Predicting Financial Stress Events in Jamaica:
A Usefulness Measure Approach

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Abstract

The global financial crisis and the high associated costs have revived the academic and policy interest in early warning indicators of crises. This study looks at the predictive ability and usefulness of evaluating early warning systems (EWSs) that incorporate policymakers' preferences between issuing false alarms and missing crises. To evaluate the usefulness of the selected EWSs to predict financial instability, a usefulness measure was employed. The results of the study suggested that the Macro-financial index was the most useful index in predicting financial stress for both the cost-ignorant and fixed cost aware policymaker. Furthermore, the results of the evaluation framework also indicate that a policymaker has to be substantially more concerned with missing bank distress than issuing false alarms for the model to be useful.

JEL classification codes*:* E44; E58; F01; F37; F47; G01

Keywords*:* Early warning indicators, crises, policymakers' preferences, misclassification costs

1. Introduction

The recent global financial crises had a crippling impact on economies around the world and underscores how vital it is to estimate financial stresses before it occurs. Financial stress however, is generally difficult to define as episodes of financial stress is often different. Notwithstanding, certain key features are frequently associated with financial stress, such as increased uncertainty about fundamental value of assets, increased uncertainty about behavior of other investors, increased asymmetry of information, decreased willingness to hold risky assets, and decreased willingness to hold illiquid assets (Hakkio & Keeton, 2009).

In Jamaica, there has been documented periods of financial stress and instability such as the 1996-1998 Jamaica banking crisis, the Jamaica Debt Exchange (JDX), the National Debt Exchange (NDX) as well as the impact of the global financial sector crisis of 2008 on Jamaica's financial markets. The Bank of Jamaica (BOJ) currently utilizes several financial indices to assess the health of the banking sector in Jamaica. These include the Macro-financial (MaFi) and Micro-prudential (MiPi) indices, the Composite Indicator of Systemic Stress (CISS), the Aggregate Financial Stability Index (AFSI), and the Insolvency ratio (Z-score index).

Against this background, the objective of this paper is to evaluate the predictive power of the various financial indices utilized by the Bank of Jamaica. This will be done by applying a usefulness measure to selected financial stress indices utilized by the BOJ for the purpose of predicting financial stress for the 2008, 2010 (JDX) and 2013 (NDX) periods for Jamaica. As indicated in study by Alessi and Detken (2011), a usefulness measure indicates whether the loss of the prediction is smaller than the loss of disregarding the model. The usefulness model will be estimated by using a crisis modeler software, a tool developed by (Sarlin, 2013) for exploring crisis predictions. The usefulness measure is intended to guide policy makers in the decision-making process.

The remainder of this paper is structured as follows: a review will be conducted on the literature surrounding predicting financial stress events. Secondly, the data collected and methodology utilized will be described. Finally, the results and policy implications will be discussed.

2. Literature Review

The high costs of crises have motivated research on predicting financial instabilities[1]. Much of the research in this area has focused on the development of financial stress indexes (FSIs) as well as Early Warning System (EWS) models which can aid in detecting vulnerabilities prior to a crisis[2]. Some of the approaches used in developing and evaluating financial stress indexes and EWS models include: the logistic and probit regression, signaling approach, leading indicator approach and usefulness measure.

In Jamaica, EWS models have been used for surveillance and forecasting purposes in order to mitigate the effects of financial crises. These models include aggregated macro-financial and micro-prudential indicators such as Langrin (2002) as well as various stress testing frameworks. Morris (2010) also created a systemic risk index (AFSI) using aggregated microeconomic, macroeconomic and international indicators to capture and forecast the joint impact on financial stability. Additionally, Millwood in 2013 developed the CISS aimed at capturing the dynamic or joint response of market players to developments in the money, equities, bond and foreign exchange markets[3].

Lo Duncan Pantoten (2013) constructed a logit model using quarterly data for 28 countries for the period 1990 to 2010. The dataset consisted of 14 macro-financial indicators that proxy for asset price developments and valuations, credit developments and leverage, as well as traditional macroeconomic measures. The model showed that real GDP growth, inflation, current account deficit and real equity growth had positive estimates and all were statistically significant in the macro-prudential model. However, real credit growth proved to be statistically insignificant.

Frankel and Rose (1996) studied the determinants of currency crashes in 100 developing countries from 1971 to 1992. They evaluated the predictive power of several indicators by looking at each indicator separately and at set of indicators jointly using a probit model. Their findings revealed that currency crashes tend to occur when FDI inflows dry up, periods of low foreign

[1] See Sarlin (1998)
[2] Demirgüç-Kunt and Detragiache, 2000, Kaminsky et al., 1998, Manasse et al. 2003
[3] See Milwood (2013)

exchange reserves, domestic credit growth is elevated, when the real exchange rate is overvalued and interest rate rises. However, according to van den Berg et al., (2008), logit analysis is preferred over probit analysis as its assumption of more fat-tailed error distribution corresponds better to the frequency of banking crises and bank distress events.

The signaling approach is one of the most commonly used early warning methodologies.[4] According to Hermansen and Rohn (2015), the advantage of the signaling approach is that it can accommodate differences in data availability across countries and allows for the inclusion of a potentially larger number of vulnerability indicators than alternatives based on multivariate regression methods. This advantage is important because it assesses the predictive ability of each individual indicator rather than to devise a composite early warning indicator. According to the signaling approach, an indicator signals a vulnerable state of the economy if it crosses a threshold. Threshold levels are chosen so as to strike a balance between the risks of missing vulnerable states (so-called type I errors) and issuing many false alarms. Langrin (2002) paper proposes a specific EWS of banking sector crisis based on the non-parametric signals approach. This approach involves the bi-variate monitoring of a comprehensive set of indicators so as to ascertain the future state of vulnerability of the banking sector. The results from this EWS model showed that the model was successful in predicting the 1996-1998 Jamaican banking crisis. The downside of this approach is that it considers early warning indicators separately.

Regarding the leading indicator approach, leading indicators as predictors of currency crises are often chosen based on economic rationales as well as the availability of data. Lo Duca and Peltonen (2013) investigated leading indicators of systemic banking crises in a panel of 11 European Union countries, with a particular focus on Finland. The methodology employed was signal extraction and multivariate logit analysis to assess what factors led the occurrence of a crisis and with what horizon the indicators lead a crisis. The results found that loans-to-deposits and house price growth are the best leading indicators. Growth rates and trend deviations of loan stock variables also yield useful signals of impending crises. While the optimal lead horizon is three years, indicators generally perform well with lead times ranging from one to four years.

[4] Kaminsky et al., 1998; Borio and Lowe, 2002; Behn et al., 2013

Behn et al. evaluate models based on the usefulness (U) measure capturing a trade-off between the two error types (missing crises, false alarms) depending on policy-makers' preferences. They find that the inclusion of global variables adds value, in particular for shorter prediction horizons. They ultimately observe that the domestic credit-to-GDP gap is the most stable single explanatory variable across different models, while the inclusion of other macro-financial variables improves in particular earlier warning model performance. Global variables and banking capitalisation are important especially as one is closer to a crisis.

Sarlin (2013) attempted to design a new policymaker's loss-function and usefulness measure for the purpose of evaluating and validating of EWS models. In particular, a loss function is used to determine the optimal thresholds, which explicitly takes into account policymaker preferences between type I and type II errors(probability of not receiving a warning conditional on a crisis occurring and of receiving a warning conditional on no crisis occurring). An indicator is labelled useful if its predictions result in a lower loss compared to a benchmark in which the indicator is ignored. A drawback of this method is that in its simplest form it ignores potential interactions among indicators and does not allow for standard statistical tests to assess the significance of the indicators. One major outcome from this model illustrates the importance of an objective criterion for choosing a final specification and threshold value

Alessi and Detken (2011) also propose a Usefulness measure that compares the loss of the model to the loss of disregarding the model. The model is Useful, if the loss of the model is smaller than the loss of disregarding it. However, while the above evaluation frameworks have become state-of-the-art, they fail to account for characteristics of imbalanced data. Rather than the share of errors in relation to class size, the relevant measure for a policymaker to be concerned about is the absolute number of errors. Thus, assuming that tranquil and pre-crisis periods are of similar frequency imposes not only a bias on the weighting of type 1 and type 2 errors, but also on the derived Usefulness measure, as a best guess of always or never signaling when disregarding a model is highly affected by the frequency of the classes.

3. Description of Data

This study utilizes quarterly data over the period 2003 to 2015. Table 1 presents the list of twenty one variables that is categorized into four broad groups – aggregated financial indices, macroeconomic variables, financial variables and bank specific variables. The financial variables of interest is the CISS, AFSI, MaFi, MiPi and the Insolvency index. These financial indices are currently use by the Bank of Jamaica to assess the development of financial stress events and generally capture recorded episodes of stress periods (see **Figure 1.0**).

The macroeconomic indicators are: Real Gross Domestic Product (GDP) growth, exchange rate, interest rate and inflation. GDP and exchange rate variables were chosen because economic recession often precedes a steady decline in the real GDP growth rate while financial crises are sometimes driven by exorbitant foreign exchange risk exposures. Additionally, interest rates directly affect credit market (loans) because higher interest rates make borrowing more costly whereas inflation is likely to be associated with high nominal interest rates.

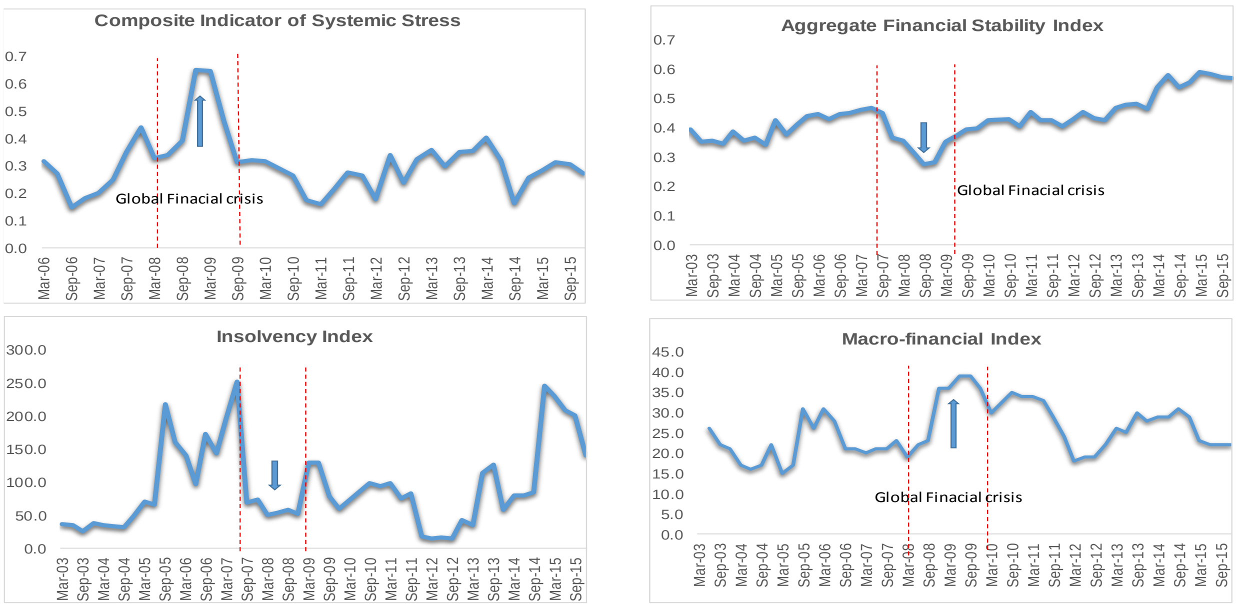
M2 to Net International Reserve (NIR) is one of the financial indicators that is included in the study as an expansionary monetary policy and/or a sharp decline in the reserves could lead to a crisis. Credit generally tends to expand before a crisis and contract after a crisis, hence the growth rate of real private credit is used to measure this impact. The current account to GDP was included because large current deficits may lead to a crisis due to the imbalances that may arise. A contagion indicator was utilized in the modelling as large values of a contagion indicator are associated with financial stress events.[5] The return on the stock market and house price indices measure the impact on falling asset prices. For instance, when housing prices fall, consumers are more likely to default on their home loans, causing the banks to lose money.

The aggregated bank specific variables include: regulatory capital to risk-weighted assets, tier 1 capital to risk-weighted assets, non-performing loans to total loans, return on assets, interest margin to income, liquid assets to total assets and net open position to capital. These indicators

[5] The amount due to other financial institutions as a percentage of statutory capital is used as a proxy for the contagion indicator.

span across all the subsections of financial soundness and they measure the general health of the banking system, vulnerabilities in the banking systems are linked to broader systemic financial stress.

Figure 1.0 Selected financial stress indices



Arrows indicate deterioration and highlighted areas reflects the gloabal financial crisis.

Table 1 - Indicators

Category	Indicator	Risk Tail
Financial Indices	AFSI	Lower Tail
	CISS	Upper Tail
	MaFi	Upper Tail
	MiPi	Upper Tail
	Insolvency Ratio	Lower Tail
Macroeconomic Indicators	Exchange Rate	Upper Tail
	Real GDP Growth	Lower Tail
	Inflation	Upper Tail
	Interest Rate	Upper Tail
Financial Indicators	M2/Net International Reserve	Upper Tail
	Current Account/GDP	Lower Tail
	Contagion indicator	Upper Tail
	Growth rate of real private sector	Upper Tail
	Return on house market index	Lower Tail
	Return on stock market index	Lower Tail
Bank Specific Variables	Regulatory capital/Risk-weighted assets	Lower Tail
	Tier 1 Capital/Risk-weighted assets	Lower Tail
	Return on assets	Lower Tail
	Interest margin/Income	Lower Tail
	Non-performing loans/Total loans	Upper Tail
	Liquid assets/Total assets	Lower Tail
	Net open position/capital	Upper Tail

4. Methodology

The methodology is similar to that which was proposed by Sarlin in 2013. This research aims to evaluate the forecasting power of several financial stress indices used by the Bank of Jamaica, namely, the CISS, AFSI, MaFi, MiPi and Z-score index.

The occurrence of a systemic financial crisis is defined by the selected financial indices outlined above. The selected financial stress indices are transformed into the predicted variable by first defining crisis periods $I\,j\,(0)\ \varepsilon\ \{0,1\}$ as those when the FSI exceeds the 90^{th} percentile and then the pre-crisis periods $I\,j\,(h)\ \varepsilon\ \{0,1\}$ where h=6, as the 6 quarters preceding the crises. The correspondence between P j and *I j* can be summarized into a contingency matrix (frequencies of prediction-realization combinations).

		Actual class I_j	
		Crisis	No crisis
Predicted class P_j	Signal	**A** *True positive (TP)*	**B** *False positive (FP)*

	No signal	**C** *False negative (FN)*	**D** *True negative (TN)*

A logit regression was utilized as this functional form essentially specifies a dichotomous dependent variable as a function of various explanatory variables. The underlying logit model assumes that the probability of crisis (P_j) can be estimated as[6]:

$$Prob(Y = 1) = F\ (X\beta) = \frac{e^{X\beta}}{1 + e^{X\beta}}$$

$$Prob(Y = 0) = 1 - F\ (X\beta) = \frac{1}{1 + e^{X\beta}}$$

Here *Y* represents the categorical dependent variable (crisis period), *X* is a matrix which contains the independent variable and β is a vector of coefficients. The predictive performance of the model is tested on the global financial crisis, the JDX and NDX. The estimates of the various logistic regressions are tabled in the appendix. The logit estimates are used for generating probabilities p_j and transformed into binary point forecast P_j. Given probabilities p_j of a model, the policy maker should focus on choosing a threshold such that his/her loss is minimized. A loss function can be written as:

$$L(\mu) = \mu T_1 P_1 + (1 - \mu) T_2 P_2$$

Where μ represent the policy maker's relative preference of missing crises and $(1 - \mu)$, the preference of issuing false alarms. T_1 are type 1 errors which represents the probability of not receiving a warning conditional on a crisis occurring and T_2 are type 2 errors which represents the probability of receiving a warning conditional on no crisis occurring. P_1 is the unconditional probability of a crises, $P_1 = P\ [I_j\ (h)=1]$ and P_2 is the tranquil period, $P_2 = P(I_j\ (h)=0) = 1 - P_1$.

Using the loss function L(μ), we can then define the Usefulness of a model. The usefulness of a model computes the extent to which a model performs better than having no model. A

[6] Since $y^*_t = a + b'x_t + \varepsilon_t$ then $Prob(Y_t = 1) = Prob\left(y_t > 0\right) = Prob(a + b'x_t + \varepsilon_t > 0)$ = Prob $(\varepsilon_t < a + b'x_t)$

policymaker could achieve a loss of min(P_1,P_2) by always issuing a signal of a crisis if P_1 >0.5 or never issuing a signal if P_2 > 0.5. However, by weighting with policymaker's preferences, as he/she may be more concerned about one of the classes, we achieve the loss min(μP_1, $P_2(1- \mu)$) when ignoring the model. The absolute Usefulness U_a (μ) of a model can be derived by computing the loss generated by the model subtracted from the loss of ignoring it. If the absolute usefulness is positive, there is a benefit in using the early warning indicator:

$$U_a\,(\mu) = \min\big(\mu P_1\,, P_2\,(1-\mu)\big) - L(\mu)$$

The ratio of the absolute Usefulness to the Usefulness that a policymaker would gain with a perfectly performing model is the relative Usefulness, $U_r\,(\mu)$. This derives simply from the fact that given the loss function equals to zero, then $U_a\,(\mu) = \min\big(\mu P_1\,, P_2\,(1-\mu)\big)$. The $U_r\,(\mu)$ allows the opportunity to compare models for policymakers with different preferences. Relative Usefulness is therefore represented as:

$$U_r\,(\mu) = \frac{U_a\,(\mu)}{\min\big(\mu P_1\,, P_2\,(1-\mu)\big)}$$

The abovementioned framework can be utilized to differentiate between types of policymakers based on their respective preferences.

4.1. Cost-ignorant policymaker

A cost-ignorant policymaker assumes the cost of missing a crisis and issuing a false alarm to be equal, that is, μ =0.5. This leads to the more frequent class being the best guess of the policymaker when disregarding the model.

However, in domains with low-probability, high-impact events, such as settings for EWSs generally are, one would assume a policymaker to also have imbalanced misclassification costs.

4.2. Fixed cost-aware policymaker

A fixed cost-aware policymaker has fixed misclassification costs for all observations, but may want to set them unequally. By varying the preference parameter μ ε [0,1], he/she can set the preferences to approximate the cost of misclassifying one class relative to the other.

A high threshold would imply few crisis signals and a higher risk of missing a crisis (Type 1 error). A low threshold on the other hand would increase the number of signals, but will also raise the number of false crisis signals (type 2 error). The optimal threshold is set by minimizing the loss function. With the global crisis, policymakers are likely to be more concerned about missing crises. Hence, the focus was on values of preference parameter in the range μ ε [0.8,0.9].

5. Empirical Results

Tables 2 and 3 display the usefulness and robustness check results for the cost-ignorant and fixed cost-aware policymaker for the selected financial stress indices. The results showed that all the Indices employed by the BOJ are useful for the fixed cost-aware policymaker who is more inclined to be concerned with missing a crisis. However, for the cost-ignorant policy policymaker, the results indicated that only the MaFi achieved a positive relative usefulness of 13.0 per cent (see Table 2). Additionally, in both the cases of the cost-ignorant and fixed cost-aware policy maker the MaFi proved to be the most effective early warning index used at the Bank of Jamaica. This as the MaFi had the highest absolute and relative usefulness as well as the most robust result as indicated by the AUC of 0.77.[7] Furthermore, the overall predictability of the MaFi based on the binomial logit model is estimated at 96.07 per cent (see **table 6b**). The explanatory variables used in estimating the logit model that were most useful in predicting the probability of a crisis were real GDP growth, stock exchange growth, private sector credit growth and inflation (see appendix).

[7] The area under the receiving operating characteristic curve (AUC) is a viable and robust measure for comparing the performance of early warning systems (Vasicek et al 2014). It measures the probability that a randomly chosen distress event is ranked higher than a tranquil period. The higher the AUC the most robust the test result.

Table 2: *Cost-ignorant Policymaker*

Index	TP	FP	TN	FN	Type I error	Type II error	Accuracy (%)	Absolute usefulness	Relative usefulness	AUROC
AFSI	6	19	16	2	0.25	0.54	51.20%	-0.151	-1.63	0.63
CISS	6	16	17	0	0.00	0.49	59.00%	-0.128	-1.67	0.62
MaFi	4	3	32	4	0.25	0.11	86.00%	0.012	0.13	0.77
MiPi	6	18	17	2	0.25	0.51	53.50%	-0.140	-1.50	0.55
Z-score	7	16	19	1	0.13	0.46	60.50%	-0.105	-1.13	0.70

Notes: The abbreviations are as follows: TP = True positives, FP = False positives, TN = True negatives, FN = False negatives. AUROC = Area under the ROC curve. Accuracy = (TP+TN)/(TP+TN+FP+FN), Type I error rate = FN/(TP+FN), Type II error rate = FP/(FP+TN).

Table 3: *Fixed cost-aware Policymaker*

Index	TP	FP	TN	FN	Type I error	Type II error	Accuracy (%)	Absolute usefulness	Relative usefulness	AUROC
AFSI	6	19	16	2	0.25	0.54	51.20%	0.023	0.16	0.63
CISS	6	16	17	0	0.00	0.49	59.00%	0.041	0.33	0.62
MaFi	6	4	31	2	0.25	0.11	86.00%	0.093	0.63	0.77
MiPi	6	18	17	2	0.25	0.51	53.50%	0.028	0.19	0.55
Z-score	7	16	19	1	0.13	0.46	60.50%	0.056	0.38	0.70

Notes: The abbreviations are as follows: TP = True positives, FP = False positives, TN = True negatives, FN = False negatives. AUC = Area under the ROC curve. Accuracy = (TP+TN)/(TP+TN+FP+FN), Type I error rate = FN/(TP+FN), Type II error rate = FP/(FP+TN).

6. Conclusion and Recommendation

In the wake of the financial global crisis there has been a greater desire to be able to predict financial instability in countries across the world. The use of various macroeconomic, microeconomic and financial indicators in conjunction with the already diversified financial indices, have been used by the BOJ to captures a wide sphere of instability, market and banking developments. This paper sought to evaluate the usefulness of several financial indices that the

Bank utilizes to guide its policy decisions regarding the threat of financial stress. The results of the study suggested that the MaFi was the most useful index in predicting financial stress for both the cost-ignorant and fixed cost aware policymaker.

The MaFi index which was identified as the most useful in the paper can be a valuable input for monitoring economic and financial risks. However, this index should be complemented with other monitoring tools including expert judgement.

APPENDIX

Table 4a: *The estimates for the AFSI model*

Variables	Estimates	Std. error	Z – Statistic	Prob
Intercept	111.6	23.7	1.7	0.09*
Real GDP growth	-8.8	4.7	-1.9	0.06*
Private sector credit growth	109.3	41.5	2.3	0.02**
Exchange Rate	-1.8	0.9	-1.8	0.08*
Treasury Bill (180 days)	0.7	0.4	1.7	0.09*
Liquidity ratio	-5.0	2.9	-1.7	0.8*

Notes: Significance levels: 1%, ***; 5%, **; 10%, *

Table 4b: *Performance of the binomial logit model AFSI*

	S=0	S=1	Total
Y=0	48	1	49
Y=1	0	2	2

Total	48	3	51
Correct	48	2	50
% of observations correctly called			98.0
% of crises correctly called			100.0
% of false alarms of total alarms			33.3
% probabilities of crisis given an alarm			66.7
% probabilities of crisis given no alarm			0.0

Table 5a: *Estimates for the CISS model*

Variables	Estimates	Std. error	Z-statistic	Prob
Interept	-13.3	2.9	-4.6	0.000***
Real GDP growth	-3.6	0.7	-5.0	0.003***
Inflation	0.2	0.1	3.0	0.000***
Private sector credit growth	46.5	10.3	4.5	0.000***

Notes: Significance levels: 1%, ***; 5%, **; 10%, *

Table 5b: *Performance of the binomial logit model CISS*

	S=0	S=1	Total
Y=0	37	1	38
Y=1	0	2	2
Total	37	3	40
Correct	37	2	39
% of observations correctly called			97.5
% of crises correctly called			100.0
% of false alarms of total alarms			33.3
% probabilities of crisis given an alarm			66.7
% probabilities of crisis given no alarm			0.0

Table 6a: *Estimates for MaFi model*

Variables	Estimates	Std. error	Z-statistic	Prob
Interept	-2.9	8.2	-0.4	0.7
Real GDP growth	-5.6	1.8	-3.1	0.002***

JSE growth	-0.4	0.2	-2.3	0.02**
M2/NIR	-7.6	7.9	-1.0	0.3

Notes: Significance levels: 1%, ***; 5%, **; 10%, *

Table 6b: *Performance of the binomial logit model MaFi*

	S=0	S=1	Total
Y=0	45	1	46
Y=1	1	4	5
Total	46	5	51
Correct	45	4	49
% of observations correctly called			96.1
% of crises correctly called			80.0
% of false alarms of total alarms			20.0
% probabilities of crisis given an alarm			80.0
% probabilities of crisis given no alarm			2.2

Table 7a: *Estimates for MiPi model*

Variables	**Estimates**	**Std. error**	**Z-statistic**	**Prob**
Intercept	-41.4	27.0	-1.5	0.1
Real GDP growth	0.4	0.4	1.1	0.3
Inflation	-0.8	0.3	-2.5	0.01**
Private sector credit growth	-29.3	18.5	-1.6	0.1
Exchange rate	-0.1	0.1	-2.1	0.03**
Return on asset	11.6	6.4	1.8	0.07*
Interest margin to income	0.9	0.5	1.8	0.07*

Notes: Significance levels: 1%, ***; 5%, **; 10%, *

Table 7b: *Performance of the binomial logit model MiPi*

	S=0	S=1	Total
Y=0	46	3	49
Y=1	0	2	2

Total	46	5	51
Correct	46	2	48
% of observations correctly called			94.1
% of crises correctly called			100.0
% of false alarms of total alarms			60.0
% probabilities of crisis given an alarm			40.0
% probabilities of crisis given no alarm			0.0

Table 8a: *Estimates of Z-score model*

Variables	Estimates	Std. error	Z-statistic	Prob
Intercept	21.4	8.9	2.4	0.02**
Real GDP growth	-1.0	0.5	-2.1	0.03**
JSE growth	-0.2	0.1	-2.2	0.03**
Inflation	-1.8	0.8	-2.1	0.04**
Exchange rate	-0.1	0.1	-2.2	0.02**
Current account/GDP	-24.3	25.1	-1.0	0.3
Housing price growth	-0.2	0.2	-1.3	0.2

Notes: Significance levels: 1%, ***; 5%, **; 10%,

Table 8b: *Performance of the binomial logit model Z-score*

	S=0	S=1	Total
Y=0	42	1	43
Y=1	0	3	3
Total	42	4	46
Correct	42	3	45
% of observations correctly called			97.8
% of crises correctly called			100.0
% of false alarms of total alarms			25.0
% probabilities of crisis given an alarm			75.0
% probabilities of crisis given no alarm			0.0

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