WP/01/30

IMF Working Paper

In Search of Coincident and Leading Indicators of Economic Activity in Argentina

Alejandro Simone

INTERNATIONAL MONETARY FUND

 WP/01/30

IMF Working Paper

Western Hemisphere Department

In Search of Coincident and Leading Indicators of Economic Activity in Argentina

Prepared by Alejandro Simone[1]

Authorized for distribution by Thomas Reichmann

March 2001

Abstract

Time series on economic activity in developing countries, in particular real GDP, are reported with important lags. Therefore, it is useful to construct indicators that coincide or lead the actual direction and level of economic activity. A general methodology to construct these indicators is proposed and adapted for Argentina. Three coincident indicators could be constructed, but no reliable leading indicator could be found. From an econometric standpoint, the coincident indicators produce satisfactory point estimates of real GDP. The series that enter the indicator are broadly consistent with what many economists believe is the main source of real GDP fluctuations in Argentina: shocks to the capital account of the balance of payments. This enhances the confidence in the econometric results.

JEL Classification Numbers: C53, E23, E27

Keywords: Argentina, leading indicators

Author:s E-Mail Address: asimone@ucla.edu

[1] University of California, Los Angeles. I would like to thank Thomas Reichmann, Bob Traa, Max Alier and Gerardo Peraza for their help and useful comments in writing this paper. I assume, of course, full responsibility for the remaining errors. I would also like to thank Gloria E. Bustillo and Carolina Worthington for their help in editorial matters and in securing the resources necessary to make my work easier.

Contents

Page

I. Introduction

The construction of Coincident and Leading Indicators of Economic Activity (CLIEA) has a long tradition, starting with the work of Moore and Shishkin in 1967. The main purpose of the CLIEA approach is to address a problem that is especially serious in developing countries. Economic time series, in particular real GDP, are reported with important time lags. In addition, the series are revised frequently to incorporate new information. If the magnitudes of these revisions are important, first estimates may not provide a good approximation of the current situation and direction of economic activity. This leaves policy makers and investors without objective measures of the current situation and direction of economic activity. The CLIEA approach is a relatively simple way to construct reliable coincident or leading indicators of economic activity.

The two most commonly used methodologies to construct coincident and leading indicators are the NBER-Department of Commerce (NBER-DOC) approach, and that of Stock and Watson (1989)(SW). The former is based on the work by Moore and Shishkin (1967), while the latter adds an econometric foundation to the NBER-DOC approach.

Both NBER-DOC and SW approaches rely on an abstract concept of economic activity which is referred as "the state of the economy". The state of the economy is an unobservable variable that must be estimated out of several available series. Real GDP is one of the series that may be used to estimate the state of the economy but is not considered to be a sufficient statistic. The estimate of the unobservable state of the economy is called a coincident indicator, and is the measure of economic activity used by these approaches. Using essentially arbitrary rules, the movements of the coincident indicator can be classified into implying that the economy is in recession or expansion.[2] In turn, a leading indicator is a variable constructed from a group of series that differs from the ones used to construct the coincident indicator. The leading indicator aims to forecast the behavior of the coincident indicator.

NBER-DOC and SW methodologies differ in the strategies used to construct the coincident and leading indicators. The selection of individual candidate series in the NBER-DOC approach is based on a scoring system. This system weights in an arbitrary manner certain desirable characteristics[3] that time series should have. This is done by assigning each characteristic a maximum possible score. The candidate series are then scored according to how close they are to possessing each characteristic and the final score is taken as an

---

[2] An example of the classification can be the following: if the indicator increases for more than two consecutive quarters, the economy is defined to be in an expansion. If the indicator decreases for more than two consecutive quarters the economy is defined to be in a recession.

[3] These characteristics are Economic Significance, Statistical Adequacy, Conformity to Historical Business Cycles, Smoothness, and Currency.

orientation of which variables to select. It is acknowledged though that the series selected are not always those with a higher score; this is to allow informal judgment in the selection process. Composite indicators (leading or coincident) are obtained by taking weighted averages of the chosen series. The weighted averages are constructed to avoid certain difficulties in combining series, such that the more volatile series will not dominate the average, or that certain series are better than others in particular aspects or criteria, while the trend and amplitude of the indexes are adjusted to ease comparison and graphic analysis. For details see Moore and Shiskin (1967) and Survey of Current Business (1984).

In the Stock and Watson approach, the series for coincident indicators are the same ones used in the NBER-DOC, but SW bring time series econometric concepts, like Granger Causality and regression analysis, to bear on the selection process. Composite indicators are again weighted averages of selected series but the weights are estimated using econometric techniques. For details see Stock and Watson (1989).

The NBER-DOC methodology has been criticized on the basis of its lack of foundation in economic theory,[4] and its lack of attention to the properties of the time series used.[5] Owing to these criticisms, for example in England, coincident and leading indicators of economic activity were no longer published. The Stock and Watson methodology shares the shortcomings of the NBER-DOC method, but it incorporates time series econometrics in the construction of indicators. While this is a step forward, a problem of this last methodology is that the econometric techniques employed involve heavy data requirements which are not met in most developing countries.

In order to overcome both the methodological flaws of NBER-DOC and the large data requirements of SW, an alternative general methodology is proposed and adapted to the limited quarterly series available for Argentina. With this methodology, three coincident indicators could be constructed. They produce information regarding the current level and direction of economic activity that otherwise would be available only much later.

From an econometric standpoint, the three indicators produce satisfactory point estimates of real GDP given the limited information on which they are based[6]. From an economic standpoint, the series that enter the indicator are broadly consistent with what many economists believe is the main source of real GDP fluctuations in Argentina: namely, shocks to the capital account of the balance of payments.

---

[4] See De Leeuw in Lahiri and Moore (1991) for details

[5] See Emerson and Hendry (1996).

[6] These point predictions are also going to be referred to as forecasts. The word forecast is used in the sense that the coincident indicators produce point estimates of real GDP series that are not available until several months in the future.

This paper is organized as follows: Section II presents the general econometric methodology. Section III describes briefly the available data . Section IV explains how the general methodology is adapted to deal with the limited number of available observations. Section V describes the final results. Section VI discusses how sensible the results are in the light of the forces that underlie the Argentine real GDP fluctuations. Section VII concludes.

II. A General Methodology to Construct Coincident and Leading Indicators

A general methodology to construct coincident and leading indicator has to address the following five issues:

1 - Definition of economic activity
2 - Turning point forecasting of economic activity, versus period by period forecasting
3 - The selection process of the individual series to be included in the indicators
4 - The construction method of the composite indicators
5 - The definition of forecast accuracy, ex ante and ex post.

II.1 Definition of economic activity

Real GDP is directly considered to be the relevant measure of economic activity for two reasons. The first is that it is the most commonly discussed measure of economic activity in practice and in the literature. The second is that in papers that use the SW methodology,[7] a common practice is to compare the estimated coincident indicator with real GDP to evaluate if it accurately describes economic activity. It seems unnecessary to develop an alternative measure of economic activity if the final benchmark ends up being real GDP anyway.

II.2 Turning point, or period-by-period forecasting

The type of forecast being sought can be either to examine the behavior of the indicators around turning points (i.e., when the economy switches from an expansion to a recession and vice versa) or at all points in time, considering their point predictions. The variable selection process depends on this issue. Certain variables may indicate precise turning points, but may not be useful for period by period point predictions, or vice versa. The main problem of the turning points approach is that results will depend crucially on how a turning point is defined, on the circumstances under which it will be considered a turning point (peak or trough), and on what the definition for a correct prediction is.[8] A further problem of the turning point approach, ignoring the definitional problems, is that even for the United States, where

[7] See Dias (1994) for example.

[8] See Gorton (1984) for a discussion of this issue.

relatively long and comparable series are available, the number of turning points of economic activity officially recognized is relatively small. This complicates the reliability of tests of forecast accuracy given that the sample of points on which they are based is relatively small. For a developing economy such as Argentina the problem is compounded, given the lack of relatively long and comparable series. The economic instability in Argentina's recent history and the changing statistical criteria used to present the data results in many structural breaks in the series that cannot be easily eliminated.

The point predictions approach has the advantage that the evaluation problem is simplified to a comparison between the forecast and the actual value. Ambiguities still exist in defining deviations from the actual value (i.e., root mean squared forecast error or mean absolute deviation for example) but they are more tractable than the evaluation of error in a turning points approach. In this paper, the all-points-in-time prediction approach is selected.

Thus, the general methodology describes how to construct composite indicators that produce level estimates of real GDP for every period. These indicators will be either coincident or leading. A composite indicator is said to be coincident when information of the series composing it up to time t is required to calculate the point estimate of real GDP at time t. A composite indicator is said to be leading by x time periods, when information of the series composing it up to time t-x is required to calculate a point estimate of real GDP at time t. The leading indicator is then said to have a lead time of x.

II.3 Selection of individual candidate series

The first step is to form a database of time series available for the country. Quality and availability of the data must be taken into account, given that there are not too many series to choose from.

The second step is to classify the data series into four categories, each representing the four general sectors where economic shocks can originate and/or propagate, namely: real sector, government sector, financial sector, and the external sector. "Economic theory screening," defined loosely as including series that have some economic rationale, will be carried out at this step. In particular, prime candidates for inclusion in the different categories would be series that represent upcoming economic activity but require an implementation lag; series that respond quickly to economic shocks; and series that reflect expectations.

The third step is to subject variables in each sector to certain econometric procedures. For the present study, these procedures are carried out with PcGive and Pcfiml 9.0 (Hendry and Doornik (1997) and are:

Unit Root tests: Real GDP generally is a trending series and usually is I(1). In their criticism of the CLIEA approach, Emerson and Hendry (1996) argue for reducing all components of indicators to a common degree of integration with the target, which in this case is real GDP. Tests of the Augmented Dickey-Fuller (ADF) type will be used to determine the order of integration of the candidate series. The criteria used to select the appropriate lag length used in the ADF tests is the one suggested in Hendry and Doornik (1997). For a detailed theoretical analysis of ADF tests see Hamilton (1994).

Bivariate Granger Causality tests: Conceptually, a variable x Granger causes another variable y if and only if past values of x can help "explain" y over and above what past values of y can already explain. In this paper, y is real GDP, and x is any candidate series considered. Granger causality will be tested in a regression framework as explained in Hamilton (1994).

Bivariate Cointegration tests: Cointegration tests among I(1) variables are implemented by using the result from Granger and Engle (1987) that establishes that if two series y and x are each I(1) and are cointegrated, then there exists an error correction mechanism (ECM) of the form (y-Kx) and conversely. The former result does not, however, entail that the ECM necessarily enters the y equation, it is sufficient that a well defined error correction mechanism exists to show that two variables y and x are cointegrated. To demonstrate the existence of a well defined error correction mechanism, unit root t tests described in detail in Hendry and Doornik (1997) are used.[9] The generally beneficial role of cointegration in constructing indicators is discussed in the next section.

Series will be discarded when their order of integration does not match the target variable order of integration, and when they fail to Granger cause the target variable. Series that are not individually cointegrated with the target variable but that Granger cause it and share its order of integration will be kept (see the detailed construction process of composite indicators is described later in the paper).

II.4 Construction of a composite index from selected individual series

Some preliminary comments

An important criticism of the NBER-DOC approach refers to the fact that the weights in the composite indicators are not obtained from the data using econometric estimation procedures. The advantage of econometric procedures is that the estimates will have some desirable properties that the weighting system proposed by the NBER-DOC may not have. In the construction of CLIEA using the NBER approach, many series said to contain complementary information on economic activity are used. The use of many individual such series,[10] attempting to capture different possible causes of output fluctuations, does not guarantee that the composite index will be capturing them. It is possible to have two subsets of variables moving synchronously but in opposite directions, therefore canceling each other

[9] For the conditions used in this paper to establish when two series or a group of them are cointegrated see the Appendix.

[10] The words "series" and "variables" are used as synonyms in this paper.

out. If the cause of fluctuations were to be recurrent, an econometric estimation will naturally give more weight to component series that captured better the nature of the fluctuations in the past. This does not mean that this nature may not change in the future and that predictive failure will be precluded. Rather, it means that at least the information contained in the past is used efficiently. With an arbitrary weighting scheme, the same problem exists regarding the future while past information will be used efficiently only by chance.

Having suggested why econometric modeling should be better than an arbitrary weighting of the candidate series, it remains to be explained which econometric modeling approach should be used. Here, the general to specific modeling approach such as proposed by Hendry and Doornik (1997) may be the appropriate choice. The main reason is that it provides a consistent set of guiding principles. Specifically, this methodology provides guidance regarding the circumstances that are necessary for econometric models to be trusted for policy analysis and forecasting, how such models are extracted from the data, and how their performance can be compared and improved. In this paper, the purpose is essentially to construct composite indicators that can provide reliable forecasts of real GDP. This methodology involves a model construction mechanism that, given a dataset and its quality, does not impose artificial constraints on the time series used. Additionally, it reduces the risk of confusing spurious relationships with real ones and adds to forecasting efficiency by incorporating the concept of cointegration. The role of cointegration must be stressed. With an I(1) target series such as real GDP, knowing that a linear combination of series is cointegrated with the target series is stating intuitively that even though the linear combination of series and real GDP will be growing in time, they will tend to "stay close". This should be helpful when trying to forecast real GDP given that this means that the possibility of bad forecast errors should be reduced. Additionally, according to Hendry (2000), a cointegrating vector has the additional beneficial property of being drift co-breaking, thus reducing the chances of forecast failure.[11]

General Model Construction Mechanism

In the next paragraphs, the model construction mechanism implied by a general to specific modeling philosophy will be briefly illustrated. For a detailed treatment and examples of the general to specific modeling philosophy see Hendry and Doornik (1997), Ericsson, Hendry and Mizon (1998), and Hendry (1995).

This modeling philosophy assumes that the underlying data generating process is present in the data themselves, and thus the modeling technique is called "data based". It imposes few priors. The starting point is to work with the most general model possible, where all the

---

[11] Error correction models are susceptible to produce bad forecasts if the equilibrium long run means change during the forecast period. This is not a terribly serious problem because usually predicted and actual values start to diverge fast, so this can quickly be detected and corrected. For details regarding these issues see Hendry (2000).

variables in the model are potentially endogenous, and test if this model is a valid representation of the data. This involves testing to make sure that the error structure is a homoskedastic innovation process against all past information (defined to be the past values of the set of variables included in the dataset) and that the parameters of the model are constant for the period under analysis. In this specific case, this would mean starting with an unrestricted VAR(p) in levels (series are supposed to be I(1) given that this is the most common type for economic time series) where p is the number of lags for each series. Different tests (autocorrelation, heteroskedasticity, misspecification tests, recursive estimation, and Chow type forecast tests) are used to corroborate that the error structure does not differ significantly from the one defined above and that parameter constancy cannot be rejected. If the general model passes these tests satisfactorily, the simplification process begins. After each simplifying step, it must be checked that the error structure satisfies the previous requirements and that the parameters are still constant. From now on, this verification step will be omitted from the description, as it is known that it must be done after every simplification.[12] If these tests are not upheld and instead indicate problems, the last simplification is invalid. This means that a new simplification must be tested from the previous accepted specification of the model.

A possible approach to the simplification of the general model is to carry out a likelihood ratio test to find out if the number of lags can be reduced. Then other tests are conducted in order to find out the number of cointegrating relationships among the candidate series, and identify what these cointegrating relationships are by imposing restrictions on the coefficients of the cointegrating vectors. By doing these tests and knowing what the parameters being sought are (in this case the parameters of the real GDP equation), additional tests can be conducted to see if some of the candidate series can be treated as "weakly exogenous". This means essentially that some of the candidate series do not add any information that may be useful to estimate the parameters of interest, and are therefore discarded. Notice that a possible outcome of this test is that a single equation model may be enough to represent the data adequately, but this is not imposed on the data directly without testing.

After obtaining the number of cointegration restrictions and identifying the cointegrating vectors, the VAR is rewritten into a Vector Equilibrium Correction form. Next, the simplification process continues by eliminating coefficients that are not significant in the equations, and testing restrictions inspired by economic theory considerations. The process stops when no more simplifying restrictions can be imposed and accepted, the simplified

---

[12] Such simplifications can come directly from economic theory. If there are structural equations relating the chosen series to indicators derived from theoretical considerations, the validity of those considerations can be tested by imposing the implied identifying restrictions to the unrestricted VAR(p).

model represents a valid representation of the data as defined above and the modeler is satisfied with the economic interpretation of the model.

The final form of the model is in the equilibrium correction form and the equation has the growth rate of real GDP ($\Delta_i y_t = y_t - y_{t-i}$)[13] on its right hand side for a given time period.[14] The i subscript stands for the lag length used for the unrestricted model. To retrieve predictions for the levels of the logarithm of real GDP, the fact that $y_t = \Delta_i y_t + y_{t-i}$ is used. By substituting the expression for $\Delta_i y_t$ in this last equation, an equation for the predicted logarithm of real GDP only as a function of levels can be obtained. It is the equivalent of the composite indicator of the CLIEA approach. The coefficients in the previously mentioned equation would be equivalent to the weights in the typical CLIEA approach.[15] The key difference between composite indicators generated with this methodology and the traditional ones is that lags of the component variables and real GDP will typically also be involved in the previously described equation.

In this ideal methodology, candidate series that satisfy the correct integration order are incorporated into a very general VAR and would then be "tested out" of the model if they were suspected to be irrelevant. In practice this is almost impossible because the number of parameters required to estimate even a small VAR may be too many for the typical size of comparable data samples that are available. This is why, in practice, prior selection criteria of some sort are needed to eliminate sufficient candidate series and estimate small VARs with these selected variables. In the case of Argentina, the size of the sample data is so small that a very unrestricted single equation model is the most general option that can be estimated.[16] This constraint, imposed by data availability, forces the assumption of weak exogeneity of the regressors. Simplification of the unrestricted single equation model will then ensue following the model construction spirit explained above. Details on how alternative unrestricted single equation models are constructed are described in Section IV.

---

[13] $\Delta_i y_t$ denotes the change in the natural logarithm of real GDP.

[14] The statements in this paragraph assume that the only transformation done to the series beyond rescaling is taking their natural logarithm.

[15] An illustration of this is provided in the results Section V.

[16] Trying to estimate VAR's would imply estimating models with only one variable and one lag given the low number of observations available. This structure is very limited and inflexible compared to the greater flexibility, especially in the number of lags and variables, that can be offered by a single equation approach. This is why the single equation modeling approach is considered to be the most general one.

II.5 Testing the composite indicators for forecasting accuracy.

To test the forecasting accuracy of composite indicators, at least two important dimensions must be taken into account. One is the performance of a particular composite indicator in generating ex ante and ex post forecasts (Ex ante performance should also be evaluated for different forecast horizons). The second is the relative performance against rival composite indicators.

In order to assess ex post forecasting accuracy, PcGive 9 offers a set of forecast tests. A subsample is used to estimate the model underlying the composite indicator. This estimated model is used to produce forecasts for the unused part of the sample. This unused part of the sample is also referred to as the forecast period. If the produced forecasts for the forecast period are close in a statistical sense to the actual values, it is evidence that the parameters of the model did not change during the sample period. This is why these ex post forecasting accuracy tests are also referred as parameter constancy tests.

For ex ante forecast accuracy testing, the dynamic forecasts option of Pcfiml will be used. The difference with ex post forecast accuracy testing is that the predicted values for the current period are computed using old predicted values for the endogenous variables that come from the regression or system, and forecasts coming from outside the model for exogenous variables. In ex post forecast accuracy testing, real values for both endogenous and exogenous variables are used instead. For details regarding all the previously described tests, refer to Hendry and Doornik (1997).

One quarter ahead ex ante forecasts for the level of real GDP, produced using the dynamic forecast option and assuming that the estimation is updated period by period as new information comes in, are presented and discussed in the results section. Based on these ex ante forecasts, the following statistics are calculated:

- *Descriptive statistics:* mean, variance and a histogram portraying the distribution of the forecast errors are calculated. A normality test of the errors is also carried out. These statistics allow to detect bias in the forecast errors.

- *Sign statistics:* These statistics measure the number of times the indicator predicted correctly the sign of four quarter and one quarter growth rates of real GDP expressed as a percent of the total number of attempts. These are all implied by the point prediction for the level of real GDP. These statistics attempt to measure the capacity of the indicators to forecast correctly the direction of changes in real GDP.

- *Measures of point forecast accuracy:* the root mean squared forecast error and the mean absolute deviation for point estimates of the level of real GDP, one quarter and four quarters growth rates are presented. These estimates try to measure how close the estimate is relative to the actual value.

- *Measure of the precision of the estimation:* The width in percentage points of a 95 percent confidence interval is reported as a way of capturing the precision of the estimates.

- *Detailed track record:* point estimates for the level of real GDP, and the one quarter and four quarter growth rates of it, are coupled with actual values. The goal of the track record is to provide a detailed account that allows to observe in which years the forecast errors and signs were significantly off track to diagnose eventual shortcomings of the model.

A comment must be made regarding the assessment of forecast accuracy at different horizons. Using a VAR model, producing predictions for different forecast horizons is simple. The low number of observations available in the case of this paper makes the single equation approach the only sensible one; however, producing predictions for different forecast horizons under this setting is more complex. Forecasts for the weakly exogenous variables are required to compute predicted values beyond the lead time[17] of the composite indicator. The fact that these forecasts have to be somehow obtained introduces an additional source of forecast error whose importance can only be evaluated ex post. To give a rough idea of the forecast horizon capabilities of the composite indicators presented, actual data for the weakly exogenous variables are used to evaluate ex ante the performance for forecast horizons up to four quarters ahead. This implies that the exercise is roughly equivalent to evaluating prediction at different forecast horizons, if the path of the weakly exogenous variables could be accurately predicted. This provides information regarding the benefit of attempting to produce good predictions of the weakly exogenous variables. Considering the purpose of this last exercise, only the sign statistics, and the measures of forecast accuracy are presented in the results section.

Finally, it is time to refer to the performance relative to other specifications of composite indicators created by rival methodologies. The only coincident and leading indicators for Argentina that the author is aware of are those constructed by *Centro Argentino de Estudio del Ciclo Económico of the University of Tucuman*. From the information available on the internet,[18] which does not describe in detail the construction process, it would appear that they are constructed using the NBER-DOC type of approach. Unfortunately, there is no formal paper available regarding the track record of these indicators to attempt a forecasting accuracy comparison. In any event, the comparison would have been difficult given the differences underlying the two approaches, especially the one regarding the definition of economic activity. In case a comparison with rival indicators becomes feasible in the future, the framework presented above can be used for those purposes. A paper with interesting ideas on how to compare the forecasting performance of competing indicators, complementary to the ones suggested here, is Camba Mendez et al (1999).

[17] The lead time of a coincident indicator is 0.

[18] www.face.herrera.unt.edu.ar/inveco/ciclos/home.htm

III. The Available Data

INDEC (*Instituto Nacional de Estadísticas y Censos*) revised most of the time series published for Argentina in the year 1999. Series were revised from 1993 onwards and therefore the newest consistent data start in 1993. The highest published frequency for real GDP is quarterly. The last observations are for the first quarter of 2000; this implies that the number of observations is 29.

Beyond these data constraints, the selected sample period is a reasonable choice given that the convertibility program and most of the important structural reforms were introduced in mid–1991 and 1992, marking a structural change.

Series are classified as pertaining to one of the following four sectors: real, financial, government, and external. All monetary and government variables are in real terms. The information sources are summarized in Table 1 in the Appendix.

Contemporaneous correlation with real GDP of each candidate series and, correlations among the series, are reported in the correlation tables in the appendix. Most series are I(1). Caution must be exercised when analyzing correlation coefficients calculated for I(1) series given that they may be spurious.[19] The unit root tests, Granger causality tests and cointegration tests with real GDP are reported in table 2 for all candidate series. Correlations, unit root tests and Granger causality tests are calculated using the original data.[20] The cointegration tests are calculated directly using transformed series that will be the ones entering the composite indicators. Table 3 summarizes the results of the tests for the candidate series that satisfy the selection criteria explained in II.3. These are series eligible to be part of a composite indicator.

Two common transformations were performed to the series before initiating the construction of indicators. First, all series with magnitudes exceeding ten thousand were rescaled dividing by one thousand. This is to avoid having coefficients and standard errors with inconveniently large numbers. Second, the natural logarithm was applied to each series to guard against non-linearities. Individual cointegration tests may be sensitive to transformations. To make sure that the series used in the construction of the composite indicators are the ones that are cointegrated, the cointegration tests are calculated on the transformed variables directly. To

---

[19] With trending series, it is possible to obtain high correlation coefficients between series even if they are not related in any way. When this is the case, the relationship among to series is named spurious.

[20] An exception to this general rule is car sales (autodosa). A PcGive sign warned that if this series was not rescaled the numerical accuracy of the tests could be endangered. The series was divided by 1000 to solve this problem. As a result, the series used is expressed in thousands of cars sold instead of the original number of units sold.

avoid investing in unnecessary new names for the transformed variables, the same names are preserved. It is important to emphasize though that from this section onwards, statements will always be referring to the transformed variables unless noted otherwise.

IV. Adapting the Proposed Methodology to a Limited Number of Observations

The starting point in the construction of a composite indicator is the formulation of an unrestricted model of real GDP using ADL (Autoregressive distributed lag) type models. In simple terms, these models involve regressing the desired dependent variable (real GDP) on lagged values of the dependent variable and current and lagged values of the independent variables. The models are going to be estimated using ordinary least squares for three basic reasons. Although it may ameliorate some potential endogeneity problems, using instrumental variables (IV) would have required estimating auxiliary regressions and is therefore too costly in terms of degrees of freedom. Notwithstanding this, IV estimation is conducted for the selected unrestricted models to evaluate the seriousness of the potential endogeneity problems. Comparing the IV estimates with the OLS estimates can provide an approximation to the importance of the previously mentioned problem. The second reason is that estimation problems, according to recent econometric studies,[21] do not seem to be very detrimental for the forecasting performance of models which is the primary purpose of constructing indicators. The third and last reason is that the marginal benefit of refining econometric procedures in a study that is based on 29 observations seems dubious compared to losing degrees of freedom.

Another issue is the choice of the number of lags to include in the ADL models. The choice made was to include either 2 or 3 lags. Models with only one lag generally suffered from autocorrelation, while in models with 2 lags the problem tended to disappear suggesting this to be a reasonable minimum lag length to work with. With quarterly data, lag length 4 is recommended. Given the lack of degrees of freedom though, if smaller unrestricted models are a valid representation of the data as defined in II.5, they are an advisable course of action. Due to the same data constraints, a maximum of 12 parameters in any attempted unrestricted model are estimated. This allows to have a three years forecast[22] period to check the forecasting capabilities of the different candidate indicators even though the first forecasts are being calculated using models estimated with one or two degrees of freedom.[23] Using up

---

[21] See Hendry (2000).

[22] The three year forecasting period is 1997 quarter 1 – 2000 quarter 1.

[23] It is important to note that calculating forecasts with models estimated with one or two degrees of freedom is a very harsh test for models. Models under these circumstances are rarely expected to perform decently.

more parameters in estimation reduces the number of observations available to test the forecasting accuracy of the composite indicators. With more than three lags, only one candidate series at a time could be used in the estimation. Given the importance of being able to test the forecasting abilities of the indicators adequately, the maximum number of lags considered for unrestricted models is three. A maximum of 12 parameter estimates for a model implies that a maximum of three series can be included in a two lag model and a maximum of two series can be included in a three lag model.

The stages towards the construction of the indicators are as follows:

1) A series that is individually cointegrated with real GDP for a given lag length is used as a starting point. Then other series are added to the regression one at a time. Once a variable is added, the expanded two variable vector is tested to see if it is also a cointegrating one. The following step is to delete the last added series and trying another one. This is repeated until all the other series in the dataset are tested. The combinations of two variables that appear to be cointegrated with real GDP as a result of these trials are recorded. Next the process is repeated for each combination of two variables that was found to be cointegrated. As a result, the combinations of three variables that seem to be cointegrated with real GDP are recorded. With less restrictive data limitations, this search process is repeated until the maximum number of variables that can be included for a given lag length is reached. In this case, for the given starting variable and lag length, the search process would stop at unrestricted models with three variable cointegrating vectors. The process can stop before if, after finding combinations of two variables that are cointegrated with real GDP, no three variables combination can be found. It must be reminded that each possible unrestricted model error terms must satisfy the conditions described in II.5. An additional condition imposed is that the coefficients of the cointegrating vector relationship must make economic sense. Both conditions are required to be accepted as a valid unrestricted model.

The same process is repeated for every series that was found to be cointegrated with real GDP. Only two and three lags are considered. This stage is completed by ranking the different unrestricted models according to their R^2 measures. A good fit is a necessary condition for a good forecasting performance and the cited measure is one of the simplest ones that can be used. Another possibility is the regression standard error.

2) The unrestricted models found in stage one are tested to see if the contemporaneous variables can be eliminated without a significant loss in the fit using zero restrictions tests. If the contemporaneous variables can be eliminated, it means that only past information can be used to obtain an estimate of real GDP. Therefore, an unrestricted model that has this property is considered to be a candidate to construct a leading indicator. The lead time will be determined by the variable with the smallest time subscript that enters the regression after stage 4 is complete. If the contemporaneous terms cannot be eliminated, then the unrestricted model is considered to be a candidate to construct a coincident indicator.

3) After stage 2, a list of unrestricted models ranked according to their fit can be produced for each of the two possibilities: leading and coincident. If there are many candidate models for

each possibility it may not be feasible to subject all of them to stages 4 and 5. Models can be screened picking the first x models with the best fit for example. Other alternatives are picking the ones whose series are available faster or the ones that make more sense from an economic theory standpoint. In this paper, the three selected unrestricted models satisfy one or more of the criteria mentioned above but there is no clear rule. A way to test if something important is being left out by the selected unrestricted models is using encompassing tests. An encompassing test tries to see if a rival model M2 captures any specific information not embodied in model M1. If M2 does not capture any information not captured already in M1, M1 is said to encompass M2. If nothing important was left out, the selected models as a group should encompass all the remaining models. That is to say that at least one of the selected models should encompass any model left out. This seems to be a reasonable criterion and it is going to be the requirement imposed at this stage. Whatever the selection criteria is for the group of unrestricted models, the selected group must encompass as a group any model left out.

4) Using the estimated coefficients of the error correction mechanisms obtained in the estimation of the unrestricted models, the models selected in stage 3 are written in the error correction form.[24] Next, they are simplified using the general to specific modeling spirit explained in Section II.6. Writing models in this way has the advantage of reducing the colinearity usually present among the different lags and easing the simplification process.

5) Forecast accuracy is assessed as explained in II.6 for the valid simplifications of the error correction models obtained in step 4.

Results of applying steps 1, 2 and 3 are presented next. Results of applying steps 4 and 5 are presented in the next section. Table 4 reminds the reader of the bivariate cointegration results. For example, M1real under the heading “2 lags” should be read as meaning that M1real is found to be individually cointegrated with real GDP using a regression equation involving two lags of real GDP, two lags of M1real and the contemporaneous M1real.

Tables 5, 6 and 7 summarize the results of stages 1 and 2. For example, in Table 5, M1real-isacest listed under the heading “two variables” should be read as follows: the two variable linear combination of M1real and isacest is found to be cointegrated with real GDP in a regression equation involving two lags of real GDP, M1real and isacest and the contemporaneous M1real and isacest. Table 6 is read in a similar fashion.

---

[24] This is always possible. Granger representation theorem applies. For details see Hamilton (1994).

Table 4. Bivariate Cointegration Results: Real GDP

2 lags	3 lags
M1real	IVIM
IVIBK	IVIBK
rigains	Rcredps
ipfiele	
rcredps	

Table 5. Results with 2 Lags

2 variables	Sig.	Type	3 Variables	Sig.	Type
M1real-isacest	5%	C	M1real-Ipfiele-IVIBC	1%	C
M1real-ipfiele	1%	C	Igains-Merval-IVIBC	1%	C
M1real-emi	1%	C	Rcredps-riva-IVIBC	1%	C
M1real-IVBK	1%	C	Rcredps-IVIABK-isacest	5%	C
M1real-IVBC	1%	C	Rcredps-IVIABK-IVIABC	1%	C
M1real-	1%	C			
IVEPMA	1%	L			
M1real-Merval	5%	C			
rigains-IVIM	1%	C			
rigains-IVIBK	1%	C			
rcredps-riva	1%	C			
rcredps-IVIABK					

Table 6. Results with 3 Lags

2 variables	Significance	Type
IVIM-quasimr	5%	C
IVIM-totaldepr	5%	C
IVIM-rcredps	5%	C
IVIM-M2	1%	C
IVIM-rigains	1%	C
IVBK-M2real	5%	C
IVBK-rigains	1%	C
IVBK-IVIBI	1%	C
IVBK-IVEPMA	1%	C
rcredps-IVA	1%	C

The column labeled significance indicates whether the variables involved in the regression equations are significant at a 1 percent level or at a 5 percent level.[25] The column labeled

[25] To consider a relationship significant at the 1 percent level, all the variables included in the relationship should be significant at the 1 percent level. If one of the variables is significant only at a 5 percent level, the relationship is considered to be significant at the 5 percent level.

type describes the results of the zero restrictions tests of stage 2. C stands for "coincident" and L stand for "Leading". As can be seen, all relationships except one did not admit the exclusion of the contemporaneous variables. This implies that there is only one unrestricted model found which could allow the construction a leading indicator.

Next, Table 7 shows the different unrestricted models listed in Tables 5 and 6 ranked according to their R^2 goodness of fit measure.

Table 7. Unrestricted Models ranked according to their R^2

Model	R^2
M1real-ipfiele-IVIBC	0.997
M1real-emi	0.993
Rcredps-riva-IVIBC	0.992
M1real-ipfiele	0.991
IVIM-rigains	0.990
M1real-IVIBC	0.990
rigains-Merval-IVIBC	0.989
rcredps-IVIABK-IVIBC	0.989
IVIBK-rigains	0.986
IVIM-M2real	0.985
IVIM-totaldep	0.984
IVIM-quasimoney	0.983
IVIM-rcredps	0.980
IVEPMA-M1real	0.978
IVIBI-IVIBK	0.978
rigains-IVIM	0.976
IVBK-IVEPMA	0.972
M1real-IVBK	0.971
M1real-Merval	0.968
M1real-isacest	0.967
Rcredps-IVIABK-isacest	0.961
rcredps-riva-isacest	0.958
rigains-IVIBK	0.946
rcredps-riva	0.944
IVIBK-M2real	0.942
rcredps-IVIABK	0.915
rcredps-riva	0.887

Of these models, only three are selected. These are M1real-ipfiele-IVIBC (M1, FIEL's industrial production index, and volume of imports of consumption goods index), M1real-emi (M1, INDEC's industrial production index) and IVIM-rcredps (Volume of imports, Real credit to the private sector). These are all unrestricted models that allow to construct coincident composite indicators. As discussed, there is no simple clear cut rule to select among these models. This is where an element of judgment is required. A combination of fit and economic theory was given priority in this selection. Fit is extremely important for forecasting performance and a clear economic theory allows to gain confidence in the econometric results. In particular, the first model is selected essentially because it has the best fit. The second model is selected because of the combination of an excellent fit and excellent availability of the series underlying it. The third model is selected because real credit to the private sector and the volume of imports are generally felt to be sensible components of a coincident index from a theoretical standpoint, considering the probable causes of the Argentine economic fluctuations in the 90s. This last point will be discussed in detail in Section VI.

The only unrestricted model that could allow the construction of a leading indicator, as defined in this paper, is not selected because in subsequent analysis it failed in many of the important forecasting dimensions discussed in II.5.

Finally, it can be shown that the model M1real-ipfiele-IVIBC (M1, FIEL's industrial production index, and volume of imports of consumption goods index) encompasses all the other models including the other two selected models.[26] If a minimalist approach were to be followed, not much information should be lost by disregarding the other possible models and focusing only on this one. Notwithstanding this fact, the explained properties of the other two models make them attractive to keep.

V. Final Models and Their Econometric Properties

All results in this section are obtained using ordinary least squares. The estimated coefficients for the unrestricted models obtained using IV are similar to the ordinary least squares[27] ones suggesting that the potential simultaneity problems are not serious.[28] The derivation of each final model from the selected unrestricted models discussed in the previous section is detailed in the appendix. Full sample estimates and goodness of fit, misspecification tests results, ex post forecasting results and ex ante forecasting results are presented next. A summary of the main conclusions closes the section.

---

[26] Test results are available from the author upon request.

[27] Coefficient are said to be "similar" if the OLS estimate is inside a 95 percent confidence interval around the IV estimate constructed using the estimated standard errors of the IV estimation.

[28] Test results are available from the author upon request.

Estimation results and goodness of fit

The following table presents the estimation results for the final models. A few notation clarifications are in order. X_j denotes the jth lag of variable X. j=0 denotes contemporaneous variables. For the IVIM-rcredps model DiX_j=X_{t-j}-X_{t-3} for j=0,1,2,3 and i=3-j. For example Drcredps_2= $rcredps_{t-2}$-$rcredps_{t-3}$. For the other two models model DiX_j=X_{t-j}-X_{t-2} for j=0,1,2 and i=2-j. For example D2M1real= $M1real_t$-$M1real_{t-2}$.

Table 8. Estimation Results for The Final Models

Model 1 *Final model derived from the unrestricted model IVIM-rcredps*
Modeling D3RGDP by OLS
The present sample is: 1993 (4) to 2000 (1)

D3RGDP = -0.4311 D2RGDP_1 +0.3386 D3IVIM +0.3182 Drcredps_2
[t test values] [-5.769] [15.323] [4.481]
-1.72 ECMfullsample_3
[-17.332]

RSS = 0.002902391592 for 4 variables and 26 observations
Standard error of the regression = 0.0114859

Long run relationship
RGDP = 2.52311 + 0.113029*rcredps + 0.246089*IVIM

ECMfullsample
RGDP - 2.52311 - 0.113029*rcredps - 0.246089*IVIM

Model 2 *Final model derived from the unrestricted model M1real-ipfiele-IVIBC*
Modeling D2RGDP by OLS
The present sample is: 1993 (4) to 2000 (1)

D2RGDP = +0.3292 DRGDP_1 +0.08848 D2M1real -0.04009 DM1real_1
[t test values][3.476] [3.751] [-1.380]
+0.2589 D2ipfiele -0.1299 Dipfiele_1 +0.09767 D2IVIBC
[7.75] [-2.021] [5.819]
-0.06779 DIVIBC_1 -0.8737 ECMfullsample_2
[-3.343] [-10.219]

RSS = 0.0004353995546 for 8 variables and 26 observations
Standard error of the regression = 0.00491822

Long run relationship
RGDP= 1.71366 + 0.312446*M1real + 0.281882*ipfiele + 0.0554509*IVIBC

Table 8. Estimation Results for The Final Models (Concluded)

ECMfullsample
RGDP - 1.71366 – 0.312446*M1real - 0.281882*ipfiele - 0.0554509*IVIBC

Model 3 *Final model derived from the unrestricted model M1real-emi*
Modeling D2RGDP by OLS
The present sample is: 1993 (4) to 2000 (1)

D2RGDP =	+0.3939 DRGDP_1	+0.08968 D2M1real	+0.4992 D2emi
[t test values]	[5.176]	[4.199]	[26.111]
	-0.3871 Demi_1	-0.5609 ECMfullsample_2	
	[-6.124]	[-7.405]	

RSS = 0.0009894768731 for 5 variables and 26 observations
Standard error of the regression = 0.00686425

Long run relationship
RGDP = 1.084 +0.3764 M1real+0.4191 emi

ECMfullsample
RGDP-1.084-0.3764 M1real -0.4191 emi

The three models are presented in the error correction form. For each model, the cointegrating vector (i.e., the long run relationship) and the corresponding error correction variable are presented below the estimates of the coefficients and their t test values. The coefficients of the error correction variables are known as the feedback coefficients. These coefficients measure the speed of adjustment of deviations from the long run relationships. The error correction variables are simply the deviations of real GDP from the long run relationship. The coefficients of the long run relationship have the expected signs.

In general, traditional t tests show that variables are statistically significant at the 5 percent and 1 percent levels. The exception is DM1real_1 in Model 2. The partial correlation coefficients[29] for every variable captures, informally speaking, the individual explanatory power when the explanatory power of the other variables is deducted. Values of this statistic (which must be lower than 1 in absolute value) below 0.1[30] may indicate poor explanatory power or co linearity. The estimated values are well above 0.1 for all variables except DM1real_1 in Model 2. DM1real_1 is kept in model 2 because the performance of the model in forecast tests worsened if removed. In general, these results suggest the lack of co linearity problems and reinforce the conclusions that all variables except DM1real_1 in Model 2 are statistically significant.

[29] Not shown in table. Results are available from the author.

[30] There is no specific critical value for this statistic. 0.1 is just a practical rule.

The standard errors of the regressions reflect the good fit of all models. For model 1 it is around 1 percent of the mean of the dependent variable. For models 2 and 3 the same statistics are 0.5 percent and 0.7 percent respectively.

The equivalent of the coincident indicators is calculated as explained in II.5. It is the prediction for the level of the transformed real GDP variable. As an example, the coincident indicator implied by Model 1 is:

CI= 4.33 -0.43*RGDP_1- 0.29*RGDP_3+ 0.34*IVIM+0.09*IVIM_3+ 0.32*rcredps_2 -0.13 *rcredps_3

CI is the predicted value of the regression for Model 1 plus RGDP_3. The above expression is obtained by replacing the definitions of the variables in the formula for the predicted value for Model 1[31] and adding up RGDP_3.

The formula to obtain the predicted value of real GDP in its original units is:

Predicted real GDP(original units) = exp(CI)*1000

Misspecification tests and ex post forecasting performance

The table below shows the misspecification tests calculated for the models when there were enough degrees of freedom to do so[32]. The table also shows the parameter constancy Chow and chi squared tests.

Table 9. Misspecification Tests

							Ex post forecasting tests	
MODEL	AR	ARCH	WH1	WH2	Normality	Reset	Chow	χ^2
Rcredps -IVIM	0.0958	0.7260	0.9196	0.5337	0.7447	0.5909	0.9463	0.9637
M1real-Ipfiele-IVIBC	0.6463	0.7937	N/A	N/A	0.7799	0.7348	0.8897	0.8819
M1real-emi	0.6039	0.7869	0.8157	N/A	0.7693	0.6130	0.6183	0.4997

[31] Estimated coefficients were rounded to two decimal places for the calculation. Details are presented in the Appendix.

[32] N/A means that there were not enough degrees of freedom to calculate the test.

The AR test is an autocorrelation test that is valid even if the dependent variable is included as a regressor. The null hypothesis of the test is the absence of autocorrelation. The ARCH, WH1 and WH2[33] are heteroskedasticity tests and their null hypotheses are the absence of heteroskedasticity. Normality is a test that tests the null hypothesis that the residuals of the regressions are normally distributed. Reset is a functional form misspecification test and its null is that the model is not misspecified. The values in the tables are the p-values of the different tests.

P-values for all the misspecification tests are all above 0.05 in the table. This means that the null hypotheses of the tests cannot be rejected at a 1 percent or 5 percent significance levels. The conclusion from all these tests is that there is no conclusive evidence suggesting that the models are misspecified beyond the fact that the result of the autocorrelation test AR is close to rejecting the null for Model 1. For details regarding these tests see the PcGive manual.

P-values for the parameter constancy tests are also above 0.05 implying that there is no conclusive evidence to reject the null of parameter constancy at 5 percent or 1 percent significance levels. Individual forecast errors t tests and recursive estimation results confirm this conclusion.[34]

Ex ante forecasting performance

The main ex ante forecasting performance statistics of the models are exhibited in table 10. The details are shown in the track record sheets for each model included in the appendix. Figures 1, 2 and 3 and illustrate the 1 step ahead performance in predicting the level of real GDP, the one quarter growth rate and the four quarter growth rate for each model. In each figure, the predicted values and the actual values are shown in the y axis while time is shown on the x axis. The solid lines are the actual values and the dashed lines are the predicted levels.

---

[33] WH1 is the standard White heteroskedasticity test and WH2 includes additionally the cross products of the independent variables.

[34] Individual forecast error t tests and recursive estimation results are available from the author upon request.

Table 10.

	SIGN ACCURACY (number of correct sign forecasts over total number of forecasts)		**Root mean square forecast error** (For the levels the unit is million of 1993 pesos. For one quarter and four quarter growth rates the unit is percentage points)			**Mean absolute Deviation** (For the levels the unit is million of 1993 pesos. For one quarter and four quarter growth rates the unit is percentage points)			**Average distance of estimates from upper and lower bound of 95% confidence interval**. (For the level the unit is percentage of the actual value. The unit for the growth rates is percentage points)		
MODEL	1QGR	4QGR	Level	1QGR	4QGR	Level	1QGR	4QGR	Level	1QGR	4QGR
Rcredps -IVIM	85%	92%	883	1.26	1.31	825	1.17	1.21	3%	3	3
M1real-Ipfiele-IVIBC	100%	100%	713	1.02	1.09	520	0.74	0.77	1%	1	1
M1real-emi	100%	93%	724	1.07	1.07	520	0.89	0.9	1.5%	1.5	1.5

Following the order of Section II.6, the distribution of the one step ahead ex ante forecast errors is discussed next. It can readily be seen, from the detailed track record sheets and the previously mentioned graphs, that in the case of Model 1 there is a tendency to underpredict the actual value of real GDP. There is no apparent bias in the case of the other two models.

Normality tests of the same type as used for the residuals of the regression cannot reject the null of normality of the forecast errors of the level, one quarter growth rate and four quarters growth rates at a 1 percent significance level in all models.[35] Based on these tests, the assumption that the errors came from a normal distribution seems reasonable. Using this assumption, it can be tested if the mean forecast error for the levels of real GDP, one quarter growth rate and four quarter growth rate are significantly different from 0 using standard statistical theory.[36] When the population variance is unknown, a t statistic is appropriate. In this case, a t statistic with 12 degrees of freedom is appropriate because there are 13 observations. The reported value for such a distribution will be in the rejection region at a 5 percent significance level if it is bigger than 2.178 in absolute value. The values reported in the track record sheet clearly satisfy the condition for Model 1 but not for the other two models. This confirms the conclusion reached graphically: Model 1 forecast errors have a

[35] Results of the tests and descriptive statistics for the one step ahead forecast errors are available from the author upon request.

[36] For a detailed description of the used t test. See for example Kazmier and Pohl (1984) but the test can be found in any standard basic statistical analysis book.

bias significantly different from 0 while for the other models no significant bias can be detected. The bias in Model 1 may exist possibly because of the omission of a fourth lag in the estimation of the unrestricted model. The reason for this is that the autocorrelation test for Model 1 presented was on the limit of rejecting the null of no autocorrelation.

Looking at the sign accuracy and measures of forecast point accuracy of the three models, it can be seen that the ranking of models based on fit (R^2) is preserved. Model 2 produces the most precise sign and point forecasts while Model 3 the least precise.

The track record sheets show that when the sign accuracy measures are calculated for 2, 3 and 4 step ahead forecasts,[37] the precision of the sign predictions of 1 quarter and 4 quarter changes stays approximately unchanged in all models. This not true for the measures of point forecast accuracy. The capacity of providing accurate point estimates diminishes substantially in Model 1. In the case of Model 1, the root mean squared forecast errors and mean absolute deviations double with respect to the one step ahead case when the four step ahead case is considered. The other models also show some deterioration but it is less dramatic.

The average distance of the estimates from the upper and lower bands of the 95 percent confidence interval in the case of Model 1 is around 3 percent of the actual level for real GDP and around 3 percentage points for the growth rates. For quarterly data this is rather large and is probably a reflection of the low number of observations with which estimation is conducted. When the same statistics for Models 2 and 3 are observed, it seems that the estimation in their case is much more precise. Model 2 looks three times more precise and Model 3 two times more precise. The IV estimates of the standard errors of the coefficients are almost three times as big as the OLS estimates in the case of Model 2 and approximately twice as big as the OLS estimates in the case of Model 3. This is not true for Model 1 though. IV and OLS standard errors are very similar. This suggests that OLS standard errors may be underestimated by a factor of 3 in Model 2 and by a factor of 2 in Model 3. If those factors are used to adjust the table, Models 2 and 3 would have the same estimation precision than Model 1.[38]

Conclusion regarding the econometric properties of the three models

The main conclusions are the following:

---

[37] It is important to remind the reader that this assumes that the path of the variables considered weakly exogenous can be perfectly predicted.

[38] The t test of the variables calculated using the IV estimation do not affect most of the conclusions regarding the significance of variables that are obtained with the OLS estimation.

- All the presented models have a good fit and do not seem to suffer from co linearity problems.

- All models pass successfully the misspecifications tests. It must be said though the first model barely passes the autocorrelation test in absolute terms and in comparison with the other two models.

- All models pass successfully the ex post forecasting accuracy tests.

- Models 2 and 3 produce more precise ex ante forecasts than Model 1. Additionally, the precision of these forecasts does not diminish as fast as in the case of Model 1 when 2, 3 and 4 steps ahead forecasts are considered.

- The model that produces the most precise ex ante forecasts is model 2. Model 3 comes next and model 1 last. This highlights the importance of a good fit in forecasting given that the rank in ex ante forecasting precision matched exactly the rank in fit.

- Model 1 produces forecasts that are downward biased by a constant 1 percent for real GDP and around 1 percentage point for growth rates. This is consistent with the remark that the model passes tightly the autocorrelation tests. The omission of a fourth lag in the unrestricted model may be the cause of the problem. Given that there are not enough degrees of freedom to conduct an estimation with 4 lags, correcting the intercept of the predictions upwards by 1 percent for the level of real GDP and by 1 percentage points for the growth rate may provide a good rule of thumb to improve the forecasting performance of this model.

VI. The Nature of Argentine Economic Fluctuations and the Relations with the Estimated Models

Papers on coincident and leading indicators seldom attempt to ground their results on an analytical framework explaining the actual developments in an economy. To minimize the risk of dealing with just spurious relationships, the indicators obtained should also make sense in the light of economic theory.

Carstens (1998) identifies three main causes of economic cycles in emerging economies: terms of trade shocks, policy uncertainty related to political events, and changing conditions in international financial markets, such as moves in the international real rates of interest. These three factors played a role in Argentina. Their adverse effect on economic activity tended to be magnified by the capital outflows or hardening of financing constraints that accompanied these shocks, and which, in the context of a currency board arrangement, found their way directly into a decline of economic activity.

In a fixed exchange rate regime, a capital outflow tends to decrease international reserves, base money, and the monetary aggregates such as M2. Domestic real interest rates increase, bank lending decreases and this has a supply effect that causes the economy's real GDP to decrease in the medium run. On the demand side, aggregate demand decreases and less tradable and non-tradable goods are demanded, with the economy tending to increase or generate a current account surplus.

The increase or generation of a current account surplus occurs by means of an increase in the trade surplus. The data for Argentina seem to suggest that imports make most of the adjustment on impact while effects on exports are seen more in the medium run. Reasons for this may be that aggregate production is adjusted gradually due to the existence of adjustment costs, sluggish adjustment of the real exchange rate and that an important part of the exported goods are agricultural goods with low income elasticity.

The cointegrating relationship of Models 1 to 3 show that real GDP is positively related to real credit to the private sector or to M1, to the volume of imports, and to indices of industrial production. This is consistent with the framework above. When capital flows out of the country, money and/or credit to the private sector is reduced and imports fall reflecting the adjustment that must occur in the current account to reflect the capital outflow. This is accompanied by a fall in real GDP, which is also reflected in reduced industrial production.

A question that may be asked is why M1real,and not other real monetary aggregates like M2real for example, is present in models 2 and 3. M1real as defined by IFS, includes currency in circulation in the hands of the private sector and checking deposits held by the private sector only. This makes M1 an excellent measure of the level of transactions in the economy which is very correlated with economic activity. Quasi-money components such as time deposits or CD's do not correspond to the transactions motive and this is probably why measures like M2 do not fare as well.

A more general question that may be asked is why certain variables which seem to capture very similar ideas do not enter a given indicator. A general point to be made is that not seeing a variable that captures a very similar idea in an indicator does not mean that the variable could not potentially enter the indicator. The only statement being made by picking a particular specification is that the variables entering the indicator seem to be more effective in capturing a given economic idea than alternatives.

VII. CONCLUSION

The construction of Coincident and Leading indicators of Economic Activity addresses a problem that is especially serious in developing countries. Economic activity time series, in particular real GDP, are reported with important time lags. In addition, often the series are subsequently revised to incorporate new information. If the magnitudes of these revisions are important, first estimates may not provide a good approximation of the current situation and direction of economic activity, leaving policy makers and investors without objective measures of the current state of the economy. The CLIEA approach is a relatively simple way to use series that are readily available to construct indicators that coincide or lead the actual direction and level of economic activity.

The two common methodologies used to construct coincident and leading indicators are the NBER-Department of Commerce (NBER-DOC) approach and Stock and Watson (1989) (SW). These methodologies, however are subject to important and well known criticisms. The NBER-DOC methodology has been mainly criticized because the weights of the series in the indicators are calculated in an arbitrary fashion. The absence of econometric techniques in the estimation of the weights makes it likely that the information in a given dataset is not efficiently used. The newer version, SW, has overcome this criticism but the data requirements are typically too high for a developing economy such as Argentina.

In order to address these issues, a general methodology to construct indicators that deals with the low number of observations available in this case was proposed. Applying the methodology to the limited quarterly data available, three coincident composite indicators could be constructed but no reliable leading indicator could be found. The three indicators were selected among other possibilities according to their fit, availability of the series required to construct them and their consistency with economic theory.

From an econometric standpoint, the three indicators produce satisfactory one step ahead forecasts in a root mean squared error sense or mean absolute deviation, given the limited information on which they are based. When 2, 3 and 4 step ahead forecast errors are analyzed, under the assumption that weakly exogenous variables can be perfectly predicted, all the models preserved their capacity to predict accurately the sign of 1 and 4 quarter growth rates. The same cannot be said regarding the measures of point forecast accuracy. Only models 2 and 3 seem to have slowly increasing forecast errors within the selected horizon. This suggests that efforts to predict accurately the variables underlying models 2 and 3 may allow the construction of reasonable forecasts up to 4 periods ahead.

From an economic standpoint, the variables in the models' cointegrating vectors and their signs are consistent with what many economists believe is the underlying source of real GDP fluctuations in Argentina in the 90's: shocks to the capital account of the balance of payments. This enhances the confidence in the econometric results and shows another aspect of the search of coincident and leading indicators exercise. Looking for coincident and leading indicators of economic activity can be a useful exercise to confirm the basic hypotheses regarding the relevant sources of economic cycles in an economy.

Bibliography

Camba-Mendez, Gonzalo et al, October 1999, "The Forecasting Performance of the OECD Composite Leading Indicators for France, Germany, Italy and the UK," National Institute of Economic and Social Research *Discussion Paper (New Series)*, No. 155:1-26 (UK).

Carstens, Agustin G., 1998, "Emerging Economies and the Business Cycle" prepared for the Federal Reserve Bank of Boston Annual Conference (U.S.). "Beyond Shocks: What Causes Business Cycles?" Cape Cod June-24-26, 1998.

De Leeuw, Frank, May 1988, "Toward a Theory of Leading Indicators," United States Bureau of Economic Analysis, *Discussion Paper* No. 24:1-(54) Rev. May 1988 (U.S.).

Días, Francisco Craveiro, January 1994, "A Composite Coincident Indicator for the Portuguese Economy," Banco de Portugal, *Estudios e Documentos de Trabalho Working Papers*, No. 18-93:1-20 (Portugal).

Doornik, Jurgen A., David F. Hendry, 1999, "An Interface to Empirical Modelling," *GiveWin*, Timberlake Consultants Ltd. (U.K.).

Doornik, Jurgen A., David F. Hendry, 1997, *Modelling Dynamic Systems Using PCFiml 9.0 for Windows*, International Thompson Business Press (U.K.).

Emerson, Rebecca A, David F. Hendry, July 1996, "An evaluation of Forecasting Using Leading Indicators," *Journal of Forecasting*, No. 15:271-91 (UK).

Engle, R. F., C.W.J., 1987, "Cointegration and Error Correction: Representation, Estimation and Testing, *Econométrica* **55**, 251-276.

Ericsson, Neil R., David F. Hendry, Grayham E. Mizon, 1998, "Exogeneity, Cointegration, and Economic Policy Analysis," *American Statistical Association Journal of Business & Economic Statistics* Vol 16 (U.S.).

Estrella, Arturo, "Predicting U.S. Recessions: Financial Variables as Leading Indicators," National Bureau of Economic Research. *Working Paper Series*, No. 5379:1-32, December 1995; Federal Reserve Bank of New York, *Research Paper*, No. 9609:1-36 May 1996; Review of Economics and Statistics, No. 80:45-61 February 1998 (U.S.).

Ferreira Gomez, Francisco, July 1995, "An Index of Leading Indicators for the Portuguese Economy" (Washington: International Monetary Fund).

Gorton, Gary, 1984, "Measuring Economic Activity with the Indexes of Leading, Lagging, and Coincident Indicators," Federal Reserve Bank of Philadelphia *Working Papers*, No. 84-6:1-22 (U.S.).

Gottschling, Andreas, March 1998, "A New Approach to the Evaluation and Selection of Leading Indicators," Deutsche Bank Research, *Economics. Research Notes in Economics and Statistics*, No. RN-98-1:1-28 (Germany).

Green, Christopher, June 1993, "Leading Indicators of Economic Activity," Reserve Bank of New Zealand *Discussion Paper*, No. 92/14:1-(17) (New Zealand).

Hamilton, James D., c1994, "Time Series Analysis" (New Jersey: Princetown University Press).

Hamilton, James D., Gabriel Perez-Quiros, January 1996, "What Do the Leading Indicators Lead?" *Journal of Business* No. 69:27-49 (U.S.).

Hendry, David F., 1995, *Dynamic Econometrics* (U.K.: Oxford University Press).

Hendry, David F., 1998, "Exogeneity, Causality, and Co-Breaking in Economic Policy Analysis of a Small Econometric Model of Money in the U.K." *Empirical Economics* 23, No. 3:267-94 (Austria).

Hendry, David F., Jurgen A. Doornik, 1999, *Empirical Econometric Modelling Using PcGive Vol. 1*, Timberlake Consultants Ltd. (U.K.).

Hendry, David, August 2000, "Course on Econometric Modelling and Economic Forecasting," IMF Institute Economics Training Program (Washington: International Monetary Fund).

Hymans, S.H., 1973, "On the Use of Leading Indicators to Predict Cyclical Turning Points," *Brookings Paper on Economic Activity*, 2, 339-75.

Kazmier, Leonard J., Norval F. Pohl, c1984, "Basic Statistics for Business and Economics," McGraw-Hill 2nd Edition (U.S.).

Lahiri, Kajal, Geoffrey Hoyt Moore, 1991, "Leading Economic Indicators: New Approaches and Forecasting Records" *Cambridge* (England), (New York: Cambridge University).

López, Humberto, Eva Ortega, Angel Ubide, 1997, "Dating and Forecasting the Spanish Business Cycle," (Badia Fiesolana, Italy: European University Institute).

Lucas, R. E., 1977, "Understanding Business Cycles," Carnegie-Rochester Conference on Public Policy 5:7-29.

Moore, Geoffrey Hoyt, Julius Shiskin, 1967, "Indicators of Business Expansions and Contractions," National Bureau of Economic Research, *Occasional Paper* (New York).

Nilsson, Ronny, July 1987, OECD Leading Indicators, OECD Economic Studies, *Organisation for Economic Co-operation and Development*, No. 9:105-45 (International).

Silver, Stephen J., 1991, "Forecasting Peaks and Throughs in the Business Cycle: On the Choice and Use of Appropriate Leading Indicator Series," Chapter 11 in Lahiri and Moore (1991), "Leading Economic Indicators: New Approaches and Forecasting Records."

Stock, James H. and Mark W. Watson, 1989, "New Indices of Coincident and Leading Economic Indicators,"*Macroeconomics Annual,* National Bureau of Economic Research (U.S.).

Stock, James H., Mark W. Watson, 1992-03, "Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience," National Bureau of Economic Research, *Working Paper Series*, No. 4014:1-79 March 1992; Federal Reserve Bank of Chicago, *Working Papers*, *Macro Economic Issues*, No. WP-92-7:1-(79) April 1992 (U.S.).

Survey of Current Business "Composite Indexes of Leading, Coincident and Lagging Indicators" November 1987.

Data Sources

"Boletín Fiscal" Ministerio de Economía y Obras y Servicios Públicos de la República Argentina. Secretaría de Hacienda.

"Comunicados de Prensa del Banco Central de la República Argentina: Reservas Internacionales del Sistema Financiero y Pasivos del BCRA" Banco Central de la República Argentina.

"Indicadores de Coyuntura" Enero-Febrero 2000. Fundación de Investigaciones Económicas Latinoamericanas.

"Indice de Precios al Consumidor" Junio 2000. Información de Prensa. Ministerio de Economía, Secretaría de Programación Económica y Regional, Instituto Nacional de Estadística y Censos. República Argentina.

"Indices de Precios y Cantidades del Comercio Exterior, Base 1993=100 Año 1999" Febrero 2000. Información de Prensa. Ministerio de Economía, Secretaría de Programación Económica y Regional, Instituto Nacional de Estadística y Censos. República Argentina.

"Información de Prensa" Febrero 2000. Asociación de Fábricas de Automotores. Argentina.

"International Financial Statistics" IFS. IMF. Published Data. Version available from IMF workstations.

www.bcra.gov.ar Menu "Información Estadística" Option "Préstamos y Financiaciones a Partir del Año 2000."

Table 1. Definition of Variables

Variable (Short name)	**Variable** Long Name and units	**Sector**	**Construction details of the series**	**Information Source**
isacest	Construction activity index	Real	Quarterly series is constructed by taking the average of the monthly published series	INDEC
isspest	Utilities activity index	Real	Quarterly series is constructed by taking the average of the monthly published series	INDEC
emiest	Manufacturing activity index	Real	Quarterly series is constructed by taking the average of the monthly published series	INDEC
ipfiele	Manufacturing activity index	Real	Quarterly series is constructed by taking the average of the monthly published series	*Fundación de Investigaciones Económicas Latinoamericanas* (FIEL)
autoprod	Total car production in units	Real	As published by source	*Asociación de Fábricas de Automotores* (ADEFA)
autodosa	Total domestic car sales in units	Real	As published by source	*Asociación de Fábricas de Automotores* (ADEFA)
resreales	Real Reserves	Financial	Real reserves are obtained by taking the gross international reserves using the end-period stock in millions of current dollars[39] and deflating that number by the consumer price index published by INDEC. The values used for nominal gross international reserves are the ones published in *Comunicados de Prensa del Banco Central de la República Argentina* (BCRA): *Reservas Internacionales del Sistema Financiero y Pasivos del BCRA*.	*Comunicados de Prensa del Banco Central de la República Argentina* (BCRA): *Reservas Internacionales del Sistema Financiero y Pasivos del BCRA*.
M1real	Real M1	Financial	IFS series named money and deflated by the consumer price index.	International Financial Statistics-IMF

[39] Reserves are published in millions of dollars but given the 1 peso per dollar exchange rate established by convertibility for the period, the amount in pesos is the same.

Table 1. Definition of Variables (Continued)

quasimr	Real Quasi money	Financial	IFS series named money and deflated by the consumer price index.	International Financial Statistics-IMF
totdepr	Real total deposits	Financial	Total deposits in pesos and dollars expressed in millions of current pesos deflated using the consumer price index. Total deposits are computed adding up the demand deposits and Time, Savings and Foreign currency deposits series that IFS publishes in its deposit money banks survey.	International Financial Statistics-IMF
rcredps	Real credit to the private sector	Financial	The real credit to the private sector series is constructed using daily information published by the Argentine Central Bank on the internet[40] and then deflated using the consumer price index. To obtain the time series used as total nominal credit to the private sector, the items "préstamos de títulos" and "intereses documentados" are deducted from the total credit to the private sector number in millions of current pesos that appears in the website.	*Banco Central de la República Argentina*
merval	Merval Index	Financial	The quarterly series of the Merval index is constructed by averaging the values of the Merval Index at the end of each month in the quarter	*Bolsa de Comercio de Buenos Aires*
M2real	Real M2	Financial	Sum of real quasimoney and real M1	International Financial Statistics
rtaxes	Real total revenues of the national government	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*
riva	Real gross value added tax revenues	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*
rigains	Real income tax revenues	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*

[40] The internet site is www.bcra.gov.ar and the referred information is obtained by clicking on the option "*Prestamos y financiaciones a partir del año 2000*"in a menu called "*Información Estadistica*".

Table 1. Definition of Variables (Concluded)

rgec	Real total current expenditures of the national government	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*
rgecc	Real total consumption expenditures including wages, salaries and purchases of goods and services	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*
rgek	Real total investment expenditures	Government	Published nominal series are deflated using the consumer price index published by INDEC	*Boletín Fiscal Ministerio de Economía*
autoexp	Car exports in units	External	As published by source	INDEC
autoimp	Car imports in units	External	As published by source	INDEC
IVIM	Volume of imports Index	External	As published by source	INDEC
IVIBI	Volume of imports of intermediate goods index	External	As published by source	INDEC
IVIBK	Volume of imports of capital goods index	External	As published by source	INDEC
IVICOM	Volume of fuel imports index	External	As published by source	INDEC
IVIABK	Volume of imports of accessories and spare parts for capital goods index	External	As published by source	INDEC
IVIBC	Volume of imports of consumption goods index	External	As published by source	INDEC
IVE	Volume of Exports index	External	As published by source	INDEC
IVEPP	Volume of Exports of Primary products index	External	As published by source	INDEC
IVEPMA	Volume of Exports of agricultural manufactured products index	External	As published by source	INDEC
IVEPM	Volume of Exports industrial manufactured products index	External	As published by source	INDEC
IVECOM	Volume of fuel exports index	External	As published by source	INDEC

Correlations tables

Real Sector

Correlation matrix

	RGDP	emi	isacest	isspest	autoprod
RGDP	1.0000				
emi	0.82298	1.00000			
isacest	0.79100	0.72328	1.00000		
isspest	0.86422	0.50104	0.71960	1.00000	
autoprod	0.60931	0.90024	0.61115	0.22374	1.0000
Rautodosa	0.34910	0.68309	0.51293	-0.016943	0.82375
ipfiele	0.92362	0.94645	0.74700	0.68318	0.81874
	Rautodosa	ipfiele			
Rautodosa	1.0000				
ipfiele	0.56073	1.0000			

Financial Sector

Correlation matrix

	RGDP	resreales	M1real	quasimr	totdepr
RGDP	1.0000				
resreales	0.81171	1.0000			
M1real	0.90162	0.85447	1.0000		
quasimr	0.84726	0.98142	0.87797	1.0000	
totdepr	0.85906	0.97985	0.89057	0.99930	1.0000
M2real	0.86927	0.97763	0.91092	0.99727	0.99861
rcred3	0.86378	0.94363	0.90770	0.98093	0.98258
fmerval	0.45561	0.30849	0.49852	0.29619	0.31799
	M2real	rcred3	fmerval		
M2real	1.0000				
rcred3	0.98542	1.0000			
fmerval	0.33215	0.26429	1.0000		

Government Sector

Correlation matrix

	RGDP	rtaxes	riva	rigains	rsscon
RGDP	1.0000				
rtaxes	0.93323	1.0000			
riva	0.79947	0.78066	1.0000		
rigains	0.86646	0.92614	0.63518	1.0000	
rsscon	-0.73072	-0.66259	-0.47065	-0.71177	1.0000
rgec	0.80841	0.80420	0.60648	0.72877	-0.59420
rgecc	0.071366	-0.029716	0.060813	-0.21383	0.28602
rgek	-0.48015	-0.50308	-0.44257	-0.61701	0.40066
	rgec	rgecc	rgek		
rgec	1.0000				
rgecc	0.28525	1.0000			
rgek	-0.62474	0.16313	1.0000		

External Sector

Correlation matrix

	RGDP	IVIM	autoimp	IVIBK	IVIBI
RGDP	1.0000				
IVIM	0.95029	1.0000			
autoimp	0.72615	0.78464	1.0000		
IVIBK	0.91587	0.97591	0.80975	1.0000	
IVIBI	0.92813	0.97039	0.68545	0.92197	1.0000
IVIBC	0.84387	0.86790	0.72881	0.85503	0.76874
IVIABK	0.87737	0.94068	0.76742	0.88869	0.90119
IVICOM	0.56118	0.58306	0.52882	0.51832	0.58732
IVE	0.89903	0.82492	0.56108	0.76666	0.87566
autoexp	0.83680	0.88559	0.81733	0.84066	0.84668
IVEPP	0.52504	0.39995	0.23691	0.38088	0.41432
IVEPMA	0.81475	0.75045	0.44963	0.67306	0.84549
IVEPM	0.92131	0.91812	0.65349	0.86139	0.94366
IVECOM	0.81955	0.84013	0.64405	0.82480	0.89549
	IVIBC	IVIABK	IVICOM	IVE	autoexp
IVIBC	1.0000				
IVIABK	0.76573	1.0000			
IVICOM	0.31313	0.61749	1.0000		
IVE	0.55734	0.78934	0.64350	1.0000	
autoexp	0.70144	0.94426	0.66762	0.75613	1.0000
IVEPP	0.18542	0.43198	0.36581	0.70583	0.34651
IVEPMA	0.52790	0.65935	0.53272	0.90605	0.60675
IVEPM	0.71189	0.86435	0.66914	0.91041	0.86408
IVECOM	0.56496	0.74144	0.59311	0.86303	0.72556
	IVEPP	IVEPMA	IVEPM	IVECOM	
IVEPP	1.0000				
IVEPMA	0.49306	1.0000			
IVEPM	0.41727	0.86402	1.0000		
IVECOM	0.37676	0.82449	0.88221	1.0000	

Table 2. Unit Root, Granger Causality and Cointegration Tests for All Candidate Series

Variable	**Order of Int.**	**Sector**	**Granger Causality XgcY**	**Cointegration**
isacest	I(1)	Real	Yes	No
isspest	I(1)	Real	No	N/A
emiest	I(1) (at)	Real	Yes	No
ipfiele	I(1) (at)	Real	Yes	Yes*
autoprod	I(0)	Real	No	N/A
autodosa	I(0)	Real	No	N/A
resreales	I(1)*	Financial	Yes	No
M1real	I(1)*	Financial	Yes	Yes*
quasimr	I(1)	Financial	Yes	No
totdepr	I(1)	Financial	Yes	No
rcredps	I(1) (at)	Financial	Yes	Yes*
Merval	I(1)	Financial	Yes	No
M2real	I(1)	Financial	Yes	No
rtaxes	I(1)* (at)	Government	No	N/A
riva	I(1)	Government	Yes	No
rigains	I(1)	Government	Yes	Yes*
rsscon	I(0)	Government	No	N/A
rgec	I(1)	Government	No	N/A
rgecc	I(0)	Government	Yes	No
rgek	I(0)*	Government	No	N/A
autoexp	I(1) (at)	External	No	N/A
autoimp	I(1)	External	No	N/A
IVIM	I(1)	External	Yes	Yes*
IVIBI	I(1)*	External	Yes	No
IVIBK	I(1)	External	Yes	Yes*
IVICOM	I(1)	External	No	N/A
IVIABK	I(1) (at)	External	Yes	No
IVIBC	I(1)	External	Yes	No
IVE	I(1)*	External	Yes	No
IVEPP	I(1)	External	Yes	No
IVEPMA	I(1)*	External	Yes	No
IVEPM	I(1)*	External	No	No
IVECOM	I(1)*	External	No	No

Notes:
In the unit root test column the * means that series could be I(2) depending on the number of lags of the ADF test. Looking at a graph of the changes in these variables, it is not clear that the difference is I(1). There are some outliners which may influence the tests results and therefore are deemed to be I(1). In the Cointegration column the * means that variables are individually cointegrated with output in a regression with a certain number of lags and not for any lag length.

Table 3. Unit Root, Granger Causality and Cointegration Tests for Series That Satisfy the Selection Criteria Described in II.C

Variable	**Order of Int.**	**Sector**	**Granger Causality XgcY**	**Cointegration**
isacest	I(1)	Real	Yes	No
emiest	I(1) (at)	Real	Yes	No
ipfiele	I(1) (at)	Real	Yes	No
resreales	I(1)*	Financial	Yes	No
M1real	I(1)*	Financial	Yes	Yes*
quasimr	I(1)	Financial	Yes	No
totdepr	I(1)	Financial	Yes	No
rcredps	I(1) (at)	Financial	Yes	Yes*
Merval	I(1)	Financial	Yes	No
M2real	I(1)	Financial	Yes	No
riva	I(1)	Government	Yes	No
rigains	I(1)	Government	Yes	Yes*
IVIM	I(1)	External	Yes	Yes*
IVIBI	I(1)*	External	Yes	No
IVIBK	I(1)	External	Yes	Yes*
IVIABK	I(1) (at)	External	Yes	No
IVIBC	I(1)	External	Yes	No
IVE	I(1)*	External	Yes	No
IVEPP	I(1)	External	Yes	No
IVEPMA	I(1)*	External	Yes	No

Derivation of final models shown in the text.

MODEL 1

EQ(1) Modeling RGDP by OLS (using coincident1paper.in7)
The present sample is: 1993 (4) to 2000 (1)

Variable	Coefficient	Std.Error	t-value	HCSE	PartR^2
Constant	4.949300	1.058600	4.675	1.53490	0.6096
RGDP_1	-0.444510	0.214590	-2.071	0.23978	0.2346
RGDP_2	-0.179800	0.203130	-0.885	0.29878	0.0530
RGDP_3	-0.337260	0.177280	-1.902	0.15741	0.2054
rcredps	0.066970	0.219580	0.305	0.26233	0.0066
rcredps_1	-0.145910	0.304660	-0.479	0.34890	0.0161
rcredps_2	0.381680	0.281010	1.358	0.18859	0.1164
rcredps_3	-0.081028	0.181950	0.445	0.15682	0.0140
IVIM	0.340730	0.051206	6.654	0.047229	0.7598
IVIM_1	-0.010362	0.117460	-0.088	0.11999	0.0006
IVIM_2	0.101020	0.109820	0.920	0.11065	0.0570
IVIM_3	0.051330	0.062785	0.818	0.056926	0.0456

R^2 = 0.980022 F(11,14) = 62.432 [0.0000] \sigma = 0.0138259
RSS = 0.002676174338 for 12 variables and 26 observations

Solved Static Long Run equation
RGDP = +2.523 +0.113 rcredps +0.2461 IVIM
(SE) (0.03865) (0.04076) (0.03276)

ECM = RGDP - 2.52311 - 0.113029*rcredps - 0.246089*IVIM;

WALD test Chi^2(2) = 1845.1 [0.0000] **

*The results above show the cointegrating vector and the error correction variable presented in the text. Below each coefficient the standard error is presented. Dividing the coefficients by their standard error, it can be seen that they all seem to be significant. The WALD test null is that all coefficients in the cointegrating vector are 0. The ** mean that the null is rejected at a 1% level.*

AR 1- 5 F(5, 9) = 1.23370 [0.3686]
ARCH 4 F(4, 6) = 0.30083 [0.8675]
Normality Chi^2(2)= 0.94028 [0.6249]
RESET F(1, 13) = 0.94166 [0.3496]

These are the same misspecification tests presented in the text but for the unrestricted model. As it can be seen, there does not seem to be any misspecification problem.

EQ(1) Modeling RGDP by OLS (using coincident1paper.in7)
The present sample is: 1993 (4) to 2000 (1) less 9 forecasts
The forecast period is: 1998 (1) to 2000 (1)

Tests of parameter constancy over: 1998 (1) to 2000 (1)
Chow F(9, 5) = 0.906530 [0.5780]

This is the same ex-post forecasting test presented in the text only that the demands are not as high as for the final model. Parameter constancy since 1998 is required to all unrestricted models and not since 1997. It can be seen that parameter constancy cannot be rejected. The combination of these results show that this unrestricted model is a valid representation of that data.

EQ(2) Modeling D3RGDP by OLS (using coincident1paper.in7)
The present sample is: 1993 (4) to 2000 (1)

Variable	Coefficient	Std.Error	t-value	HCSE	PartR^2
D2RGDP_1	0.44451	0.18771	-2.368	0.22917	0.2480
DRGDP_2	-0.17980	0.17476	-1.029	0.27432	0.0586
D3IVIM	0.34073	0.037859	9.000	0.039276	0.8265
D2IVIM_1	-0.010362	0.10121	-0.102	0.10874	0.0006
DIVIM_2	0.10102	0.097933	1.032	0.097992	0.0589
D3rcredps	0.06697	0.16821	0.398	0.21373	0.0092
D2rcredps_1	-0.14591	0.27443	-0.532	0.31581	0.0164
Drcredps_2	0.38168	0.25341	1.506	0.17014	0.1177
ECMfullsample_3	-1.96160	0.35746	-5.488	0.57999	0.6392

sigma = 0.0125468
RSS = 0.002676174338 for 9 variables and 26 observations

This is the same model as above. Notice that the residual sum of squares is identical. The difference is that it is written in the error correction form. The estimated cointegrating coefficients are used to calculate the error correction term.

AR 1- 5 F(5, 12) = 1.34520 [0.3107]
ARCH 4 F(4, 9) = 0.45124 [0.7696]
Normality Chi^2(2)= 0.94028 [0.6249]
RESET F(1, 16) = 0.17054 [0.6851]

The misspecification tests show that there does not seem to be any misspecification problem.

WALD test for linear restrictions: Subset
LinRes F(5, 17) = 0.2874 [0.9135]

Zero restrictions on:
DRGDP_2 D2IVIM_1 DIVIM_2 D3rcredps D2rcredps_1

The above test shows that the null that the coefficients of DRGDP_2 D2IVIM_1 DIVIM_2 D3rcredps D2rcredps_1 are all equal to 0 cannot be rejected at 5% or 1% significance levels. Imposing this constraints on the previously shown model gives the final version analyzed in the main text. Since the process is exactly the same for the other two models, results are shown without any explanation.

MODEL 2

EQ(1) Modeling RGDP by OLS (using coincident2.in7)
The present sample is: 1993 (4) to 2000 (1)

Variable	Coefficient	Std.Error	t-value	HCSE	PartR^2
Constant	1.497200	0.320180	4.676	0.254810	0.6097
RGDP_1	0.329200	0.111830	2.944	0.073669	0.3823
RGDP_2	-0.202870	0.102660	-1.976	0.100590	0.2181
M1real	0.088485	0.046172	1.916	0.029836	0.2078
M1real_1	-0.040092	0.033260	-1.205	0.036918	0.0940
M1real_2	0.224580	0.043024	5.220	0.051749	0.6606
ipfiele	0.258890	0.051331	5.044	0.045018	0.6450
ipfiele_1	-0.129880	0.076412	-1.700	0.063933	0.1711
ipfiele_2	0.117260	0.064271	1.825	0.061852	0.1921
IVIBC	0.097673	0.021287	4.588	0.012927	0.6006
IVIBC_1	-0.067790	0.023203	-2.922	0.020390	0.3788
IVIBC_2	0.018563	0.024878	0.746	0.022307	0.0382

R^2 = 0.99675 F(11,14) = 390.29 [0.0000] \sigma = 0.00557673
RSS = 0.0004353995546 for 12 variables and 26 observations

Solved Static Long Run equation

RGDP =	+1.714	+0.3124 M1real	+0.2819 ipfiele
(SE)	(0.2192)	(0.02946)	(0.07408)
	+0.05545 IVIBC		
	(0.01876)		

ECM = RGDP - 1.71366 - 0.312446*M1real - 0.281882*ipfiele -0.0554509*IVIBC;

WALD test Chi^2(3) = 1792.7 [0.0000] **

AR 1- 5 F(5, 9) = 1.45730 [0.2934]
ARCH 4 F(4, 6) = 0.24948 [0.8999]
Normality Chi^2(2)= 0.49721 [0.7799]
RESET F(1, 13) = 0.70423 [0.4165]

EQ(1) Modeling RGDP by OLS (using coincident2.in7)
The present sample is: 1993 (4) to 2000 (1) less 9 forecasts
The forecast period is: 1998 (1) to 2000 (1)

Tests of parameter constancy over: 1998 (1) to 2000 (1)
Chow F(9, 5) = 1.0988 [0.4848]

The model presented in the text is this same model just written in the error correction form given that no further simplification is possible without damaging substantially the results of the forecast tests.

MODEL 3

EQ(1) Modeling RGDP by OLS (using coincident3solo.in7)
The present sample is: 1993 (4) to 2000 (1)

Variable	Coefficient	Std.Error	t-value	HCSE	PartR^2
Constant	0.61783	0.27189	2.272	0.266890	0.2330
RGDP_1	0.29164	0.11628	2.508	0.138900	0.2701
RGDP_2	0.13855	0.12285	1.128	0.094862	0.0696
M1real	0.061595	0.043706	1.409	0.038688	0.1046
M1real_1	0.058652	0.045888	1.278	0.040983	0.0877
M1real_2	0.094209	0.053286	1.768	0.056620	0.1553
emi	0.53729	0.051151	10.504	0.045958	0.8665
emi_1	-0.37479	0.074992	-4.998	0.097127	0.5950
emi_2	0.076340	0.067822	1.126	0.076099	0.0694

R^2 = 0.993318 F(8,17) = 315.89 [0.0000] \sigma = 0.00725614
RSS = 0.0008950767697 for 9 variables and 26 observations

Solved Static Long Run equation

RGDP =	+1.084	+0.3764 M1real	+0.4191 emi
(SE)	(0.3363)	(0.03449)	(0.08267)

ECM = RGDP - 1.08428 - 0.376367*M1real - 0.419143*emi;

WALD test Chi^2(2) = 562.89 [0.0000] **

AR 1- 5 F(5, 12) = 0.50083 [0.7702]
ARCH 4 F(4, 9) = 0.47381 [0.7544]
Normality Chi^2(2)= 1.62110 [0.4446]
RESET F(1, 16) = 0.17686 [0.6797]

EQ(1) Modeling RGDP by OLS (using coincident3solo.in7)

The present sample is: 1993 (4) to 2000 (1) less 9 forecasts
The forecast period is: 1998 (1) to 2000 (1)

Tests of parameter constancy over: 1998 (1) to 2000 (1)
Chow F(9, 8) = 1.599 [0.2599]

EQ(2) Modeling D2RGDP by OLS (using coincident3solo.in7)
The present sample is: 1993 (4) to 2000 (1)

Variable	Coefficient	Std.Error	t-value	HCSE	PartR^2
DRGDP_1	0.29164	0.10228	2.851	0.132170	0.2890
D2emi	0.53729	0.032155	16.709	0.028754	0.9332
Demi_1	-0.37479	0.062182	-6.027	0.083484	0.6449
D2M1real	0.061595	0.028408	2.168	0.039804	0.1903
DM1real_1	0.058652	0.040385	1.452	0.040396	0.0954
ECMfullsample_2	-0.56981	0.074078	-7.692	0.080483	0.7474

\sigma = 0.00668983
RSS = 0.0008950767697 for 6 variables and 26 observations

AR 1- 5 F(5, 15) = 0.58358 [0.7124]
ARCH 4 F(4, 12) = 0.63175 [0.6493]
Normality Chi^2(2)= 1.62110 [0.4446]
Xi^2 F(12, 7) = 1.45940 [0.3167]
RESET F(1, 19) = 0.24390 [0.6271]

WALD test for linear restrictions: Subset
LinRes F(1, 20) = 2.1093 [0.1619]

Zero restrictions on:
DLM1real_1

Cointegration tests

All cointegration tests in the paper are done in exactly the same way. They are calculated using the Dynamic analysis option in PcGive's test menu. As explained in the text, the existence of cointegration is determined by showing that the error correction mechanism is well defined. An error correction mechanism is considered to be well defined in this paper if:

The unit root t test for the feedback coefficient rejects the null of it been equal to 0
Unit root t tests for each variable in the candidate cointegrating vector is above 2.3
Each independent variable (i.e., contemporaneous and lagged terms of it) is significant at least at a 5% level

Note: The constant is not considered a variable.

MODEL 1

Tests on the significance of each variable

Variable	F-test	Value	Probability		Unit-root t-test
RGDP	F(3, 14) =	2.6629	[0.0884]		-4.7744**
Constant	F(1, 14) =	21.8570	[0.0004]	**	
rcredps	F(4, 14) =	3.3402	[0.0406]	*	2.3085
IVIM	F(4, 14) =	17.6700	[0.0000]	**	4.337

*The reported F tests null hypotheses are that the coefficients of the contemporaneous term of a variable and all its lags are 0. The value of the F test and the associated probabilities are interpreted just like in the text. This means that rcredps and IVIM are significant at a 5% level. The unit root test presented in the row of real GDP (RGDP) is the unit root t test for the feedback coefficient. The ** asterisks mean that the null of it been equal to 0 is rejected at a 1% level. Finally unit root tests for each variable are above 2.3. According to the definition of cointegration used in this paper, the error correction mechanism is considered to be well defined. Results for the other two models follow and the interpretation is exactly the same. Bivariate cointegration tests are not reported due to space constraints. Results are available from the author upon request.*

MODEL 2

Tests on the significance of each variable

Variable	F-test	Value	Probability		Unit-root t-test
RGDP	F(2, 14) =	4.6538	[0.0282]	*	-7.5798**
Constant	F(1, 14) =	21.8660	[0.0004]	**	
M1real	F(3, 14) =	12.3140	[0.0003]	**	5.223
ipfiele	F(3, 14) =	10.1610	[0.0008]	**	4.0783
IVIBC	F(3, 14) =	8.2939	[0.0020]	**	2.5561

MODEL 3

Tests on the significance of each variable

Variable	F-test	Value	Probability		Unit-root t-test
RGDP	F(2, 17) =	8.2363	[0.0032]	**	-5.2143**
Constant	F(1, 17) =	5.1637	[0.0363]	*	
M1real	F(3, 17) =	7.6608	[0.0019]	**	4.2464
emi	F(3, 17) =	44.5310	[0.0000]	**	5.1252

Algebra to derive the equivalent of a coincident indicator for Model 1.

The predicted value of the equation for model 1 (PV1) is:

-0.4311 D2RGDP_1+0.3386 D3IVIM +0.3182 Drcredps_2 -1.72 ECMfullsample_3 where:

ECMfullsample_3=RGDP_3 - 2.52311 - 0.113029*rcredps_3 0.246089*IVIM_3
D2RGDP= $RGDP_{t-1}$-$RGDP_{t-3}$
D3IVIM= $IVIM_t$-$IVIM_{t-3}$
Drcredps_2= $rcredps_{t-2}$-$rcredps_{t-3}$

The prediction for $RGDP_t$= CI = PV1 + $RGDP_{t-3}$. This means that after rounding the numbers in the above definitions and doing the appropiate substitutions the following expression is obtained:

$$CI = -0.43\,(RGDP_{t-1}-RGDP_{t-3}) + 0.34\,(IVIM_t-IVIM_{t-3}) + 0.32(rcredps_{t-2}-rcredps_{t-3})$$

$$-1.72\,(RGDP_{t-3} - 2.52 - 0.11*\,rcredps_{t-3} - 0.25*\,IVIM_{t-3}) + RGDP_{t-3}$$

Rearranging this expression yields:

$$CI = +2.52*1.72 - 0.43*\,RGDP_{t-1} + (0.43-1.72+1)*RGDP_{t-3} + 0.34*IVIM_t$$

$$+(-0.34+ 0.25*1.72)\,IVIM_{t-3} + 0.32*rcredps_{t-2} + (-0.32+0.11*1.72)*\,rcredps_{t-3}$$

Simplifying yields the expression shown in the text:

$$CI = 4.33-0.43*\,RGDP_{t-1} - 0.29*RGDP_{t-3} + 0.34*IVIM_t + 0.09*IVIM_{t-3}$$

$$+0.32*rcredps_{t-2} - 0.13*\,rcredps_{t-3}$$

Figure 1: Model 1

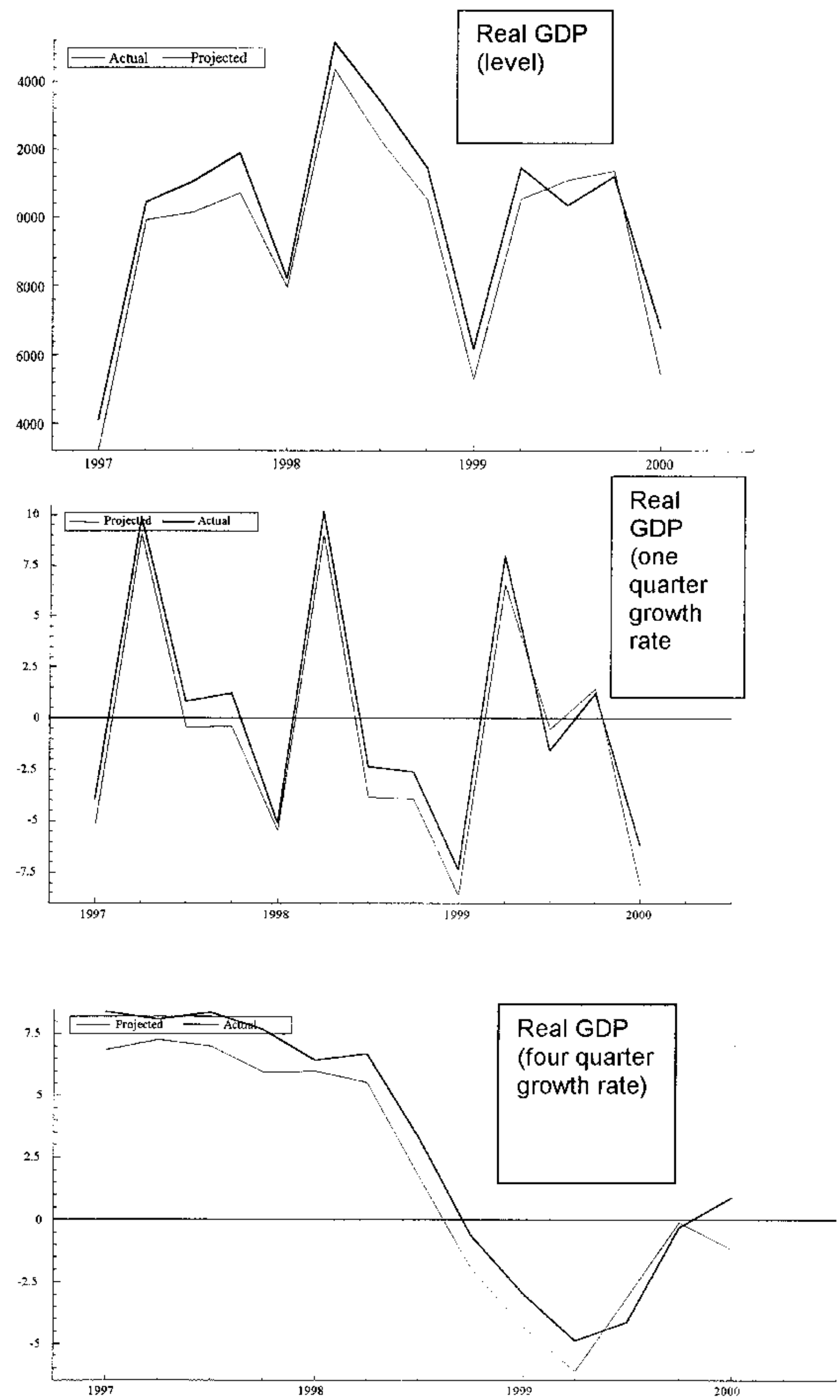


Figure 2: Model 2

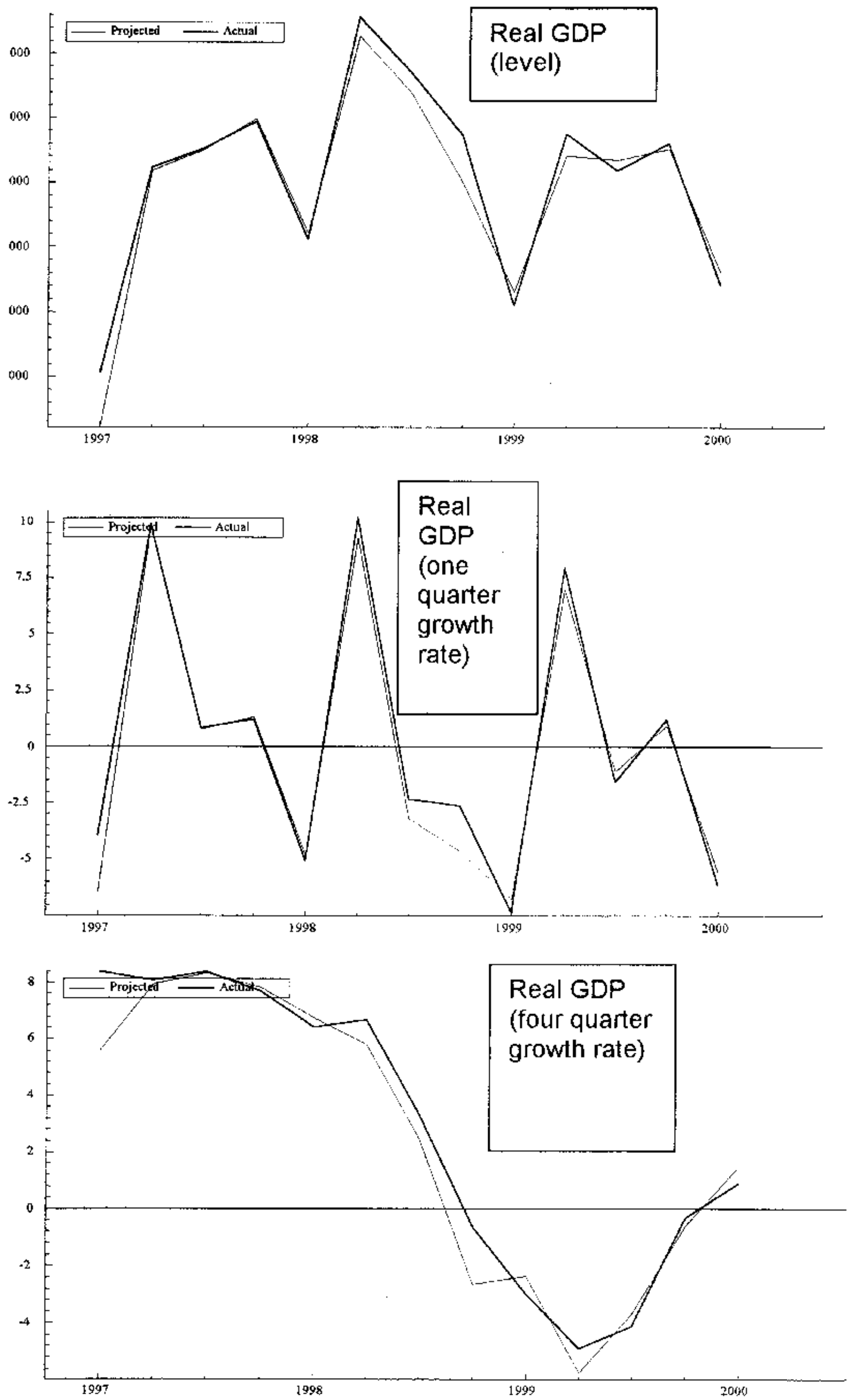
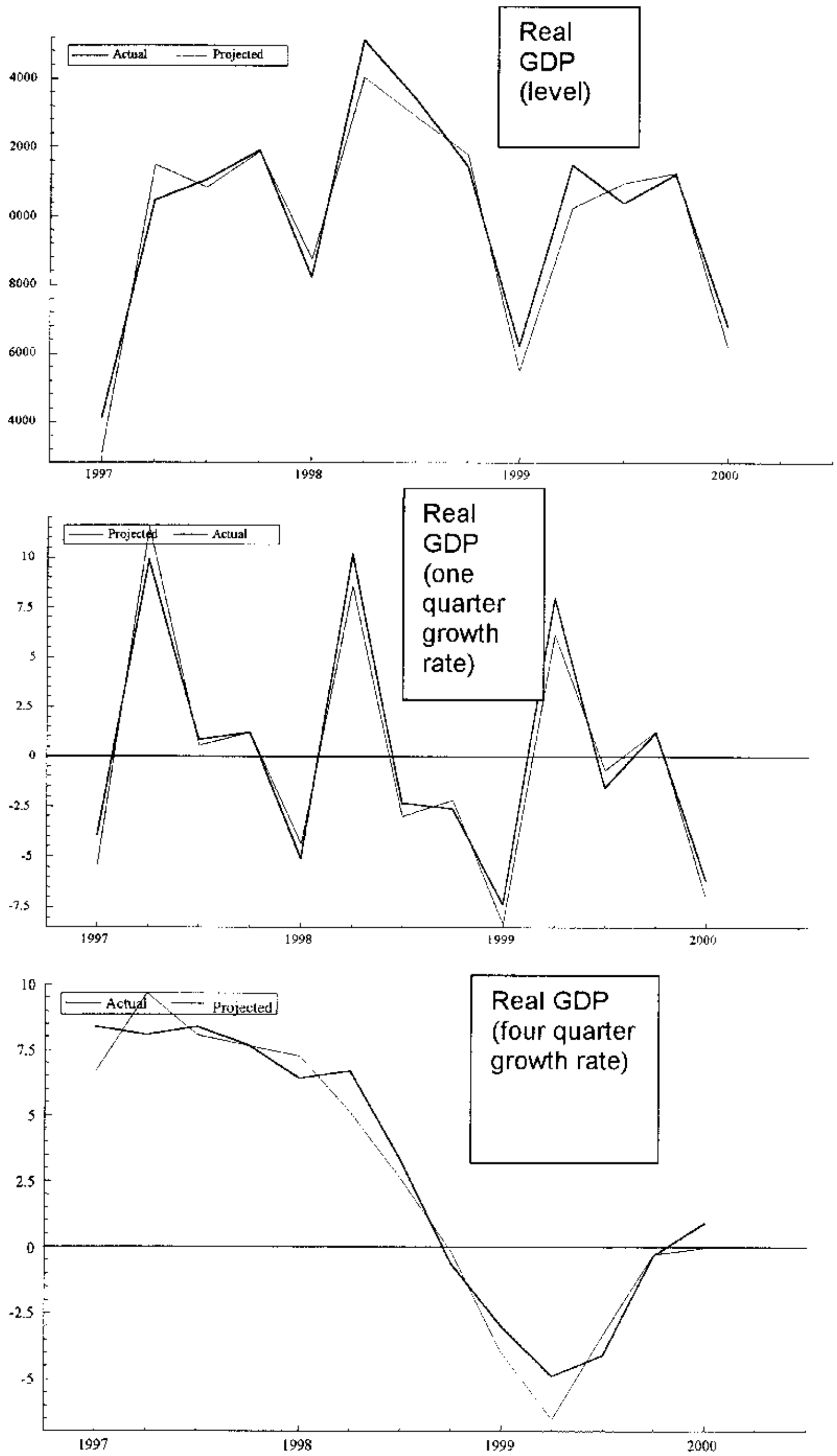


Figure 3: Model 3



Track Record Sheet number 1

Coincident 1 (Past RGDP,
IVIM,Cred.priv.sector)
Ex Ante Performance 1-step ahead forecasts

# if For.	13

Signs	1Q	4Q
% correct	84.62%	92.31%

Measures of Point Forecast Accuracy

	Level	1Q GR	4Q GR
RMSFError	888.7748	1.26	1.31
MAD	825.4283	1.17	1.21

Precision of the Estimates

AUBDE	3.02%	3.0	3.1
ALBDE	2.93%	2.9	3.0

DTR	Level	Pr. Level	E%ac.val	1Q GR	Pr 1QGR	pp error	4Q GR	Pr 4QGR	pp error
1997Q1	64096.93	63206.31	-1.39%	-3.98%	-5.32%	1.33	8.38%	6.87%	1.51
1997Q2	70442.43	69902.188	-0.77%	9.90%	9.06%	0.84	8.06%	7.23%	0.83
1997Q3	71023.04	70135.621	-1.25%	0.82%	-0.44%	1.26	8.36%	7.01%	1.35
1997Q4	71878.76	70715.185	-1.62%	1.20%	-0.43%	1.64	7.68%	5.93%	1.74
1998Q1	68208.65	67943.605	-0.39%	-5.11%	-5.47%	0.37	6.41%	6.00%	0.41
1998Q2	75149	74343.042	-1.07%	10.18%	8.99%	1.18	6.68%	5.54%	1.14
1998Q3	73391.5	72262.494	-1.54%	-2.34%	-3.84%	1.50	3.33%	1.75%	1.59
1998Q4	71445.75	70505.967	-1.32%	-2.65%	-3.93%	1.28	-0.60%	-1.91%	1.31
1999Q1	66185.5	65276.925	-1.37%	-7.36%	-8.63%	1.27	-2.97%	-4.30%	1.33
1999Q2	71469.5	70533.074	-1.31%	7.98%	6.57%	1.41	-4.90%	-6.14%	1.25
1999Q3	70352.5	71076.254	1.03%	-1.56%	-0.55%	-1.01	-4.14%	-3.15%	-0.99
1999Q4	71207	71363.672	0.22%	1.21%	1.44%	-0.22	-0.33%	-0.11%	-0.22
2000Q1	66783.75	65400.257	-2.07%	-6.21%	-8.15%	1.94	0.90%	-1.19%	2.09

t test for bias in 1 step forecast errors

	Level	1QGR	4QGR
t value	-4.25761	4.3393676	4.378060611
SM	-0.98846	0.983846	1.026154
SSTD	0.837077	0.817471	0.845089
SQRN	3.605551	3.6055513	3.605551275

Forecasting Accuracy for different time horizons (see text for underlying assumption)

		Levels	1QGR	4QGR
	Signs	N/A	85%	92%
1-step-FE	RMSFE	889	1.26	1.17
	MAD	825	1.31	1.21
	Signs	N/A	83%	83%
2-step-FE	RMSFE	1298	1.85	1.9
	MAD	1215	1.73	1.77
	Signs	N/A	75%	83%
3-step-FE	RMSFE	1678	2.37	2.47
	MAD	1448	2.04	2.11
	Signs	N/A	90%	90%
4-step-FE	RMSFE	1845	2.6	2.69
	MAD	1661	2.34	2.41

References

# of for.	Number of Forecasts
RMSFE	Root mean squared forecast error
MAD	Mean Absolute Deviation
Levels	Levels of real GDP
1QGR	1 quarter growth rate
4QGR	4 quarter growth rate
AUBDE	Average distance of estimates from upper band of 95% confidence interval
ALBDE	Average distance of estimates from lower band of 95% confidence interval
DTR	Detailed Track Record
SM	1-step ahead forecast error sample mean
SSTD	1 step ahead forecast error sample standard deviation
SQRN	Square root of the number of forecasts
E%ac.val	Forecast error as a percent of actual real GDP
pp.error	Forecast error in percentage points

Track Record Sheet number 2

Coincident 2 (Past RGDP, M1rcal,ipficlc,IVIBC)
Ex Ante Performance 1-step ahead forecasts

# if For.	13

Signs	1Q	4
% correct	100.00%	100.00

Measures of Point Forecast Accuracy

	Level	1Q GR	4Q GR
RMSFError	713.3063	1.02	1.09
MAD	519.9568	0.74	0.77

Precision of the Estimates

AUBDE	1.15%	1.2	1.2
ALBDE	1.14%	1.1	1.2

DTR	Level	Pr. Level	E%ac.val	1Q GR	Pr 1QGR	pp error	4Q GR	Pr 4QGR	pp error
1997Q1	64096.93	62448.294	-2.57%	-3.98%	-6.45%	2.47	8.38%	5.59%	2.79
1997Q2	70442.43	70353.76	-0.13%	9.90%	9.76%	0.14	8.06%	7.92%	0.14
1997Q3	71023.04	71000.724	-0.03%	0.82%	0.79%	0.03	8.36%	8.33%	0.03
1997Q4	71878.76	71965.99	0.12%	1.20%	1.33%	-0.12	7.68%	7.81%	-0.13
1998Q1	68208.65	68415.467	0.30%	-5.11%	-4.82%	-0.29	6.41%	6.74%	-0.32
1998Q2	75149	74537.017	-0.81%	10.18%	9.28%	0.90	6.68%	5.81%	0.87
1998Q3	73391.5	72753.7	-0.87%	-2.34%	-3.19%	0.85	3.33%	2.44%	0.90
1998Q4	71445.75	69977.015	-2.06%	-2.65%	-4.65%	2.00	-0.60%	-2.65%	2.04
1999Q1	66185.5	66601.368	0.63%	-7.36%	-6.78%	-0.58	-2.97%	-2.36%	-0.61
1999Q2	71469.5	70819.608	-0.91%	7.98%	7.00%	0.98	-4.90%	-5.76%	0.86
1999Q3	70352.5	70691.529	0.48%	-1.56%	-1.09%	-0.47	-4.14%	-3.68%	-0.46
1999Q4	71207	71014.159	-0.27%	1.21%	0.94%	0.27	-0.33%	-0.60%	0.27
2000Q1	66783.75	67173.372	0.58%	-6.21%	-5.66%	-0.55	0.90%	1.49%	-0.59

t test for bias in 1 step forecast errors

	Level	1QG	4QGR
t value	-1.54377	1.615761	1.553778894
SM	-0.42615	0.43307	0.445385
SSTD	0.995302	0.96640	1.033518
SQRN	3.605551	3.605551	3.605551275

Forecasting Accuracy for different time horizons (see text for underlying assumption)

		Level	1QGR	4QGR
	Signs	N/	100%	100%
1-step-FE	RMSFE	71	1.02	1.09
	MAD	52	0.74	0.77
	Signs	N/	100%	100%
2-step-FE	RMSFE	65	0.91	0.92
	MAD	47	0.67	0.68
	Signs	N/	100%	100%
3-step-FE	RMSFE	86	1.22	1.21
	MAD	69	0.98	0.99
	Signs	N/	90%	100%
4-step-FE	RMSFE	97	1.38	1.37
	MAD	79	1.13	1.13

References

# of for.	Number of Forecasts
RMSFE	Root mean squared forecast error
MAD	Mean Absolute Deviation
Levels	Levels of real GDP
1QGR	1 quarter growth rate
4QGR	4 quarter growth rate
AUBDE	Average distance of estimates from upper band of 95% confidence interval
ALBDE	Average distance of estimates from lower band of 95% confidence interval
DTR	Detailed Track Record
SM	1-step ahead forecast error sample mean
SSTD	1 step ahead forecast error sample standard deviation
SQRN	Square root of the number of forecasts
E%ac.val	Forecast error as a percent of actual real GDP
pp.error	Forecast error in percentage points

Track Record Sheet number 3

Coincident 3 (Past RGDP, M1real,emi)
Ex Ante Performance 1-step ahead forecasts

# if For.	13	
Signs	1Q	4
% correct	100.00%	92.31

Measures of Point Forecast Accuracy

	Level	1Q G	4Q GR
RMSFError	723.8911	1.0	1.07
MAD	611.6618	0.8	0.90

Precision of the Estimates

AUBDE	1.42%	1.	1.5
ALBDE	1.40%	1.	1.4

DTR	Level	Pr. Leve	E%ac.val	1Q GR	Pr 1QGR	pp error	4Q GR	P 4QGR	pp error
1997Q1	64096.93	63078.72	-1.59%	-3.98%	-5.51%	1.53	8.38%	6.66%	1.72
1997Q2	70442.43	71494.02	1.49%	9.90%	11.54%	-1.64	8.06%	9.67%	-1.61
1997Q3	71023.04	70818.90	-0.29%	0.82%	0.53%	0.29	8.36%	8.05%	0.31
1997Q4	71878.76	71873.58	-0.01%	1.20%	1.20%	0.01	7.68%	7.67%	0.01
1998Q1	68208.65	68740.22	0.78%	-5.11%	-4.37%	-0.74	6.41%	7.24%	-0.83
1998Q2	75149	74050.60	-1.46%	10.18%	8.56%	1.61	6.68%	5.12%	1.56
1998Q3	73391.5	72854.58	-0.73%	-2.34%	-3.05%	0.71	3.33%	2.58%	0.76
1998Q4	71445.75	71770.83	0.46%	-2.65%	-2.21%	-0.44	-0.60%	-0.15%	-0.45
1999Q1	66185.5	65489.7	-1.05%	-7.36%	-8.34%	0.97	-2.97%	-3.99%	1.02
1999Q2	71469.5	70243.3	-1.72%	7.98%	6.13%	1.85	-4.90%	-6.53%	1.63
1999Q3	70352.5	70961.30	0.87%	-1.56%	-0.71%	-0.85	-4.14%	-3.31%	-0.83
1999Q4	71207	71235.54	0.04%	1.21%	1.26%	-0.04	-0.33%	-0.29%	-0.04
2000Q1	66783.75	66162.50	-0.93%	-6.21%	-7.08%	0.87	0.90%	-0.03%	0.94

t test for bias in 1 step forecast errors

	Level	1QG	4QGR
t value	-1.1169	1.080568	1.096846615
SM	-0.31846	0.31769	0.322308
SSTD	1.028055	1.06004	1.05949
SQRN	3.605551	3.605551	3.605551275

Forecasting Accuracy for different time horizons (see text for underlying assumption)

		Level	1QGR	4QGR
	Signs	N/	100%	92%
1-step-FE	RMSFE	72	1.07	1.07
	MAD	61	0.89	0.9
	Signs	N/	100%	100%
2-step-FE	RMSFE	67	0.98	0.95
	MAD	50	0.73	0.72
	Signs	N/	100%	100%
3-step-FE	RMSFE	76	1.1	1.07
	MAD	65	0.94	0.94
	Signs	N/	100%	90%
4-step-FE	RMSFE	132	1.93	1.89
	MAD	106	1.52	1.52

References

# of for.	Number of Forccasts
RMSFE	Root mean squared forecast error
MAD	Mean Absolute Deviation
Levels	Levels of real GDP
1QGR	1 quarter growth rate
4QGR	4 quarter growth rate
AUBDE	Average distance of estimates from upper band of 95% confidence interval
ALBDE	Average distance of estimates from lower band of 95% confidence interval
DTR	Detailed Track Record
SM	1-step ahead forecast error sample mean
SSTD	1 step ahead forecast error sample standard deviation
SQRN	Square root of the number of forecasts
E%ac.val	Forecast error as a percent of actual real GDP
pp.error	Forecast error in percentage points