

Macrofinancial vulnerabilities and future financial stress: assessing systemic risks and predicting systemic events

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1. Introduction

The current financial turmoil has demonstrated the importance of understanding and measuring systemic risks and predicting systemic events, ie events *when financial instability becomes so widespread that it impairs the functioning of the financial system to the extent that economic growth and welfare suffer materially.*²

Borio and Lowe (2002, 2004) show that widespread financial distress typically arises from the unwinding of financial imbalances that build up disguised by benign economic conditions, such as periods of stable and low inflation. Using annual data for 34 countries for the period 1960–99, they show that sustained rapid credit growth combined with large increases in asset prices increased the probability of episodes of financial instability. Recently, Cardarelli et al (2011), using data for 17 major advanced economies, show that the likelihood that stress in the financial system will cause more severe economic downturns is higher when stress is preceded by the building up of balance sheet vulnerabilities in the form of a rapid expansion of credit, and a run-up in house prices. Moreover, in a paper closely related to our study, Misina and Tkacz (2009) investigate whether credit and asset price movements can help to predict financial stress in Canada by using linear and nonlinear threshold models. According to their findings, business credit emerges as an important leading indicator among all variables considered in their study.

This paper builds upon the above studies and contributes to the financial crisis literature by developing a unified framework for assessing systemic risks, stemming from domestic and global macrofinancial vulnerabilities, and for predicting (out of sample) systemic events ie periods of extreme financial instability with potential real costs. Within this framework it is possible to assess the relative importance of the factors contributing to the probability of a systemic event. It is also possible to identify potential vulnerabilities on the basis of a scenario analysis of the evolution in the domestic and global macrofinancial environment.

We extend the existing literature on predicting financial crises in several ways. First, we identify past systemic events by using a composite index measuring the level of systemic tensions in the financial system of one country. Second, in predicting the identified systemic events, we evaluate the joint role of domestic and global vulnerabilities as sources of financial instability. Third, we evaluate both “standalone” macroprudential indicators of vulnerabilities and composite indicators calculated using discrete choice models. The evaluation of the two categories of indicators is done with a common methodology that takes into account policymakers’ preferences between issuing false alarms and missing systemic events.

The remainder of the paper is organised as follows: Section 2 introduces the measure for financial stress and defines systemic events, Section 3 reports the empirical analysis and Section 4 concludes.

¹ ECB.

² See the definition of the concept of systemic risk in the *ECB Financial Stability Review*, December 2009.

2. Measuring financial stress and identifying systemic events

We identify past systemic events using a composite index to measure the level of systemic tensions in the financial system of a given country. This approach provides an objective criterion for the definition of the starting date of a crisis and it contrasts with the standard way of identifying crises based on qualitative information (see eg Laeven and Valencia (2008)).

Furthermore, systemic events are identified as episodes of extreme financial stress that have led to negative real economic consequences on average. In this way, we avoid the selection bias that would occur if we chose only cases where extreme financial stress has always led to negative real economic consequences. The selection bias could emerge because a policy action (that we do not control for) might have prevented the negative economic outcome.³

In our benchmark case we identify systemic events when the Financial Stress Index (FSI) crosses the 90th percentile of the country distribution. We adopt this threshold because on average it anticipates real consequences in terms of negative deviation of real GDP from trend. Following this approach, we identify a set of 94 systemic events in a sample of 28 countries over a period spanning from 1990 Q1 to 2009 Q4. We find the following starting dates for well known crisis episodes in the 1990s and 2000s: 1994 Q1 for Brazil, 1994 Q4 for the Mexican crisis; 1997 Q2 for the Asian crisis in Thailand, 1997 Q3 for Hong Kong and other main Asian countries, 1998 Q3 for the Russian crisis, 1999 Q1 for the Brazilian crisis; 2001 Q3 for the Argentinean crisis; 2007 Q3 for the most recent financial crisis in the United States. In many cases, these episodes spread to several other economies. For example, after starting in 2007 Q3 with severe problems in money markets and volatility in other market segments in the United States and in the euro area, the latest crisis spread internationally in successive waves in 2008 Q1 and 2008 Q3, finally reaching the emerging markets in 2008 Q4. Several of the episodes that we identify are also in the list of crises compiled by Laeven and Valencia (2008).

Our approach to identifying systemic events can be seen as an extension of Eichengreen et al (1996), where an index of exchange market pressure is used to identify currency crises. Compared to Eichengreen et al (1996), our financial stress index is broader than the exchange market pressure index because it includes several market segments. This enables us to identify episodes that are truly systemic and not segment-specific. In addition, by defining systemic events as episodes of extreme financial stress with potential real economic consequences, we focus on financial crises that are relevant for policymakers who want to avoid real costs. The real cost dimension is absent in Eichengreen et al (1996), where a simple statistical rule is used to identify crisis periods.

³ The detailed description of the index is in Lo Duca and Peltonen (2011). In short, our Financial Stress Index (FSI) is a country-specific composite index, covering the main segments of the domestic financial market. It is calculated as the average of following five components after they are standardised: (1) the spread of the three-month interbank rate over the three-month government bill rate; (2) negative quarterly equity returns (multiplied by minus one, so that negative returns increase stress; positive returns are disregarded and set to zero); (3) the realised volatility of the main equity index; (4) the realised volatility of the nominal effective exchange rate; and (5) the realised volatility of the yield on the three-month government bill.

3. Predicting systemic events

Definition of the dependent variable

The objective of the study is to predict the occurrence of systemic events within a given time horizon that in our benchmark specification is set to six quarters.⁴ To do this, we proceed in three steps to calculate our dependent variable.

First, we transform the Financial Stress Index into a binary variable that we call “systemic event”. The variable takes value 1 in the quarter when the FSI moves above the predefined threshold of the 90th percentile of the country distribution.

Second, we set the dependent variable to 1 in the six quarters preceding the systemic event and to 0 in all the other periods. The dependent variable mimics an ideal leading indicator that perfectly signals “systemic events” by “flashing” in the six quarters before the event.

Finally, we drop from the sample all the observations that are not informative about the transition from tranquil times to systemic events. This means that we drop the periods when financial stress remains above the predefined threshold that identifies systemic events. We also drop tranquil periods that are not longer than six quarters, as the short distance between the extreme stress episodes delimiting them suggests that we should not consider these periods as “normal”.⁵

Predicting systemic events

We test the performance of standalone indicators of vulnerabilities and discrete choice models in predicting systemic events. Our empirical analysis covers a set of 28 emerging market and advanced economies with quarterly data between 1990 Q1 and 2009 Q4.

Regarding standalone indicators, we test several domestic and global measures of vulnerabilities inspired by the literature on early warning systems (for example, Bussière and Fratzscher (2006)) and leading indicators of crises (for example, Borio and Lowe (2002)). The standalone indicators that we test are based on asset price (equity and property prices), credit (credit and monetary aggregates) and macro (GDP, inflation, government deficit, current account deficit) developments. Our analysis is conducted as much as possible in a real-time analysis fashion.⁶ At each point in time, only information available to the policymakers up to that point in time is used. This implies that we take into account that certain variables, such as GDP, are not available to the policymakers in real time because of publication lags. To take into account publication lags, we use lagged variables. For GDP,

⁴ The time horizon of six quarters is chosen because within this time interval policy makers can adopt measures to prevent the materialisation of systemic events. Shorter time horizons are less relevant for policy making because the potential for effective pre-emptive actions is lower. For robustness check, we also try time horizons of two, four and eight quarters. The results are discussed at the end of this section on the robustness tests.

⁵ Bussière and Fratzscher (2006) point out that including in the estimation of early warning models the period of economic recovery after a crisis produces the so called “post-crisis bias”. In recovery periods, economic variables go through an adjustment process before reaching again the path they have during tranquil periods. The recovery period therefore should be excluded from the analysis as it is not informative of the path leading from the pre-crisis regime to the crisis.

⁶ The literature on early warning models deals with large datasets of macro data for many countries, several of which are emerging markets. “Real-time datasets” that contain information on the revisions of data after the first publication do not exist yet for several countries in our sample. Our analysis is therefore a real-time analysis in the sense that we take into account publication lags, as in other early warning models (Alessi and Detken (2011)).

money and credit related indicators, the lag ranges from one to two quarters depending on the country. The real-time analysis also implies that de-trended variables are computed using only real-time information. Therefore, we recursively calculate trends at each time t , using only the information available up to that moment.

We also evaluate the performance of several discrete choice models including different sets and different combinations of the standalone indicators of vulnerabilities. Specifically, we test whether considering jointly domestic and international vulnerabilities improves the performance of the model in predicting systemic events. In particular, we test the following models:

- “Currency crisis” model: includes explanatory variables often used in the currency crises literature, as for example the real exchange rate, macro conditions and credit growth.
- “Macroprudential” model: adds equity price growth and valuation to the set of explanatory variables of the “currency crisis” model.
- “Domestic” model: includes the explanatory variables of the “macroprudential” model with the addition of (i) the general government deficit, (ii) the interaction between equity growth and equity valuation, and (iii) the interaction between credit growth and leverage.⁷
- “Domestic and international (no interactions)” model: includes the explanatory variables of the “domestic” model with the exclusion of the interactions terms. It also includes global growth and inflation, global credit growth and leverage, and global equity growth and valuation.
- “Benchmark” model: among the explanatory variables, this includes all the domestic and international indicators of fragilities of the previous model, as well as the interactions among the international and domestic variables.

The evaluation of standalone indicators and discrete choice models is done following the procedure suggested by Alessi and Detken (2011).⁸ For each indicator (either a standalone indicator or the probability estimated with a discrete choice model), we calculate thresholds signalling that a systemic event is going to occur within six quarters. These thresholds for policy action (or early warning thresholds) are calibrated on the basis of their performance in predicting past systemic events. More precisely, they are optimised on the basis of a measure of utility (named “usefulness”) that takes into account policymakers’ preferences between Type I and Type II errors.⁹ Indicators are therefore ranked according to the “usefulness” score that they achieve.

⁷ All interactions are calculated as the product between the relevant indicators.

⁸ Bussière and Fratzscher (2008) also address the issue of policymakers’ preferences in calibrating the optimal early warning thresholds and the timing of policy interventions.

⁹ Regarding policymakers’ preferences, in our benchmark analysis we take the point of view of a policymaker who is equally concerned about issuing false alarms and missing systemic events. This could be considered the point of view of a neutral external observer who does not want to commit any mistakes and is only concerned about correctly calling a systemic event. The point of view of local policymakers or international institutions in charge of giving policy recommendations could be different, as the costs of missing systemic events and issuing false alarms are different (eg through reputational costs or real costs). It is likely that the last financial crisis increased the concerns of policymakers about missing systemic events. However, it is difficult to assess whether policymakers could be assumed to be relatively more concerned about missing crises than about issuing false alarms.

Table 1

Performance of the different indicators and models in predicting systemic events

Model\Indicator	U	NtSr	% predicted	Cond prob	Prob diff
e	0.33	0.22	84.73%	63.24%	35.99%
Benchmark	0.32	0.20	80.95%	65.83%	37.83%
Benchmark (no interactions)	0.31	0.31	88.80%	55.52%	27.52%
Domestic	0.26	0.28	71.71%	57.79%	29.79%
Macroprudential	0.24	0.34	74.23%	53.32%	25.32%
Percentage deviation of the ratio of equity market capitalisation to GDP from Hodrick-Prescott ($\lambda=400000$) trend	0.21	0.45	76.91%	48.44%	18.72%
Percentage deviation of the ratio of private credit to GDP from Hodrick-Prescott ($\lambda=1600$) trend	0.21	0.43	73.09%	49.36%	19.63%
Currency crisis	0.19	0.38	60.33%	49.16%	22.33%

Note: Forecasting horizon is six quarters. The preferences of policymakers are assumed to be balanced between missing crisis warnings and false alarms. The table reports in columns the following measures to assess the efficiency of indicators: (1) usefulness “U” (according to Alessi and Detken (2011)); (2) noise to signal ratio (NtSr) ie the ratio between (i) false signals as a proportion of periods in which false signals could have been issued and (ii) good signals as a proportion of periods in which good signals could have been issued; (3) the percentage of correct signals predicted by the indicator (% predicted); (4) the probability of a crisis conditional on a signal (Cond prob); (5) the difference between the conditional (to a signal) and the unconditional probability of a crisis (Prob diff).

Table 1 summarises the results of our study by reporting the measure of “usefulness” (U) and other statistics to evaluate the efficiency of the indicators. For brevity, we report the results of discrete choice models, and we include in the table only the two best performing standalone indicators.

Overall, our results show that standalone measures of asset price misalignments and credit booms are in general useful leading indicators of systemic events. Interestingly, global measures of credit expansion and asset price developments perform better than indicators of domestic fragilities.¹⁰ Interactions between domestic variables as well as between global and domestic variables are among the best standalone indicators. However, our results (Table 1) highlight the importance of considering jointly various indicators in a multivariate framework, as we find that discrete choice models outperform “standalone” indicators in predicting systemic events. We find that jointly taking into account domestic and global macrofinancial vulnerabilities greatly improves the performance of discrete choice models in forecasting systemic events. In addition, consideration of the interactions between domestic and global macrofinancial vulnerabilities further improves the performance of the model.

All these results survive a battery of robustness tests, including changes in the way vulnerabilities are measured. The insertion of additional explanatory variables capturing

¹⁰ These results are also supported by the conclusions of Borio and Lowe (2002), Gerdesmeier et al (2009) and Alessi and Detken (2011).

contagion effects and net capital inflows neither alters the results nor improves the performance of the models. The models have good forecasting performance over different time horizons (two, four, six and eight quarters) and the results are stable under different assumptions for policymakers' preferences, as long as the preferences are not too strong either against missing crises or against issuing false alarms.

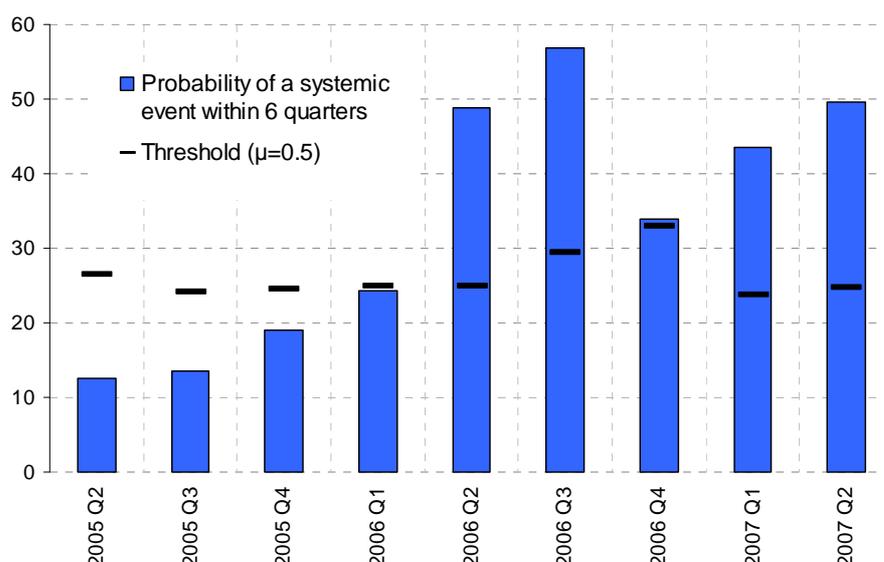
4. Conclusions

This paper contributes to the financial crisis literature by developing a unified framework for assessing systemic risks, stemming from domestic and global macrofinancial vulnerabilities, and for predicting systemic events, ie periods of extreme financial instability with potential real costs.

We extend the existing literature on predicting financial crises in several ways. First, we identify past systemic events by using a composite index measuring the level of systemic tensions in the financial system of one country. Second, in predicting the identified systemic events, we evaluate the joint role of domestic and global vulnerabilities. In addition, we also analyse the role of the interactions between domestic factors and the interplay of global developments with the domestic conditions. Third, we evaluate both “standalone” macroprudential indicators of vulnerabilities, and composite indicators calculated using discrete choice models. The evaluation of the indicators is done with a common methodology that takes into account policymakers' preferences.

Our empirical analysis covers a set of 28 emerging market and advanced economies with quarterly data since 1990. Our results highlight the importance of considering jointly various indicators in a multivariate framework, as we find that discrete choice models outperform “standalone” indicators in predicting systemic events. We find that jointly taking into account domestic and global macrofinancial vulnerabilities greatly improves the performance of discrete choice models in forecasting systemic events. In addition, consideration of the interactions between domestic and global macrofinancial vulnerabilities further improves the performance of the model.

Figure 1
Predicting (out of sample) the latest financial crisis in the United States



Note: The X-axis represents time (in quarters), while the Y-axis represents the probability of a systemic event within the next six quarters (threshold optimised for $\mu=0.5$). The probability is the output of the benchmark logit model.

Our framework displays a good out-of-sample performance in predicting the last financial crisis. Our model would have issued an early warning signal for the United States in 2006 Q2, five quarters before the emergence of the tensions in money markets that started the crisis in August 2007 (Figure 1). Our analysis reveals that both domestic (credit cycle and macro-overheating) and global factors (equity valuations and macro-overheating) were important determinants of systemic risk in the United States in the period before the crisis. Knowing the sources of systemic risk can guide the policymaker in choosing policy responses. Some risks can be mitigated by domestic policies. However, the importance of global factors as sources of systemic risk suggests that international cooperation and coordinated policy actions are crucial in preserving global financial stability.

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