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Predictive Indicators of Financial Crises

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OUTLINE

There is renewed interest in 'early warning models' after each wave of crises. Much of that literature was developed in the aftermath of the emerging market crises of the 1990s.[1] But interest soon began to fade, driven in part by a combination of the inherent difficulty in predicting crises (particularly timing), and a benign global environment in which fewer crises occurred. But the global financial crisis has renewed interest in this type of model.

A comprehensive survey of the early literature on early warning models is provided in Kaminsky et al. (1998). A recent paper by Frankel and Saravelos (2012) provides an updated survey that includes the work done in the 2000s. This chapter discusses some of the key contributions to that literature. But given those comprehensive surveys of the academic literature already available, much of our focus is on how that line of work has been applied at the IMF, and the key lessons that can be learned by applying that class of tools in a policy environment.

SURVEY OF EARLY WARNING MODELS

Broadly speaking, there are three main ingredients to an early warning model: the crisis definition (what is it that it is trying to predict), the list of explanatory indicator variables, and the approach through which the information in those indicators is combined to predict crises.

Most of the literature has focused on measures of currency crises. These can be defined either based on sufficiently large nominal and real movements in the exchange rate or on indices of currency market pressure. For example, Frankel and Saravelos (2012) define a crisis as a 25% increase in the nominal exchange rate that is also at least a 10 percentage point increase in the rate of nominal depreciation from the previous year. Eichengreen et al. (1995) consider an index of speculative pressure that includes a weighted average of changes in the nominal exchange rate, percentage changes in gross international reserves, and in the domestic interest rate, coding an episode as a crisis when that index surpasses two standard deviations above its mean. Other crisis definitions considered include the drop in Gross Domestic Product (GDP) (Ghosh and Ghosh, 2003), and a measure of capital account crises (Chamon et al., 2007).

A wide range of explanatory variables has been considered. Kaminsky et al. (1998) have cataloged 105 variables, covering the external, financial, real, and fiscal sectors, as well as institutional and political variables, and measures of 'contagion.' Other extensive reviews of previous work are provided by Hawkins and Klau (2000) and Abiad (2003). Frankel and Saravelos (2012)

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[1] There is an earlier literature, for example, Kamin (1988), but much of its focus was on explaining timing, as opposed to which countries would be affected by the crisis.

The Evidence and Impact of Financial Globalization
http://dx.doi.org/10.1016/B978-0-12-397874-5.00042-7

perform a meta-analysis based on those reviews and on seven more recent papers published since 2002. Foreign exchange reserves, the real exchange rate, the growth rate of credit, GDP growth, and the current account to GDP balance are the most frequent statistically significant indicators in the 83 papers reviewed by them.

Most of the approaches used to combine information from those indicators in order to explain the prevalence of crises can be grouped into two broad categories: those that use a regression approach (typically a limited dependent variable model such as probit), and those that rely on nonparametric techniques. Examples of regression based approaches to explain currency crises include Eichengreen et al. (1995) and Frankel and Rose (1996). This approach became popular, as it involves techniques that the profession is familiar with. But there are some limitations to this approach. For example, there is a long list of candidate explanatory variables, and it is difficult for regressions to (meaningfully) consider a large number of indicators.

As an alternative, some studies have adopted nonparametric techniques. In a seminal contribution, Kaminsky et al. (1998) proposed a signal-extraction approach. This involves establishing thresholds above/below which crises are more likely to occur. The thresholds are country specific, but based on a common reference percentile (e.g., the 10% worst realizations of an indicator for each country). They consider a range of thresholds that leave 10–20% of observations in the risky side for each country, picking as the optimal threshold the one that minimizes the noise-to-signal ratio. A signal is considered good (false) when it is followed (not followed) by a crisis within 24 months. Their adjusted noise-to-signal ratio is defined as: (false alarms/number of noncrises)/(good signals/number of crises).[2] The signals from the different indicators can then be combined in an overall measure. Another nonparametric approach that is related to this signaling model consists of binary classification trees (e.g., Ghosh and Ghosh, 2003). These also rely on threshold rules, but allow for successive splitting of the data by different indicators, resulting in a decision tree.

As expected, these models perform much better in-sample than out-of-sample. Berg et al. (1999) checks the out-of-sample performance of some of the earlier models, including Kaminsky et al. (1998), Frankel and Rose (1996) and a model developed in the IMF, drawing on Berg and Pattillo (1999), which uses a probit regression approach with monthly data. The last one is found to provide the best out-of-sample performance. They use data up to mid-1995 to predict crises in 1997. When that model issues a crisis signal (based on a 25% probability cut-off), a crisis occurs 59% of the time within 24 months, and when it does not issue a signal, crises occur 11% of the time. Although this is a fairly strong performance, (bearing in mind it is out-of-sample), it still implies a sizable number of false alarms (including some of the high-profile crises). Moreover, focusing the analysis in 1997 (a year where most emerging markets experienced distress, at least to some extent) attenuates one of the main weaknesses of this type of model: the need to issue lots of alarms in order not to miss crises (which in more tranquil periods tends to lead to a large share of false alarms). When a similar exercise is performed using data up to 2000 (Berg et al., 2005), that same model yields a probability of crisis given a signal of only 22%, with false alarms accounting for 78% of all alarms. This large number of false alarms that are required in order not to miss most crises has been the main limitation in the use of these models. This can be particularly problematic during tranquil times, leading to 'signal fatigue.' That, plus the relatively few crises episodes from 2003 up to 2008, contributed to a decline in interest in this class of tools.

We draw two main lessons from this literature: (1) we have a reasonably good idea of what indicators tend to be associated with crises, and (2) predicting the timing of crises is very hard. For example, few people would dispute that an overvalued exchange rate peg is an important source of vulnerability (although determining the extent of that overvaluation ex ante can be difficult), that a large current account deficit financed by debt inflows is risky. But countries may be highly vulnerable for a long time without experiencing a crisis. Some of that delay may be due to the time it takes for these vulnerabilities to accumulate to the point when they become unsustainable (e.g., run a series of current account deficits to the point that foreigners become reluctant to finance it). But some of the timing may be driven by exogenous triggers. It is likely that sooner or later the foreign financed lending booms in parts of Eastern Europe (including foreign currency loans to households) would have led to a crisis, but the events in 2008 provided a trigger. Crises are rare events. If the average sample frequency of a crisis is 5%, even if a model were to estimate a crisis probability of 20% (four times that sample average), it would have an 80% chance of being wrong. But chances are that that country would have a number of vulnerabilities vis-à-vis the average emerging market that the model would have helped identify.

Trying to predict crises, particularly their timing, is likely to remain a disappointing exercise for the reasons described above. Instead, it seems far more promising to use this type of early warning model to help identify

[2] If the range of thresholds was not restricted to 10–20% of the worst observations, minimization of this ratio would likely lead to corners where few false alarms are issued, but many crises are missed.

underlying vulnerabilities. The distinction between underlying vulnerabilities and crisis risks is important, because the former are necessary but not sufficient for a crisis to occur. For instance, underlying balance sheet vulnerabilities (excessive borrowing or currency and maturity mismatches) can exist for prolonged periods without a crisis occurring. However, combined with a suitable crisis trigger (such as an interest rate hike by a major advanced economy central bank, or a pullback from risk assets in financial markets), these vulnerabilities can lead to a crisis. At the same time, a country without these vulnerabilities could face the same crisis trigger and survive unscathed. Not only is identifying vulnerabilities more feasible, but also more likely to be relevant for policy makers.[3] In fact, this is the direction which some policy makers have taken, including the IMF, whose work on early warning systems is described below.

EARLY WARNING MODELS BY INVESTMENT BANKS

Several investment banks have developed early warning models of crises. As these are not typically covered in most literature surveys, we briefly describe their methodology below.

The Bank of America (November 2002) Currency Crisis Indicator (Monograph 182, Volume 30) measures the risk of a currency depreciation in 18 emerging market economies. It includes three variables for global market conditions, and eight country-specific indicators. Observations are mapped into a five-tier scoring system, with scores linked to percentile buckets from a panel data set. Aggregation of scores is based on weights reflecting each variable's significance in a regression on 3-month spot rate moves.

The UBS (2006) financial vulnerability indicator (UBS Investment Research, 6/2006) measures sovereign default risk in order to identify cheap/rich valuations in 16 emerging markets. The methodology focuses on determining the proportion of external financing needs covered by different sources.

Lehman Brothers (2006) Damocles model (Lehman Brothers, Global Economics, 24 May 2006) predicts, within a one year horizon, month-on-month changes in exchange rate against the US dollar of more than three standard deviations from the sample mean. It covers 17 emerging markets. It uses ten macroeconomic and financial variables updated monthly. These are mapped into 0/1 scores with thresholds reflecting the analyst's experience and judgment, which are then aggregated into a composite index based on how well each variable predicted crises in the sample period.

Deutche Bank's Alarm Clock (October 2002), estimates the probability of sharp movements in the exchange rate or local interest rate in 22 emerging markets. It uses monthly data on macroeconomic and financial variables to estimate simultaneous logit regressions.

Citibank's Currency Crisis Index for Risk Management (July 2004) is a composite index of underlying vulnerabilities in emerging markets. It maps macroeconomic and financial variables into 0, 1, 2 scores based on 2 thresholds. Noise-to-signal ratios are used to select thresholds and weights for the aggregation of the scores.

IMF WORK ON EARLY WARNING SYSTEMS

The IMF originally established its vulnerability exercise (VE) in 2001, as part of a broader initiative to strengthen fund surveillance of emerging market economies in the wake of the capital account crises of the 1990s. The original exercise used the Berg and Pattillo (1999) model, but drew extensively on the qualitative judgments of IMF staff. In 2007 the VE was subject to a comprehensive review, as a result of which the methodology was substantially revised. The new methodology differed in two important ways. First, it clarified the distinction between underlying vulnerabilities and crisis risks or triggers. Second, it complimented the judgment-based assessments of underlying vulnerabilities with a more systematic assessment based on an early warning type country risk model. However, the overall focus of the VE – on capital account crises in emerging markets – remained unchanged.

Whereas the precise timing of crises is hard to predict, as discussed above, assessing which countries are vulnerable, conditional on a particular crisis risk materializing, may be a more fruitful exercise. This is particularly true for a surveillance institution such as the IMF, whose motivation lies in responding preemptively to emerging crisis risks by quickly identifying potentially vulnerable countries, for example, in the context of a second round of contagion from an initial crisis. By contrast, for institutions whose primary interest is in the timing of crises (e.g., a financial institution hoping to identify a crisis ahead of the market and exploit potentially fleeting arbitrage opportunities), this distinction between vulnerabilities and crisis risk is presumably less important.

The VE focused on capital account crises. These crises typically involve a high degree of exchange rate

[3] While timing crises is of the essence from a private sector/market perspective, for a policy maker it is more important to identify growing vulnerabilities early on (so that they can be addressed).

volatility, a reversal in capital flows, and other signs of financial market distress. Crisis dates (years and countries) are identified by combining quantitative indicators with an analysis of the narrative record. Specifically, several crisis indicators were used to generate a set of potential crisis episodes: these included two measures of sudden stops in capital flows; a measure of exchange market pressures; sovereign defaults; IMF programs; and banking and corporate sector crises. This set of potential crises was then reviewed by the relevant IMF desk economists. This helped to resolve ambiguities about crisis dates as also to eliminate some spurious crisis events picked up by the indicators (e.g., sharp drops in capital flows following the completion of a privatization program, not a crisis) and to introduce some new dates that the indicator-based approach had missed. The resulting set of 33 crisis dates represents around 5% of the total sample in 1995–2006.

The set of vulnerability indicators includes 19 variables across four different sectors of the economy: external, public, financial, and real sectors. The full list of variables is available in IMF (2011). The data used is annual, with a 1-year lag (consistent with the data that would be available in real time for the exercise).

To relate these vulnerability indicators to crisis incidence, a signal-extraction approach similar to that in Kaminsky et al. (1998) was used. The main differences were adopting a common level of the threshold for all countries (as opposed to a common country-specific percentile), and the loss function.[4] In this approach, the values of the indicator above (or below) a threshold are assumed to signal a crisis, and values below (or above) a noncrisis. The level of this threshold is common for all countries in the sample, and its value is chosen by minimizing the percentage of crises missed and the percentage of noncrises misclassified (type 1 and type 2 errors). Note that by defining the loss function in terms of the percentages of crises and noncrises, the model makes missing a crisis observation much more costly than issuing a false alarm (e.g., if crises are 5% of the sample, missing one crisis is as costly as issuing 19 false alarms).

Each continuous indicator can then be mapped into a 0/1 'flag.' These individual signals are then combined by taking a weighted average. Whenever an indicator is missing for a given country, its weight is redistributed to the other indicators with available data in its sector. The weights placed on each signal are determined by a combination of ex ante judgment (particularly in the weight given to each of the four sectors) and the relative noisiness of each indicator as a signal (for the weight given to individual indicators within a sector). The aggregate index was found to perform significantly better than any of the individual indicators, suggesting complementarities, and that there are large benefits from combining information across a range of sectors and individual variables.

This approach has a number of benefits compared to the more standard parametric or regression techniques (such as probit or logit). First, because the calculations are initially univariate, carried out on a variable-by-variable basis, the very real problem of nonavailability of data across countries and time periods is dealt with in a computationally simple way. Second, this approach allows information from a broad set of indicators to be combined without overfitting the model (a problem even in the absence of missing observations, but considerably exacerbated by the sample size restrictions imposed by missing data in a multivariate setting). Essentially, the model estimates the unconditional effect of each variable rather than the conditional effect on the value of other variables. In theory, the conditional impact is more informative, but in the context of a small sample the probability of successfully extracting this conditional relationship from the data is low, and we would expect the univariate approach to be a more robust method.

A final benefit of this approach is that it is relatively transparent. The manner by which the weights and thresholds are arrived at is clear, and the thresholds in particular are easy to interpret, aiding communications both internally and externally. They can also provide useful intermediate inputs to policy discussions. These benefits, though perhaps of secondary importance if the aim of the exercise were solely crisis prediction, are critical in a policy institution.[5]

The in-sample performance of the VE's aggregate vulnerability index for emerging markets was fairly good. The same technique of minimizing misclassification errors with respect to the aggregate index – with values above the threshold associated with a crisis – led to 88% of crises and 77% of noncrises correctly classified. Particularly because noncrises are more prevalent (comprising 95% of the sample), this implies that the model identifies a large number of 'vulnerable' episodes in which a crisis did not occur. However, recall that the model aims to pick up vulnerabilities rather than simply predict crises.

[4] Using country-specific thresholds, as in Kaminsky et al. (1998), helps to capture cases where some countries have had risky values for an indicator (e.g., relatively high debt) without running into crises. Setting a common threshold for all countries, as in the IMF's VE, would 'flag' those cases for that particular variable, but not necessarily for overall vulnerability (assuming countries that have a weak indicator without having crises do so because they have strong indicators in other variables).

[5] While an aggregation of univariate regression results could yield similar benefits to this methodology in terms of handling missing observations, it would not provide the simple rules of thumb that the threshold approach does.

An out-of-sample test of the VE country risk model's performance was provided by the 2007–09 global financial and economic crisis. Here, the model was found to perform relatively well. Of the 15 emerging market economies that had a standby arrangement or SBA with the fund (including precautionary SBAs) or were discussing such a program in 2009, all were rated in September 2007 as exhibiting high or medium vulnerability relating to the external sector as well as in either the fiscal or financial sector (or both). By contrast, only six countries covered by the VE which received similar ratings at that time did not seek a program.[6]

Just as the IMF's efforts at early warning and crisis prevention received a boost in the wake of the emerging market crises of the mid-1990s, so the 2007–09 financial and economic crisis, centered on advanced economies, led to an expansion of the Fund's efforts in this area, with a new toolkit developed to identify emerging vulnerabilities among advanced economies. This new Vulnerability Exercised for Advanced Economies (VEA) sits alongside a revamped Vulnerability Exercise for Emerging Economies, and both feed into a broader assessment of emerging risks and vulnerabilities, the Early Warning Exercise, a joint effort with the Financial Stability Board. IMF (2011) describes that exercise.

The VEA is a modular exercise, encompassing a broad range of tools. Although it does have a crisis risk model that follows a similar methodology to the one described above, it also includes 32 other modules (described below). The crisis risk model has many similarities to the emerging market one. Perhaps the main difference is the crisis definition. Crises in emerging markets are relatively easy to identify, taking the predictable form of a sudden stop in capital flows, often (but not always) accompanied by a sharp adjustment in the exchange rate. By contrast, advanced economy crises are both rarer (at least up to now) and more heterogeneous (typically the external sector does not play as prominent a role as in emerging markets). We considered three crisis definitions for advanced economies: a financial crisis using the episodes identified by Laeven and Valencia (2010),[7] a severe growth slowdown (growth relative to the average in past 5 years is in the bottom 5% of the sample as a whole), and a sharp fiscal consolidation (an increase in the cyclically adjusted primary balance to GDP ratio of at least 2.5% from a negative balance of at least 2.5% during the course of the year).

This model also considers a different set of variables than its emerging market counterpart. Some variables highly pertinent for sudden stops in emerging markets – such as the share of external borrowing denominated in foreign currency or the level of government debt – seemed less relevant for the kind of financial and growth crises that affect advanced economies, and so were dropped from the analysis. At the same time, other variables – including indicators of asset price booms and busts (e.g., in the housing market) and measures of balance sheet imbalances (e.g., household liabilities) – seemed more relevant, and so were added to the set of indicators. Data availability as well as relevance led to a general increase in the number of financial indicators included. At the same time, traditional macroeconomic indicators – such as inflation, the current account deficit, and measures of external indebtedness – were kept in the indicator set.

The methodology for linking indicators to crises was broadly the same as that employed in the VE. However, unlike in the VE case, weights were determined solely based on this goodness of fit measure, rather than allocated across sectors according to some predetermined formula. This reflected the fact that – whereas emerging market crises were thought to be relatively well-understood by IMF staff with some sense of the relative contribution of external, financial, macroeconomic and corporate sector factors already known – crises in advanced economies were less well-understood and staff were more willing to 'let the data speak' on the relative contribution of different factors. In addition, in part because sectoral contributions were not delineated ex ante, some attempt was made to reduce the weight placed on variables when several indicators appeared highly collinear.

The modules that make up the VEA are grouped into five areas. The first relates to current economic and financial indicators. The modules under this heading can in turn be divided into three subgroups. The first is the latest growth projections from the IMF's World Economic Outlook, including risks around the central projection. The second subgroup is a set of fiscal risk indicators, including rollover and financing risks; the market's risk assessment; an assessment of medium- and long-term adjustment needs; the estimated fiscal impact of a negative growth shock; an assessment of contagion risks; and the estimated probability of the necessity for a significant fiscal adjustment. The third set of modules in this area groups together a number of financial risk indicators, including financial stability indicators and assessments of risks across different asset classes drawn from

[6] For a detailed discussion of how ex ante vulnerabilities affected the intensity with which countries experienced the crisis, please refer to IMF (2009).

[7] Under their methodology, a financial crisis is defined by either a banking crisis or a currency crisis. The first is identified when a country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time, with the result that NPLs rise sharply. The second is identified as a nominal depreciation of the currency of at least 30 percent that is also at least a 10 percent increase in the rate of depreciation compared to the year before.

the IMF's Global Financial Stability Report and assessments of the market price of systemic risk and tail risks in key markets.

The second set of modules looks at macroeconomic imbalances and capital flows. The analysis includes an assessment of capital inflows for key economies and measures of exchange rate misalignment among the G3 currencies (US dollar, euro, and Yen); an assessment of savings and investment trends and current account imbalances in key countries and regions; fiscal sustainability measures and an assessment of sectoral balance sheets.

The third set of modules analyzes market risks. These include an assessment of sovereign financing risks and financing needs; an analysis of risks and potential misalignment in real estate markets (both residential and commercial); and an assessment of corporate vulnerability focusing on bond and equity market indicators, as well as balance sheet indicators.

The fourth set of modules looks at country-specific risks. These include the empirical crisis models discussed in detail above, but also four other sets of models: a measure of GDP and financial stability at risk (focusing on estimated tail risks to growth and financial stability); an assessment of growth and inflation risks from an estimated general equilibrium model of the global economy; a crisis duration model; and a model that projects the likely deterioration in asset quality (measured via the share of nonperforming bank assets).

The final set of modules takes a broader focus, centered on contagion and systemic risk. The first set of tools looks at interdependence of sovereign risks, estimating the degree of contagion (inward and outward) for different countries' sovereigns. The second set of tools assesses vulnerabilities in large complex financial institutions (i.e., large cross-border banking groups), using both balance sheet and market indicators as well as systemic tail risks – assessed via joint probabilities of default for groups of financial institutions. The final set of tools assesses the likelihood of contagion through banking and trade channels by using matrices of bilateral exposure on bank balance sheets and via international trade.

The results from all these modules are then aggregated to yield an overall assessment of high, medium, or low vulnerability. Thresholds are first derived for each model and indicator to determine the level of vulnerability for a given country. The identified vulnerabilities for the indicators and models are then aggregated by sector (external, fiscal, financial, asset prices, macro, and cross-border exposures) to derive sectoral vulnerability ratings, which are then aggregated using equal weights into an overall country vulnerability rating.[8]

Assessing the out-of-sample performance of the VEA is less easy, as the exercise is relatively new, and was not in place prior to the crisis. However, using data available through 2006, it would have identified the United Kingdom, United States, and Iceland as being highly vulnerable to a financial crisis in 2007 (although that framework was developed with the benefit of hindsight).

CONCLUSION

This chapter has surveyed the work on early warning models, including both the academic literature and applications by market participants and policy institutions. Whereas different models have been tailored to suit different needs, on balance, practitioners seem to favor signal based models. The usefulness of thresholds and simple rules of thumb in communicating the results may have been an important consideration.

Many different strands of work seem to point to a handful of variables playing a leading role in explaining crises in emerging markets. But predicting the timing of crises has remained very challenging. For market participants, timing is of the essence. But for policy makers, it seems preferable to focus on identifying vulnerabilities (preferably with enough advance notice so they can be tackled before they materialize into a crisis). This is the direction that some institutions, including the IMF, have moved toward.

In the case of advanced economies, the work on early warning methods is still relatively new. Applications to advanced economies are more challenging than to emerging market ones, because the crises experienced by the former are rarer and tend to be more idiosyncratic in nature. It is possible that interest in this class of models will wane (as was the case with emerging market models in the 2000s), particularly if the events of 2008 indeed prove to be a 'one in a century' crisis.

SEE ALSO

Crises: Sudden Stops in Capital Flows; Definitions and Types of Financial Contagion.

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[8] Typically, high or medium vulnerabilities are assigned if the number of sector flags is more than one standard deviation, or within one standard deviation above the mean, respectively. For the crisis risk model, high or medium ratings are based on an estimated crisis probability above 20 or 10% respectively.

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