Understanding Financial Crisis:
Fields–Mitacs Undergraduate Summer Research Programs (2011,2012)

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Executive Summary

This is a technical report for the work conducted during the past two Fields–Mitacs Undergraduate Summer Research Programs.

Section 1 summarizes our results for early warning indicators for currency and banking crises. This portion of the work was carried out with the assistance of Garence Staraci, Lucas Bentivenha, Euijun Kim, Nikita Reymer, Rafael Rocha, Hyung-Bin Ihm, and Richard Cerezo, as part of the Fields–Mitacs Undergraduate Summer Research Program at the Fields Institute during the months of July and August, 2011.

Section 2 summarizes our results for early warning indicators for stock market crises. This portion of the work was carried out with the assistance of Aditya Maheshwari, Camelia Yazdani, Francesc Rullan, Saul Toscano Palmerin, and Zixuan Wang, as part of the Fields–Mitacs Undergraduate Summer Research Program at the Fields Institute during the months of July and August, 2012.

1 Building an Early Warning System For Financial Crises

In this new section, we propose a summary of the second part of the summer project which was done at the Fields Institute during the months of July and August 2011, by a group of six undergraduate students participating in the Fields-MITACS Undergraduate Summer Research Program.

A first subsection will be devoted to an introduction of this project, and will describe its motivation together with its goal. A second subsection will detail the methodology used by the group whereas a last subsection will provide the obtained results and give a brief discussion about its possible future directions.

1.1 Introduction And Motivation

The aim of this latter part of the project was to examine the empirical evidence of several types of financial crises, and to develop a *early warning system* specific to each of them, using our now extensive database. As noted by Kaminsky, Lizondo and Reinhart [9], accurately forecasting the timing of financial crises is likely to remain an elusive goal for academics and policymakers alike. However, developing a warning system that helps monitor whether a country may be slipping into a potential crisis would be of special interest in a political, financial or academic setting. Indeed, policymakers could use this system to avoid the crisis, market practitioners could use it to make money, and academics for research purposes.

As our approach will be exclusively empirical, a first step in our work was to survey the empirical literature in order to be aware of the various approaches used to assess the usefulness of potential indicators - for any given type of crisis - but also to identify the specific indicators that have been found to be most reliable. However, as we will soon observe, the selection of indicators taken into account in a given empirical study often emerges from theoretical considerations. Moreover, the results of all these empirical studies indicate that an effective warning system should consider a broad variety of indicators, since a specific type of financial crisis can sometimes be preceded by a broad range of economic problems.

The warning system we will implement in this project is entitled the *signal approach*, and involves monitoring the evolution of a number of economic indicators that tend to behave differently prior to a given crisis. At a given time, we will interpret the *warning signal* - that a crisis may take place within the next windows (usually 24 months) - as being the event that changes in the level of an indicator exceeds a certain threshold value. We will compute the threshold values so as to strike a balance between the risk of having many false signals (when a signal is issued at the slightest possibility of a crisis), and the risk of missing the crisis altogether (when the signal is issued only when the evidence is overwhelming). Of course, if our implementation is efficient, we will be able to identify the group of indicators issuing signals. This will provide information about the sources of the problems that underlie a crisis.

In the remaining part of this section, we choose to introduce our approach using the specific example of currency crises. This choice has only been made for sake of clarity. Of course, we will soon realize that our implementation allows to study any given type of financial crisis without significant modifications. We start now by providing a motivation for this approach, and we finally give our results for currency and banking crises.

1.2 Examples of indicators for currency crisis

1.2.1 Theoretical Foundations

As we previously mentioned, the choice of indicators in empirical work on crises is often motivated by previous theoretical work. Following the presentation of [9], we quickly summarizes here the main explanations for speculative attacks and balance of payments crises that have been presented in the theoretical literature.

The theoretical literature on balanced of payments crisis has grown since Krugman's seminal paper of 1979 [11]. His model shows that, under a fixed exchange rate, domestic credit expansion in excess of money demand growth leads to a gradual but persistent loss of international reserves and, ultimately, to a speculative attack on the currency. As a consequence to this attack, the reserves are consumed and the authorities are forced to abandon the parity. The whole process will naturally end with an attack because economic agents understand that the fixed exchange rate regime will eventually collapse, and that in the absence of an attack they would suffer a capital loss on their holdings of domestic money. Hence, since this model implies that the period of time preceding a currency crisis would be characterized by a gradual but persistent decline in international reserves together with a rapid growth of domestic credit relative to the demand for money, these indicators could be used within an empirical study. Also, to the extent that excessive money creation may result from the need to finance the public sector, fiscal imbalances and credit to the public sector could also serve as indicators of a looming crisis.

Of course, Krugman's model has been extended since then in various directions. In some of these extensions, speculative attacks would generally be preceded by a real appreciation of the currency and a deterioration of the trade balance. Other models suggest that expectations of a future crisis lead to an increase in nominal wages and lower competitiveness. Additionally, models introducing uncertainty about credit policy or about the level of reserve losses that the authorities are willing to sustain to defend the parity show that domestic interest rates would increase as the event of a crisis becomes more apparent. Therefore, the models so far suggest that the evolution of *real exchange rate*, the *trade or current account balance*, *real wages*, and *domestic interest rates* could be used as leading indicators of crises.

Contrary to what we have described so far, more recent models have shown that a crisis may develop without a significant change in the "economic fundamentals". In these latter models, economic policies are not fixed or predetermined, but respond to changes in the economy, and economic agents take this relationship into account in forming their expectations. These recent theoretical developments have highlighted the importance that other variables may have in helping to predict those crises.

Ozkan and Sutherland [19], built a model in which the authorities objective function depends positively on certain benefits derived from keeping a fixed nominal exchange rate and negatively on the deviations of output from a certain target level. Under this fixed exchange rate, we observe that increases in foreign interest rates lead to higher domestic rates and lower levels of output, making it more costly for the authorities to maintain the parity. As a consequence, the cost of keeping the exchange rate fixed surpasses the benefits when foreign exchange rates exceed some critical level, and the authorities abandon the parity. In conclusion, based on this model, useful indicators for currency crises would be the evolution of *output*, and *domestic* and *foreign interest rates.*

This model explicitly suggest that a variety of factors that may impact the authorities' objective function could be used as leading indicators of currency crises. Among the multiple factors, higher interest rates for instance could weaken the banking system, and the authorities may choose to devaluate rather than incur the cost of bailout that could result from an explicit or implicit guarantee on the banking system liabilities. Hence, banking problems (that could emerge from large decline in deposits, price of bank stocks or central bank credit to banks for instance), could indicate a higher likelihood of a crisis. This problem was explicitly studied in details by Kaminsky and Reinhart [10]. In Obsfeld [18], higher wages and lower employment are consequences of the expectation of a collapse, and prompt the government to abandon the parity out of concern for output. Finally, some models have focused on contagion effects as the spark of of balance of payment crisis. As shown by the model of Gerlach and Smets [7], the devaluation by one country leads its trading partners to devaluate in order ot avoid a loss of competitiveness. *Contagion effects* also may arise if investors pay little heed to countries' economic fundamentals, and thus do not discriminate properly among countries. A crisis in a neighbouring country may therefore be an indicator of a future domestic crisis if contagion effects are present.

1.2.2 Previous Empirical Work

Here we briefly describe the different methodologies and variables that have been used in the empirical literature to characterize the period of time preceding a given currency crises and to assess the probability of such crises, together with the associated results.

A summary of 28 selected empirical studies on currency crises is given in [9]. For each study the authors explicit the sample periods and the periodicity of the data, provide informations on the countries covered and the type of episode examined, and list the political and economic variables that have been used as indicators. They also explain certain features of the methodology used and the principal goal of the study in question. Even though these studies tend to put more emphasis on emerging economies, they cover advanced ones as well. They consider sample periods that run from the early 1950s to the 1990s, and for about half of them, use monthly data (the rest using mostly annual ones). Only a few of the studies are country-specific, most of them examine various countries and study several crisis episodes at the same time.

Of course, one of the central questions is how a currency crisis is defined. In our project, we will work with the specific definition used by Reinhart and Rogoff in their book [23]. We now wish to underline that most of the empirical studies previously mentioned focus exclusively on devaluation episodes. However, a few studies adopt a broader definition of crises. Indeed, they include *unsuccessful speculative attacks* episodes in addition to devaluations, that is, attacks that were averted without a devaluation, but at the cost of a large increase in domestic interest rates and/or a sizeable loss of international reserves.

In terms of methodology, the studies can be classified into four broad categories:

1. Studies providing *only* a quantitative discussion of the causes and developments leading to the currency crises. They stress the evolution of one or more indicators, but not formal tests are conducted to evaluate the usefulness of the various indicators in predicting crises.

2. Studies examining the period leading up to and immediately following the currency crisis. Using a control group of countries in which no crisis occurred, parametric and nonparametric tests are used to assess whether there are systematic differences between the pre–crisis episodes and the control group. Here we can narrow the list of potential indicators, since not all variables included in the analysis ended up showing 'abnomal' behaviour ahead of crises.

3. Studies estimating the probability of devaluation one or several periods ahead, usually on the basis of an explicit theoretical model. They include individual and multi–country panel stud-

ies. Again, we can here narrow the list of potential indicators using the notion of significance in a regression setting.

4. Studies using the Kaminsky and Reinhard approach, i.e a nonparametric approach to evaluating the usefulness of several variables in signalling an impending crisis. This method will be explained later in this section.

The whole sample of mentioned empirical studies used a total of 105 indicators, grouped into six broad categories and some subcategories, including the *external sector*, the *financial sector*, the *real sector*, and *public finances*; *institutional and structural variables*, *political variables*, and *contagion effects*. The complete list of indicators, classified by category, is given below.

- *Capital Account*: international reserves, capital flows, short-term capital flows, foreign direct investment, and differential between domestic and foreign interest rates.
- *Debt Profile*: public foreign debt, total foreign debt, short-term debt, share of debt classified by type of creditor and by interest structure, debt service and foreign aid.
- *Current Account*: real exchange rate, current account balance, trade balance, exports, imports, terms of trade, price of exports, savings, and investment.
- *International Variables*: foreign real GDP growth, interest rates, and price level.
- *Financial Liberalization*: credit growth, change in the money multiplier, real interest rates, and spread between bank lending and deposit interest rates.
- *Other Financial Variables*: central bank credit to the banking system, gap between money demand and supply, money growth, bond yields, domestic inflation, 'shadow' exchange rate, parallel market exchange rate premium, central exchange rate parity, position of the exchange rate within the official band, and M2/international reserves.
- *Real Sector*: real GDP growth, output, output gap, employment/unemployment, wages, and changes in stock prices.
- *Fiscal Variables*: fiscal deficit, government consumption, and credit to the public sector.
- *Institutional/Structural Factors*: openness, trade concentration, dummies for multiple exchange rates, exchange controls, duration of the fixed exchange rate periods, financial liberalization, banking crises, past forein exchange market crises, and past foreign exchange market events.
- *Political Variables*: dummies for elections, incumbent electoral victory or loss, change of government, legal executive transfer, illegal executive transfer, left-wing government, and new finance minister.

The appendix A4 of [9] shows the number of studies in the overall sample that tested the statistical significance of the indicators, and reports the number of studies in which the indicator was found to be significant in *at least* one of the tests conducted. A careful comparison of results across all the studies reveals that there is unfortunately no clear-cut answer concerning the usefulness of each of the potential indicators of currency crisis. This could have somehow been expected a lot of factors differ among the studies, for instance the periodicity of the data, the estimation technique, and the set of variables simultaneously included in the tests. However, five conclusions can be derived from these studies:

1. *An effective warning system should consider a broad variety of indicators.* Indeed, financial crises can be preceded by multiple economic, and sometimes political, problems.

2. For the specific case of currency crises, those individual variables that receive ample support as indicators are *international reserves, the real exchange rate, credit growth, credit to the public sector, and domestic inflation.* The results also provide support for the trade of balance, export performance, money growth, M2/International Reserves, real GDP growth and the fiscal deficit.

3. *Only tentative conclusions can be drawn regarding the other indicators.* The primary reason is that most of them are included in only one or two of the studies under review.

4. *Variables associated with the external debt profile did not fare well.* Moreover, contrary to the previous expectations, *the current account balance did not receive much support as a useful indicator of crises.* A possible reason could be that the behavior of the current account balance to some extent may have already been reflected in the evolution of the real exchange rate. More details on this point can be found in [9].

5. *Market variables*, such as exchange rate expectations and interest rate differentials *do not do well in predicting currency crises*, whether these were preceded or followed by deteriorating economic fundamentals or not.

Most of the quantitative studies included in the reviewed sample have used two distinct methodologies that could serve as the basis for an early warning system of currency crises. The most common approach has been to estimate the one-step (or k-step) ahead probability of devaluation in the context of a *multivariate logit or probit* model. This approach has the advantage of summarizing information about the likelihood of a crisis in one useful number, the probability of devaluation. It also considers all the variables simultaneously, and disregards those variables that do not contribute information that is independent from that provided by the other variables already included in the analysis. However, this approach does not provid a metric for ranking the indicators in terms of their abilities to detect crises, since a variable enters the regresion significantly or it does not. Moreover, the nonlinear nature of these models makes it difficult to assess the marginal contribution of an indicator at a point in time to the probability of a crisis.

Our implementation of the *signal approach*, which will now describe until the end of this section, will allow us to overcome some of these limitations by considering the performance of individual indicators, and will thus provide information on the source and breadth of the problems that underline the probability of a crisis. It will also allow to estimate the probability of a crisis, which will depend directly on the reliability of the indicators that are sending the signals. This will turn out to be better suited to serve as the basis for the design of an early warning system.

1.3 The Signals Approach

The origin of our implementation lies in the discussion of Kaminsky and Reinhart in the 1996 version of the paper [10]. In this paper, they examine 76 currency crises from a sample of 15 developing and 5 industrial countries during 1970-95. We will also implement the methodological improvement described in [9], that is, ranking the indicators by three alternative metrics: (i) the probability of a crisis conditional on a signal from that indicator, (ii) the average number of months prior to the crisis in which the first signal is issued, and (iii) the persistence of signals ahead of crises.

As previously mentioned, the *signal approach* involves monitoring the evolution of a number of economic variables. When one of these variables will deviate from its *normal* level beyond a certain *threshold* value, within a specified time period, we will interpret this event as a **warning signal** about a possible financial crisis (a currency in our example). Of course in our implementation, we will additionally be able to use our extensive database, instead of only focusing on a short period of time and on a small number of countries. Contrary to the previous studies using this approach, our implementation will also consider the definition of currency crisis given by Reinhart and Rogoff in their book [23].

For sake of completeness, we underline the fact that for most of the empirical studies done on currency crises, a crisis is identified by the behaviour of an *index of exchange market pressure*. This index is built on a weighted average of monthly percentage changes in the exchange rate, and the negative of monthly percentage changes in gross international reserves. The weights are usually chosen so that the two components of the index are comparable. Since it is observed that changes reserves are typically a lot more volatile than changes in the exchange rate, the weights are chosen so that their conditional variances are roughly of the same order. As the index increases with a depreciation of the currency and with a loss of international reserves, an increase in the index reflects stronger selling pressure on the domestic currency. Periods in which the index is above its mean by more than three standard deviations are defined as crises.

For some of the indicators we consider, the variable we monitor is the percentage change in the level of indicator on a given month with respect to its level a year earlier. This filtering using

12-month percentage changes was done in order to remove all seasonality trends from the data, and to make sure that the measurements units are comparable across countries. This applies, for example, to imports, exports and international reserves, whose levels vary quite a lot from one country to another and exhibit strong seasonality. For other indicators, we monitor the level of the indicator itself, with a trend (either linear or exponential) removed. This applies for example to real interest rates, terms of trade, or inflation rates, whose values are easily comparable between countries and do not exhibit any obvious seasonalities. In whichever case we say that the indicator issues a signal if the variable of interest (e.g year-to-year percentage change, linearly de-trended level, etc) departs from its mean beyond a given threshold level.

We then choose the *signalling horizon*, that is, the period of time within which the indicators would be expected to have an ability for anticipating crises. We set 24 months as the base signalling horizon, but also compare it with other choices. Therefore a signal, at a given time, that is followed by a crisis within 24 months is considered to be a *good signal*, while a signal not followed by a crisis during that interval of time is called *bad signal* or *noise*. We must be careful when setting these thresholds, since if it is too low, the data will be issuing too many signals whereas if it is set too high, we won't obtain enough signals (and therefore miss crises). We must therefore find the *optimal* set of country-specific thresholds. In order to do so, we define thresholds in relation to percentiles of the distribution of observations of changes in the indicator. For *each* country, we look at the distribution of changes of the indicator and search for the value that would leave say 10 % of the observations above it. Repeating this process using percentiles from 10 to 20 %, we select the percentile which minimizes the *noise-to-signal* ratio; that is, the ratio of false signals to good signals. This specific percentile will be our *optimal threshold*.

We can now examine the effectiveness of the signals approach at the level of individual indicators and do a performance analysis. This performance will be studied in terms of the following matrix:

	Crisis (within 24 months)	No Crisis (within 24 months)
Signal Issued	A	B
No Signal Issued	C	D

Where we therefore have:

A: Number of months in which the indicator issued a *good* signal.

B: Number of months in which the indicator issued a *bad* signal, or *noise*.

C: Number of months in which the indicator *failed* to issue a signal (which would have been a good signal).

D: Number of months in which the indicator refrained from issuing a signal (which would have been a bad signal).

Clearly, in the ideal case of a perfect indicator, $B = C = 0$ and $A > 0, D > 0$. We clearly do not expect any of the indicators to fit the profile of a perfect indicator. However, we can use this matrix as a reference to assess how close or how far is each indicator from that profile. Indeed, we are now able to compute the following quantities:

- Associated to each indicator is the *number of good issued signals as a percentage of possible good signals.* Using the notation of the above matrix, this number would be $\frac{A}{A+C}$, and would be an alternative measure of tendency of individual indicators to issue good signals.

- Similarly, the *number of bad signals as a percentage of possible bad signals.* This would be $\frac{B}{B+D}$. Other things equal, the lower this ratio is, the better is the indicator.

- By dividing the previous two results, we obtain the *adjusted noise-to-signal ratio* as:

$$NSR := \frac{B/(B+D)}{A/(A+C)} \tag{1}$$

  Other things constant, the lower the number in this column, the better the indicator. This ratio can certainly be used as a criterion for deciding which indicators to drop from the list of possible indicators. Indeed, it is obvious that those indicators with an adjusted noise-to-signal ratio equal to or higher than unity introduce excessive noise, and so are not helpful in predicting crises.

- In addition, we compute the *percentage of crises detected* (PCD) as the percentage of crises in which the indicator issued <u>at least</u> one signal in the previous signalling horizon (e.g 24 months), out of the total number of crises for which data are available

- The probability of a crisis *conditional* on a signal from the indicator:

$$P_{c|s} = P(\text{crisis} \mid \text{signal}) := \frac{A}{A+B} \tag{2}$$

- The *unconditional* probability of a crisis:

$$P_c = P(\text{crisis}) = \frac{A+C}{A+B+C+D} \tag{3}$$

To the extent that the indicator has useful information, the conditional probability would be higher than the unconditional one.

We close this subsection by noticing that so far, we have ranked the indicators based on their abilities to predict crises while producing few false alarms. However, from the point of view of a policymaker who wants to implement preemptive measures, this ranking will not be especially useful since it does not distinguish whether an indicator sends signals well before the crisis occurs, or only when the crisis is imminent. Indeed, in the 24-month window we consider prior to the onset of the crisis, the criteria does not distinguish between a signal given 12 months prior to the crisis and one given one month prior to the crisis. Finally, another desirable feature in a potential leading indicator would be a high number of signals issued prior to a crisis (during the 24-month window). Based on these remarks, we additionally computed the following two quantities:

- The *average lead time* (ALT), defined as the average number of months in advance of the crisis when the **first** signal occurs.
- The *persistence*, defined as the average number of signals issued prior to a crisis during the 24-month window.

In the remaining part of this section, we provide the results of our implementation on both currency and banking crises.

1.4 Summary Of Results

In our implementation, we will use the same set of indicators for both currency and banking crises. The indicators for which we monitor the year-to-year percentage change in level are Reserves, M2–to–Reserves Ratio, Output, Exports, and Imports, whereas those for which we monitor a de-trended level are Exchange Rate, Real Interest Rates, Terms of Trade, and Lending–to–Deposit Ratio.

1.4.1 Currency Crises

We first consider annual data from 1960 to 2010 for the larger collection of 70 countries, using the definition of crises in the book of Reinhart and Rogoff [23], that is, a change of 20% or more in the exchange rate with respect to a reference currency or basket of currencies in a given year. According to this definition of currency crisis, there were 628 currency crisis episodes for the countries and period considered. Because of the annual frequency in both the indicators and the crises dates, neither the persistence nor the average lead time for the signal could be accurately computed.

The results are summarized in the following table:

If we restrict to a smaller subset of the 22 countries considered in the original paper by Kaminski and Reinhart [10], then we can work with monthly data frequency, using the definition of crises based on the index of exchange market pressure discussed previously. Accordingly, there were 112 crises episodes for the countries and period considered. The results are presented in the table below, where we also investigate the effect of different signalling horizons by showing the results for 6, 12, 18, and 24 months horizons.

The results clearly demonstrate that both NSR and PCD decrease as we decrease the window size. This is due to the fact that on an average we would be getting first signal at ALT. So, when ALT is say 15 months then on an average first signal was issued 15 months prior to the crash. The

	A	B	C	D	NSR	%-ile	A/(A+C)	B/(B+D)	$P_{c\|s}$	$P_{c\|s} - P_c$
Reserves	173	135	821	1910	0.38	11	0.17	0.07	0.5617	0.2346
M2/Reserves	128	136	761	1570	0.55	90	0.14	0.08	0.4848	0.1423
Exchange Rate	121	142	761	1710	0.56	10	0.14	0.08	0.4601	0.1375
Real Interest Rates	180	186	468	999	0.57	80	0.28	0.16	0.4918	0.1383
Terms of Trade	75	69	489	792	0.60	11	0.13	0.08	0.5208	0.1250
Output	220	280	634	1371	0.66	20	0.26	0.17	0.4400	0.0991
Exports	284	394	829	1786	0.71	20	0.26	0.18	0.4189	0.0809
Imports	199	419	898	1781	1.05	82	0.18	0.19	0.3220	-0.0107
Lending/Deposit	31	117	532	965	1.96	90	0.06	0.11	0.2095	-0.1328

Table 1: Indicators for currency crises based on annual data for 70 countries from 1970 to 2010.

remaining 9 data points in a 24-month window were increasing the value of C in signal matrix as there was a crisis but was no signals were issued by points between 24 to 15 months prior to crash. Since C is proportional to NSR, thus NSR would increase we increase window length and decrease as we decrease window length.

	Currency Crisis - Monthly Frequency - 24 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	593	731	1604	5358	0.78	0.44	6.75	14.96	84
Exports	366	471	1865	5651	0.85	0.47	4.11	15.58	10
International reserve	364	491	1852	5824	0.71	0.47	4.05	11.14	10
Output	279	376	1606	4297	0.62	0.54	3.04	13.75	10
Domestic Credit/GDP	296	506	1813	5450	0.50	0.61	3.46	11.90	90
M2 multiplier	404	911	1822	5092	0.73	0.84	4.25	16.01	84
Real interest rate	163	428	1377	3948	0.26	0.92	1.95	13.52	90
Imports	180	619	1968	5221	0.43	1.26	2.08	17.21	90
Lending to deposit rate	199	915	1194	3302	0.28	1.52	1.73	13.85	80

	Currency Crisis - Monthly Frequency - 18 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	375	539	1407	5965	0.64	0.39	3.97	9.94	89
Exports	327	510	1480	6036	0.81	0.43	3.44	12.35	10
International reserve	366	576	1431	6158	0.69	0.42	3.86	9.69	11
Output	257	398	1277	4626	0.57	0.47	2.59	10.21	10
Domestic Credit/GDP	270	532	1431	5832	0.45	0.53	2.93	8.38	90
M2 multiplier	335	980	1466	5448	0.65	0.82	3.26	11.45	84
Real interest rate	148	443	1113	4212	0.23	0.81	1.59	9.69	90
Imports	138	661	1601	5588	0.34	1.33	1.43	13.23	90
Lending to deposit rate	199	915	1194	3302	0.28	1.52	1.73	13.85	80

	Currency Crisis - Monthly Frequency - 12 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	327	587	988	6384	0.59	0.34	3.26	7.21	89
Exports	261	576	1071	6445	0.71	0.42	2.59	8.40	10
International reserve	286	569	1041	6635	0.60	0.37	2.89	5.90	10
Output	216	439	921	4982	0.48	0.43	2.00	6.89	10
Domestic Credit/GDP	229	573	1019	6244	0.41	0.46	2.22	6.16	90
M2 multiplier	171	652	1154	6252	0.38	0.73	1.49	7.84	90
Real interest rate	118	473	819	4506	0.20	0.75	1.22	7.28	90
Imports	123	919	1161	5785	0.38	1.43	1.16	9.60	87
Lending to deposit rate	105	789	755	3961	0.20	1.36	0.82	6.99	84

	Currency Crisis - Monthly Frequency - 6 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	228	686	518	6854	0.55	0.30	2.12	4.11	89
Exports	165	672	590	6926	0.57	0.40	1.57	4.50	10
International reserve	206	649	547	7129	0.54	0.31	1.95	3.58	10
Output	131	524	509	5394	0.38	0.43	1.22	3.22	10
Domestic Credit/GDP	139	663	568	6695	0.35	0.46	1.27	3.61	90
M2 multiplier	110	797	638	6684	0.31	0.72	0.97	4.48	89
Real interest rate	74	517	462	4863	0.17	0.70	0.75	3.58	90
Imports	54	827	673	6434	0.23	1.53	0.48	4.19	89
Lending to deposit rate	81	1033	418	4078	0.23	1.25	0.62	4.38	80

Figure 1: Indicators for currency crises based on monthly data for 22 countries from 1960 to 2010

1.4.2 Banking Crises

We start again with annual data for 70 countries from 1960 to 2010, for which there are 451 banking crises episodes. The results for the different indicators are summarized in the table below.

	A	B	C	D	NSR	%-ile	A/(A+C)	B/(B+D)	$P_{c\|s}$	$P_{c\|s} - P_c$
Real Interest Rate	82	92	370	1293	0.37	90	0.18	0.07	0.471	0.225
Output	93	150	474	1775	0.48	20	0.16	0.08	0.383	0.155
Terms of Trade	66	77	381	905	0.53	10	0.15	0.08	0.462	0.149
Exports	144	331	526	2233	0.60	14	0.21	0.13	0.303	0.096
M2/Reserves	70	188	464	1834	0.71	90	0.13	0.09	0.271	0.062
Reserves	76	232	533	2147	0.78	11	0.12	0.10	0.247	0.043
Exchange Rate	59	208	474	1955	0.87	10	0.11	0.10	0.221	0.023
Imports	96	486	563	2093	1.29	82	0.15	0.19	0.165	-0.039
Lending/Deposit	36	263	383	966	2.49	81	0.09	0.21	0.120	-0.134

Table 2: Indicators for banking crises based on annual data for 70 countries from 1970 to 2010.

As with currency crises, we present in the table below the results for monthly data restricted to the smaller set of 22 countries, for which there were 41 episodes of crises.

	Banking Crisis - Monthly Frequency 24 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	171	1069	815	6231	0.59	0.84	4.12	15.33	85
Domestic Credit/GDP	179	870	774	6242	0.56	0.65	4.45	18.54	87
M2 multiplier	263	1219	703	6044	0.76	0.62	5.67	14.77	82
Exports	133	874	870	6476	0.76	0.90	3.64	15.36	12
Real interest rate	269	914	617	4116	0.49	0.60	7.05	18.56	80
Output	130	1049	647	4732	0.66	1.08	3.72	15.83	18
Imports	166	1434	788	5600	0.73	1.17	4.03	19.82	80
International reserve	137	1486	868	6040	0.61	1.45	3.37	15.50	19
Lending to deposit rate	97	1017	758	3738	0.34	1.89	1.52	20.21	80

	Banking Crisis - Monthly Frequency - 18 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	146	1262	607	6271	0.59	0.86	3.36	11.62	83
Domestic Credit/GDP	133	916	593	6423	0.46	0.68	3.18	13.99	87
M2 multiplier	229	1420	505	6075	0.73	0.61	5.10	11.29	80
Exports	121	1045	642	6545	0.68	0.87	3.14	10.38	14
Real interest rate	151	676	525	4564	0.39	0.58	3.81	15.35	86
Output	110	1069	485	4894	0.59	0.97	3.32	10.76	18
Imports	110	1490	616	5772	0.61	1.35	2.51	13.91	80
International reserve	105	1605	660	6161	0.56	1.51	2.34	11.61	20
Lending to deposit rate	65	1049	588	3908	0.32	2.13	0.98	13.33	80

	Banking Crisis- Monthly Frequency - 12 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	64	850	453	6919	0.37	0.88	1.31	5.92	89
Domestic Credit/GDP	94	1037	402	6532	0.44	0.72	2.43	9.03	86
M2 multiplier	133	1182	371	6543	0.63	0.58	3.05	8.00	84
Exports	78	929	445	6901	0.59	0.80	2.10	7.02	12
Real interest rate	104	663	356	4793	0.37	0.54	2.63	10.17	87
Output	77	1102	330	5049	0.49	0.95	2.34	6.14	18
Imports	74	1526	424	5964	0.51	1.37	1.53	9.75	80
International reserve	74	1636	451	6370	0.44	1.45	1.55	6.27	20
Lending to deposit rate	48	1066	401	4095	0.32	1.93	0.72	8.40	80

	Banking Crisis - Monthly Frequency - 6 month window								
	A	B	C	D	PCD	NSR	Persist	ALT	Threshold
M2/Reserve	41	788	240	7217	0.32	0.67	0.83	3.00	90
Domestic Credit/GDP	55	1233	211	6566	0.34	0.76	1.38	4.04	84
M2 multiplier	56	851	218	7104	0.37	0.52	1.35	4.91	89
Exports	47	960	238	7108	0.49	0.72	1.34	3.97	12
Real interest rate	42	549	204	5121	0.24	0.57	1.09	5.07	90
Output	39	750	182	5587	0.34	0.67	1.25	3.31	12
Imports	20	1022	251	6695	0.24	1.79	0.32	3.88	87
International reserve	49	1486	236	6760	0.32	1.05	1.10	3.86	18
Lending to deposit rate	29	1085	210	4286	0.27	1.66	0.44	4.19	80

Figure 2: Indicators for banking crises based on monthly data for 22 countries from 1970 to 2003

2 Stock Market Crises

Since the early beginnings of stock markets two centuries ago, many periods of crises have occurred. Being able to forecast and understand the nature of these periods has been a major goal for both academics and business people. These periods have shown to be very rooted to how the share prices work, because neither developed countries nor growing economies have been capable of avoiding crises, even in our days.

In this work we used the monthly data corresponding to 46 developed and growing economies for the period between 1960 and 2012. In this section we describe how this data was collected and processed. We then describe the results of the signals approach for such crises. Finally we build a global index from the best indicators for each country.

2.1 Indicators for Stock Market Crises

As described in Section 1.3, the signals approach involves monitoring the evolution of several indicators that tend to exhibit an unusual behaviour in the periods preceding a crisis. When an indicator exceeds a certain threshold value, this is interpreted as a warning signal that a stock market crisis may take within the following 24 months.

The indicators used are GDP, domestic credit, imports, exchange rate, exports, M2, real interest rate, lending rate, deposit rate, industrial production, reserves, current account, inflation and CPI. The source for GDP is The World Bank, and for the others is International Monetary Fund. The data was collected in monthly frequency from 1960 to 2010.

The countries used are Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kenya, Korea, Malaysia, Mauritius, Mexico, Netherlands, New Zealand, Norway, Peru, Phillipines, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, The United Kingdom, The United States and Venezuela.

From the data collected we built 31 indicators, each consisting of some initial data and a transformation, as summarize in table 3, where the two different transformations are:

- **Percentage change(PC)** : year-to-year relative change for a given month, multiplied by 100.
- **Second derivative (SD)**: difference of two percentage changes already calculated.

The data for most of the countries was incomplete. To deal with this incompleteness we used interpolation in some cases. The data for which only quarterly data was available, we considered that linear interpolation between the missing two months would not introduce much noise. If more than two months were missing, no interpolation was used.

The exception to this rule is GDP. For this crucial indicator we only had annual data. The limited data from IFS database pushed us towards using the World Bank database, which only had annual data available. The low volatility of GDP compared to lending rates or deposit rates is the reason why we interpolated the GDP using cubic splines. By this we converted the annual data into monthly data.

Name	Transformation	Name	Transformation
Current Account	PC	Industrial Production	PC
Current Account Acceleration	SD	Industrial Production Acceleration	SD
Current Account by GDP	PC	Inflation	PC
Deposit Rate	PC	Lending Rate	PC
Deposit Rate Acceleration	SD	Lending Rate Acceleration	SD
Domestic Credit (National Currency)	PC	M2 by Reserves (NC)	PC
Domestic Credit (NC) by GDP	PC	M2 by Reserves (US)	PC
Domestic Credit (US dollars)	PC	M2 (NC)	PC
Domestic Credit (US) by GDP	PC	M2 (NC) Acceleration	SD
Exchange Rate (SDR)	PC	M2 (US)	PC
Exchange Rate (SDR) Acceleration	SD	M2 (US) Acceleration	SD
Exchange Rate (US)	PC	Real Interest Rate	PC
Exchange Rate (US) Acceleration	PC	Reserves (NC)	PC
Exports	PC	Reserves (SDR)	PC
GDP Acceleration	SD	Reserves (US)	PC
Imports	PC		

Table 3: Data transformation used for each indicator

2.2 Crisis Definition

In order to be able to implement the signals approach, we had to define what is a crisis. Reviewing the literature, we found a definition of crisis quite widespread known as `CMAX`. It is defined as follows:

$$\mathtt{CMAX}_t = \frac{P_t}{\max(P_{t-W} \dots P_{t-1}, P_t)}$$

where P_{t-i} is the share price at time $t-i$ and W is the window length chosen for the calculation. We used a window length of 24 months. By changing this period we may be more or less sensible to what we consider as a crisis, by comparing the present moment to the past months.

Once we have obtained the `CMAX` for a particular data set, the next step is to calculate its mean and standard deviation for each country, and then compute:

$$
\begin{aligned}
&\texttt{if}(\texttt{CMAX}_t < \texttt{mean} - n \cdot \texttt{std})\\
&\qquad \texttt{Crisis} = 1\\
&\texttt{else}\\
&\qquad \texttt{Crisis} = 0
\end{aligned}
$$

In this case n is also a parameter that should be used to fix the sensibility. We used both 1.5 and 2 standard deviations in the work presented here.

Apart from `CMAX` index, we also used a variable called `Return`. It works in a different way:

$$\texttt{Return} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

So given the dataset corresponding to share prices, we computed the `Return` index and then proceeded in the same way as we did for `CMAX`, by calculating the corresponding mean and standard deviation and considering the values below 2 standard deviations from the mean as crisis. Both definitions lead to crisis periods widely known as crisis, and the difference between them arises when it comes to number of crises pointed out: for the `CMAX` the number is nearly half of the one given by `Return`.

2.3 Results for Indicators

In this part we present part of the results obtained while working on the signals approach. Some discussion will be made upon the differences among them and how we dealt with them. The number of A, B, C and Ds is computed for every country and then added with the other countries for every indicator. At this point we calculated the quality measurements as an overall for the whole sample of countries, instead of taking each separately.

As before, we initially use a 24–month window to evaluate the performance of each indicator. Later on, we moved to a window of 12 months, since stock market index is more volatile than currency exchange or banking situation: it seems rather difficult to prove the relationship between what occurs today and the stock market prices in 2 years time. Most of the results have been obtained with both windows, in order to be able to compare their performance.

CMAX

Using 2 standard deviations from Cmax gave us 204 crises. The results for this case are presented in Figures 3 and 4 below for 12 and 24-month time windows, respectively, with the indicators ordered according to their noise–to–signal ratio (NSR). As expected, both the noise–to–signal ratio (NSR) and the percentage of crises detected (PCD) increase with the longer window. Whereas the average

NSR increased from 0.67 to 0.75 (a 12% increase), the average PCD increased from 0.62 to 0.74 (a 20% increase), leading us to conclude that the a 24-month window is preferable for prediction purposes. Interestingly, the ranking of the indicators based on either of these two performance criteria change depending on which window is selected.

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Lending Rate	338	1193	1284	12224	0.41	0.43	2.35	8.07	90
M2 US	448	1560	1783	16377	0.62	0.43	2.61	6.20	10
Industrial Production	352	1248	1399	13002	0.52	0.44	2.55	7.30	10
Imports	503	1830	2010	18969	0.52	0.44	2.72	7.58	10
Industrial Production Acceleration	321	1241	1416	12605	0.57	0.49	2.26	7.29	10
Exports	446	1903	2061	19076	0.60	0.51	2.32	7.19	10
Current Account	322	1264	1567	12679	0.39	0.53	2.16	9.04	10
Domestic Credit US	394	1723	1926	17252	0.75	0.53	2.22	6.95	10
GDP Acceleration	401	1838	1955	18287	0.81	0.54	2.22	7.77	10
Deposit Rate	338	1731	1312	12805	0.55	0.58	2.02	8.47	90
Reserves US	391	1947	2064	19044	0.68	0.58	2.07	7.68	10
Real Interest Rate	264	1407	1310	12317	0.40	0.61	2.08	6.55	11
Reserves SDR	389	2022	2180	19581	0.70	0.62	2.02	7.77	10
M2 US Acceleration	326	1671	1896	16080	0.81	0.64	1.80	7.68	10
Exchange Rate US Acceleration	452	2560	2155	19489	0.78	0.67	2.15	8.10	10
Reserves NC	345	1984	2110	19073	0.36	0.67	1.76	8.14	10
Deposit Rate Acceleration	340	2036	1304	12417	0.74	0.68	2.08	8.50	12
Current Account with GDP	263	1316	1626	12557	0.38	0.68	1.69	8.26	10
M2 by Reserves NC	286	1630	1826	15544	0.61	0.70	1.60	7.77	10
M2 by Reserves US	286	1630	1826	15544	0.61	0.70	1.60	7.77	10
Domestic Credit US with GDP	301	1774	1969	16803	0.74	0.72	1.65	7.72	10
Lending Rate Acceleration	215	1333	1433	12397	0.60	0.74	1.46	8.25	10
Exchange Rate SDR Acceleration	317	2130	2290	19928	0.62	0.79	1.61	8.46	10
M2 NC Acceleration	324	2071	1898	15680	0.84	0.80	1.70	8.48	12
Domestic Credit NC	280	1864	2040	17116	0.53	0.81	1.48	8.18	10
Exchange Rate SDR	307	2173	2300	19907	0.61	0.84	1.65	8.58	10
M2 NC	330	2339	1896	15455	0.74	0.89	1.79	7.87	13
Domestic Credit NC with GDP	398	2949	1872	15628	0.72	0.91	2.12	8.75	16
Exchange Rate US	441	3440	2166	18640	0.67	0.92	2.10	8.99	12
Current Account Acceleration	396	2859	1517	11531	0.76	0.96	2.62	8.60	20
Inflation	297	2415	2119	17862	0.60	0.97	1.66	7.16	12

Figure 3: Indicators for stock market crises defined by Cmax variation of 2 standard deviations, based on monthly data for 46 countries from 1960 to 2010 (12–month window)

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Lending Rate	485	1046	2230	11278	0.50	0.48	3.69	13.90	90
Current Account	502	1084	2647	11599	0.51	0.54	3.63	16.35	10
M2 US	593	1433	3166	15086	0.70	0.55	3.65	11.05	10
Deposit Rate	562	1519	2215	11969	0.69	0.56	3.99	15.32	90
GDP Acceleration	593	1659	3390	16974	0.90	0.60	3.71	16.88	10
Industrial Production	438	1164	2511	11890	0.61	0.60	3.51	12.55	10
Industrial Production Acceleration	508	1370	2390	11317	0.77	0.62	4.07	13.09	12
Imports	597	1736	3621	17360	0.61	0.64	3.41	12.47	10
Exports	592	1758	3627	17511	0.70	0.65	3.34	12.99	10
Domestic Credit US	539	1605	3421	15846	0.87	0.68	3.34	13.85	10
Reserves US	559	1799	3594	17626	0.78	0.69	3.27	14.62	10
Reserves SDR	572	1856	3767	18109	0.81	0.71	3.27	15.28	10
M2 US Acceleration	488	1522	3248	14812	0.92	0.71	3.05	16.93	10
Current Account with GDP	404	1175	2745	11438	0.49	0.73	2.86	15.85	10
Deposit Rate Acceleration	493	1739	2273	11663	0.78	0.73	3.24	15.65	11
M2 by Reserves NC	452	1489	3106	14349	0.70	0.74	2.91	16.79	10
M2 by Reserves US	452	1489	3106	14349	0.70	0.74	2.91	16.79	10
Exchange Rate US Acceleration	681	2350	3720	18056	0.88	0.74	3.50	15.78	10
Domestic Credit US with GDP	469	1629	3393	15471	0.84	0.78	3.04	17.71	10
Real Interest Rate	574	2192	2074	10521	0.71	0.80	4.56	13.75	18
Reserves NC	588	2238	3568	17251	0.54	0.81	3.55	14.63	12
M2 NC Acceleration	524	1886	3212	14448	0.91	0.82	3.19	18.38	12
Exchange Rate SDR Acceleration	514	1965	3887	18451	0.76	0.82	2.82	16.27	10
Lending Rate Acceleration	353	1356	2426	11267	0.75	0.85	2.56	15.80	11
Exchange Rate SDR	852	3380	3549	17073	0.86	0.85	4.83	18.77	17
Domestic Credit NC	426	1719	3534	15747	0.60	0.91	2.45	16.39	10
Domestic Credit NC with GDP	657	2701	3205	14399	0.76	0.93	3.81	18.94	16
Exchange Rate US	729	3160	3672	17293	0.79	0.93	3.75	17.35	12
M2 NC	522	2161	3222	14223	0.82	0.95	3.30	17.37	13
Current Account Acceleration	658	2615	2567	10523	0.84	0.98	4.68	17.60	20
Inflation	486	2255	3577	16496	0.78	1.01	2.86	15.93	12

Figure 4: Indicators for stock market crises defined by Cmax variation of 2 standard deviations, based on monthly data for 46 countries from 1960 to 2010 (24–month window)

Alternatively, using 1.5 standard deviations from Cmax gave us 351 crises. The results for this case are presented in Figures 5 and 6 below for 12 and 24-month time windows, respectively, with the indicators ordered according to their NSR as before. As we increased the time window, we observe the average NSR changing from 0.70 to 0.76 (an 8.5% increase) and the average PCD changing from 0.60 to 0.72 (a 12% increase), leading us to conclude again in favour of the 24-month window.

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Industrial Production	576	1024	2536	11865	0.52	0.43	2.25	7.52	10
M2 US	689	1322	3122	15046	0.55	0.45	2.25	6.79	10
Lending Rate	498	1033	2246	11273	0.37	0.46	2.09	8.07	90
Imports	755	1579	3580	17409	0.50	0.48	2.23	7.83	10
Industrial Production Acceleration	505	1057	2561	11460	0.57	0.51	2.00	7.09	10
Exports	704	1647	3649	17497	0.54	0.53	2.06	7.64	10
GDP Acceleration	606	1633	3425	16817	0.76	0.59	1.92	7.91	10
Domestic Credit US	598	1519	3443	15744	0.74	0.59	1.87	7.37	10
Current Account	476	1110	2779	11467	0.37	0.60	1.85	8.63	10
Reserves US	608	1731	3591	17527	0.68	0.62	1.80	7.78	10
Deposit Rate	557	1680	2316	11644	0.54	0.65	1.98	8.18	89
Reserves SDR	601	1811	3801	17970	0.69	0.67	1.76	7.63	10
Reserves NC	626	1938	3575	17384	0.35	0.67	1.80	8.86	11
Real Interest Rate	403	1269	2352	11285	0.37	0.69	1.68	6.52	11
M2 US Acceleration	503	1496	3280	14705	0.82	0.69	1.63	7.60	10
Exchange Rate US Acceleration	712	2301	3752	17902	0.75	0.71	1.98	8.06	10
Lending Rate Acceleration	367	1182	2427	11413	0.59	0.71	1.56	8.03	10
Current Account with GDP	416	1163	2839	11344	0.35	0.73	1.63	8.07	10
Deposit Rate Acceleration	534	1843	2327	11404	0.72	0.75	1.91	8.28	12
M2 by Reserves NC	435	1482	3151	14229	0.53	0.78	1.41	8.27	10
M2 by Reserves US	435	1482	3151	14229	0.53	0.78	1.41	8.27	10
Exchange Rate SDR Acceleration	539	1908	3925	18304	0.64	0.78	1.51	7.93	10
Domestic Credit US with GDP	471	1604	3508	15273	0.70	0.80	1.53	8.03	10
Exchange Rate SDR	578	2148	3886	18086	0.66	0.82	1.67	8.16	11
M2 NC Acceleration	523	1874	3260	14327	0.83	0.84	1.70	8.39	12
Domestic Credit NC	512	1848	3529	15420	0.57	0.84	1.54	8.28	11
M2 NC	569	2101	3220	14141	0.73	0.86	1.90	8.26	13
Inflation	453	1807	3727	16717	0.56	0.90	1.39	7.38	10
Domestic Credit NC with GDP	719	2838	3260	14039	0.76	0.93	2.23	9.21	17
Exchange Rate US	649	2770	3815	17464	0.64	0.94	1.79	8.57	10
Current Account Acceleration	501	1943	2838	11021	0.67	1.00	1.90	7.79	15

Figure 5: Indicators for stock market crises defined by Cmax variation of 1.5 standard deviations, based on monthly data for 46 countries from 1960 to 2010 (12–month window)

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Lending Rate	788	1058	3614	9590	0.49	0.56	3.88	14.53	88
M2 US	882	1147	5212	13048	0.66	0.56	3.38	12.78	10
Current Account	730	856	4395	9851	0.50	0.56	3.21	16.26	10
Industrial Production	703	899	4197	10204	0.64	0.56	3.29	12.55	10
Imports	920	1414	5927	15064	0.60	0.64	3.24	16.77	10
Industrial Production Acceleration	641	923	4170	9851	0.72	0.64	3.15	13.69	10
Exports	912	1440	5988	15159	0.70	0.66	3.08	13.02	10
GDP Acceleration	848	1404	5594	14770	0.84	0.66	3.16	14.16	10
Deposit Rate	838	1414	3773	10251	0.68	0.67	3.62	15.63	89
Reserves US	868	1491	5845	15385	0.78	0.68	3.08	15.82	10
Current Account with GDP	649	930	4476	9707	0.48	0.69	2.86	16.00	10
Domestic Credit US	823	1321	5683	13593	0.85	0.70	3.04	14.94	10
Reserves SDR	887	1542	6139	15747	0.80	0.71	3.10	15.95	10
Reserves NC	984	1844	5752	15076	0.52	0.75	3.47	16.26	12
Exchange Rate US Acceleration	1043	1989	6068	15718	0.84	0.77	3.39	16.16	10
M2 US Acceleration	721	1291	5327	12742	0.90	0.77	2.82	16.86	10
Deposit Rate Acceleration	752	1481	3834	10112	0.80	0.78	3.11	16.20	11
Lending Rate Acceleration	533	1020	3964	9896	0.71	0.79	2.57	16.34	10
Real Interest Rate	919	1849	3509	9095	0.68	0.81	4.21	15.05	18
Exchange Rate SDR Acceleration	815	1664	6296	16053	0.78	0.82	2.74	16.54	10
M2 by Reserves NC	652	1290	5094	12371	0.66	0.83	2.57	16.69	10
M2 by Reserves US	652	1290	5094	12371	0.66	0.83	2.56	16.69	10
Domestic Credit US with GDP	717	1381	5679	13194	0.82	0.85	2.83	17.71	10
M2 NC Acceleration	808	1604	5240	12429	0.91	0.86	3.17	18.44	12
Exchange Rate SDR	1251	2735	5861	15018	0.84	0.88	4.21	18.88	16
Domestic Credit NC	775	1586	5731	13343	0.64	0.89	2.77	17.65	11
Inflation	841	1902	5797	14285	0.80	0.93	3.09	17.46	12
M2 NC	848	1836	5211	12244	0.83	0.93	3.37	17.93	13
Domestic Credit NC with GDP	1134	2435	5262	12140	0.80	0.94	4.15	19.69	17
Exchange Rate US	1151	2740	5961	15013	0.76	0.95	3.70	17.74	12
Current Account Acceleration	899	1881	4366	9217	0.78	0.99	4.00	17.37	17

Figure 6: Indicators for stock market crises defined by Cmax variation of 1.5 standard deviations, based on monthly data for 46 countries from 1960 to 2010 (24–month window)

Surprisingly, when comparing the definitions of crises based on 2 and 1.5 standard deviations from Cmax we find that moving to the latter both increased the NSR and decreased the PCD, which leads us to strongly favour the use of 2 standard deviations.

Return

Using returns more than 2 standard deviations below their mean as a definition for stock market crises we found XXX episodes of crises. The results for this case are presented in Figures 7 and 8 below for 12 and 24-month time windows, respectively, with the indicators ordered according to their noise–to–signal ratio (NSR).

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Lending Rate	675	855	3055	10450	0.38	0.42	2.32	7.92	90
GDP Acceleration	739	1496	4420	15811	0.78	0.60	1.95	6.92	10
Current Account	586	999	3620	10621	0.41	0.62	2.20	8.19	10
Current Account with GDP	552	1026	3652	10526	0.39	0.68	1.90	7.62	10
Deposit Rate	740	1647	3095	10696	0.51	0.69	2.20	8.13	88
M2 US Acceleration	615	1377	4133	13838	0.78	0.70	1.67	6.71	10
M2 US	620	1391	4183	13964	0.45	0.70	1.65	5.50	10
Reserves US	677	1660	4601	16496	0.62	0.71	1.71	7.20	10
Domestic Credit US	639	1479	4377	14788	0.67	0.71	1.69	6.12	10
Exchange Rate US Acceleration	886	2130	4779	16845	0.76	0.72	1.84	7.80	10
Industrial Production	513	1087	3541	10855	0.42	0.72	1.36	6.68	10
Exchange Rate SDR Acceleration	719	1734	4946	17250	0.63	0.72	1.45	7.98	10
Exports	690	1659	4757	16367	0.47	0.73	1.45	7.37	10
Exchange Rate SDR	713	1767	4952	17239	0.67	0.74	1.70	8.01	10
Reserves SDR	690	1721	4860	16889	0.65	0.74	1.71	7.08	10
Imports	654	1678	4770	16196	0.40	0.78	1.33	7.00	10
Exchange Rate US	1126	2989	4539	16017	0.76	0.79	2.41	9.23	13
Reserves NC	687	1874	4607	16332	0.33	0.79	1.70	8.25	11
Industrial Production Acceleration	563	1312	3414	10288	0.55	0.80	1.63	6.90	12
Real Interest Rate	675	1757	2943	9915	0.46	0.81	2.14	8.20	16
Domestic Credit US with GDP	572	1506	4326	14432	0.72	0.81	1.50	7.72	10
M2 by Reserves US	521	1394	3965	13396	0.52	0.81	1.38	7.60	10
M2 by Reserves NC	521	1395	3965	13395	0.52	0.81	1.38	7.60	10
M2 NC Acceleration	596	1595	4152	13620	0.79	0.84	1.54	7.72	11
Lending Rate Acceleration	431	1117	3348	10479	0.55	0.84	1.24	7.44	10
M2 NC	548	1538	4209	13715	0.66	0.88	1.42	7.45	10
Domestic Credit NC	552	1590	4464	14682	0.54	0.89	1.32	8.13	10
Deposit Rate Acceleration	532	1536	3286	10735	0.60	0.90	1.39	7.58	10
Domestic Credit NC with GDP	725	2207	4173	13731	0.70	0.94	1.77	9.12	14
Inflation	684	2255	4602	15141	0.63	1.00	1.53	7.04	13
Current Account Acceleration	807	2434	3458	9598	0.73	1.07	2.43	7.66	20

Figure 7: Indicators for stock market crises defined using returns, based on monthly data for 46 countries from 1960 to 2010 (12–month window)

	A	B	C	D	PCD	NSR	Persistence	Leading Time	Percentile
Lending Rate	853	677	5188	8317	0.49	0.53	3.60	13.45	90
GDP Acceleration	1075	1176	7276	13076	0.88	0.64	3.31	16.38	10
Current Account	834	751	5861	8380	0.52	0.66	3.71	15.64	10
M2 US	967	1057	6845	11397	0.60	0.69	2.88	12.54	10
Exchange Rate US Acceleration	1352	1678	7822	13940	0.86	0.73	3.34	15.94	10
Current Account with GDP	778	800	5910	8268	0.51	0.76	3.15	14.71	10
Deposit Rate	939	1143	5352	8824	0.58	0.77	3.44	15.47	90
Reserves US	1010	1348	7601	13607	0.75	0.77	2.90	15.35	10
Domestic Credit US	951	1192	7246	12010	0.81	0.78	2.79	14.25	10
Reserves SDR	1039	1389	7952	13912	0.78	0.79	2.96	15.51	10
M2 US Acceleration	894	1128	6906	11283	0.85	0.79	3.05	15.11	10
Exchange Rate SDR Acceleration	1048	1429	8126	14198	0.77	0.80	2.63	16.19	10
Exchange Rate US	1735	2387	7441	13276	0.82	0.81	4.49	18.56	13
Reserves NC	1264	1796	7376	13196	0.55	0.82	3.70	16.52	13
Exports	985	1364	7745	13380	0.59	0.82	2.47	14.09	10
Industrial Production	722	879	5782	8614	0.55	0.83	2.45	12.65	10
Exchange Rate SDR	1023	1460	8153	14203	0.78	0.84	2.93	16.00	10
Industrial Production Acceleration	851	1025	5532	8170	0.71	0.84	2.94	13.77	12
M2 by Reserves US	895	1237	6480	10774	0.64	0.85	2.80	16.85	11
M2 by Reserves NC	893	1239	6482	10772	0.64	0.85	2.80	16.95	11
Real Interest Rate	1039	1417	4905	7993	0.63	0.86	3.48	14.80	16
M2 NC Acceleration	922	1286	6826	11027	0.89	0.88	2.91	17.66	11
Domestic Credit US with GDP	864	1234	7138	11715	0.81	0.88	2.66	17.25	10
Imports	934	1398	7755	13212	0.52	0.89	2.22	13.19	10
Lending Rate Acceleration	718	989	5422	8270	0.71	0.91	2.33	15.72	11
Domestic Credit NC with GDP	837	1261	7165	11688	0.71	0.93	2.34	18.50	10
Deposit Rate Acceleration	824	1251	5434	8652	0.73	0.96	2.56	16.35	10
Domestic Credit NC	833	1311	7364	11906	0.61	0.98	2.35	17.21	10
M2 NC	1038	1643	6723	10714	0.81	0.99	3.08	16.94	13
Inflation	1181	2014	7334	12274	0.86	1.02	3.29	17.29	14
Current Account Acceleration	922	1371	5897	8167	0.73	1.06	3.09	16.76	14

Figure 8: Indicators for stock market crises defined using returns, based on monthly data for 46 countries from 1960 to 2010 (24–month window)

In this case, as we increased the time window, we observe the average NSR changing from 0.77 to 0.82 (a 6% increase) and the average PCD changing from 0.58 to 0.69 (a 19% increase), leading us to conclude once more in favour of the 24-month window. Interestingly, when compared to Cmax with 1.5 standard deviations (our least preferred Cmax criterion), using returns as a criterion both increase the average NSR of the indicators and decrease their PCD, showing that returns are an overall bad criterion for defining crises.

The comparison between the three different criteria for defining stock market crises and the two different time windows for the indicators are summarized in Table 4, where each entry is in the format (NSR,PCD) standing for average noise–to–signal ratio and average percentage of crises detected. Our overall conclusion is to use Cmax with 2 standard deviations and a 24-month window.

	24-months	12-months
Cmax 2	(0.75,0.74)	(0.67,0.62)
Cmax 1.5	(0.76,0.72)	(0.70,0.60)
returns	(0.82,0.69)	(0.77,0.58)

Table 4: Average NSR and PCD for the three different definition of crises and two different time windows.

2.4 Crisis Index

The results for the signals approach show that some indicators are better than others. So it seemed reasonable that combining the signals of these indicators we could come up with a *crisis index* that would indicate the likelihood of a stock market crisis based on several indicators weighted according to their performance. Since the economy of every country is different, all the calculations described below are county specific, that is, each country has its own index composed of indicators with country specific weights.

For this, we first assign to each performance criterion (NSR, PCD, PER, ALT) a uniform score from 0 to 10. For example, perfect scores would be a noise-to-signal ratio equal to 0, percentage of crises detected equal to 1, persistence equal to 24, and an average lead time equal to 24 months (the length of the forecasting window). We then declare that the average score for each indicator (itself a number between 0 and 10) will be the weight assigned to that indicator to compute the crisis index. It is surprising that there is a considerable variation between the signals that give better results for different countries. Every signal appears at least once among the top five indicators for our entire sample of countries, and none of them is consistently part of the top five for all countires.

Next we assign a numerical value to the signal given by each indicator every month. For this, we defined a function that depends explicitly on the empirical distributions of the indicator. This function is either increasing or decreasing, depending on whether the indicator is expected to be high or low in crisis periods. This can be viewed as a refinement of the procedure used to define a signal to begin with: instead of assigning 1 when the indicator crosses a threshold (signal) and 0 otherwise (no signal), we assign a value from 0 to 10 depending on where the indicator lies for that particular month with respect to several percentiles.

The value of the crisis index I_{ij} for country i at time (month) j is then calculated as

$$I_{ij} = \sum_{k \in \mathbb{K}} w_{ik} s_{ij}^{k}, \tag{4}$$

where $\mathbb{K}$ is the set of indicators, w_{ik} are the country–specific weights for each indicator, and s_{ij}^{k} are their numerical values at time j. An example of the crises index for Chile is shown in Figure 9

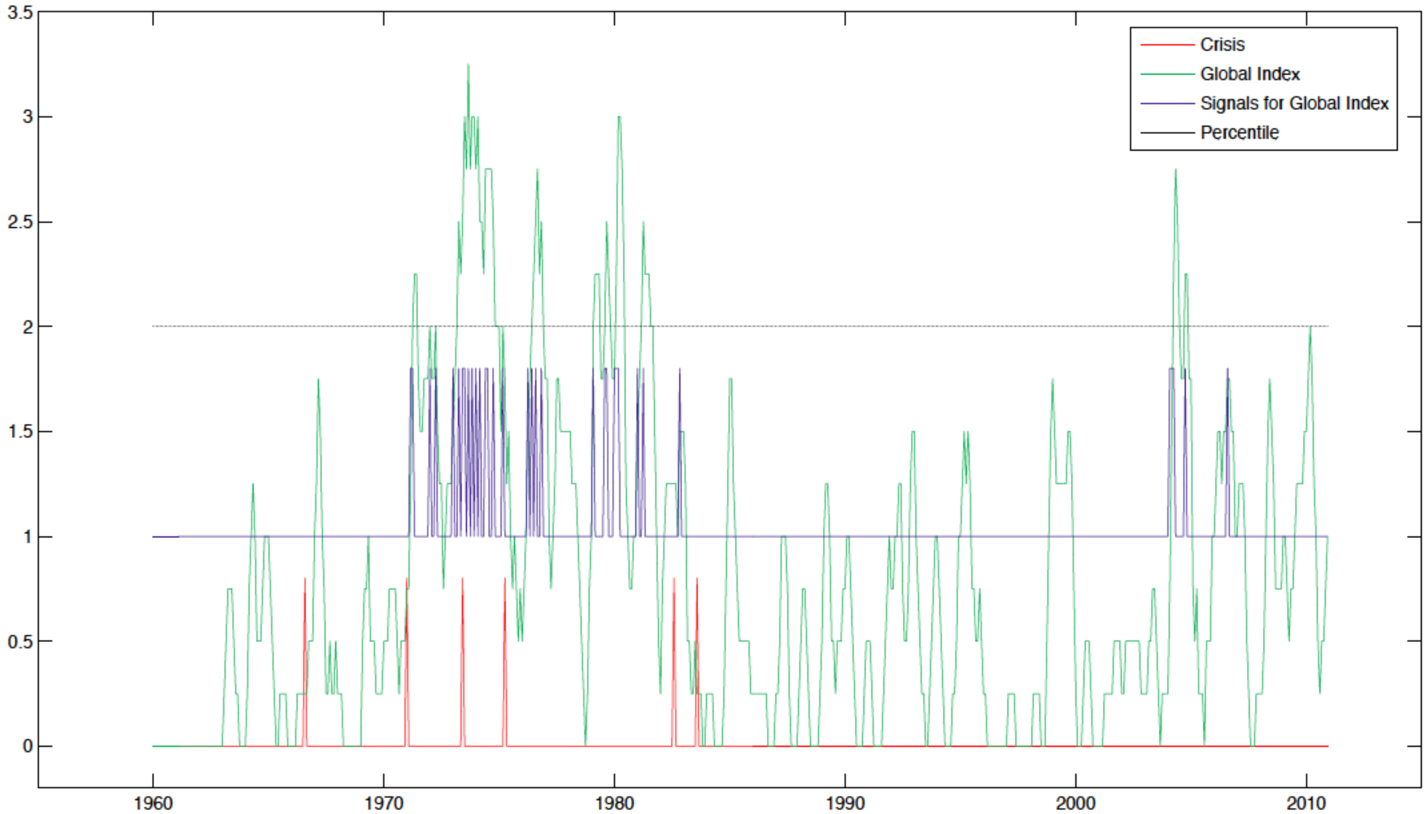

Figure 9: Crisis index for Chile from 1960 to 2010.

2.5 Logit model for stock market crises

A panel data set is one where there are repeated observations of the same collection of variables, that is, both cross-sectional data and time series data. In our example, we have 46 countries (panels), and each country has monthly time series data from Jan 1960 to Dec 2010 corresponding to the different indicators. Since the time series data of different country has different periods, our panel data is unbalanced.

In our model, the probability of a crisis is the explained variable, whereas the macroeconomic indicators (i.e. GDP, Current Account, M2, etc.) are explanatory variables. We do a regression to analyze how does each indicator contributes to the probability of a crisis. Those indicators that are highly significant are supposed to have a strong relationship with the outburst of a crisis.

The starting point for a discussion of regression models using panel data is a linear equation of the form:

$$Y_{ij} = \alpha_i + \sum_{k=1}^{K} \beta_k X_{ij}^k + \varepsilon_{ij} \tag{5}$$

Here Y_{ij} is the binary data of the crisis, that is, $Y_{ij} = 1$ is a crisis happens for country i at time

j and $Y_{it} = 0$ otherwise. The observation X_{ij}^k is the value of the k–th macroeconomic indicator for the i–th country at the j–th month. The term α_i is the country–specific intercept, whereas the parameter β_k is the coefficient of the k–th explanatory variable. The larger the coefficient, the more the indicator contributes to the occurrence of a crisis. As usual, we assume that the disturbance term ε_{ij} is an i.i.d. $N(0, \sigma_\varepsilon^2)$ random variable.

A simplified linear model is shown in Figure 10. An obvious drawback of the model for our purposes is that the predicted values for the variables Y_i can become greater than one or less than zero if we move far enough on the X-axis. But for the probability of a crisis, such values are theoretically inadmissible. Thus we transform our previous linear model into

$$Y_{ij} = \frac{1}{1 + e^{-Z_{ij}}} \tag{6}$$

where

$$Z_{ij} = \alpha_i + \sum_{k=1}^{K} \beta_k X^k ij + \varepsilon_{ij}. \tag{7}$$

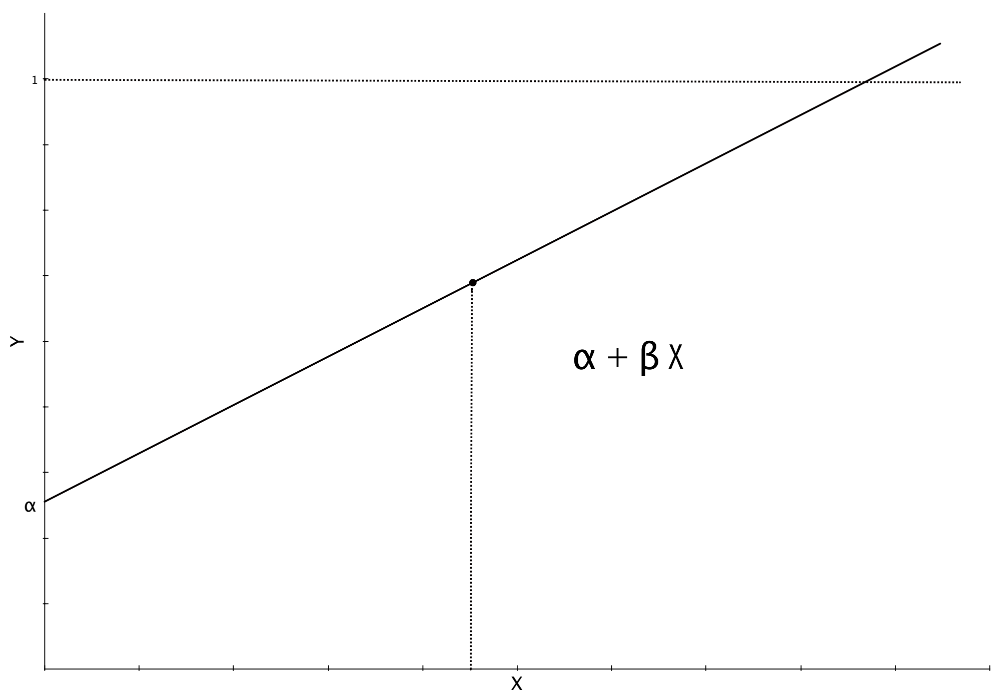

Figure 10: A linear regression model.

The transformation (6) is illustrated in Figure 11. We have that

$$Pr[Y_{ij} = 1 | Z_j] = \frac{1}{1 + e^{-X_{ij}}} \tag{8}$$

$$Pr[Y_{ij} = 0 | Z_{ij}] = 1 - Pr[Y_{ij} = 1 | Z_{ij}] = \frac{e^{-Z_{ij}}}{1 + e^{-Z_{ij}}}, \tag{9}$$

from which we can estimate the coefficients in (7).

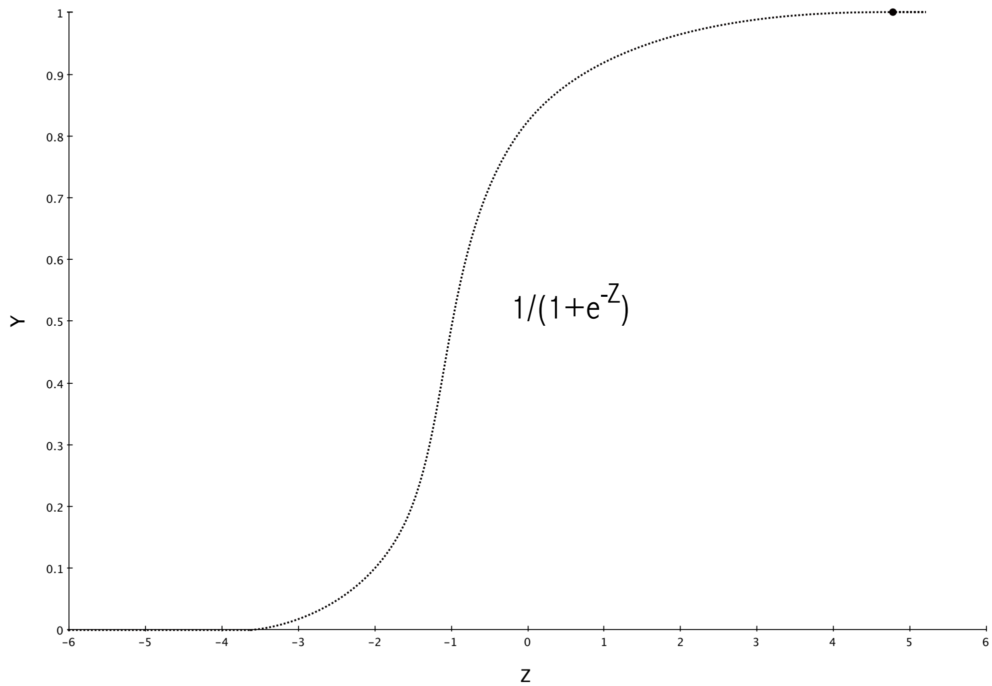

Figure 11: A logistic regression model.

We proceed with the estimation by maximizing the log-likelihood function

$$\max_{\beta} \sum_{j=1}^{T} \left(\sum_{i=1}^{I} Y_{ij} \ln(F(Z_{ij})) + \sum_{i=1}^{I} (1 - Y_{ij}) \ln(1 - F(Z_{ij})) \right) \tag{10}$$

where

$$F(z) = \frac{1}{1 + e^{-z}}. \tag{11}$$

We first did several univariate logistic regressions of stock market crisis on lagged values of banking crisis and currency crisis. The results shown in Tables 5 indicate that both banking crisis and currency crisis have strong influence on stock market crises for the same period.

Explained Variable	Explanatory Variable	Coefficient	p value	log likelihood	LR Chi2(1)
Stock Crisis$_t$	Bank Crisis$_t$	1.259*** (0.000)	0.0000	-226.8	24.37
Stock Crisis$_t$	Bank Crisis$_{t-1}$	0.469 (0.065)	0.0679	-236.9	3.33
Stock Crisis$_t$	Bank Crisis$_{t-2}$	-0.299 (0.277)	0.2706	-237.5	1.21
Stock Crisis$_t$	Currency Crisis$_t$	1.233*** (0.000)	0.0001	-231.3	15.35
Stock Crisis$_t$	Currency Crisis$_{t-1}$	0.454 (0.155)	0.1622	-237.6	1.95
Stock Crisis$_t$	Currency Crisis$_{t-2}$	-0.480 (0.198)	0.1821	-237.2	1.78

Table 5: Univariate logistic models for stock market, banking, and currency crises.

Secondly, we did a multivariate logistic regression, regressing the macroeconomic indicators on the stock market crisis. The results presented in Table 6 show that current account by GDP, M2 by Reserve, Deposit Rate, Inflation, Real Interest Rate, GDP Growth are significant indicators. And the general regression is significant as well.

Stock crisis versus	Coefficient	p Value
Current account/GDP	-0.0444	0.041*
Domestic Credit/GDP	0.0035	0.070
Terms of Trade	-0.0059	0.352
M2/Reserve	0.0201	0.010**
Reserve by GDP	0.0209	0.219
Lending Rate	-0.0075	0.447
Deposit Rate	0.2709	0.012*
Inflation	-0.2280	0.025*
Real Interest Rate	-0.2682	0.028*
GDP Growth	-0.2062	0.000***

Table 6: Multivariate logistic models for stock market crisis. The summary statistics are a p-value of 0.0000***, log likelihood of -783.5 and LR Chi2(10) of 141.29.

Finally, we did several simultaneous regression to investigate stock, banking and currency crisis at the same time. By taking stock market crisis as the explained variable, we find that both banking crisis and currency crisis are significant indicators, and other macroeconomics indicators, such as real interest rate and GDP growth are also significant, as shown in Table 7. By putting banking crisis as the explained variable, we find that stock market crisis remain significant, whereas currency crisis do not, while other macroeconomic indicators such as reserve by GDP, domestic credit by GDP,lending rate, GDP growth are significant as well, as shown in Table 8. Similarly, by taking currency crisis as the explained variable, we find that stock market crisis remain significant again, whereas banking crisis do not, while other macroeconomic indicators such as lending rate and real interest rate are also significant.

Stock Crisis versus	Coefficient	p Value
Bank Crisis	1.1163	0.000***
Currency Crisis	0.8504	0.017*
CA by GDP	-0.0517	0.120
DC by GDP	0.6879	0.084
M2 by Reserve	-0.0143	0.210
Hot Money	$-7.89e^{-12}$	0.105
Inflation	0.0399	0.152
Real Interest Rate	-0.0783	0.016*
GDP Growth	-0.0986	0.041*

Table 7: Multivariate logistic models for stock market crisis with banking and currency crisis as explanatory variables. The summary statistics are a p-value of 0.0000***, log likelihood of -194.1 and LR Chi2(10) of 55.68.

Banking Crisis versus	Coefficient	p Value
Stock Crisis	0.8863	0.004**
Currency Crisis	-0.1679	0.724
Reserve by GDP	-7.3194	0.009**
DC by GDP	1.6999	0.000***
Real Interest Rate	0.0320	0.550
Lending Rate	0.3150	0.001***
Deposit Rate	-0.0948	0.244
GDP Growth	-0.2758	0.000***
Inflation	-0.0639	0.310

Table 8: Multivariate logistic models for banking crisis with stock market and currency crisis as explanatory variables. The summary statistics are a p-value of 0.0000***, log likelihood of -139.5 and LR Chi2(10) of 111.93.

Currency Crisis versus	Coefficient	p Value
Stock Crisis	1.1636	0.001***
Banking Crisis	0.0856	0.844
CA by GDP	-0.0600	0.221
DC by GDP	-0.4632	0.489
M2 by Reserve	0.0321	0.110
TOT Change	1.2669	0.522
Lending Rate	0.2369	0.005**
Deposit Rate	-0.1664	0.055
Real Interest Rate	-0.0743	0.048*

Table 9: Multivariate logistic models for banking crisis with stock market and currency crisis as explanatory variables. The summary statistics are a p-value of 0.0001***, log likelihood of -99.7 and LR Chi2(10) of 35.15.

From out empirical result above, we could conclude that banking, currency and stock market crisis have strong correlation, and they influence each other through a mechanism that is still unclear. Some macroeconomic indicators, such as lending rate, deposit rate, M2, domestic credit also have strong influence on the crisis. We expect some further work could be done to determine the mechanism by which the financial crisis moves through the economy. But this research is also challenging. One way to investigate is to build the mechanism into a model, write down the structural equations implied by the model, and estimate it. This approach works well if the model is correct, but of course leads to some misleading conclusions if it is not. The other approach is to leave the structure out of the estimation, and estimate some very general set of equations, like a vector auto-regression, and then try to look at things like Granger causality. We propose to investigate these open questions in further research.

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