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Financial and Real Sector Leading Indicators of Recessions in Brazil using Probabilistic Models

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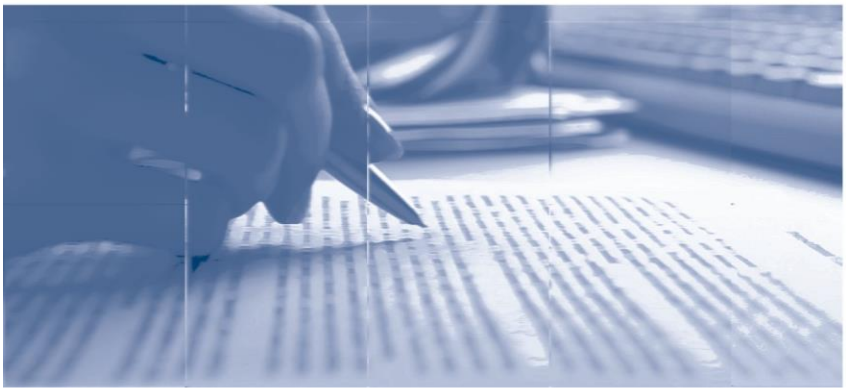

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Fernando N. de Oliveira*

Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central do Brasil.

We examine the usefulness of various financial and real sector variables to forecast recessions in Brazil between one and eight quarters ahead. We estimate probabilistic models of recession and select models based on their out-of-sample forecasts, using the Receiver Operating Characteristic (ROC) function. We find that the predictive out-of-sample ability of several models vary depending on the numbers of quarters ahead to forecast and on the number of regressors used in the model specification. The models selected seem to be relevant to give early warnings of recessions in Brazil.

Key Words: Recession, Forecasts, Receiver Operating Characteristic (ROC)
JEL Classification: E2, E27

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1. Introduction

The most recent financial crises showed, once again, the relevance of forecasting the downturns of business cycles. Economists in general did not anticipate the financial crisis and the consequent severity of recessions that took place worldwide.

Economies evolve over time and are subject, sometimes, to large unanticipated structural breaks. Such breaks may be precipitated by sudden changes in economic policy, major scientific and technological discoveries and innovations, political turmoil or permanent macroeconomic shocks.

Economists often use complex mathematical models to forecast the path of the GDP and the likelihood of a recession.[1] The models used to understand and forecast processes as complicated as GDP are far from perfect representations of their behavior. [2]

Simpler indicators such as interest rates, spread of interest rates, stock price indexes, monetary aggregates, and some readily available real sector indicators contain very relevant information about future economic activity. [3]

These indicators can be used to verify both econometric and judgmental predictions by flagging a problem that might otherwise have gone unidentified. If forecasts from an econometric model and forecasts from these indicators agree, confidence in the model's results can be enhanced. In contrast, if these indicators forecasts give a different signal, it may be worthwhile to review the assumptions and relationships that led to the prediction of the more complex econometric models.

Such indicators, in general, are associated with expectations regarding the occurrence of future events, as shown by Estrella and Mishkin (1997) and Stock and Watson (2001), and therefore are natural candidates for leading indicators of economic activity. They also present some of the necessary properties of leading indicators. They conform to the business cycles; have economic significance, statistical accuracy and little need for revisions. Thus, the development, as well as the monitoring, of such indicators can be

[1] See Bank of England (1999) and Hatch (2001).
[2] There is a known lag in GDP series all over the world. GDP series receives several revisions as time goes by. So we may interpret our exercise as one in which our projections may be understood as nowcast os even backcasts.
[3] See Estrella and Mishkin (1997) for a discussion.

very relevant for the formulation and implementation of macroeconomic policies, given that they give additional evidence about the state of the economy.

In this paper, we examine the usefulness of various financial and real sector variables in out-of-sample predictions of whether or not the Brazilian economy will be in a recession between one and eight quarters in the future. Variables with potential predictive content are selected from a broad array of candidates and are examined by themselves and in some plausible and parsimonious combinations.

We focus simply on predicting recessions rather than on quantitative measures of future economic activity. We believe that this is a useful exercise because it addresses a question frequently posed by policy makers and market participants.[4]

We also are not concerned with misspecified models. As Clement and Hendry (2002) posit, it is by now well documented in the literature the fact that well specified models based on historical data may forecast out-of-sample worse than misspecified ones. The fundamental reason for this is the existence of unanticipated shifts or structural breaks in the economy in the future. [5] After such a shift, a previously well-specified model, one with casual regressors, may forecast less accurately than one that is misspecified, with no casual variables. The best causal description of the economy may not be robust to such sudden shifts. [6]

To assess how well each indicator variable predicts recessions, we use the so-called extreme value model - a particular case of a probabilistic model - which, in our applications, directly relates the probability of being in a recession to specific groups of explanatory variables. [7]

We also assess the capacity of variables to forecast recessions, and by this contribute to the literature, by selecting models based on out-of-sample forecasts, using a metric

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[4] Hamilton (1989) states that it makes sense to think of the economy as evolving differently within distinct discrete states.

[5] Hansen (2001), Stock and Watson (1996), Koop and Potter (2000) are interesting discussions about the limitations of forecasting in the presence of structural breaks.

[6] As Clement and Hendry (2002) point out the distributions of future outcomes are not the same as those in-sample. That means that well specified in-sample models will not necessarily forecast out-of-sample better than badly specified in-sample models. It may also be the case that variables that seem irrelevant will forecast better than relevant ones. Also, further ahead interval forecasts generally lead to worst forecasts than near-horizon ones. All these facts seem highly damaging to the forecasting endeavor.

[7] The extreme value model is necessary due to very few episodes of recession in Brazil in recent years.

related to the Receiver Operating Characteristic (ROC) curve. [8] The ROC curve plots the fraction of true positives (crisis=1) that a given model signals (out of all positives in the sample) vs. the fraction of false positive signals (out of all negatives in the sample) along contiguous threshold settings. The best model according to this criterion is the one that delivers the highest trade-off frontier between true and false alarms.[9,10]

We find that the predictive out-of-sample ability of several models vary depending on the numbers of quarters ahead to forecast and on the number of regressors used in the model specification. The variables that perform best to forecast out-of-sample are financial variables, such as stock indexes (IBRX100 and Ibovespa), swaps of interest rate, and some real sector variables, such production of intermediary goods, paper production and the total supply of credit.

There is a vast literature by now that search for good leading indicators of recessions such as we do in this paper. Just to mention some, Estrella and Mishkin (1997) use a probit model to evaluate the usefulness of financial variables to predict U.S. recessions, both in- and out of- sample. Their full sample covers a number of recessions. Their main findings are that stock prices are the best leading indicators of recessions at the 1- and 2-quarter horizons.

Bernard and Gerlach (1996) examine the ability of the term structure to predict recessions in eight countries (Belgium, Canada, France, Germany, Japan, the Netherlands, the United Kingdom and the United States) between the period 1972:1 and 1993:4. For all the countries, their study also shows that the yield curve provides information about the likelihood of future recessions up to eight quarters ahead.

Lamy(1997) studies several macroeconomic indicators, to verify if they predict recessions in Canada. He finds the Department of Finance index of leading indicators of

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[8]The Receiver Operating Characteristic (ROC), or simply ROC curve, is commonly used in signal detection theory. It is a graphical plot, which describes the performance of a binary classifier system as its discrimination threshold is varied. It is built by plotting the fraction of true positives out of the total actual positives (TPR = true positive rate) vs. the fraction of false positives out of the total actual negatives (FPR = false positive rate), at various threshold settings. The ROC curve is then the sensitivity as a function of fall-out. ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones independently from (and prior to specifying) the cost context or the class distribution. ROC analysis is related in a direct and natural way to cost/benefit analysis of diagnostic decision making. The ROC curve was first developed by electrical engineers and radar engineers during World War II.

[9] We define the model ROC as the value of the integral of the ROC function of the model from 0 to 1.

[10] See Newbold (1993) for a discussion on the limitations of using mean squared errors to compare out-of-sample models forecasts.

economic activity and the Bank of Canada nominal monetary conditions index to be strongest at predicting recessions for a forecast horizon of one quarter. At the horizon of two to four quarters, he finds the yield curve to be the best variable to predict recession.

Our results are relevant for the literature of forecasting rare events, such as recessions.[11] The best models selected can be thought as early warning signals of recessions in Brazil. Our selected models do good job in anticipating this recession.

Two forecasting principles emerge from our analysis. First and most important, the criteria to select models for forecast should be always out-of-sample performance. Second, it is important to determine the optimal out-of-sample horizon for each forecasting model. As Clement and Hendry (2002) point out the distributions of future outcomes are not the same as those in sample. That means that well specified in-sample models will not necessarily forecast out-of-sample better than badly specified in-sample models. It may also be the case that variables that seem irrelevant will forecast better than relevant ones. Also, further ahead interval forecasts generally lead to worst forecasts than near-horizon ones. All these facts seem highly damaging to the forecasting endeavor.

Our results also confirm that despite its non-specific assumptions, a theory of forecasting which allows for unanticipated structural breaks in an evolving economic mechanism for which the econometric model is misspecified in unknown manners may provide a useful basis for interpreting, and potentially circumventing, systematic forecast failure in economics.

The rest of the paper is the following. Section 2 describes the data. Section 3 presents the empirical analysis. Section 4 presents a case study analysis. Section 5 concludes.

2. Data

The macroeconomic indicators have an established performance record in predicting real activity. This record is not always subject to comparison tests, and most of the predictive lead times are not as long as users might prefer. The financial series we look at may be less subject to the over fitting problem than the traditional macroeconomic indicators.

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[11] See Osborn et al (2001)

Another important consideration is the possible lag in the availability of the data for the explanatory variables. Some variables, such as interest rates and stock prices, are available on a continuous basis with no informational lag. In contrast, many monthly macroeconomic series are only available one or two months after the period covered by the data, and GDP has a lag of almost one full quarter.

Our sample has quarterly data and goes from the first quarter of 1991 to the fourth quarter of 2012. Table 1 Panel A shows all the names of all the real sector variables we use in our empirical exercise. We have 87 real sector variables. We use both the level and first difference of these variables. Table 1 Panel B shows the financial sector variables. We have 26 variables. Again, we use the level as well and the first difference of these variables.

The recession variable is built using the standard two consecutive quarters of negative variation of GDP with seasonal adjustment. We have 4 quarters of recession which are: 1999Q1, 2001Q3, 2003Q2 and 2009Q1. [12]

In the next section, we will present our empirical analysis.

3. Empirical Analyses

3.1 Forecasting Methodology

We now turn to the question of how to choose the models that best forecast out-of-sample recessions. Model misspecification by itself cannot account for forecast failure: in the absence of changed economic conditions, a model's out-of-sample forecast performance will on average be the same as its in-sample fit to the data.

Suppose we included variables that have small effects (conditional on the remaining specification) but are genuinely relevant. Because their impacts need to be estimated, their elimination could improve forecast accuracy. Forecast failure could result if irrelevant variables were included which then changed substantially in the forecast period, again pointing to the key role of parameter non-constancies–and suggesting potential advantages from model selection.

[12] Another possibility to define a recession in Brazil is to use the chronology of "Comitê de Datação de Ciclos Econômicos (CODACE)" of IBRE/FGV, that establishes reference chronologies for business cycles in Brazil.

If forecast failure is primarily due to forecast-period location shifts as Hendry and Clement (2002) stress, then there are no possible within-sample tests of the models. Structural breaks happen all the time in the economy. Therefore, choosing models to forecast based on in-sample forecast performance seems to be a great mistake.

To address these issues we utilize measures out-of-sample performance to discriminate between the best forecast models. We decided not to use Mean Squared Errors (MSE) or any of its variants as our main criteria to select models. The growing consensus among researchers who have been making comparisons among forecasting methods is that the MSE should not be used. Newbold (1993) explores the deficiencies of mean squared errors as a performance measure.

Thompson (1990) also concluded that MSE is not appropriate. He also proposed a variation on the MSE, the log mean squared error ratio (LRM), that would be appropriate for making comparisons across series. The LMR takes the log of the ratio calculated by dividing the proposed model's MSE by the MSE of a benchmark model.

The out sample performance of the models is gauged with the so-called ROC curve as a model selection tool. The ROC curve plots the fraction of true positives (crisis=1) that a given model signals (out of all positives in the sample) vs. the fraction of false positive signals (out of all negatives in the sample) along contiguous threshold settings. The best model according to this criterion is the one that delivers the highest trade-off frontier between true and false alarms. Such a choice will be guided by the relative cost of failing to predict a crisis vs. that of a false alarm, credibility cost.

A clear advantage of this approach over traditional model selection criteria previously used in the forecast literature is that the analyst does not have to take a stand a priori on which region of the trade-off to pick. Distinct models deliver a distinct ROC curve and the overall “best” is the one that delivers the highest area under the curve, i.e., the higher outward frontier above the 45-degree line, where the latter traces out the good vs. false positive trade-off under random guesses.

There are other several advantages of ROC in comparison to other possible metrics of forecasting comparisons. For example, Estrella and Mishkin (1997) use out-of-sample Pseudo R2 as a metric to compare the performance of models. As the authors acknowledge, in some cases out-of-sample Pseudo R2 furnish negative results. This makes it a much worse metric than ROC in our view to compare the out-of-sample performance of models. [13]

The ROC methodology focuses on a fundamental characteristic of forecasting, that is, its ability to capture the occurrence of an event with an underlying high hit rate, while maintaining the false alarm rate to some acceptable level. We ponder that a better approach to forecast performance should concentrate on the hit rate of the infrequent event, instead of the percentage correctly predicted. The latter is the very nature of different goodness of fit measures cited above and extensively used in the literature.

Recent applications of the ROC curve methodology to historical data on domestic bank credit in 14 advanced countries are provided in Jordá et al (2011), whereas Satchell and Wei (2006) present an earlier application to credit rating models. Catao et al (2013) use it in an in-sample framework to forecast financial crisis. Yet, we are not aware of any other paper that uses it in the same way and context that we do in this paper.[14]

ROC, as any other empirical methodology, has also some drawbacks. As it is only based on a forecast of binary value it ignores the magnitude of the forecast errors. It may have low power in small samples, because it does not consider the magnitudes of these forecast errors. ROC can be understood as a criteria of unconditional evaluation, because it does not make a distinction between the existence (or not) of temporal clusters of the binary variable. [15] Finally, although very useful to establish a forecast ranking among different models, one cannot verify if two models produce forecasts that are statistically significant and different.

To address some of the issues above, we will, as a robustness analysis, compare our results with some more traditional forecast models of rare events, such as the directional tests of Pesaran and Timmermman (1992, 2009).

[13] Lahiri and Wang (2013) stress that often conventional goodness-of-fit statistics in probabilistic models, such as Pseudo R2, among others fail to identify the type of I and type of II errors in predicting the event of interest. Lahiri and Wang examine the quality of probability forecasts in terms of calibration, resolution and alternative variance decompositions. They discuss several measures of goodness of fit, like, for instance, the Brier´s Quadratic Probability Score, the Prequential Test for Calibration, the Skill Score and the Murph and Yates Decompositions.

[14] See Catao et al (2013) for a utilization of ROC to forecast financial crisis.

[15] See Kupiec (1995) and Christoffersen (1998).

We are interested in selecting one to four regressors models that best forecast recessions in Brazil from 1 to 8 quarters ahead.[16] Being more specific, our methodology is the following. We estimate an equation such as (1) below using a probabilistic extreme value model with only one regressor.

$$\Pr\left(Y_{t+K}=1|X_t\right)= f(X_t), \qquad (1)$$

where $f(X_t)=\exp(-\exp(-X\beta))$ (extreme value function), and K=1 to 8

Our first estimation period goes from 1991Q1 to 2002Q1. Then we forecast K periods ahead (K from 1 to 8), considering levels of cutoff probabilities that range from 0.005 to 1 and that vary in each step by 0.005. If the forecast value of recession is less that the cutoff probability that we are considering we take the forecast to be zero. Otherwise, the forecast is one. We compare these values with the values of the recessions that occurred after the estimation period. [17]

We then increase the estimation period by one quarter and repeat the process above for every forecast period until we reach our final estimation period that goes from 1991Q1 to 2010Q1. We then calculate the number of success (correct forecasts) divided by the total number of successes (recessions); we also calculate the number of failures (false positive signals) and divide that by the total number of failures (all periods in which there were no recessions). By doing this we are able to build a ROC function for each model with one regressor for every K quarters ahead forecast. We then integrate this function from 0 to 1 and name this value the ROC of the model. The best models are the one with the highest ROCs for each K forecast period.

We use the regressors of the models selected with one regressor in the specifications of the models with two regressors. We repeat the methodology above for every one of these models and select the best models as the ones with the highest ROCs for every K forecast period. After selecting the two regressor models, we repeat the process with three regressors, where two of them are the ones that proved best in forecasting. Finally,

[16] We follow Mitchell and Burns (1938), Moore (1950), Stock and Watson (1989) that select a small group of leading indicators from a great number of possible candidates.

[17] The projections in this paper are of direct forecast type. The parameters of the model are estimated in separate for each forecast horizon. See Marcellino, Stock e Watson (2006) for a comparison of recursive models with direct forecast ones.

we choose the four regressor models using the same process and considering the three regressor models selected as the basis for the four regressor models. We also look at the statistically significance of the ROC areas of the models selected using Birnbaum and Klose (1957) maximum variance.

3.2 Results

Table 1 Panel A presents the forecast for one year ahead. For one quarter ahead forecasts, with one regressor the best model is the one that total credit (credtotal) as the only regressor. The out-of-sample ROC of this model is 0.9937. If we include another regressor then this second one is IBRX and the ROC of this best model is 0.9937. With three regressors the best model is the one that has trade balance as an additional regressor and with four regressors we also have swap_30_average. The ROC of the first former model is 0.9874 and of the latter is 0.9500.

In the case of the forecasts of two quarters, with one regressor the best model is the one that has the supply of intermediary goods (piminterm) as the only regressor. The out-of-sample ROC of this model is 0.9837. If we include another regressor then this second one is nominal foreign exchange rate and the ROC of this model is 0.9499. With three regressors the best model is the one that has abatement of meat as an additional regressor and with four regressors we also would the first difference of exports. The ROC of the first former model is 0.9999 and of the latter is also 0.9999.

When we consider three quarters ahead forecasts, with one regressor the best model is the one that has the supply of intermediary goods (piminterm) as the only regressor. The out-of-sample ROC of this model is 0.9500. If we include another regressor then this second one is the first difference of the nominal exchange rate and the ROC of this model is 0.9249. With three regressors the best model is the one that has abatement of meat as an additional regressor and with four regressors we also would the first average swap 30 days. The ROC of the first former model is 0.9749 and swap average 30 days of the latter is also 0.9500.

For the four quarters ahead forecasts, with one regressor the best model is the one that Ibovespa as the only regressor. The out-of-sample ROC of this model is 0.9874. If we include another regressor then this second one is the value of trade balance. The ROC of this model is 0.9374. With three regressors the best model is the one that has the average of 120 days swap and with four regressors we also have the supply of fertilizers (adubo). The ROC of the former model is 0.9749 and of the latter is 0.9874.

For forecasts of more than one year, the results are presented in Table 1 Panel A. The best models in terms of ROC are: for 5 periods ahead, the best model (ROC 0.9937) is the one that has selic, gvd, first difference of Ibovespa and imports of intermediary goods; for six quarters in advance, the model with the highest ROC (0.9749) is the one that has as selic, accumulated selic, first difference of selic and paper supply as regressors; for seven quarters ahead, the best model (ROC 0.9749) is the one that has 4 regressors, which are accumulated selic, icms of the state of São Paulo, supply of fertilizers and swap of interest rate 30 days end of period; finally, to forecast 8 periods in the future the best model in terms of ROC (0.9862) is the one that has the first difference of imports, the first difference of inpc, m3 and swap of interest rate 30 days end of period.

As the t-statistics, presented in Table 1, built with the maximum variance of Birnbaum and Klose (1957), show, all ROC areas are statistically significant. As one can observe from the results, financial variables are relevant for forecasting. There are few specifications in which these variables do not take part as a regressor. They are observed individually over their respective primary horizons, or they may be combined to produce a very reliable model.

In general, prices of financial assets are supposed to contain expectations about the future path of the economy. The most convincing theoretical foundation of this assumption is the expectations theory of the term structure. The expectations hypothesis postulates that, for any choice of holding period, investors do not expect to realize different returns from holding bonds or bills of different maturities.

Not consistent with the findings of Estrella and Mishkin(1997), Estrella and Hardouvelis (1991), Bernard and Gerlach (1998) and Plosser and Rouwenhorst (1994), we have not shown that the term spread has significant information content for forecasting recessions in Brazil. The term structure of interest rate is an important leading indicator for recessions in USA. In contrast to the term structure, some swap derivatives market of interest rate seem to be better forecasters.

Some real sector indicators seem also relevant to forecast. The supply of paper and the imports of intermediary goods as well as trade balance are the ones that are more important. Their appearance in the best models is expected, due to the fact that they reflect earlier than other real sector variables the possibility of a recession in the near future.

With surprise, the confidence indicators and some monetary aggregates do not play any special role in forecasting recessions in Brazil. In the case, of confidence indicators, we ponder that this may occur because households have difficulties in understanding completely the dynamics of business cycles. In the case of monetary aggregates, we think the reason may be related to the fact that as the demand of money is highly unstable in Brazil even for monetary aggregates higher than M1 or M2. Other real sector variables seem to adjust in a much slower pace and therefore do not seem important enough to forecast recessions. [18]

In-sample results are based on equations estimated over the entire sample period. Their predictions or fitted values are then compared with the actual recession dates. Three types of results are presented: an in-sample ROC, a pseudo R2, and a MAE. We present the statistics of the same models we selected from the out sample forecasts analysis above in Table 2.

As one can see from Panels A and B of Table 2, the in-sample forecasts measures give a different indication of the forecast capacity of the models selected. Some models that have better out-of-sample performance, perform worse if we consider in-sample measures.

In Table 3, we present the Pesaran and Timmermann (1992, 2009)) statistic of the directional test, that gives an idea of how well our models selected are good in forecasting change in direction of the variable of interest and the MSE statistic associated with each one of the models. The results show clearly that all the models selected with the ROC criteria reject the null Hypothesis of not being able to forecast the changes in directions. They also show low MSE.

[18] We looked at the ROCS of random walk models (that are commonly used as benchmark reference for forecasts in the literature). They are much less (lower than 50%) of the ROCS of the models that we selected foe each forecast period.

4. Case Study: Forecast Indexes and Recessions in Brazil from 2000Q1 to 2012Q4

Predicting the future is a tricky business. A good example of what may happen is provided by the experience with the Stock and Watson (1989) leading indicators. Stock and Watson (1993) describe and analyze the disappointing performance of their indicator predicting the 1990-1991 recession.

Here we examine the performance of our chosen forecast models to predict recessions in Brazil in the period from 2000Q1 to 2012Q4. We consider the eight models that gave us the best out-of-sample ROC for each forecast period. We construct three indexes. The first one (Index1) is an equal weighted average of the forecasts of our best models in terms of ROC for each forecast horizon. The second one (Index2) is a weighted average of our best forecast models (the one quarter ahead forecast with weight equal to 8 and the others with weights decreasing until 1). The third one (Index3) is an equal weighted average of the best ROC models selected (1 to 4 regressors) for all horizons

Our comparison basis is of three types: we look at how these series behaved graphically to forecast the recessions; then we compare our forecasts with those made by a leading financial indicator of GDP that we built; and finally we look at how our forecasts compare with those made by the market and for this we use the GERIN database of GDP forecasts in Brazil the market.

In Figures 1 to 3, one can see that there is a pattern in predicting recession for our 3 indexes. Between 2 or 3 quarters before the recessions, the indexes start to fall until the recession when they start to rise again. This seems to be evidence that they are doing a good job in anticipating recessions. They seem relevant as early warnings of recessions.

We also build a leading financial indicator index based on Index of Economic Activity – Brazil (IBC-Br), that incorporates the pathway of the variables considered as proxies to the development of three most important economy sectors (agriculture and livestock:, industry and services).

To build the index, we considered the same 27 financial series we used in this paper. Initially, we calculated the current and lagged correlations between these series and the first difference of IBC-BR seasonally adjusted. Then, these series were submitted to Granger causality tests to find the final selection: end of period monthly return of

IBOVESPA and end of period monthly return of IBRX-100. The correlations of these financial series with the first difference of quarterly GDP with seasonal adjustment were 0.63, 0.66, respectively.

Figure 4 presents the dynamics of this index. The figure shows that the leading indicator does a good job in anticipating the 2009Q1 recession. However, we think that our models selected with the ROC criteria do a better job in signaling the recession.

Finally, we compare our forecasts with the market forecasts. The Central Bank of Brazil collects every week forecasts of market participants with respect to the one year growth of GDP in Brazil and to the growth of GDP until the end of the year. We create a market signal variable of recession if the market forecasts two consecutive quarters of negative growth. Otherwise, this variable is zero. Then we take the quarterly average of this variable. Figure 5 shows the market signal together with the out-of-sample ROCs of our selected models. As one can see, the market signal is very strong in 2008Q1, but then decreases in the other quarters of 2008. This does not happen with the forecasts of our selected models.

5. Conclusion

Economic forecasting that allows for structural breaks and misspecified models has radically different implications from one that considers stationary and well-specified ones. It is well known by now in the literature that models that are well specified in-sample may perform very poorly out sample. There are many reasons for this, but maybe the most important is the occurrence of structural breaks in out-of-sample.

In this paper, we examine the usefulness of various financial and real sector variables in out-of-sample predictions of whether or not the Brazilian economy will be in a recession between one and eight quarters in the future. Variables with potential predictive content are selected from a broad array of candidates and are examined by themselves and in some plausible combinations.

The models selected, in our view, adapt quickly after any shift is discovered, therefore avoiding systematic failure of forecasting. We think they capture some of the robustness characteristics of the models that win forecasting competitions.

The predictive out-of-sample capacity of several models vary depending on the numbers of quarters ahead to forecast and on the number of regressors used in the model specification. The variables that do well in forecast out-of-sample are financial variables, such as stock indexes (IBRX100 and Ibovespa), swap interest rate derivatives, some real sector variables, such production of intermediary goods, paper production and the total supply of credit.

We think that our results are relevant for the literature of forecasting rare events, such as recessions. The best models selected can be thought as early warning signals of recessions in Brazil.

Of course, we do not propose that these indicators substitute macroeconomic models and judgmental forecasts. Rather, we conclude that our selected models can usefully supplement the former models and other forecasts, and can serve as a quick, reliable check of more elaborate predictions.

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Table 1. Descriptive Analysis of the Database

Our sample has quarterly data and goes from the first quarter of 1991 to the fourth quarter of 2012. Our leading indicators of recessions are composed of 87 real sector variables and 27 financial variables. We use both levels and first difference of these variables. Panel A presents the real sector variables, while Panel B presents the financial sector ones.

Panel A Real Sector Variables

pib	GDP constant prices
abatave	Abatment of Chicken
abatcarne	Abatment of Meat
adubo	Fertilizer
balcom	Trade Balance
cambio	Foreign Exchange Rate
cimento	Cement
credito	Free Credit
credpriv	Total Credit
credhab	Credit Housing
credpf	Credit Households
credpriv	Private Credit
credtotal	Total Credit
defensivo	Agricultural Defensive
desempr	Unemployment rate
desemproc	Non observable unemployment rate
desocupserv	Non ocupation rate
embmetal	Metal Packaging
embpapel	Paper Packing
embplast	Plastic Packaging
embvidro	Glass Packaging
empformconst	Formal Employment Construction
empformpub	Formal Employment Govenment
empformserv	Formal Employment Service Sector
empformtot	Total Formal Employment
energia	Energy Consumption
energiacarga	Energy Load
energiadem	Demand of Energy
expbasicos	Quantum of Exports by Type of Product
expmanuf	Quantum of Exports of Manufactured Goods
export	Quantum of Exports
fluxoveic	Flux of heavy vehicles
folha	Payroll
horastrab	Hours Worked
ia_usa	Leading Indicator USA
icc	Consumer Confidence Index
icc_exp	Consumer Confidence Index- Expectation
icc_fecom	ICC-Consumer Confidence Index
icc_pres	Consumer Confidence Index- Present
icea_fecom	ICEA-Index of Economic Conditions
icms	States revenues
icms_sp	Stateof SP revenues
iec_fecom	IEC - Consumer Expectations Index
igpm	General Price Index

impbk	Quantum of Imports Index Capital Goods
impinterm	Quantum of Intermediary Imports
import	Quantum of Imports Total
inadspc	Consultation to SPC
inaduse	Consultation to users of Checks
inpc	General Price Index
ipa_di	General Price Index
ipa_og	General Price Index
ipca12m	General Price Index
mampli	Ample Payroll Mass
mamplireal	Real Ample Payroll Mass
m1	Monetary Aggregate
m2	Monetary Aggregate
m3	Monetary Aggregate
m4	Monetary Aggregate
nuci	Capacity Utilization São Paulo State
papel	Paper Production
papel2	Paper Producion by subsectors of the economy
pessoalocupind	Ocuppied Individuals with no seasonal adjustment
pessoasacup	Individuals over 10 years occupied in the week of reference
pimcap	Phsical Production Capital Goods
pimcons	Phsical Production Consumer goods
pimconsdur	Phsical Production Durable Goods
pimconssemidur	Phsical Production Semi-Durable Goods
piminterm	Phsical Production Intermediary Goods
pimtot	Total Phsical Production
prodauto	Total car production
prodferro	Ore Production
prodmaqagric	Production of Agricultural Machines
prodmoto	Production of Motorcycles
prodoleolgn	Production of oil and gas
recfed	Revenues Federal Government
rendmedio	Average Income of main work
soja	Production of Soy
sond	Industry Confidence without seasonal adjustment
sond_exp	Industry Confidence Expectations without seasonal adjustment
sond_pres	Industry Confidence Expectations without seasonal adjustment Present State
trabserv	Service Sector Workforce
vendascom	Volume of Wholesale sales
vendascomampl	Volume of Wholesale Sales Ample
vendasind	Real Sales - Industry
vendauto	Sales of cars Domestic Market
volcom	Index of Sales in th e Wholesale Market

Panel B Financial Sector Variables

Name Used in Regressions	Definitio
Ibovespa	Bovespa Index
deb_spread	Spread Debentures AA e AAA (-) Public Bond
GVD	Measures of the Amount of Capitalization of Large firms
IBRX	wit
m1	Monetary Agregate
m2	Monetary Agregate
m3	Monetary Agregate
m4	Monetary Agregate
selic	Monthly accumulated SELIC
selic_anual	Annual Accumulated Selic
spread	Average Spread of Bank
spread_pre	Spread betwwen long term and short term pulic bonds
swap120_fim	Swap DI 120 days end of period
swap120_media	Swap DI 120 days average of period
swap180_fim	Swap DI 180 days end of period
swap180_media	Swap DI 180 days average of period
swap30_fim	Swap DI 30 days end of period
swap30_media	Swap DI 30 days average of period
swap360_fim	Swap DI 360 days end f period
swap360_media	Swap DI 360 days average of period
swap60_fim	Swap DI 60 Days end of Period
swap60_media	Swap DI 60 days average of period
swap90_fim	Swap DI 90 Days end of Period
swap90_media	Swap DI 90 days average of period
termo	Term Structure of Interest Rate Swap180_fim -
termo_real	Term StructureReal Termo-

Table 2 Out-of-sample ROCs

Our sample has quarterly data and goes from the first quarter of 1991 to the fourth quarter of 2012. Our leading indicators of recessions are composed of 87 real sector variables and 27 financial variables. We use both levels and first difference of these variables. We use a probabilistic extreme value model with only one regressor. Our first estimation period goes from 1991Q1 to 2002Q1. Then we forecast K periods ahead (K from 1 to 8), considering levels of cutoff probabilities that range from 0.005 to 1 and that vary in each step by 0.005. If the forecast value of recession is less that the cutoff probability that we are considering we take the forecast to be zero. Otherwise, the forecast is one. We compare these values with the values of the recessions that occurred after the estimation period. We then increase the estimation period by one quarter and repeat the process above for every forecast period until we reach our final estimation period that goes from 1991Q1 to 2010Q1. We then calculate the number of success (correct forecasts) divided by the total number of successes (recessions); we also calculate the number of failures (false positive signals) and divide that by the total number of failures (all periods in which there were no recessions). By doing this we are able to build a ROC function for each model with one regressor for every K quarters ahead forecast. We then integrate this function from 0 to 1 and name this value the ROC of the model. The best models are the one with the highest ROCs for each K forecast period. We use the regressors of the models selected with one regressor in the specifications of the models with two regressors. We repeat the methodology above for every one of these models and select the best models as the ones with the highest ROCs for every K forecast period. After selecting the two regressor models, we repeat the process with three regressors, where two of them are the ones that proved best in forecasting. Finally, we choose the four regressor models using the same process and considering the three regressor models selected as the basis for the four regressor models. Under parenthesis we have the t statistics of ROCs, built with the maximum variance of Birnbaum and Klose (1957).

Panel A One Year Ahead Forecasts

Pr(Recessao(t+K))=f(X)			
K=1		K=2	
credtotal	0.9937	pimiterm	0.9748
(credtotal,ibrx)	0.9874	(piminterm,cambio)	0.9499
(credtotal,ibrx,balcom)	0.9937	(piminterm,cambio,abatcarne)	0.9999
(credtotal,ibrx,balcom,inpc)	0.9937	(piminterm,cambio,abatcarne,dlogexport)	0.9999
K=3		K=4	
pimiterm	0.9500	ibovespa	0.9874
(pimiterm,dlogpapel)	0.9249	(ibovespa,balcom)	0.9374
(piminterm,dlogpapel,abatcarne)	0.9687	(ibovespa, balcom,swap120media)	0.9749
(piminterm,dlogpapel,abatcarne,swap30_average)	0.9999	(ibovespa, balcom,swap120media,adubo)	0.9874

Panel B Two Years Ahead Forecast

Pr(Recessao(t+K))=f(X)			
K=5		K=6	
pimiterm	0.9500	ibovespa	0.9874
(pimiterm,dlogpapel)	0.9249	(ibovespa,balcom)	0.9374
(pimintrm,dlogpapel,abatcarne)	0.9687	(ibovespa, balcom,swap120media)	0.9749
(piminterm,dlogpapel,abatcarne,swap30_average)	0.9999	(ibovespa, balcom,swap120media,adubo)	0.9874
K=6		K=7	
pimiterm	0.9500	ibovespa	0.9874
(pimiterm,dlogpapel)	0.9249	(ibovespa,balcom)	0.9374
(pimintrm,dlogpapel,abatcarne)	0.9687	(ibovespa, balcom,swap120media)	0.9749
(piminterm,dlogpapel,abatcarne,swap30_average)	0.9999	(ibovespa, balcom,swap120media,adubo)	0.9874

Table 3 In-sample Forecasts Statistics

Our sample has quarterly data and goes from the first quarter of 1991 to the fourth quarter of 2012. Our leading indicators of recessions are composed of 87 real sector variables and 26 financial variables. We present in sample ROC, Pseudo R2 and MAE of the models selected with out-of-sample ROC.

Panel A One Year Ahead

Pr(Recessao(t+K))=f(X)

K=1			K=2		
ROC	Pseudo R2	Mae	ROC	MAE	Pseudo R2
0.9937	0.0016	0.0881	0.9748	0.0881	0.0188
0.9874	0.3108	0.0878	0.9499	0.0878	0.0462
0.9937	0.3227	0.0868	0.9999	0.0868	0.0760
0.9937	0.3333	0.0876	0.9999	0.0876	0.0894

K=3			K=4		
ROC	MAE	Pseudo R2	ROC	MAE	Pseudo R2
0.9500	0.0892	0.0173	0.9874	0.0904	0.0101
0.9249	0.0901	0.0178	0.9374	0.0818	0.2273
0.9687	0.0891	0.0713	0.9749	0.0980	0.2889

Panel B Two Years Ahead

Pr(Recessao(t+K))=f(X)					
K=5			K=6		
ROC	Mae	Pseudo R2	ROC	MAE	Pseudo R2
0.9937	0.0463	0.0463	0.9748	0.0463	0.0540
0.9874	0.0727	0.0727	0.9499	0.0727	0.0670
0.9937	0.0797	0.0797	0.9999	0.0797	0.0630
0.9937	0.1104	0.1104	0.9999	0.1104	0.1456
K=7			K=8		
ROC	MAE	Pseudo R2	ROC	MAE	Pseudo R2
0.9748	0.0463	0.0463	0.9748	0.0463	0.0463
0.9499	0.0727	0.0727	0.9499	0.0727	0.0727
0.9999	0.0797	0.0797	0.9999	0.0797	0.0797
0.9999	0.1104	0.1104	0.9999	0.1104	0.1104

Table 3 Pesaram and Timmermman (1999, 2009) statistic and MSE

Our sample has quarterly data and goes from the first quarter of 1991 to the fourth quarter of 2012. Our leading indicators of recessions are composed of 87 real sector variables and 27 financial variables. We use both levels and first difference of these variables. We use a probabilistic extreme value model with only one regressor. Our first estimation period goes from 1991Q1 to 2002Q1. Then we forecast K periods ahead (K from 1 to 8), considering levels of cutoff probabilities that range from 0.005 to 1 and that vary in each step by 0.005. If the forecast value of recession is less that the cutoff probability that we are considering we take the forecast to be zero. Otherwise, the forecast is one. We compare these values with the values of the recessions that occurred after the estimation period. We then increase the estimation period by one quarter and repeat the process above for every forecast period until we reach our final estimation period that goes from 1991Q1 to 2010Q1. We then calculate the number of success (correct forecasts) divided by the total number of successes (recessions); we also calculate the number of failures (false positive signals) and divide that by the total number of failures (all periods in which there were no recessions). By doing this we are able to build a ROC function for each model with one regressor for every K quarters ahead forecast. We then integrate this function from 0 to 1 and name this value the ROC of the model. The best models are the one with the highest ROCs for each K forecast period. We use the regressors of the models selected with one regressor in the specifications of the models with two regressors. We repeat the methodology above for every one of these models and select the best models as the ones with the highest ROCs for every K forecast period. After selecting the two regressor models, we repeat the process with three regressors, where two of them are the ones that proved best in forecasting. Finally, we choose the four regressor models using the same process and considering the three regressor models selected as the basis for the four regressor models. The t-statistics of the Pesaran and Timmerman (1999, 2009) directional tests are presented and under parenthesis we show the MSE statistic.

Panel A One Year Ahead

K=1		K=2	
credtotal	-2.20	pimiterm	-2.20
	(0.043)		(0.044)
(credtotal,ibrx)	-14.80	(piminterm,cambio)	-6.94
	(0.038)		(0.0044)
(credtotal,ibrx,balcom)	-15.94	(piminterm,cambio,abatcarne)	-6.94
	(0.048)		(0.044)
(credtotal,ibrx,balcom,inpc)	-15.94	(piminterm,cambio,abatcarne,dlogexport)	-7.37
	(0.18)		(0.045)

K=3		K=4	
pimiterm	-2.20	ibovespa	-2.20
	(0.04)		(0.044)
(pimiterm,dlogpapel)	-2.20	(ibovespa,balcom)	-3.13
	(0.044)		(0.048)
(pimintrm,dlogpapel,abatcarne)	-7.00	(ibovespa, balcom,swap120media)	-2.20
	(0.045)		(0.044)
(piminterm,dlogpapel,abatcarne,swap30_average)	-16.86	(ibovespa, balcom,swap120media,adubo)	18.46
	(0.045)		(0.049)

Panel B Two Year Ahead

K=5		K=6	
selic	-3.13	selic	-8.18
	(0.043)		(0.044)
(selic,gvd)	-5.05	(selic,selic_acum)	-10.80
	(0.043)		(0.49)
(selic,gvd,dlogbovespa)	-6.51	(selic,selic_acum,dlogselic)	-10.80
	(0.43)		(0.07)
(selic,gvd,dlogbovespa,impinterm)	-9.33	(selic,selic_acum,dlogselic,papel)	-20.34
	(0.044)		(0.07)

K=7		K=8	
(selic_acum)	-2.20	dlogimport	-2.20
	(0.43)		(0.038)
(selic_acum,icmssp)	-7.37	(dlogimport,dloginpc)	-2.20
	(0.041)		(0.039)
(selic_acum,icms_sp,adubo)	-7.37	(dlogimport,dloginpc,m3)	-8.95
	(0.042)		(0.039)
(selic_acum,icms_sp,adubo,swap30_fim)	-7.37	(dlogimport,dlog_inpc,m3,swap_30fim)	-8.95
	(0.042)		(0.039)

Figure 1 Recession Probabilities with Index of Equal Weighted Average of Forecast of Best ROC Models (Index1)

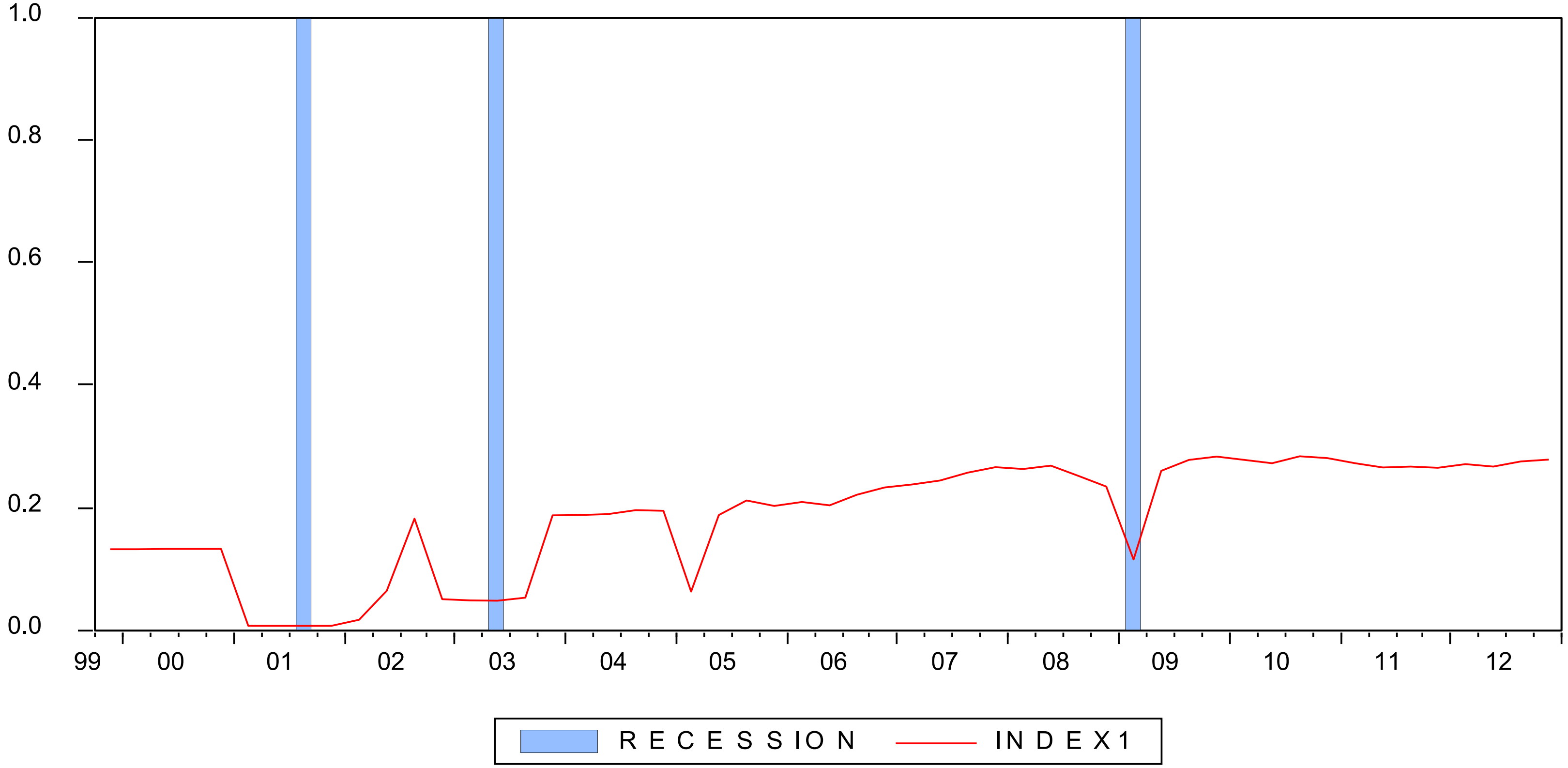

Figure 2 Recession Probabilities with Index of Weighted Average of Forecast of Best ROC Models (Index2)

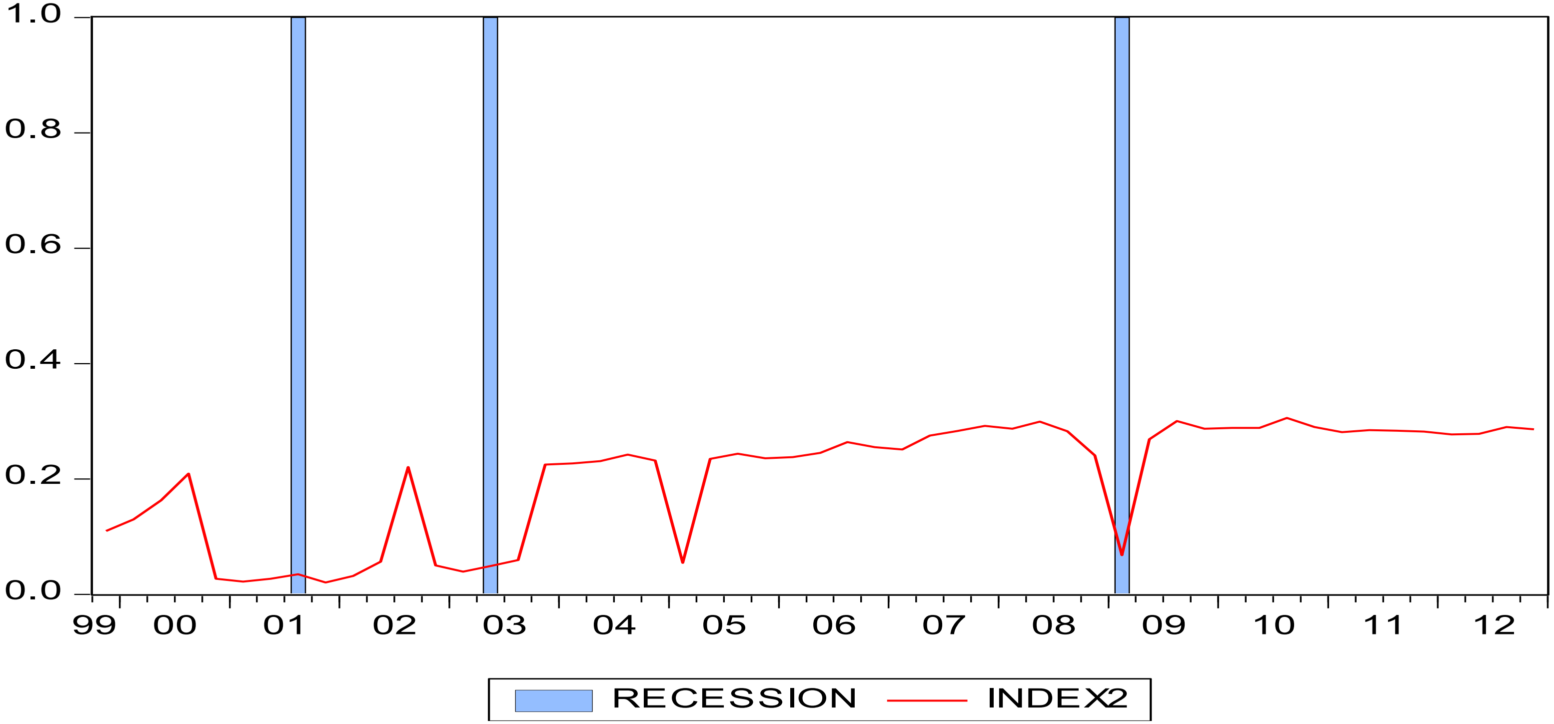

Figure 3 Recession Probabilities with Index of Weighted Average of Forecast of All ROC Models Selected(Index3)

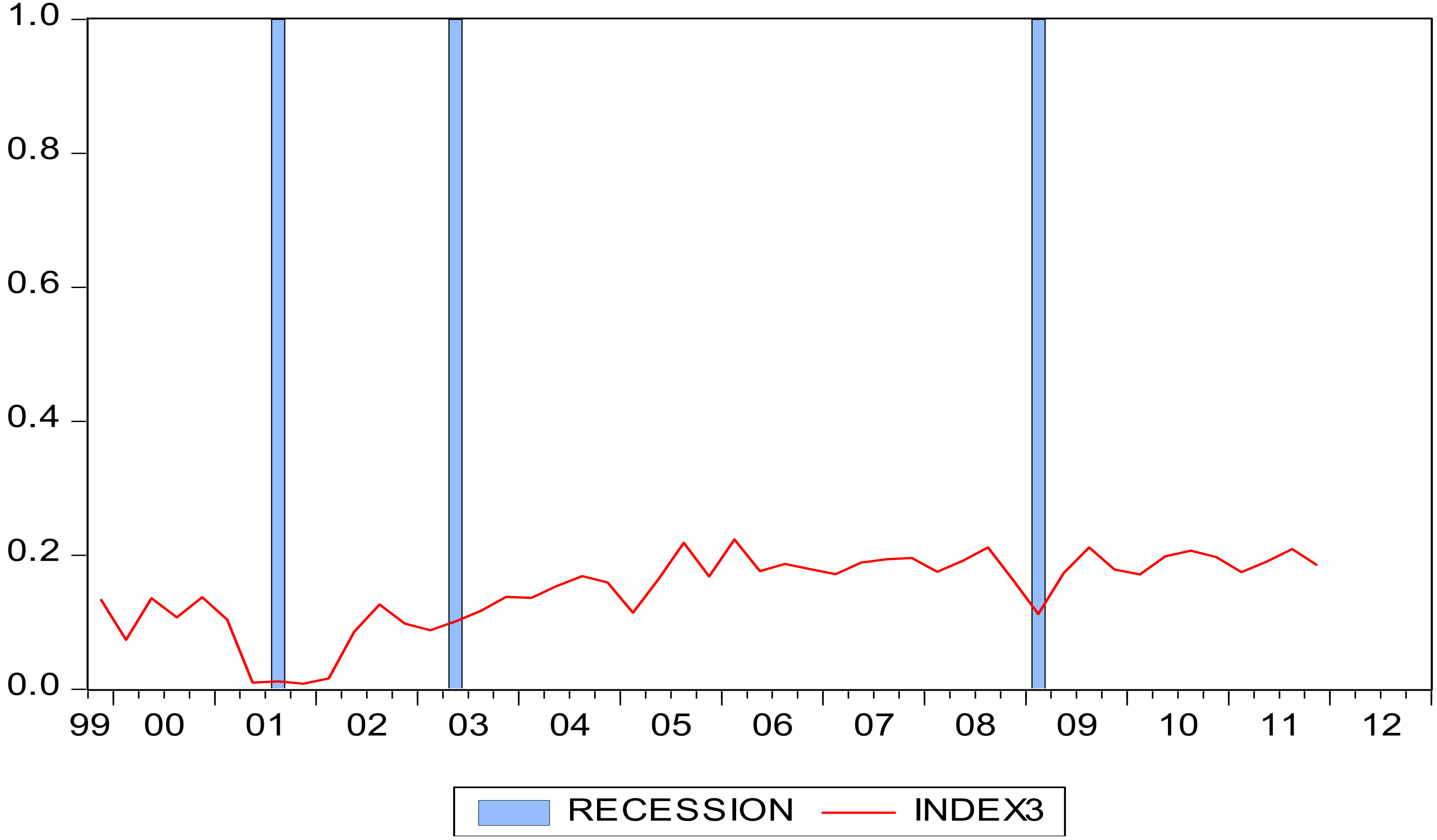

Figure 4 Recessions and Leading Financial Indicators

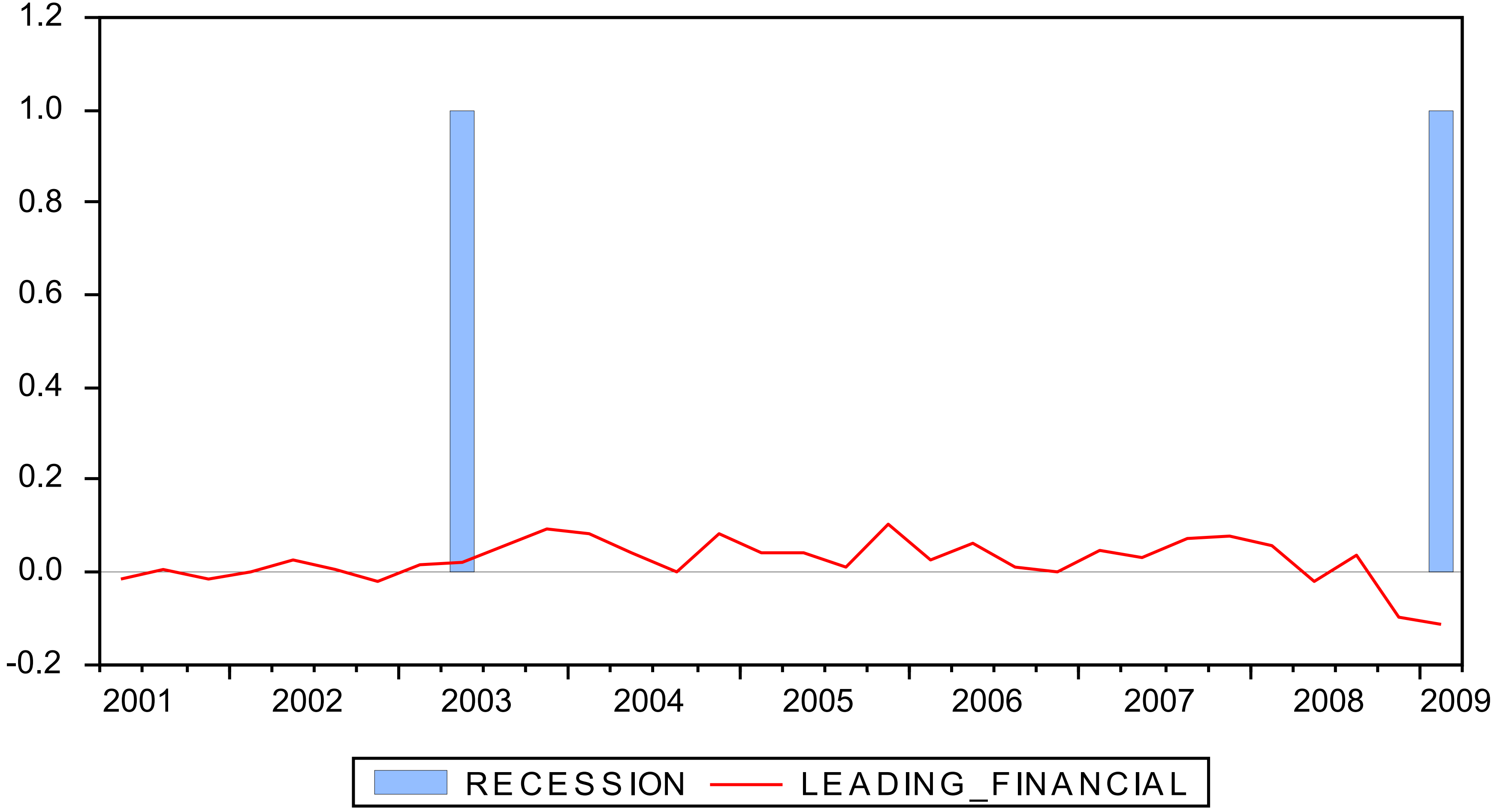

Figure 5 Recessions, Market Signal and ROC Forecasts