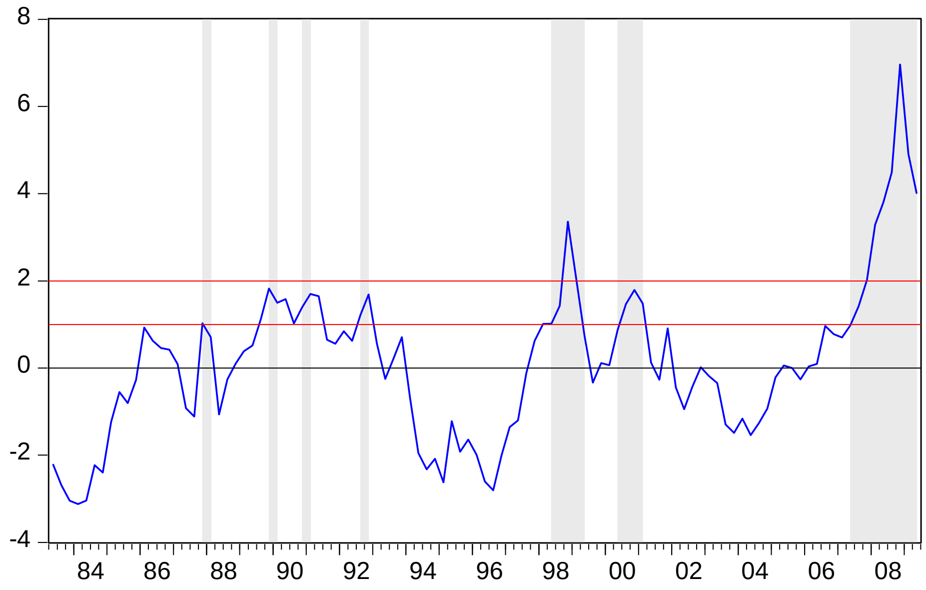
Inspecting graph 1, it is easy to infer that, apart from the initial phase of this period and the recent financial crisis (since 2007Q2), the last decade was a somehow tranquil period for the world economy. It is reasonable to expect that, in some cases, worsening of a country's financial health does not, necessarily, entail a similar aggravation for the global economy. By and large, the two stress periods depicting in graph 1, seem to have had a, somehow, similar effect in the global economy. The first one, having lasted for two quarters (1998Q4 to the first quarter of 1999), shows that the index was about 3 standard deviations above the mean value of the FSI, decreasing quite fast, compared to the subprime crisis period. In the latter, the index started picking up since mid-2006, exerting the threshold of one standard deviation at the second quarter of 2007. The value of the index was constantly increasing until the fourth quarter of 2008, after which, it started to decrease. Nevertheless, it still remains close to the two standard deviations above the mean (at the end of the sample period), implying that global financial markets are still under severe strain. It will not be misleading if we would suggest that, the first stress period captured by the index can, possibly, be mostly attributed to the financial instabilities prevailing in the emerging markets at that time (financial crises was a common phenomenon in countries like Brazil and Argentina, while the Asian economies were still struggling with the serious problems caused by the crisis of 1997-99), while, the second one is (as it will also become clearer in the analysis that follows) a crisis that has, mainly, affected the developed economies. The period, from 1999 to late 2006, is a period of robust growth and prosperity in the world economy. Solitary cases of crises episodes occurred, but their effect was not that important, according to the global FSI[19]. It does worth mentioning here that, as it can be seen in the graph, the FSI present a persistently upward kinesis, since early 2004. This suggest that, although the index was rather low and did not provide any alerts for the forthcoming financial turmoil, it can be said that the increasing value of it could have worked as an early warning indicator of the forthcoming financial meltdown.

The last row in table 1 provides an account of the overall number of stress periods identified in the world, over the last 30 years. In total, 189 stress periods were found, with an average duration of four quarters. The episodes stemmed out of the securities markets are quite often, lasting more than the banking crises, which are the second most popular source of financial instability. Foreign exchange markets cannot be blamed for many of the stress periods in our sample, something attributed to the shorter time periods covered by the series available for the emerging markets. Nevertheless, these results offer an additional reason justifying the paradigm shift from researching for market-specific crises to systemic-wide ones.

[19] Still, we can notify a shift on the FSI behaviour in some cases, like during the dot-com bubble burst on 00's or during the Argentinean and Russian/LTCM crisis (second half of 2001). Of course, these upward shifts on the index values were not as strong as it would be necessary, in order to register these period as financially stressful ones.

Graph 2 illustrates the performance of the OECD index, with the grey columns underscoring the relevant stress periods[20]. The OECD FSI covers the period 1983Q2 to 2009Q2. The index does not seem to follow a specific trend. It has a number of peaks and troughs, reaching various levels of excessive financial stress throughout the three decades covered. It is more than clear that the current crisis is the most severe one for this group of countries, having reached at its peak a value close to seven standard deviations above the average value of the FSI. Additionally, this financially instable period is the most prolonged one, having lasted nine quarters, until the end of our sample,

Graph 2: OECD Financial Stress Index



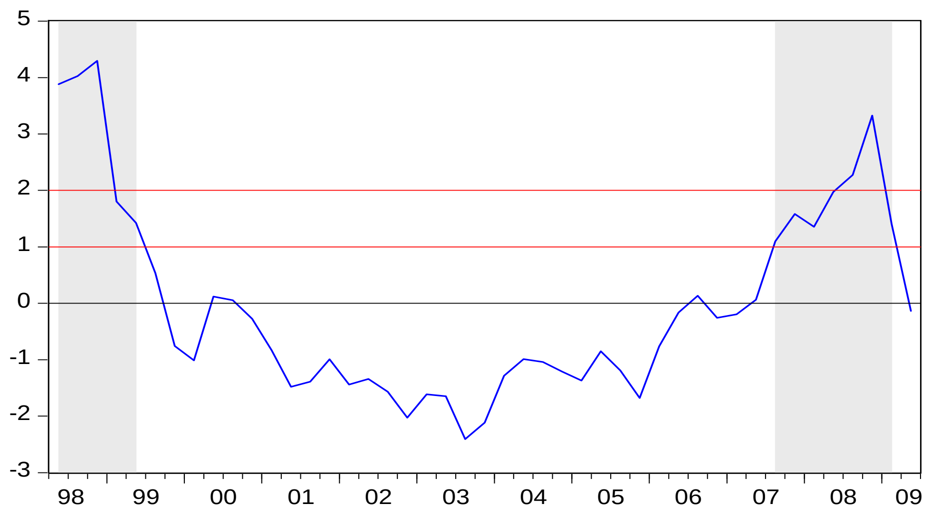
while it still exhibits high levels of stress, even though it was only 4 standard deviations above the mean at mid-2009. Thus, it is more than obvious that the recent crisis brutally hit the world's most advanced economies while, following the upward trend of the index, the use of such a metric of financial strain could have been proved quite useful for central bankers and financial stability surveyors. While the index has initiated from very low values, its first peak is defined at the first quarter of 1986, though not assigned as a stress period[21]. Nevertheless, the following spike of it, during the fourth quarter of 1987, captures one of the most famous financial crises periods, the well known "Black Monday" stock market crash, which affected nearly every developed country's stock market[22]. After a period of decreasing values for the index, it starts rising, breaching the threshold of one standard deviation from early 90's and it remains above it until the last months of 1992. During these years, a number of financial upheavals took place that

[20] Tables with an analytical representation of the number and duration of financial distress episodes for each country can be provided upon request.
[21] On 1986Q1, the FSI value is 0.92 <1. Thus, technically, it is not a registered stress period.
[22] Most of these countries (like USA, UK, Australia, Spain, Canada etc.) are part of the OECD FSI.

shook most of the global markets[23]. In all these cases, the OECD FSI reached values of, almost, two standard deviations above its mean value. In 1998, it remained above the threshold of one standard deviation for about a year, a period characterized by a series of stress episodes inflicting serious turmoil to the markets, such as the Asian and Russian crises, the LTCM collapse and the upcoming vulnerabilities because of the crises followed to the emerging markets (many of which are major suppliers of raw materials and oil, like Brazil). Finally, graph's 1 index underscores another period of financial stress, at the end of 2000- beginning of 2001, clearly related to the dot-com bubble burst, which created a series of abnormalities to international stock markets. In total, 147 periods of financial stress occurred in OECD area, with an average duration of 4 quarters. The most recurrent type of crises is the securities ones, with 68 episodes throughout the period under investigation, with duration of 5 quarters. Currency-induced type of stress is not that common. Only, about, 2 out of 10 episodes have been sourced from instabilities in this market.

Figure 3 shows the evolution of the Asian FSI. It starts with quite high values, around four standard deviations above the mean value, something totally expected, considering that the legendary Asian financial crisis was still unfolding at that period (mid 1998). From the end of 1998, the index has started decreasing while, during the second semester of 1999, it reached values below the threshold of one standard deviation. Thus, Asian continent seems to be influenced by the current financial crisis, with the Asian index picking on the fourth quarter of 2008. Beyond that date, the index has degraded, indicating the end of the stressful period. The number of financially instable periods for these five Asian countries was twenty, with an average duration of six quarters. Most of these episodes are identified as securities-related, which also present the longest stoutness.

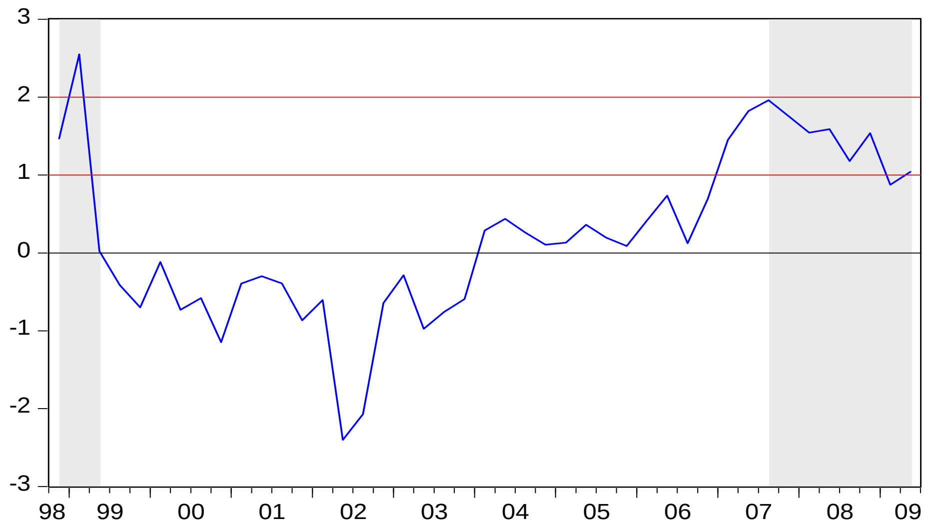
Graph 3: Asian Financial Stress Index



[23] Some of them, like the junk bond collapse at late 80's – beginning of 90's and the S&L crisis of the same period, were mainly focused on single country, while others (such as the Scandinavian banking crisis of early 90's and the ERM II crisis in 1992-93) had a multilateral dimension.

The South American FSI shows a clustering of financially stressful periods, at the beginning and the end of the sample period. More precisely, the end of 1998 and early 1999 have been proved quite volatile for Latin America, with the financial stress index having reached a value of 2.5 standard deviations above the mean. This is, clearly, the spillover outcome of the financial crisis in Asia which, later on, contributed to the emergence of financial crises in Brazil, at first, and then, in most of the countries in South America. The FSI clearly exposes that this region of the world remains in a financially instable period. Regarding the types of financial stress and their duration, Latin America faced, in total, 22 such episodes, with an average duration of three quarters[24]. Again, the most frequent provenance of such crises is the stock and, in more general terms, the securities markets.

Graph 4: Latin American Financial Stress Index



5. Predicting Economic Conditions with Financial Conditions

In this section, the main concern is the establishment of a clear relationship between the prevailing financial conditions and the respective economic situation. In order to do this, a number of forecast evaluations are conducted with models containing both variables of real economic activity and the financial stress indices constructed and analyzed in the previous sections of this paper. The main question here is, whether the prevailing financial markets conditions (as depicted by the financial stress indices) can offer some insights on the evolution of the real economy's conditions. In other words: whether the utilization of financial distress indicators can be useful as predictors of the forthcoming macroeconomics conditions. Until recently, most of the research effort has focused on the tools and techniques that can be implemented in the construction of these composite financial indicators. Very few papers move one step further, providing

[24] As it can be seen from table 1.

evidence on the usefulness of these FSIs as tools able to predict the course of the economy. Relevant literature, like the work by Claessens et al. (2011), empirically supports the interweaving nature of real economy and financial conditions. Additionally, some of the papers mentioned in the review of the literature have established a relationship, with rather mixed results, between indices like the ones computed here and their predictive power for important macroeconomic variables, like GDP growth, unemployment and so on. A couple of them have also tried to forecast the index itself. The restrictive feature of these studies is that they, almost, entirely focus on US, especially those that deal with the predictive power of financial distress on the real economy. Additionally, Eurozone has been treated as a whole, for instance in the papers by Grimaldi (2010) and Mallick and Sousa (2011), while, in our knowledge, there are no studies for the prediction of the economic conditions from the financial conditions for the emerging markets yet[25]. Hence, this paper is among the first ones to provide evidence for the real economy – financial stress nexus in country level and for such a diverse group of countries (both advanced and emerging economies).

5.1. Model Specification and Methodologies Used for the Forecasting Exercise

A model similar to the one used by Hatzius et al. (2010) is employed. Here, we focus on out-of-sample predictions, since this is the crucial aspect and essence of using these financial stress indexes as predictors of future economic developments. Thus, the model's specification, in this case, is the following:

$$y_{t+h} - y_t = \beta_0 + \sum_{i=1}^{p_y} \phi_i \Delta_{y_{t+1-i}} + \sum_{i=1}^{p_x} \gamma_i FSI_{t+1-i} + e_{t+i} \qquad (21)$$

Here, y_t denotes the real economy's variables and FSI is the financial stress indices constructed here. So, the main objective here is to check whether the inclusion of lagged values of each country's FSI can improve the predictive performance of a simple autoregressive model of y_t. It is not by chance that the baseline model is a simple AR one, since it is well justified that most of the macroeconomic variables follow such autoregressive behavior[26]. If equation (21) is superior in predicting y_t, strong evidence in favor of using FSIs as predictors of economic activity is provided. In the aforementioned model, subscript h represents the time horizons for which forecasts were estimated. That is one, three and six months ahead forecasts, with the exception of Switzerland, for which only quarterly data for the series under investigation exist. As a proxy of real economic activity, industrial production index for each country has been used.

Two, similar, approaches were followed in the estimation of equation (21). First, a simple dynamic forecasting procedure was followed. According to this, the regression is estimated with data up to date *t* and, then, we use these initial estimations to obtain the forecast values for the first value in the forecast sample. Then, for period *t+2* in the forecast sample, we use the forecasted values of the previous period and so on until the end of the sample period (that is, May 2009). The second approach implements rolling

[25] The paper by Chortareas et al. (2011) implements static and dynamic probit analysis, but for predicting the financial distress for 17 developing economies.

[26] Hence, previous values of the variable itself can be used to predict future ones.

regression estimations. In this approach, we consider a constant window sample, different for each group of countries because of the time coverage limitations. So, for the forecast sample period, a recursive procedure is followed, where the window sample size "rolls" over the entire forecast period, by moving the window by one observation in each estimation (and, on the same time, dropping the initial observation of the previous sample period). In this way, more accurate forecasts can be obtained, exactly because of the sample renewal and the use of the most recent information in the estimation procedure. In both cases, the forecast evaluations were based on the root mean squared forecast errors of the models, compared to the baseline AR model. That is, the roots mean squared forecast error ratios. Whenever the values of these ratios are lower than one, this implies an improvement on the forecast accuracy, when the FSI model is implemented. Finally, we should mention that the lag length selection for both AR and the FSI model has been done by the AIC criterion.

5.2. Forecasting Results

The following four tables present the outcome of the forecast estimations conducted with the simple dynamic and the rolling window approach[27]. The first two tables depict OECD countries and the performance of their FSIs as predictors of their respective industrial production, while the last two focus to the other two regions studied in this paper (Asia and Latin America). The important results are the ones depicted in the last two columns of the tables, where the RMSFE ratios are provided. Just to remind, that when the RMSFE ratio is below one, this is a clear indication that the model where the FSI is included performs better, in terms of forecasting accuracy.

As a first general comment, we can say that the results are quite promising. In all cases, the forecast error when rolling window approach is employed is lower for the FSI model. In some cases, especially for some of the OECD countries, there is an improvement even with the simple dynamic forecasting approach, even though it is a rather negligible one. For instance, for table 8.A, Austria, Belgium, Denmark, Finland and Germany are countries with RMSFE lower than one, in the case of dynamic forecasting. The same holds for Sweden and Switzerland in table 8.B. In any case, the striking improvement is the one with the rolling window approach. Even for the countries that exhibit lower forecast errors with the first approach in the FSI model, the improvement is even bigger with the rolling window estimations. The cases of Denmark, Belgium are impressive, in terms of forecast error decline between the two approaches used, while the same holds for UK and, especially, US forecasts. On average, it can be said that forecast errors are smaller by around 31 percent, when rolling window methodology is implemented. Regarding forecasting horizons, the improvement is impressive in all three cases, with somehow better results in the case of short and medium term forecasts (one and three months ahead, which are improve, on average, by thirty to thirty five percent when the second methodology was followed). Focusing on the Euro zone member countries included in our sample[28], the predictive performance of both models is quite good, especially for the rolling regression forecasts. Even with the simple dynamic approach, the FSI model performance, even if it is worse than the AR forecasts

[27] The series have been tested for stationarity. Results are available upon request.
[28] These are Austria, Belgium, Finland, France, Germany, Italy, Netherlands,

Table 8.A: Out of Sample Forecasting Performance for OECD Countries - 1

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Austria	1	0.0197	0.0198	0.0153	1.0062	0.7750
	3	0.0198	0.0195	0.0161	0.9837	0.8128
	6	0.0198	0.0196	0.0157	0.9926	0.7929
Belgium	1	0.1031	0.1020	0.0644	0.9895	0.6244
	3	0.1032	0.1020	0.0779	0.9886	0.7548
	6	0.1030	0.0806	0.0656	0.7824	0.6366
Canada	1	0.0060	0.0072	0.0048	1.1987	0.8083
	3	0.0059	0.0066	0.0049	1.1056	0.8240
	6	0.0060	0.0065	0.0048	1.0778	0.7986
Denmark	1	0.0655	0.0656	0.0388	1.0016	0.5923
	3	0.0655	0.0655	0.0477	0.9996	0.7284
	6	0.0655	0.0647	0.0493	0.9871	0.7525
Finland	1	0.1099	0.1093	0.0659	0.9944	0.5994
	3	0.1102	0.1098	0.0749	0.9966	0.6799
	6	0.1103	0.1095	0.0805	0.9930	0.7299
France	1	0.0121	0.0123	0.0101	1.0138	0.8280
	3	0.0121	0.0122	0.0103	1.0014	0.8516
	6	0.0122	0.0121	0.0097	0.9915	0.7983
Germany	1	0.0157	0.0154	0.0131	0.9829	0.8351
	3	0.0157	0.0153	0.0125	0.9740	0.7941
	6	0.0157	0.0156	0.0133	0.9948	0.8472

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

in general, for some of them there is an improvement in the index-augmented model in case like Germany or Finland[29]. But again, with the second approach, the declines in

[29] Even if this improvement cannot justify the FSI usefulness as predictor.

forecast errors provide strong evidence in favor of using financial distress indicators as predictors of future economic activity.

Table 8.B: Out of Sample Forecasting Performance for OECD Countries – 2

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Italy	1	0.0139	0.0152	0.0126	1.0913	0.9063
	3	0.0144	0.0145	0.0119	1.0107	0.8280
	6	0.0145	0.0145	0.0123	1.0035	0.8478
Netherlands	1	0.0758	0.0762	0.0609	1.0044	0.8024
	3	0.0758	0.0751	0.0568	0.9909	0.7495
	6	0.0757	0.0762	0.0600	1.0071	0.7923
Sweden	1	0.0199	0.0197	0.0163	0.9946	0.8196
	3	0.0198	0.0198	0.0162	0.9996	0.8184
	6	0.0198	0.0197	0.0161	0.9948	0.8105
Switzerland	2	0.0231	0.0223	0.0187	0.9619	0.8072
	4	0.0230	0.0223	0.0177	0.9682	0.7688
UK	1	0.0092	0.0097	0.0078	1.0595	0.8540
	3	0.0092	0.0099	0.0078	1.0835	0.8538
	6	0.0092	0.0098	0.0076	1.0701	0.8298
US	1	0.0070	0.0075	0.0050	1.0767	0.7181
	3	0.0070	0.0085	0.0053	1.2204	0.7576
	6	0.0070	0.0081	0.0055	1.1639	0.7812

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts (except Switzerland where the horizons are 2 and 4 quarters, because of the data frequency). (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

Turning to the other two groups of countries, Asian and Latin American ones, the effect of the financial stress indexes on the prediction of industrial production growth rate is, again, important. As it can be observed from tables 9 and 10, the forecast errors when the rolling window approach was adopted, are decreased in an important extent. Again, there are two countries (Korea and Brazil), for which even the first forecasting methodology gave, marginally, better results with the FSI model. But, in broad terms, this approach does not offer satisfactory results. On the other hand, it is easily verifiable that the FSI model here is not that effective, as in the case of OECD countries.

Table 9: Out of Sample Forecasting Performance for Asian Countries

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Japan	1	0.0179	0.0180	0.0149	1.0042	0.8315
	3	0.0179	0.0182	0.0148	1.0167	0.8296
	6	0.0179	0.0187	0.0150	1.0474	0.8393
Korea	1	0.0283	0.0281	0.0249	0.9924	0.8796
	3	0.0282	0.0281	0.0236	0.9946	0.8358
	6	0.0282	0.0280	0.0235	0.9907	0.8344
Thailand	1	0.0306	0.0379	0.0298	1.2356	0.9717
	3	0.0339	0.0388	0.0286	1.1433	0.8431
	6	0.0316	0.0339	0.0263	1.0736	0.8322

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

Even if there are more favorable results, in terms of higher forecasting accuracy with the implementation of the FSI model, the change is not that big, especially for the countries that FSI model showed promising results with the simple dynamic approach as well (Korea, Brazil). Another distinctive feature of these groups of countries is the thing that, the lower RMSFE ratios are mostly observable in the three-month and six-month forecast horizon, in contrary to the OECD countries where the short and medium term forecasts exhibited the greatest improvement.

It is also noteworthy that, for countries like Thailand (from the Asian group), Brazil and, especially, Venezuela (from South American cluster) the short term forecasts are on the verge of proclaiming the FSI-augmented model as the appropriate one for real economy's conditions forecast. Particularly, Venezuela's results are, by far, the worst ones for the countries under scrutiny.

To sum up, it seems that there is evidence that financial conditions can offer a, pretty, clear indication of forthcoming changes in real economic activity. Especially for OECD countries, the results are quite promising, while the same hold for emerging markets in Asia and South American, to a similar extent. Of course, as it has been emphasized before, this is the first main effort to empirically investigate this interrelation of financial stress indices and macroeconomic variables in such a big and divergent group of countries. Many more can be done, from implementing alternative forecast techniques to trying to get deeper in to the nature of this interrelation. For instance, it would be interested to study whether excessive financial stress in linked with periods of recession and, if this is the case, if the continuous nature of these aggregate indicators can offer useful insights in the duration and the magnitude of the recessionary periods. Also, the study of the several financial stress transmission channels seems promising, as a research avenue, given the fact that modern economies are quite interconnected. Thus, the contagion of financial stress from one country to another, or from a region to another one, is crucially important, due to the established relation between financial stress and changes in the macroeconomic environment. This kind of questions is left for future research.

Table 10: Out of Sample Forecasting Performance for Latin American Countries

		RMSFE			RMSFE Ratios	
Countries	h	(a) AR	(b) Dynamic	(c) Rolling	(b)/(a)	(c)/(a)
Argentina	1	0.0185	0.0193	0.0158	1.0407	0.8537
	3	0.0187	0.0188	0.0147	1.0058	0.7824
	6	0.0185	0.0185	0.0149	1.0003	0.8044
Brazil	1	0.0217	0.0214	0.0195	0.9881	0.9014
	3	0.0217	0.0216	0.0176	0.9988	0.8114
	6	0.0217	0.0217	0.0178	0.9988	0.8212
Mexico	1	0.0111	0.0121	0.0093	1.0941	0.8454
	3	0.0110	0.0119	0.0092	1.0750	0.8358
	6	0.0111	0.0118	0.0091	1.0705	0.8190
Peru	1	0.0457	0.0484	0.0367	1.0600	0.8023
	3	0.0461	0.0467	0.0385	1.0134	0.8359
	6	0.0461	0.4438	0.0429	9.6286	0.9299
Venezuela	1	0.1763	0.1861	0.1625	1.0559	0.9219
	3	0.1763	0.1846	0.1732	1.0475	0.9829
	6	0.1755	0.1621	0.1616	0.9237	0.9208

Note: Column h represents the time horizons for which forecasts are provided. These are 1, 3 and 6 months ahead forecasts. (a), (b) and (c) columns report the root mean squared forecast errors (RMSFE) for the AR, dynamic and rolling window models respectively.

6. Conclusions and Implications for Future Research

Financial crises are recurrent and catastrophic phenomena for the world economies. It affects both developed and emerging economies, with severe repercussions on their economic growth and welfare. Previously, research on crises was mainly focused on solitary kind of crises, either balance of payments, currency or banking crises and, in this way, the authors were trying to offer type-specific proposals for overcoming each kind of financial turmoil. Today, it is well justified and established the view that modern economies face systemic-wide financial upheavals which, as it is commonly agreed, require special attention and monitoring modeling. On the other hand, previous econometric approaches do not seem to adequately cover the need for timely and accurate representation of the degree of (in-) stability of the financial markets. Additionally, there is a lack of empirical investigation on whether financial conditions and, particularly, excessive financial stress can offer some insights and work as a kind of predictor for changes in future economic activity, as represented in several macroeconomic variables and indicators. Hence, there is a need for the development of new tools, able to satisfy these policymakers' needs.

This paper contributes towards the aforementioned targets. It does so by, first, constructing a number of financial stress indices, following the approach proposed by Lall et al. (2008), slightly transformed for a number of emerging economies, for which we faced a lack of suitable data. From this work, it can be confirmed the fact that, for most of the countries and for each region, securities-prone financial abnormalities are the most frequent one, also lasting longer than any other type of crises, while banking turmoils are, also, quite frequent. Moreover, the recent financial crisis, initiated in 2007 is, by far, the most strenuous one, causing huge losses, in financial and economic terms, to the world's markets, especially those of the most advanced economies. Hence, it seems that this kind of financial stress index performs quite well, efficiently capturing past stress episodes and it is promising as a predictor of future financial instabilities.

We also proceeded one step further by providing empirical evidence on the interrelation of financial and economic conditions. In doing so, we employ an autoregressive model of each country's industrial production, where lagged values of the respective financial stress index were included. Using this model, we compared it's out of sample forecasting performance with a baseline AR model. In our knowledge, this is the first attempt to empirically test FSI functionality as a predictor of a macroeconomic variable in such a diverse group of (developed and emerging) economies. Using the RMSFE ratios, it was shown that financial conditions can be used from the monetary authorities as trustworthy indicators of forthcoming changes in real economy, especially for short and medium term periods (in the case of OECD countries) and longer period for Asian and Latin American economies.

Of course, many more should be done, in order to improve these tools and render them efficacious forecasting tools. First of all, it is important to work towards the improvement of the accuracy of such financial stability measures, through the implementation of better weighting schemes. The equal-variance approach is a good initial approach, offering simple and quick indexes' calculations, although it might not be the most proper one, due to the fact that it assumes normality in the series distributions (something rarely happened in financial data). Additionally, as was mentioned before, the importance of each of the three financial sectors incorporated in the indices, changes through time. Thus, it is reasonable to assume that a weighting scheme of a time-varying nature should be more appropriate. It is also noteworthy, for the case of the regional and global indexes, to take into account the relevant importance of each economy to the total effect exerting to its region. Thus, the relevant contribution of each country's financial markets to the overall performance of the regional indices should, somehow, be measured. In the same line of thought, contagion issues, not included in this piece of research, would be interesting to be embodied (through the use of relevant variables of interest).

Financial stability issues are quite crucial nowadays. After the shock of the subprime crisis, policymakers around the world are more than interested in the development of relevant tools, able to provide clear and on time evidence of the financial system health. It is an uncharted territory, yet to (and should) be discovered.

References

Balakrishnan, R., Danninger S., Elekdag S. and Tytell I. (2009), "The Transmission of Financial Stress from Advanced to Emerging Economies", *IMF Working Paper*, no. 133

Borio, C. and Drehmann M. (2009), "Towards an Operational Framework for Financial Stability: "Fuzzy" Measurement and its Consequences", *Central Bank of Chile Working Paper Series*, no. 544

Brave, S. and Butters A. (2011), "Monitoring Financial Stability: A Financial Conditions Index Approach", *Federal Reserve Bank of Chicago Economic Perspectives*, 1Q/2011

Cardarelli, R., Elekdag S. and Lall, S., (2008), "Financial Stress and Economic Downturns", *chapter 4 of IMF World Economic Outlook*, October

Cardarelli, R., Elekdag S. and Lall, S., (2009), "Financial Stress, Downturns and Recoveries", *IMF Working Paper Series*, no. 09/100

Chortareas G., Cipollini A. and Kapetanios G. (2011), "Forecasting Financial Distress in Emerging Markets: A Dynamic Probit Analysis", mimeo

Claessens, S., Aynan Kose, M. and Terrones M., (2011), "How Do Business Cycles and Financial Cycles Interact?", *IMF Working Paper Series*, no. 11/88

Grimaldi, M. (2010), "Detecting and Interpreting Financial Stress in the Euro Area", *ECB Working Paper Series*, no. 1214

Goodhart, C., Surinand, P. and Tsomocos D. (2006), "A Model to Analyse Financial Fragility", *Economic Theory*, vol. 27: pp. 107-142

Hakkio, C. and Keeton W. (2009), "Financial Stress: What is it, How Can it be Measured, and Why does it matter?", *Federal Reserve Bank of Kansas Economic Review*

Hatzius, J., Hooper, P., Mishkin, F., Schoenholtz, K. and Watson M. (2010), “Financial Conditions Indexes: A Fresh Look after the Financial Crisis”, *NBER Working Paper Series*, no. 16150

Illing, M. and Liu Y. (2006), “Measuring Financial Stress in a Developed Country: An Application to Canada”, *Journal of Financial Stability*, vol. 2(3): pp. 243-265

Kaminsky, G., Lizondo S. and Reinhart C. (1998), “Leading Indicators of Currency Crises”, *IMF Staff Papers*, vol. 45(1)

Mallick, S. and Sousa R. (2011), “The Real Effects of Financial Stress in the Euro Zone”, *University of Minho Working Paper Series*, no. 12

Melvin, M. and Taylor, M. (2009), “The Crisis in the Foreign Exchange Market”, *Journal of International Money and Finance*, vol. 28(8): pp. 1317-1330

Morales, M. and Estrada D. (2010), “A Financial Stability Index for Colombia”, *Annals of Finance*, 6:555-581

Nelson, W. and Perli R. (2007), “Selected Indicators of Financial Stability”, *in Risk Measurement and Systemic Risk: Proceedings of the Fourth Joint Central Bank Research Conference*, Frankfurt am Main, Germany; European Central Bank, pp. 343-372