THE POTENCY OF ECONOMIC AND FINANCIAL INDICATORS IN PREDICTING ECONOMIC RECESSIONS IN THE CARIBBEAN

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Introduction

In the past several decades, Caribbean economies have been wrecked by economic recessions, which have had serious impacts on the countries' social development. Structural reforms put in place after the economy has fallen into recession have often resulted in high unemployment levels, lower real wages and an increase in poverty. Hence, if policy makers could accurately predict economic recessions several periods in advance, they might be able to adjust economic policy to respond accordingly.

Typically, economists have used indicators such as the growth in domestic credit, the ratio of reserves to imports, and the expansion in the money supply, as indicators of the economy's ability to achieve sustainable economic growth. However, how good are these indicators? Do they really foretell a coming recession and are they applicable to Caribbean economies?

To date, Caribbean economists have paid very little attention to the actual prediction of economic crises or the accuracy of the economic and financial variables used in forecasting. Most of the research has focused on 'what if' scenarios; for example, what impact would a change in x variable have on the economy. Caribbean economists have tended to concentrate on comparing various models that predict specific variables such as aggregate employment (Craigwell et. al., 2000) and currency demand (Williams, 1997). Worrell (1991) took this approach a step further and proposed a model that would allow users to vary state and policy variables in an attempt to forecast their impact on the economy. While this model may indicate the probability of future recessions based on the variables that were changed, it depends highly on the assumptions that form its foundation and does not lend itself easily to the use of these variables as signals.

The paper's objective, therefore, is to determine which economic and financial variables are most prevalent in indicating impending recessions. To the authors' knowledge, this is the first study for the Caribbean that seeks to identify the most potent indicators of recessions. The study utilises two approaches, namely "Signals" models and probit models, to investigate these issues. The variables are first evaluated using the "Signals" model to determine which gave the strongest indication that a crisis was imminent. The indicators are then evaluated in a probit methodology using both in and out-of-sample testing techniques.

The remainder of the paper is organised as follows: section two examines the studies conducted on forecasting economic recessions as well as currency crises; section three presents the methodology for both the "Signals" approach and the probit models; section four analyses the results for the indicators; and the final section summarises the findings.

Literature Review

The vast majority of the studies conducted on predicting economic crises have focussed on current account or currency crises. They have utilised a variety of techniques including the ‘signals’ approach and probit models. In the first method, changes in the values of several key ratios are observed before a crisis to determine if they have predictive powers. In the second set of studies, multivariate probit models are used to determine the probability of a crisis. It is important to note however, that several researchers also combine both methods in their investigations in order to compare the performance of the different models.

Kaminsky, Lizondo and Reinhart (1997) were the first to propose the “Signals” Approach in forecasting currency crises. They defined a signal as a deviation of a variable from its normal level beyond a certain threshold value. Their study used monthly information for several key variables including the real exchange rate, the terms of trade and excess real M1 balances and evaluated the effectiveness of each indicator using a matrix of possible signal outcomes. The authors found that all of the indicators were important in predicting a currency crisis at a maximum of 24 months before the crisis started, with the real exchange rate indicator being the most potent.

Berg and Pattillo (1999) evaluated the performance of the Kaminsky et al (KLR) ‘Signals’ model and other models in predicting the 1997 Asian financial crisis. For the given model, the authors attempted to replicate the original procedure, using two samples of countries. The first sample was the same as that contained in the respective papers, while the second sample consisted of Asian countries. The writers then generated a ranking of countries according to the predicted probability or severity of a crisis in 1997, and used it to compare the predicted and actual rankings. The authors found that the KLR model had limited success in predicting the probability of a crisis in out-of-sample forecasting for 1997, however, a Chi-squared test revealed that overall, the model performed better than a comparable uninformative model. Additionally, an analysis of the cross-sectional predictive power of the test in identifying countries that were the most vulnerable to the 1997 crisis showed that the model was somewhat successful in ranking countries by the projected severity of the crisis. However, when select Asian countries were evaluated against another subset of developing countries, which were spared from the effects of the crisis, the KLR model consistently predicted abnormally high risks for the two non-crisis countries, while one crisis country was incorrectly forecasted as having acceptable risks. The results were somewhat improved with the inclusion of additional variables but overall, the model appeared to have weak predictive power.

Atta-Mensah and Tkacz (1998) analysed the ability of financial variables to predict recessions in Canada. The authors used the probit methodology to determine the accuracy of each indicator in forecasting Canadian recessions. The pseudo-R^2 and t-test were employed to test each variable. Based on both in-sample and out-of-sample regressions, the writers determined that the spread between ten-year Government of Canada bonds and ninety-day commercial paper was the best at predicting Canadian recessions up to five quarters ahead. Furthermore, it was found that the quarterly M1 growth rate was reasonably good at predicting recessions.

Estrella and Hardouvelis (1991) examined the term structure of interest rates as a possible predictor of future economic activity. The authors utilised the difference between the average quarterly 3-month US T-bill rate and the average quarterly 10-year US government bond rate as a measure of the slope of the yield curve i.e. the spread. The dependent variable was computed as the annualised cumulative percentage change in the seasonally adjusted revised GNP estimates. Using both Ordinary Least Squares and Probit models, the authors found that for in-sample forecasting, the spread was accurate in predicting future changes in real GDP up to seven quarters ahead in some instances. The probit model which used the spread as the only explanatory variable, also outperformed similar models which included variables such as lagged values of the real federal funds rate, the index of leading indicators, the growth in real output and the rate of inflation. The situation was reversed for out-of-sample forecasting however, as a forecasts based on all the indicators previously mentioned, exhibited marginally greater predictive power than a forecast that used the spread as the only explanatory variable.

In their 1998 paper, Estrella and Mishkin analysed the question of whether financial variables were better at predicting recessions in the US than traditional macroeconomic variables. The authors used probit methodology and examined the power of several key variables[1] in predicting recessions, over the sample period 1959:1 to 1995:1, for a forecast horizon of up to eight quarters ahead. The variables were first tested individually using in-sample estimation techniques, followed by testing using a combination of the yield curve spread[2] and each variable sequentially. The two procedures were then repeated for the out-of-sample forecast. The results, as indicated by the pseudo R^2, the t-statistic and indicators of significance at the 5% and 1% level, showed that the variables which consistently performed best both by themselves and in combination were the yield curve spread and stock prices.

Frankel and Rose (1996) utilised a combination of graphical inspection and multivariate probit models to investigate the causes of currency crises in a panel of over 100 developing countries from 1971 through to 1992. The writers defined a currency crash as a nominal depreciation in the currency of at least 25% that is at least a 10% increase in the rate of depreciation. They then constructed key indicators of currency crises using four main categories, namely: domestic macroeconomic variables, the level of indebtedness, the composition of debt stock and foreign indicators. The study’s main findings were that currency crashes tended to occur when domestic variables such as credit growth, external debt and the real exchange rate rise, while decreases in the level of foreign direct investment to external debt, reserves and recessions in the various economies all seem to contribute to currency crashes. Finally, external factors such as increases in northern interest rates also raised the probability of currency crises among the developing countries. The results appeared to be relatively robust as they were unaffected by the use of lagged independent variables and the introduction of new variables such as a measure of currency exposure and continent dummy variables[3]. Surprisingly, variables which one would intuitively expect to be significant in predicting a currency crisis such as the fiscal deficit, the current account to GDP ratio, short-term debt and the ratio of public sector debt to total debt appeared to be insignificant. However, the authors did concede that the use of a large number of

[1] See Estrella and Mishkin (1995) p. 10 for the list of variables used in the study.
[2] Proxied by the difference between the 3-month treasury bill rate and the 10-year treasury bond rate.
[3] Incidentally, both theses regressors were insignificant in the analysis.

variables could have over-parameterised the model, which may have reduced the accuracy of the results.

Other authors have utilised a variety of techniques aimed at modelling economic activity. Aylward and Glen (2000) used the Seemingly Unrelated Regression (SUR) procedure in an attempt to analyse the relationship between lagged stock prices and economic growth for a variety of countries. The writers found that in the case of the developed countries, stock price changes tended to lead GDP changes. Similarly, Wells (1999), employed Granger Causality tests in a VAR framework to determine the ability of several variables used by the Bureau of Economic Analysis to predict future movements in economic activity[4]. Real money balances emerged as one of the best indicators in this analysis. More recently, McMillan (2002) used linear regression analysis with a Newey West (1987) correction to determine the ability of the spread between the 3-month T-bill rate and the 10yr government bond to forecast changes in GDP growth. The findings indicated that the spread variable had predictive ability although it's significance was much weaker than those obtained in similar studies for the US and Canada.

Methodology for the "Signals" Approach

The procedure adopted, follows the approach used by Kaminsky et al (1997). The following explanation was reproduced from their study.

Signaling horizon: This is the period within which the indicators would be expected to have the ability to anticipate a crises. This period was defined a-priori as 24 months. Thus a signal that is followed by a crisis within 24 months is called a good signal, while a signal not followed by a crisis within that interval of time is call a false signal, or noise.

Signals and thresholds: An indicator is said to issue a signal whenever it departs from its mean beyond a given threshold level. Threshold levels are chosen so as to strike a balance between the risks of having many false signals (which would happen if a signal is issued at the slightest possibility of a crisis) and the risk of missing many crises (which would happen if the signal is issued only when the evidence is overwhelming).

For each of the indicators, the following procedure was used to obtain the "optimal" set of thresholds that were employed in the empirical application. Thresholds were defined in relation to percentiles of the distribution of observations of the indicator. For example, a possible set of thresholds for the rate of credit growth would be the set of rates of growth that would leave 10 percent of the observations above the threshold. The procedure was repeated using a grid of reference percentiles above 10 percent, and the "optimal" set of thresholds was defined as the one that minimized the noise-to-signal ratio' i.e., the ratio of false signals to good signals.

The effectiveness of the signal approach can be examined at the level of individual indicators (the extent to which a given indicator is useful in anticipating crises) and at the level of a set of indicators (the extent to which a given group of indicators taken together is useful in anticipating crises). The discussion below examines the effectiveness of individual indicators. It extends some of the analysis presented in Kaminsky et al (1996) by ranking the various indicators according to their forecasting ability, and by examining the lead-time and persistence of their signals.

[4] Proxied by the index of industrial production.

In order to examine the effectiveness of individual indicators, the performance of each indicator was considered in terms of the following matrix:

	Crisis (within 24 months)	No crisis (within 24 months)
Signal was issued	A	B
No signal was issued	C	D

In this matrix, A is the number of months in which the indicator issued as good signal, B is the number of months in which the indicator issued a bad signal or "noise," C is the number of months in which the indicator failed to issue a signal when it should have, and D is the number of months in which the indicator correctly failed to issue a signal. A perfect indicator would only produce observations that belong to the northwest and southeast cells to this matrix. It would issue a signal in every month that is to be followed by a crisis (within the next 24 months), so that A>0 and C=0, and it would refrain from issuing a signal in every month that is not to be followed by a crisis (within the next 24 months), so that B=0 and D>0.

Methodology for the Probit Binary Choice Model

Probit and other "binary choice" models were created to model the choice between two discrete alternatives. As Verbeek (2000) shows, probit models are used when the dependent variable either takes on the value of 0 or 1.

In general we have:

$$P\left[y_i = 1/x_i\right] = F\left(x_i^{'}, \beta\right) \tag{1}$$

For some function $F(.)$, the equation can only take on the values in the interval $[0,1]$ and has distribution

$$F(w) = \Phi(w) = \int_{-\infty}^{w} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt \tag{2}$$

The parameters of the model are estimated by the method of maximum likelihood, where the likelihood function is given by:

$$\log L(B) = \prod_{i=1}^{N} P\left(y_i = 1/x_i ; \beta\right)^{yi} P\left(y_i = 0/x_i ;\ \beta\right)^{1-y_i} \tag{3}$$

The inclusion of β shows that the likelihood function is a function of β. Substituting $P\left(y_i = {}^{1}\!/_{x_i} ; \beta\right) = F\left(x_i^{'}\beta\right)$ we obtain

$$\log L(\beta) = \sum_{i=1}^{N} y_i \log F\left(x_i^{'}\beta\right) + \sum_{i=1}^{N}\left(1 - y_i \ \log\left(1 - F\left(x_i^{'}\beta\right)\right)\right) \tag{4}$$

Substituting the appropriate form of F gives an expression that can be maximized with respect to (wrt) to β. To maximize we differentiate to find the first order conditions of the of the ML problem. Differentiating wrt β yields:

$$\frac{\partial \log L(\beta)}{\partial \beta} = \sum_{i=1}^{N}\left[\frac{y_i - F(x_i^{'}\beta)}{F(x_{i'}^{'}\beta)(1-F(x_i^{'}\beta))} f(x_i^{'}\beta)\right] x_i = 0 \tag{5}$$

Where $f = F^{'}$ is the derivative of the distribution function (so f is the density function). The term in the square brackets is referred to as the generalized residual of the model. It equals $f(x_i^{'}\beta)/F(x_i^{'}\beta)$ for the y = 1 observations and $-f(x_i^{'}\beta)/1-F(x_i^{'}\beta)$ for the y = 0 observations.

The first order conditions therefore state that each explanatory variable should be orthogonal to the generalized residual. The second order conditions of the ML problem state that the matrix of second order conditions is negative definite (assuming that the xs are not collinear). Therefore the loglikelihood function is globally concave and convergence of the maximum likelihood algorithm is guaranteed.

It is worth mentioning, however, that in univariate dichotomous models, the choice between the probit model, which utilises the standard normal distribution, and the logit model, which assumes the data follows a logistic distribution function, does not matter. As Amemiya (1981) notes, this is mainly due to the close similarity between the two distributions, which results in relatively similar estimates[5] particularly in small data series.

Several criteria have been proposed to determine the goodness of fit of limited dependent variable models. For example, Estrella (1998) and Amemiya (1981) present a number of statistics that can be used to evaluate the performance of limited dependent variable models. One of the most popular measures that emerged is the Pseudo R^2 statistic proposed by McFadden in 1974 suitably titled McFadden R^2. This measure is the ratio of the maximum loglikelihood value of the model of interest lB_{ML} to the maximum loglikelihood function when all parameters except the intercept are set to zero l_0. Therefore:

$$McFadden\ R^2 = 1 - \frac{lB_{ML}}{l_0} \tag{6}$$

As Estrella (1998) notes, the McFadden R^2 and other Pseudo R^2 statistics correspond intuitively to the coefficient of determination R^2, used in a standard linear regression case. However, Windmeijer (1995) acknowledges that these "closeness" criteria may be influenced by simple transformations, which could potentially improve the results obtained.

Authors such as Cozier and Tkacz (1994) and McMillan (2002) note that, as in the linear regression case, the pseudo R^2 is a useful measure of fit, but it is not sufficient for statistical hypothesis testing. As a result, the significance of the individual lagged regressors was obtained using the p-values associated with the Chi-squared statistics, which indicated significance at the 1% and 5% level. However, for predicting horizons of two or more quarters, the overlapping data problem occurs in that the forecast horizon is longer than the observation interval. As a result, forecast errors are likely to be serially correlated, raising the possibility that the estimates of the significance of individual variables using conventional test statistics may be misstated. Therefore, significance statistics are calculated using standard errors adjusted for the overlapping data problem by applying the Newey-West (1987) technique to the first-order conditions of the maimum-likelihood estimates[6], which is defined as follows:

Given:

$$F_t \equiv F(\beta^{'} x_t), \tag{7}$$

and

$$f_t \equiv F^{'}(\beta^{'} x_t) \tag{8}$$

let

$$h_t \equiv \frac{y_t - F_t}{F_t(1-F_t)} f_t x_t, \tag{9}$$

and

$$h \equiv \sum_{t=1}^{T} h_t. \tag{10}$$

The first-order condition for the probit estimates may then be expressed as $h = 0$. Further, compute the sample autovocariances of h_t,

$$\hat{\Omega}_j \frac{1}{T}\sum_{t=j+1}^{T} h_t h_{t-j}^{'} \tag{11}$$

and construct an estimator of the covariance of h from

$$\hat{S} = \hat{\Omega}_0 + \sum_{j=1}^{m}\lambda_j(\hat{\Omega}_j + \hat{\Omega}_j^{'}) \tag{12}$$

[5] The main exception relates to data which is heavily concentrated in the tails of the distribution.

[6] Estrella and Mishkin used the Newey-West procedure to compute t-statistics.

where $\lambda_j = 1 - j/(m+1)$. Using the notation $H \equiv (1/T)(\partial h/\partial \beta)$, the variance-covariance matrix of the coefficient estimates is given by

$$V = \frac{1}{T}\left(H'H\right)^{-1} H'\hat{S}H\left(H'H\right)^{-1} \tag{13}$$

The coefficient estimates are consistent even in the presence of serial correlation and therefore, this variance estimator is consistent.

Data

The majority of the data used to estimate the economic, debt and financial indicators were obtained form the International Monetary Fund's "International Financial Statistics" and the statistical digests of the various countries. The information used to calculate the percentage changes in the stock index data was acquired from the different stock exchanges. The data series used for each country varied based on the availability of real GDP data. Hence with respect to Jamaica, the series used consisted of data from 1997:1 to 2002:4, Barbados 1990:1-2003:4 and Trinidad and Tobago 1984:1-2002:4. All of the estimation and forecasting procedures were conducted using the Regression Analysis of Time Series (RATS) programme.

The change in real GDP was the natural candidate for measuring aggregate output. For the purpose of the analysis, a recession was defined to have occurred if the economy suffered two consecutive quarters of negative real GDP growth. Hence if the economy is experiencing a recession the dependent variable takes on the value 1 and 0 otherwise. The year-to-year quarterly growth rates were obtained from the data, as opposed to data over shorter horizons such as one-quarter changes, since these changes are likely to contain more measurement error[7]. Moreover, quarter-on-quarter changes tend to be misleading when GDP is cyclical as is the case in some Caribbean countries. The estimates of quarterly real GDP were obtained from the various Central Banks[8].

The majority of the economic indicators were standard ratios used by macroeconomic policy analysts. The indicators, along with their *a priori* signs, are defined in Appendix A, Table 1. The *a priori* signs were, for the most part, derived from the results obtained by other authors such as Berg and Pattillo (1999), Frankel and Rose (1996) and Kaminsky et al (1997) in predicting different types of crises. As a result of the unavailability of quarterly nominal GDP values for all of the countries over the sample period, the temporal disaggregation procedure proposed by Boot et al (1967) was utilised to obtain mathematically consistent, quarterly GDP estimates from annual GDP values for Trinidad & Tobago and Jamaica.

The study also examined the performance of financial indicators such as the change in the major stock market index and the inter-market nominal[9] yield spread. The spread was calculated using the difference between the annualised yields on the treasury bills of the respective countries and the annualised yields on US treasury bills. The US T-bill rate was chosen since it is widely considered as a default free debt instrument. The spread is therefore equal to:

$$SPREAD = R_t^L - R_t^{US} \tag{14}$$

where: R_t^L is the local treasury bill rate at time t

and R_t^{US} is the US treasury bill rate at time t

Authors such as McGuire and Schrijvers (2003) have suggested that changes in spreads between emerging market debt issues and benchmark series *inter alia* reflect investors risk tolerance and their expectations of the future state of the emerging market economies (i.e the nation's credit worthiness). The SPREAD variable therefore seeks to model investors' perception of the state of the economy; thus expansions in the spread variable indicate investors' beliefs that the economic outlook is not favourable and vice versa.

Another widely used interest rate spread variable was the inter-market spread or the spread between government short-term t-bill rates and long-term interest rates. However, such a measure would not be useful for the Caribbean because unlike short-term instruments, long-term instruments are not issued as frequently and therefore suffer from stale pricing. Hence, changes in the inter-market spread are unlikely to reflect rapid changes in investor perceptions.

Results "Signals" Approach

Tables 1-3 in Appendix B shows the individual country results from the "Signals" Approach. Column 1 provides the list of economic, financial and debt indicators[10]. Column 2 calculates the good signals issued as a percentage of total possible good signals, while column 3 shows the number of bad signals issued by the indicator as a percentage of total bad signals. A good indicator would be expected to produce a high percentage of good signals and a low percentage of bad signals. The following column combines the two previous results to obtain a measure of the indicator's ability to issue good signals and avoid sending bad signals, or the "noisiness" of the indicator. As expected, the better the indicator the lower the "adjusted" noise to signal ratio. Moreover, as Kaminsky et al (1997) show, an indicator which has no intrinsic predictive power would issue signals at random and hence would have a noise-adjusted ratio ∃1.

Column 5 illustrates another way of calculating the noisiness of the indicator, under the assumption that a useful indicator will have a conditional probability (A/(A+B)), which is higher than the unconditional one ((A+C)/(A+B+C+D)). Hence the value of an indicator with no predictive power will be negative in this column.

Jamaica

The year-to-year quarterly change in the treasury bill rate (CTBILL) variable, was the best indicator for Jamaica, as it had the highest ratio of good signals to possible good signals (40%)

[7] See Hu (1993)

[8] The exception was the Central Bank of Trinidad which provided quarterly growth rates based on an index of real output.

[9] The spread is nominal because it does not take into account the exchange rate risk.

[10] For the purpose of this study, an indicator was determined to issue a signal when the set of values of the observations were at and above the 20th percentile.

and the lowest ratio of bad signals to possible bad signals (0%). Moreover, it had the lowest noise-to-signal ratio (0%) and its conditional probability was greater than its unconditional probability (28.6%). Other important indicators were: the year-to-year quarterly change in total deposits (TDG), the ratio of external debt to GDP (EXTDEBTGDP), the year-to-year quarterly change in domestic credit (DOMCRE), the ratio of government's fiscal balance to GDP (GOVT), the ratio of exports to GDP (EXPGDP) and the ratio of imports to GDP (IMPGDP). In contrast, the ratio of gross reserve to imports (RESIMP), the ratio of the money supply to gross reserves (M2RES), the ratio of real lending to deposit rates (RRLDR), the year-to-year quarterly percentage changes in the major stock market index (STOCK) and the difference between the domestic and US interest rates (SPREAD), all appeared to be poor indicators of a recession[11]. The worse performing indicator was the real interest rate on deposits (RIRD), as shown, it had a perfect ratio of bad signals (100%) and no good signals.

Barbados
For Barbados, the most significant indicator was STOCK, followed by M2RES, DOMCRE and RESIMP. Other significant indicators included: GOVT, EXPGDP and RRLDR. In contrast, IMPGDP, TGD, RIRD, CTBILL and EXTDEBTGDP appeared to be insignificant indicators. The SPREAD variable was the most insignificant variable as it had the lowest percentage of good signals to possible good signals (0%) and the highest percentage of bad signals to possible bad signals (52%).

Trinidad and Tobago
With respect to Trinidad and Tobago, the most significant indicator was EXPGDP, as evidenced by the highest ratio of good signals to potential good signals (72.73%) and the lowest ratio of bad signals to potential bad signals (16.13%). Additionally, it recorded the lowest level of noise and the difference between the conditional probability and the unconditional probability was positive. Other significant variables included DOMCRE, GOVT, RESIMP, TGD, STOCK and CTBILL while IMPGDP, RIRD, RRLDR, SPREAD and EXTDEBTGDP were insignificant indicators. It is somewhat surprising that EXTDEBTGDP was insignificant considering that the level of external debt increased during the sample period. This may be as a result of high levels of debt relief in the early part of the review period combined with increased domestic financing.

Results (Probit Models)

In-Sample

Following the work of Estrella and Mishkin (1998), the in-sample results were computed by estimating alternate equations for each indicator, using diffent lags, and the dependent variable. The estimated equations were then used to forecast values of the dependent variable over the relevant sample period and the forecasts values were then evaluated against the recession data using the McFadden R^2 and Chi-Squared statistics. The in-sample results are given in Appendix C, Tables 1-3.

Jamaica
The in-sample results for Jamaica indicate that overall the indicators were relatively poor predictors of economic recessions. Among the economic indicators, the strongest performer was the real interest rate on deposits (RIRD), it was significant at the 5% level for lags 4 and 6 and at the 1% level in lag 5. This was closely followed by the ratio of Exports to GDP(EXPGDP), which was significant at the 1% level in lags 4 and 5. Other economic variables that exhibited marginal predictive power in at least one lag were: RRLDR, TGD, GOVT and IMPGDP. With regards to the financial variables, the most important indicator was the change in the CTBILL rate, which was significant in lags 4,5 and 6. In addition, changes in the major stock index series (STOCK) demonstrated predictive power at the more distant lags of 7 and 8, which may conform to the traditional finance theory, which states that stock prices tend to be forward looking. The debt indicator, EXTDEBTGDP, showed significance at lags 7 and 8.

Barbados
With regard to Barbados, the M2RES variable seemed to be the economic variable with the most predictive power. It was significant for the first six lags and, moreover, the level of significance (as shown by the McFaden R^2 statistic) grew over the first five lags indicating that the model fit improved as the number of lags increased. Other important economic indicators included: TDG, RESIMP and GOVT, which demonstrated predictive ability in at least three lags. Interestingly, the GOVT variable was significant in the later lags, which may be indicative of the ability of fiscal deficits in Barbados to predict economic recessions more than one year before they occur.

With regard to the financial variables, the most potent indicator was the STOCK variable, which demonstrated predictive ability in all of the lags. This result may appear to be somewhat surprising for Barbados, however, as Estrella and Mishkin (1998) state "... Stock prices may be interpreted as expected present values of future dividend streams. Although the discounting reduces the effective predictive horizon, projections should be relatively long-term" (pages 49-50). Hence the fact that the stock price indicator is significant up to the eighth quarter is consistent with this notion. Moreover Craigwell and Grandbois (1994) found that the lags of real return on stock prices (as proxied by the stock market index) were important in explaining the current value of real GDP in Barbados. The debt variable (EXTDEBTGDP) also appeared to be an important predictor of economic recessions. The fact that the EXTDEBTGDP was one of the top indicators, is consistent with the conclusions of authors such as Dalrymple (1995) who reported that prior to the 1991 BOP crisis, the level of external debt rose quite dramatically. Moreover, the significance of the M2RES indicator is expected given the fact that the 1991 BOP crisis was associated with rapid declines in the level of the country's Net International Reserves (NIR). Given that Barbados has a fixed exchange rate, drastic declines in the NIR would signal to the authorities that the country's ability to defend the peg was in jeopardy and hence prompt them to introduce harsh measures to protect the reserves, which may lead to adjustments in GDP.

Trinidad and Tobago
The in-sample results for Trinidad and Tobago were in sharp contrast to those for Jamaica. All of the economic variables, with one exception (M2RES), were significant for the majority of the

11 This was shown by the fact that the indicators had a low percentage of good signals to possible good signals, a high percentage of bad signals to possible bad signals and difference between the conditional and the unconditional probability was negative.

lags. Among the financial variables, both the STOCK and the SPREAD variables were good predictors of recessions during all 8 lags, while the variable CTBILL was a good indicator for the first 5 lags. Again, as in the case of Jamaica, the ratio of external debt to GDP (EXTDEBTGDP) proved to be a relatively poor predictor of economic recessions, as its level of significance waned after lag 2.

Out-of-Sample Results

Tables 4 – 6 in Appendix C give the results for the out-of-sample forecasts. The procedure followed first involved the selection of a certain time period to estimate the regression equation. The period chosen for all three series included at least one recession in order to obtain correct parameter estimates[12]. Next, the estimates were used to form a projection k quarters ahead. After the forecast was obtained, the sample was augmented by the addition of another quarter and the procedure repeated to obtain a forecast at period k+1. The resulting series was then regressed against the dependent variable and the McFadden R^2 recorded. As Estrella and Mishkin note, the advantage of this technique is that out-of-sample forecasts provide a more realistic and fairer test of the predictive power of the various indicators than the in-sample results. Moreover, Tashman(2000) highlighted the fact that for a given forecasting method, in-sample errors are likely to understate forecasting errors and additionally a method's best in-sample fit may not best predict post-sample data. However, Estrella and Mishkin admit that the out-of-sample procedure suffers from several drawbacks such as: the statistical test of significance becomes invalid and the McFadden R^2 statistic, which lies between 0 and 1 in the in-sample test may be less than zero[13]; implying that the out-of-sample forecast for the combination of the indicator and the constant term is worse than the forecast generated using solely the constant term. Another disadvantage of the out-of-sample procedure, is that it requires a long data series in order to produce meaningful results, which in the case of Jamaica, limited the number of possible lags for out-of-sample forecasts to 4.

Nevertheless, following Estrella and Mishkin, the procedure used to obtain out-of-sample results involved the estimation of the probit models over a specified period called the fit period. The estimated regression equation is then used to form forecasts for a particular number of quarters ahead known as an N-step ahead forecast. Finally the sample period used in the probit model is extended by one quarter and the same procedure applied. The model therefore replicates what a statistical model would predict at time t+k given data available up to time t. As the authors note, the resulting forecast methodology provides a more realistic test of the predictive abilities of various models than the methodology applied to obtain in-sample forecasts. Moreover, another benefit is seen in the fact that the sample used in the forecast is continuingly updated, which avoids the corruption problems caused by using dynamic forecasts which are based on occurrences unique to a specific origin[14]. That said, the in-sample forecasts provide an adequate basis for evaluating whether or not the out-of-sample results indicate improved or deteriorating forecasting performance.

Jamaica
An analysis of the results for Jamaica reveals a pattern for the out-of-sample forecasts, which is similar to the results for the in-sample forecasts. Namely, most of the indicators seemed to be poor predictors of economic recessions. In contrast to the in-sample results, the ratio of government's fiscal balance to GDP (GOVT) emerged as the most potent indicator, although it is clear from the low value of the McFadden R^2 that it has only weak forecasting ability. The ratio of imports to GDP, like GOVT also exhibited significance in two lags, however, the level of predictive ability deteriorated rapidly after the first lag. The only other indicator, that exhibited significance in one lag was RRLDR, which showed predictive ability at lag 3. In contrast, the RIRD EXPGDP and TGD variables, which exhibited significant in the in-sample forecast for a few of the lags, appeared to have no predictive ability in the out-of-sample forecast. This was shown by the fact that the McFadden R^2 for all three of these variables in all of the lags were negative, inferring that the indicators performed worse than the forecasts based solely on the constant term. Among the financial variables, the STOCK variable again exhibited significance in at least one of the lag periods, but similar to some of the economic indicators the CTBILL variable exhibited no forecasting ability in the out-of-sample forecasts. Likewise, the debt indicator was insignificant in all four of the lag periods tested.

Barbados
The pattern of the out-of-sample results for Barbados mirror those found by Estrella and Mishkin in the US. The results show significant deterioration of the out-of-sample performance compared to the in-sample performance for most of the indicators. For example, the M2RES variable, which was one of the most potent indicators in in-sample forecasts, fails to exhibit any predictive ability in the out-of-sample forecasts. Similarly, the GOVT variable, which was significant for three lags of the in-sample forecast, is now insignificant for all 8 lags. In addition, the performance of the RRLDR indicator deteriorated in the out-of-sample forecast compared to the in-sample forecast. In contrast, the forecasting performance of the TGD and the IMPGDP variables appeared to show slight improvement in the out-of-sample forecasts, as shown by the fact that both indicators had significant McFadden R^2 in the first lag of the forecast period which were higher than their in-sample counterparts. Also in the case of TGD, the McFadden R^2 remained positive for most of the lags, although there was significant deterioration after lag 2. The financial indicators experienced a similar level of deterioration. The STOCK variable, which exhibited a high degree of predictive ability for all 8 lags of the in-sample forecasts, was only marginally positive in the out-of-sample forecast for lags 3-8, indicating a significant loss of predictive power. Likewise, the SPREAD variable showed only slight predictive power in lag 6 in the out-of-sample forecast. In sharp contrast to the in-sample results, the out-of-sample performance of the debt indicator revealed that they exhibited no predictive ability.

Trinidad and Tobago
With regards to Trinidad and Tobago, the comparison between the in-sample and the out-of-sample forecasts revealed mixed results. Several of the indicators experienced predominantly improved forecasting performance in the out-of sample forecasts, including economic indicators such as: GOVT, IMPGDP, EXPGDP, RIRD and RRLDR. For example, in the case of GOVT, the indicator registered higher McFadden R^2 in the out-of-sample forecasts compared to the in-sample forecasts. The performance of other economic indicators deteriorated marginally however, including: TGD, RESIMP and DOMCRE. As an example, the TGD variable, which

[12] See Estrella and Mishkin (1998).
[13] See McFadden (1974)
[14] See Tashman (2000), pp. 439.

was significant in all 8 lags of the in-sample forecasts, was only significant for 6 lags of the out-of-sample forecast period. There was general improvement among all the financial variables in the out-of-sample calculations compared to the in-sample calculations. The SPREAD and CTBILL variables registered a higher McFadden R^2 in almost all of the lagged periods in which there was significance, however, the out-of-sample forecasting performance of the STOCK indicator waned appreciably behind its in-sample counterpart after lag 5. The EXTDEBTGDP variable showed significant improvement, compared to the in-sample case, in forecasting recessions over one and two lags, as evidenced by the high McFadden R^2. However, as in the in-sample case, the forecasting performance deteriorated rapidly after lag 2.

Analysis of the Combined Signal and Probit Results

As expected, the results of the signals approach are more in line with those of the in-sample forecasts as both methods analyse the predictability of recessions using historical data. In contrast, the out-of-sample forecasts as previously noted, utilise data available up to time t to predict recessions in time t+k. Overall, the results showed that there was no dominant indicator for all three of the Caribbean economies, as the unique features of each country perhaps served to influence the performance of each of the indicators over time.

Arguably the most potent economic indicator for Jamaica overall appeared to be the GOVT variable. This may not be that surprising however, as information from the Planning Institute of Jamaica revealed that just prior to the recession of 1988, government's recurrent deficit expanded due to *inter alia* higher wages and salaries and interest payments. In addition, the fiscal deficit expanded significantly in 2001, the year before the recession, as a result of several shocks to the economy[15]. The other economic variable which exhibited marginal predictive ability in all three of the tests was the ratio of Imports to GDP (IMPGDP). Imports appeared to expand in the quarters before the 1997 recession partly in response to the impending election, which encouraged stockpiling and higher capital goods imports. Imports of mainly capital goods and raw materials also rose prior to the 2002 recession. Other economic variables which seemed to have predictive power in at least two of the tests include: EXPGDP, and TGD and RRLDR. Financial variables that seemed to exhibit marginal predictive ability in two sets of forecasts were the STOCK and CTBILL variables. Interestingly the SPREAD variable failed to show predictive power in either of the tests, which could be a sign that changes in the interest rate gap fail to influence capital flows and hence cannot be used to predict impending recessions in Jamaica. Additionally, the debt variable (EXTDEBTGDP) was significant in two of the tests.

With regard to Barbados, the ratio of real lending to deposit rates (RRLDR) was the only economic variable which exhibited significance in all three tests. The ratio is perhaps simply a reflection of Central Bank policy adjustments made in an attempt to steer the economy before major problems occurred. Indeed before both the 1998 and 2001 recessions the Central Bank made changes to *inter alia* deposit rates. Other variables which exhibited signficance in two tests were: GOVT, RESIMP, IMPGDP, M2RES, TGD and RIRD. With respect to the financial variables the STOCK indicator showed the most predictive ability as it exhibited significance in all three tests. This result reinforces the above-mentioned findings of Craigwell et al (1994). The SPREAD variable exhibited marginal significance in both the in-sample and out-of-sample tests, while the CTBILL indicator failed to show any predictive ability. The debt variable (EXTDEBGDP) exhibited predictive power in two of the tests, namely the Signal and in-sample test. This result is inline with the previously mentioned study of Dalrymple (1995). Moreover, the fact that both of the debt indicators are insignificant in the out-of-sample forecasts may indicate that the out-of-sample results are sensitive to the forecast time period used in the study.

The results for Trinidad and Tobago are in sharp contrast to those obtained for Jamaica and Barbados. As an example, the tests revealed that five of the economic indicators, namely: DOMCRE, GOVT, RESIMP, EXPGDP and TGD, were significant in all three tests, the highest number for any of the countries tested. Indeed, only the RIRD, RRLDR and IMPGDP variables were significant in two tests, while the M2RES indicator failed to exhibit predictive ability in any of the probit models. Among the financial variables, both the STOCK and CTBILL indicator exhibited predictive ability in all three tests, while the SPREAD variable showed significance in two out of the three methods of analysis. Similarly, EXTDEBTGDP showed predictive ability in the probit model but failed to show significance in the Signals approach. Interestingly, an examination of the reports on the economy, both before and during the crisis periods reveal that significant changes in output were predominately the result of problems experienced in the oil and gas sector which formed a significant part of the Trinidad economy.

It is not surprising that variables such as DOMCRE performed well because during the period in question there was a persistent increase in credit. In addition, before the 1992 –93 recession, the money supply in Trinidad and Tobago increased every year. The increase in M2 was enough of a concern to monetary authorities that they tightened monetary policy in an attempt to slow the expansion. Despite the increasing money supply, and declining exports, however, the level of reserves did not fall consistently during this period. The occasional increase may have occurred when contractions in import levels offset the negative impact of declining exports. This is possibly why the M2RES, did not perform as well as other indicators. Additionally, as touched upon in the preceding explanation, imports fell from time to time during the review period and this may have reduced the predictive power of the IMPGDP variable.

[15] These shocks included: civil disturbances in the western area of Kingston in July, the terrorist attacks on the USA on September 11th, and devastating flood rains in November.

Conclusion

The study was conducted to determine which indicators were most potent in predicting recessions in the Caribbean. The paper used results from the "Signal Approach", as well as in-sample and out-of-sample results from probit models to determine the predictive ability of specific indicators. The study found that the most potent variables varied with each country and no single indicator exhibited predictive ability for all three countries, although the ratio of government's fiscal balance to GDP (GOVT) did exhibit good predictive ability in the case of Jamaica and Trinidad and Tobago. Interestingly, financial variables such as the STOCK varible outperformed some of the traditional economic variables indicating stock prices in the Caribbean may contain important information about investors' expectation for the future outturn of the respective economies and hence this indicator may warrant closer scrutiny by policy makers.

An interesting extension to the study would be to determine an optimal series of economic and financial indicators for each country, either by combining several variables in the study to form a probability index or by using variables specific to each country to forecast recessions. These indicators could include world oil prices in the case of Trinidad and Tobago, a measure of tourism (Barbados) and bauxite prices (Jamaica). A similar technique was used by Jordan, Skeete and Coppin to forecast the likelihood of current account crises a certain number of quarters ahead.

The research has therefore proved useful in its attempts to stimulate future research into predicting recessions in the Caribbean. However, it is important to note that unlike other studies conducted for developed countries, the work carried out for the Caribbean was limited by the unavailability of extensive data series.

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Appendix A

Table 1

Indicators Used, Definitions and A Priori Signs

VARIABLE	DEFINITION	EXPECTED SIGN*
CTBILL	The year-to-year quarterly Change in the Annualised Domestic Three-Month Treasury Bill Rate	+
SPREAD	Difference between the Domestic Annualised Three-Month Treasury Bill Rate and the Three-Month US Treasury Bill Rate	+
STOCK	The year-to-year quarterly Change in the major Stock Market Index	-
EXPGDP	The ratio of Domestic Exports to Nominal GDP	-
RRLDR	The spread between the Real Rate of Interest on Lending and Deposit Rates	+
RIRD	The Real Rate of Interest on Deposits	+
TGD	The year-to-year quarterly Change in Total Deposits	-
RESIMP	The Ratio of Gross Reserves to Total Imports	-
M2RES	The ratio of the Money Supply to Gross Reserves	+
IMPGDP	The Ratio of Total Imports to GDP	+
GOVT	The Ratio of Government's Fiscal Deficit to Nominal GDP	+
DOMCRE	The year-to-year quarterly Change in Domestic Credit	+
EXTDEBTGDP	The Ratio of Total External Debt to Nominal GDP	+

Source: International Monetary Fund's "International Financial Statistics",
The Central Bank of Jamaica "Quarterly Economic Reports"
Central Bank of Trinidad and Tobago "Monthly Economic Bulletin"

*A +/- sign indicates that an expansion/reduction in the variable increases/decreases the probability of a recession.

Appendix B

Table 1

Results of the Signals Approach for Jamaica

INDICATORS	Good Signals as Percentage of possible good Signals (A/A+C)	Bad Signals as Percentage of Bad Signals B/(B+D)	Noise/Signal (adjusted)/2 ((B/B+D)/(A/(A+C))	P(Crisis/Signal) -P(Crisis)
Economic Indicators				
DOMCRE	**30.00**	**25.00**	**0.83**	**3.57**
GOVT	**30.00**	**25.00**	**0.83**	**3.57**
RESIMP	10.00	75.00	7.50	-46.43
EXPGDP	**30.00**	**25.00**	**0.83**	**3.57**
IMPGDP	**30.00**	**25.00**	**0.83**	**3.57**
M2RES	10.00	75.00	7.50	-46.43
TGD	**40.00**	**25.00**	**0.63**	**8.57**
RIRD	0.00	100.00	N/A	-71.43
RRLDR	20.00	75.00	3.75	-31.43
Financial Indicators				
STOCK	10.00	75.00	7.50	-46.43
CTBILL	**40.00**	**0.00**	**0.00**	**28.57**
SPREAD	20.00	50.00	2.50	-21.43
Debt Indicators				
EXTDEBTGDP	**30.00**	**20.00**	**0.67**	**8.33**

N/A Could not produce a result because of division by zero

Table 2
Results of the Signals Approach for Barbados

INDICATORS	Good Signals as Percentage of possible good Signals (A/A+C)	Bad Signals as Percentage of Bad Signals B/(B+D)	Noise/Signal (adjusted)/2 ((B/B+D)/(A/(A+C))	P(Crisis/Signal) -P(Crisis)
Economic Indicators				
DOMCRE	**50.00**	**20.00**	**0.40**	**22.51**
GOVT	**43.75**	**24.00**	**0.55**	**14.82**
RESIMP	**50.00**	**20.00**	**0.40**	**22.51**
EXPGDP	**43.75**	**24.00**	**0.55**	**14.82**
IMPGDP	25.00	36.00	1.44	-8.26
M2RES	**50.00**	**16.00**	**0.32**	**27.64**
TGD	18.75	36.00	1.92	-14.02
RIRD	6.25	44.00	7.04	-30.69
RRLDR	**31.25**	**24.00**	**0.77**	**6.43**
Financial Indicators				
STOCK	**50.00**	**11.76**	**0.24**	**31.52**
CTBILL	12.50	40.00	3.20	-22.36
SPREAD	0.00	52.00	N/A	-39.02
Debt Indicators				
EXTDEBTGDP	25.00	35.29	1.41	-8.48

N/A Could not produce a result because of division by zero

Table 3
Results of the Signals Approach for Trinidad and Tobago

INDICATORS	Good Signals as Percentage of possible good Signals (A/A+C)	Bad Signals as Percentage of Bad Signals B/(B+D)	Noise/Signal (adjusted)/2 ((B/B+D)/(A/(A+C))	P(Crisis/Signal) -P(Crisis)
Economic Indicators				
DOMCRE	**36.36**	**29.03**	**0.80**	**4.58**
GOVT	**54.55**	**22.58**	**0.41**	**19.96**
RESIMP	**63.64**	**19.35**	**0.30**	**27.66**
EXPGDP	**72.73**	**16.13**	**0.22**	**35.35**
IMPGDP	0.00	38.71	N/A	-26.19
M2RES	**63.64**	**16.13**	**0.25**	**32.14**
TGD	**54.55**	**22.58**	**0.41**	**19.96**
RIRD	0.00	41.94	N/A	-26.19
RRLDR	18.18	41.94	2.31	-12.86
Financial Indicators				
STOCK	**54.55**	**22.58**	**0.41**	**19.96**
CTBILL	**54.55**	**22.58**	**0.41**	**19.96**
SPREAD	9.09	38.71	4.26	-18.50
Debt Indicators				
EXTDEBTGDP	27.27	28.57	1.05	-0.93

N/A Could not produce a result because of division by zero

Appendix C

Table 1
JAMAICA
Measures of Fit and P-Values for In-Sample Probit Models
K= Quarters Ahead

X Variable		1	2	3	4	5	6	7	8
Economic Indicators									
DOMCRE	McFadden R^2	0.056	0.123	0.197	0.210	0.248	0.314	0.402	0.557
	p-value	0.574	0.509	0.702	0.252	0.066	0.147	0.483	0.865
GOVT	McFadden R^2	0.069	0.123	0.272	0.366	0.222	0.280	0.393	0.665
	p-value	0.416	0.523	0.097	0.040*	0.192	0.358	0.617	0.039*
RESIMP	McFadden R^2	0.053	0.110	0.192	0.177	0.160	0.254	0.386	0.580
	p-value	0.633	0.882	0.936	0.611	0.446	0.629	0.779	0.149
EXPGDP	McFadden R^2	0.065	0.113	0.312	0.471	0.362	0.290	0.386	0.582
	p-value	0.419	0.728	0.131	0.001**	0.001**	0.238	0.805	0.358
IMPGDP	McFadden R^2	0.217	0.124	0.217	0.361	0.191	0.252	0.434	0.558
	p-value	0.043*	0.497	0.380	0.035*	0.258	0.744	0.257	0.796
M2RES	McFadden R^2	0.047	0.110	0.195	0.173	0.149	0.254	0.385	0.581
	p-value	0.855	0.865	0.746	0.704	0.680	0.641	0.902	0.342
TGD	McFadden R^2	0.047	0.110	0.198	0.235	0.417	0.408	0.406	0.641
	p-value	0.905	0.849	0.659	0.121	0.011*	0.029*	0.447	0.183
RIRD	McFadden R^2	0.064	0.115	0.229	0.402	0.533	0.418	0.401	0.597
	p-value	0.434	0.665	0.302	0.013*	0.000**	0.027*	0.495	0.084
RRLDR	McFadden R^2	0.116	0.175	0.322	0.311	0.186	0.252	0.428	0.587
	p-value	0.189	0.182	0.026*	0.023*	0.252	0.734	0.244	0.159
Financial Indicators									
STOCK	McFadden R^2	0.097	0.110	0.200	0.187	0.148	0.282	0.553	0.814
	p-value	0.211	0.829	0.582	0.409	0.686	0.343	0.029*	0.000**
CTBILL	McFadden R^2	0.048	0.114	0.193	0.280	0.420	0.395	0.437	0.558
	p-value	0.829	0.711	0.865	0.046*	0.000**	0.044*	0.257	0.757
SPREAD	McFadden R^2	0.055	0.170	0.202	0.182	0.211	0.338	0.447	0.626
	p-value	0.612	0.224	0.572	0.540	0.173	0.158	0.241	0.141
Debt Indicators									
EXTDEBTGDP	McFadden R^2	0.069	0.118	0.192	0.168	0.158	0.271	0.546	0.700
	p-value	0.394	0.594	0.967	0.916	0.506	0.408	0.027*	0.001**

* Significant at the 5 per cent level
** Significant at the 1 per cent level

Table 2
Barbados
Measures of Fit and P-Values for In-Sample Probit Models
K= Quarters Ahead

X Variable		1	2	3	4	5	6	7	8
Economic Indicators									
DOMCRE	McFadden R^2	0.027	0.042	0.068	0.108	0.137	0.182	0.220	0.263
	p-value	0.429	0.692	0.681	0.365	0.463	0.325	0.453	0.724
GOVT	McFadden R^2	0.043	0.088	0.095	0.144	0.162	0.241	0.360	0.327
	p-value	0.217	0.098	0.181	0.100	0.163	0.024*	0.002**	0.031*
RESIMP	McFadden R^2	0.058	0.082	0.136	0.167	0.198	0.257	0.275	0.311
	p-value	0.119	0.111	0.045*	0.041*	0.047*	0.021*	0.056	0.088
EXPGDP	McFadden R^2	0.022	0.053	0.078	0.095	0.134	0.169	0.212	0.261
	p-value	0.637	0.372	0.371	0.853	0.562	0.703	0.814	0.910
IMPGDP	McFadden R^2	0.064	0.077	0.068	0.096	0.152	0.231	0.254	0.290
	p-value	0.075	0.107	0.672	0.753	0.216	0.038*	0.121	0.185
M2RES	McFadden R^2	0.288	0.285	0.336	0.351	0.366	0.325	0.289	0.299
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.011*	0.073	0.189
TGD	McFadden R^2	0.172	0.195	0.180	0.168	0.168	0.176	0.211	0.266
	p-value	0.002**	0.001**	0.006**	0.030*	0.111	0.461	0.946	0.585
RIRD	McFadden R^2	0.109	0.082	0.078	0.097	0.129	0.170	0.214	0.266
	p-value	0.025*	0.116	0.354	0.676	0.926	0.669	0.667	0.529
RRLDR	McFadden R^2	0.142	0.151	0.137	0.120	0.131	0.176	0.226	0.273
	p-value	0.001**	0.002**	0.011*	0.171	0.683	0.424	0.298	0.339
Financial Indicators									
STOCK	McFadden R^2	0.227	0.216	0.222	0.239	0.241	0.289	0.329	0.355
	p-value	0.000**	0.001**	0.002**	0.003**	0.007**	0.008**	0.009**	0.015*
CTBILL	McFadden R^2	0.025	0.058	0.088	0.122	0.152	0.193	0.240	0.291
	p-value	0.529	0.354	0.311	0.293	0.328	0.312	0.299	0.301
SPREAD	McFadden R^2	0.085	0.089	0.081	0.095	0.146	0.212	0.262	0.313
	p-value	0.018*	0.041*	0.268	0.983	0.313	0.112	0.092	0.082
Debt Indicators									
EXTDEBTGDP	McFadden R^2	0.408	0.367	0.299	0.298	0.300	0.276	0.266	0.283
	p-value	0.000**	0.000**	0.000**	0.001**	0.001**	0.010**	0.064	0.237

* Significant at the 5 per cent level
** Significant at the 1 per cent level

Table 3
Trinidad and Tobago
Measures of Fit and P-Values for In-Sample Probit Models
K= Quarters Ahead

X Variable		1	2	3	4	5	6	7	8
Economic Indicators									
DOMCRE	McFadden R^2	0.097	0.126	0.149	0.169	0.188	0.197	0.179	0.187
	p-value	0.001**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.001**
GOVT	McFadden R^2	0.185	0.125	0.161	0.239	0.294	0.308	0.190	0.183
	p-value	0.000**	0.001**	0.000**	0.000**	0.000**	0.000**	0.001**	0.002**
RESIMP	McFadden R^2	0.071	0.080	0.092	0.121	0.161	0.203	0.251	0.316
	p-value	0.006**	0.005**	0.004**	0.001**	0.000**	0.000**	0.000**	0.000**
EXPGDP	McFadden R^2	0.389	0.443	0.475	0.486	0.405	0.355	0.324	0.258
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
IMPGDP	McFadden R^2	0.274	0.250	0.268	0.262	0.218	0.197	0.211	0.271
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
M2RES	McFadden R^2	0.006	0.018	0.038	0.041	0.046	0.074	0.074	0.090
	p-value	0.946	0.500	0.212	0.352	0.650	0.191	0.603	0.620
TGD	McFadden R^2	0.229	0.308	0.329	0.276	0.247	0.212	0.169	0.151
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.001**	0.005**	0.017*
RIRD	McFadden R^2	0.286	0.226	0.192	0.179	0.187	0.215	0.261	0.330
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
RRLDR	McFadden R^2	0.288	0.270	0.236	0.235	0.249	0.273	0.309	0.320
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Financial Indicators									
STOCK	McFadden R^2	0.203	0.244	0.304	0.348	0.327	0.328	0.296	0.240
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
CTBILL	McFadden R^2	0.062	0.081	0.118	0.168	0.127	0.073	0.071	0.094
	p-value	0.024*	0.017*	0.004**	0.000**	0.007**	0.216	0.961	0.391
SPREAD	McFadden R^2	0.356	0.358	0.344	0.344	0.382	0.436	0.482	0.521
	p-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Debt Indicators									
EXTDEBTGDP	McFadden R^2	0.140	0.147	0.173	0.269	0.250	0.227	0.210	0.200
	p-value	0.007**	0.036*	0.129	0.134	0.200	0.358	0.449	0.378

* Significant at the 5 per cent level
** Significant at the 1 per cent level

Table 4
JAMAICA
Measures of Fit and P-Values for Out-of-Sample Probit Models

		K= Quarters Ahead			
X Variable		**1**	**2**	**3**	**4**
Economic Indicators					
DOMCRE	McFadden R^2	-2.269	-0.591	-0.427	-3.058
GOVT	McFadden R^2	-0.445	-0.231	0.171*	0.144*
RESIMP	McFadden R^2	-0.380	-0.763	-2.890	-3.879
EXPGDP	McFadden R^2	-0.538	-0.374	-0.050	-0.956
IMPGDP	McFadden R^2	0.270**	0.009*	-0.291	-0.734
M2RES	McFadden R^2	-0.346	-0.883	-0.610	-0.395
TGD	McFadden R^2	-0.044	-0.023	-0.013	-0.705
RIRD	McFadden R^2	-0.052	-0.028	-0.032	-0.120
RRLDR	McFadden R^2	-0.040	-0.388	0.923**	-10.942
Financial Indicators					
STOCK	McFadden R^2	0.041*	-0.124	-0.105	-0.058
CTBILL	McFadden R^2	-0.184	-0.608	-0.015	-0.107
SPREAD	McFadden R^2	-0.354	-2.336	-0.334	-0.264
Debt Indicators					
EXTDEBTGDP	McFadden R^2	-0.272	-0.624	-1.123	-1.850

* Value is Positive
** Value is Positive and > In-Sample McFadden R^2

Table 5

Barbados
Measures of Fit and P-Values for Out-of-Sample Probit Models

X Variable		K= Quarters Ahead 1	2	3	4	5	6	7	8
Economic Indicators									
DOMCRE	McFadden R^2	-0.062	-0.184	-0.334	-0.683	-0.794	-0.621	-0.271	-0.036
GOVT	McFadden R^2	-0.108	-0.110	-0.139	-0.222	-0.274	-0.458	-1.163	-2.057
RESIMP	McFadden R^2	-2.339	-4.002	-5.979	-7.181	-73.749	-4.609	-2.202	-1.110
EXPGDP	McFadden R^2	-0.026	-0.012	-0.002	-0.035	-0.009	-0.024	-0.018	0.000*
IMPGDP	McFadden R^2	0.074**	0.058*	-0.028	-0.026	-0.034	0.021*	-0.007	-0.044
M2RES	McFadden R^2	-1.229	-1.292	-1.773	-3.110	-7.032	-0.722	-0.276	-0.118
TGD	McFadden R^2	0.175**	0.228**	0.111*	0.091*	0.040*	0.003*	0.001*	-0.019
RIRD	McFadden R^2	0.167**	0.083**	0.022*	-0.014	-0.017	0.013*	0.023*	-0.030
RRLDR	McFadden R^2	-0.186	-0.149	-0.099	-0.064	-0.025	0.013*	-0.001	0.008*
Financial Indicators									
STOCK	McFadden R^2	-0.110	-0.099	0.015*	0.140*	0.169*	0.230*	0.214*	0.198*
CTBILL	McFadden R^2	-0.119	-0.185	-0.250	-0.172	-0.096	-2.170	-2.164	-2.900
SPREAD	McFadden R^2	-0.084	-0.138	-0.200	-0.130	-0.005	0.042*	-0.089	-0.585
Debt Indicators									
EXTDEBTGDP	McFadden R^2	-0.905	-0.905	-0.848	-54.187	-20.621	-20.229	-7.532	-4.629

* Value is Positive
** Value is Positive and > In-Sample McFadden R^2

Table 6
Trinidad and Tobago
Measures of Fit and P-Values for Out-of-Sample Probit Models

X Variable		K= Quarters Ahead 1	2	3	4	5	6	7	8
Economic Indicators									
DOMCRE	McFadden R^2	0.112**	0.096*	0.073*	0.048*	0.042*	0.053*	0.082*	0.076*
GOVT	McFadden R^2	0.245**	0.189**	0.229**	0.312**	0.351**	0.329*	0.219**	0.184**
RESIMP	McFadden R^2	-0.014	0.020*	0.050*	0.082*	0.134*	0.172*	0.227*	0.304*
EXPGDP	McFadden R^2	0.598**	0.622**	0.630**	0.616**	0.560**	0.514**	0.471**	0.340**
IMPGDP	McFadden R^2	0.454**	0.391**	0.388**	0.379**	0.238**	0.102*	0.186*	0.367**
M2RES	McFadden R^2	-0.076	-0.020	-0.024	-0.052	-0.072	-0.100	-0.065	-0.086
TGD	McFadden R^2	0.397**	0.484**	0.489**	0.422**	0.338**	0.209*	-0.012	-0.337
RIRD	McFadden R^2	0.482**	0.369**	0.263**	0.181**	0.159*	0.225**	0.335**	0.492**
RRLDR	McFadden R^2	0.486**	0.455**	0.379**	0.348**	0.344**	0.356**	0.395**	0.342**
Financial Indicators									
STOCK	McFadden R^2	0.269**	0.284**	0.319**	0.347*	0.319*	0.277*	0.193*	0.078*
CTBILL	McFadden R^2	0.081**	0.093**	0.137**	0.142*	0.131**	-0.020	-0.255	-0.530
SPREAD	McFadden R^2	0.582**	0.592**	0.580**	0.584**	0.661**	0.755**	0.827**	0.883**
Debt Indicators									
EXTDEBTGDP	McFadden R^2	0.884**	0.711**	0.049*	-0.281	-1.814	-8.168	-13.862	-8.929

* Value is Positive
** Value is Positive and > In-Sample McFadden R^2