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USING THE FLOW OF CONJECTURAL INFORMATION FOR SHORT TERM FORECASTING OF ECONOMIC ACTIVITY IN ARGENTINA.

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Using the flow of conjectural information for short term forecasting of economic activity in Argentina* †

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Abstract

We exploit the richness of a large data set of daily and monthly business cycle indicators by combining them to produce nowcast of contemporaneous real GDP growth as well as forecast. Nowcast outperforms two benchmark models: the one-quarter ahead forecast of an AR(1) in the previous quarter and previous quarter actual value of GDP growth used as current value predictor. When we combine indicators to produce forecasts, the RMSE forecast pooling outperforms the AR(1) benchmark model predictions at the 3, 6 and 12 month horizons. The methodology offers a valuable approach for providing timely information for policy decision making.

Abstract

Explotamos la riqueza de un gran conjunto de indicadores del ciclo de frecuencia diaria y mensual para producir predicciones en tiempo real y pronósticos del crecimiento del producto real en Argentina. Las predicciones en tiempo real superan en capacidad predictiva a dos predictores usados como benchmark: el pronóstico de un AR(1) en el trimestre previo y el propio valor observado en ese trimestre. El pronóstico fuera de la muestra utilizando ponderaciones basadas en RMSE supera al modelo AR(1) en capacidad predictiva. La metodología ofrece una alternativa valiosa para proveer información en tiempo para la toma de decisiones de política económica.

Key words: Forecast pooling, Large dataset, Real time forecast
JEL classification:C22, C53, E17

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1 Introduction

While real time assessment of the state of the economy as well as forecast of its future path are key for the conduct of monetary policy, the main source of information on economic activity are the national accounts, which are released in a quarterly basis.

Recent advances in the forecasting literature, focused on working in a rich-data environment could be very helpful to deal with this problem.[1]This literature has developed two strategies to profit from the availability of a large number of business cycle indicators to improve forecast: Factor models and forecast pooling (see Stock and Watson, 2006). Both have proved to deliver good results in terms of forecast accuracy.

In terms of producing real time forecast, pooling has the advantage of being flexible to develop a strategy to update forecast at the time new information is released.

Rich data sets can also be profited from at different frequencies during the quarter. In fact, a large data set of daily, weekly and monthly indicators are available to predict GDP within the quarter, what is known as *nowcast* in literature. This approach is real time because the estimate for current quarter GDP growth can be updated using the flow of conjectural information as new data become available.

Using a large set of daily, weekly and monthly business cycle indicators we construct a pooling and conduct nowcast and forecast of GDP growth. In the case of data based nowcast of contemporaneous GDP growth we asses the information content of these indicators in terms of the improvement they produce in forecast accuracy when they are sequentially added to the information set used to estimate current GDP growth. In this case individual estimations are combined using *Rsquared* values of fitted models, what appears to be the natural weighting method when prediction is based on estimated fitted values. We compare the performance of this combination against two benchmarks: a one quarter ahead forecast of an AR(1) model and the previous quarter GDP growth used as a benchmark.

When we forecast GDP growth one quarter ahead, we use two weighting criteria: Sample accuracy (*Rsquared*) and out of sample performance (*RMSE*). We evaluate the out of sample predictive performance of the forecast pooling compared to a univariate model taken as a benchmark.

The paper is organized as follows. In section 2 we briefly describe the

[1]See in this respect Timmerman (2006).

new developments in the forecasting literature related to working on a rich data environment. We present our empirical approach in section 3. The empirical results are shown in section 4 while section 5 concludes.

2 Methodology: Forecasting in a rich data environment

Causal econometric models often provide a satisfactory representation of the data-generating process (DGP) in terms of the behavior suggested by economic theory. These models do however tend to perform poorly when forecasting relevant time series, compared to autoregressive models. One reason for this is that the latter tend to respond better to unanticipated changes in the data-generating process, given their intrinsically adaptive nature.

In recent years the forecasting literature has made progress in several directions in order to deal with these difficulties. Models employing a large number of predictors for forecasts are now widely used. These models were developed in two avenues:

(i) Forecast pooling, which combines a considerable number of models using different weighting criteria.

(ii) Factor models, which make it possible to find summarized measures of the variability of a large number of relevant business cycle indicators.

In the first case, the path chosen aims to preserve the causal models and eventually to achieve better forecasts by expanding the group of predictors. In the second case, a large set of business cycle indicators is considered, and by means of multivariate statistical techniques, a reduced number of factors underlying those series is extracted that explain a significant portion of their variability. Empirical evidence indicates that these variables add relevant information.

2.1 Real time pooling of forecasts

Real time forecast (*nowcast*) of a given economic indicator y_t implies to conduct contemporaneous assessment of incoming information to produce continuous updates of forecast as flows of conjectural information become available. Similar to the Principal Component approach, real time forecast uses a wide variety of x_t indicators and their bivariate relationships with y_t to predict it within the quarter. Then, these individual-indicator forecasts are aggregated using different weighting criteria to asses an overall forecast of y_t. Individual autorregresive distributed lag models are estimated for each indicator and their fitted values are combined to produce a prediction of y_t for the current period. Although alternative combination procedures for combining individual bivariate forecasts are available, the use of weights based on in sample relative explanatory power *(R^2)*, seems natural when producing nowcast.

The real time forecast procedure works as follows: (i) selects the most recent data available by indicator, (ii) estimates the bivariate equation based on the last data available by indicator, (iii) produces forecast by indicator and (iv) combines the individual forecasts according to their explanatory power. One of the benefits of this approach is that the regressions do not use forecasts of the independent variables.

2.2 Pooling of forecasts

As stressed in the literature the combination of forecasts provides advantages at various levels:

(i) Forecast combinations provide diversification. Intuitively, when there is a quadratic loss function, even if one of the models outperforms another in predictive power, by generating a lower loss, a linear combination could be preferable.[2]

(ii) In the case of economies subject to structural changes, forecast combinations offer better prediction than individual models. In general, the speed at which models adapt to structural changes tends to differ. In such an instance, combination of models with differing adaptability to changes could improve on individual models forecast.

(iii) Forecast combination could be seen as a way of making forecasts more robust in the face of specification bias and variable measurement errors in individual forecasts. For example, if two forecasts have

[2] For a detailed view of the advantages of combining forecasts, see Hendry and Clements (2002), Marcellino (2002) and Timmermann (2006).

different biases, in opposing directions, it is easy to imagine that combination could generate an improvement in the forecast.

(iv) As stressed by Clements and Hendry (2006) forecast pooling can help dealing with structural breaks. In fact, they propose a battery of forecasting models that take into account break points in the mean and changes in deterministic trend.

The pooling or combination of forecasts implies combining two or more forecasts derived from models that use different predictors to produce a forecast. This technique was originally developed by Bates and Granger (1969), and the basic idea is as follows:[3]

Let $\left\{Y^h_{i,t+h}, i = 1, ..., n\right\}$ be a panel of n forecasts. The combined forecast or forecasting pool will be given by the linear combination

$$Y^h_{t+h/t} = w_0 + \sum_{i=1}^{n} w_{it} Y^h_{i,t+h/t}$$

where w_{it} is the weight of the i^{th} forecast in period t.

Bates and Granger (1969) show that the weights that minimize the mean squared forecast error (RMSE) are given by the projection to the population of $Y^h_{t+h/t}$ in a constant and the individual forecasts. Frequently the constant is omitted, and by imposing $\sum\limits_{i=1}^{n} w_{it} = 1$ it is determined that if each of the forecasts is unbiased, so is $Y^h_{t+h/t}$. As long as none of the forecasts is generated by the real model, the optimal combination of forecasts spreads the weight over a multiple combination of forecasts. The minimum $RMSE$ combining those forecasts will be variable over time if the variance and covariance matrixes for $\left(Y^h_{t+h/t}, \left\{Y^h_{i,t+h/t}\right\}\right)$ change over time.

In practice, optimal weightings are not viable because the variance and covariance matrixes are unknown. Granger and Ramanathan (1984) propose estimating weights using minimum least squares or restricted least squares, if $w_0 = 0$ and $\sum\limits_{i=1}^{n} w_{it} = 1$ is imposed, although if n is large it is expected that estimates will perform poorly, simply because by estimating a

[3]A detailed description of forecast pooling techniques and the principal developments contained in this literature can be found in Stock and Watson (2006), and in even greater detail in Timmerman (2006).

large number of parameters, uncertainty is introduced into the sample. If n is proportionate to the size of the sample, the OLS estimator is not consistent, and the combinations that use it are not asymptotically optimum. For this reason, research into the combination or pooling of forecasts has concentrated on imposing greater structure on the combination of forecasts. Among several weighting techniques we use the following two:

(i) *Weights based on in sample relative explanatory power (R^2)*: which combines forecast according to the strength of the estimated past relationship between each indicator and GDP growth.[4]

$$w_i = R_i^2 / \sum_{j=1}^{n} R_j^2$$

where $j = 1, ...n$ are the monthly indicators considered to forecast GDP growth.

(ii) *Weights based on out of sample performance (RMSE)*: In this case the combined forecast is constructed assigning weights which are inversely related to individual forecast *RMSE*

$$w_{it} = m_{it}^{-1} / \sum_{j=1}^{n} m_{jt}^{-1}, \quad where\ m_{it} = \sqrt{\sum_{s=t+1}^{t-h} \left(\hat{y}_{t+h} - y_{t+h} \right)^2 / h}$$

Here we use a variant of the weights based on the RMSE proposed by Marcellino (2002).

3 Our empirical approach

The data comprises a broad set of 55 economic indicators ranging from financial indicators to tax collection data, business surveys, disaggregated data on industrial production, use of energy at the industry level and cars sales.[5] The sample used to estimate models is 1993:QI-2006:QIV. We perform nowcast and out of sample forecast for the period 2007:QI-2007:QIV.

Series were seasonally adjusted when needed, de-trended as to make them stationary and log transformed.

[4] See Kitchen and Monaco, 2003.

[5] See Table A.1. in *Appendix I* for details.

In order to produce nowcast and forecast we estimate autoregressive distributed bivariate models with four lags for GDP for each of the corresponding business cycle indicators.

$$y_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i y_{t-i} + \sum_{i=0}^{4} \beta_i x_{jt-i} + \epsilon_t$$

Where y is real GDP growth and x_j corresponds to the j^{th} indicator calculated at a quarterly rate as to make it homogeneous with output.

Following Drechsel and Maurin (2008) we estimate simple models regressing GDP growth on individual indicators, what helps to reduce the problem of over-fitting and poor forecast performance.

Models were specified as to ensure white noise, homoskedastic and normally distributed residuals. Although very simple, models fit to the data very well.[6] This is a promising property of models for forecasting purposes, since it is highly probable that combining them would produce good out of sample forecast.

4 Empirical results

4.1 Nowcast of GDP growth

The nowcast procedure is based on updating predictions according to incoming information. Given the diversity in the publication lags of the different indicators, the series are merged into six groups and converted to a quarterly basis to sequentially update the prediction of GDP for the current quarter. In *Appendix I* we provide a description of the indicators included in each group and their frequency.

[6] See Table A.2. in *Appendix I* for details on models.

Table 1: Nowcast performance

	Sequential Updating of current GDP growth predictions						
	Actual	15 days	1 month	45 days	2 months	75 days	3 months
2007-Q1	0.01716	0.01770	0.01685	0.01287	0.01396	0.01341	0.01778
2007-Q2	0.02322	0.01807	0.02080	0.01660	0.01643	0.01782	0.01779
2007-Q3	0.01927	0.02222	0.01897	0.01632	0.01756	0.02112	0.02101
2007-Q4	0.02379	0.02301	0.02296	0.02369	0.02387	0.02127	0.02130

	Sequential Updating: Evolution of predictive preformance						
	Actual	15 days	1 month	45 days	2 months	75 days	3 months
2007-Q1	0.01716	0.00054	0.00031	0.00429	0.00320	0.00375	0.00062
2007-Q2	0.02322	0.00515	0.00242	0.00661	0.00679	0.00539	0.00542
2007-Q3	0.01927	0.00294	0.00030	0.00295	0.00171	0.00185	0.00173
2007-Q4	0.02379	0.00079	0.00084	0.00011	0.00008	0.00253	0.00250

In Table 1 we present the sequentially updated predicted values of GDP growth and their performance measured by the absolute value of the difference between actual and fitted values. It can be seen from the Table that nowcast performs exceptionally well for every quarter. Although the analysis is conducted for only one year, it seems not to be biased to over or under-predict. It can be noticed that it is not clear that performance improves with the addition of information. In fact, the prediction for the first month outperforms the prediction using the complete set of information for the current quarter. The set of variables available at the end of the first month which is used to produce this forecast includes monetary and financial indicators such interest rates, stock prices, money aggregates, as well as tax revenues, automobile sales, steel and portland cement production, and energy demand, among others.

In order to evaluate the predictive performance of nowcast relative to a benchmark we compare the three months nowcast estimation with forecast one quarter ahead of an AR(1) model for GDP growth for the same quarter. We also use as a benchmark the previous quarter actual value of GDP growth as an alternative predictor.

Table 2: Nowcast comparison

	Actual	Forecast			Relative Forecasting Performance		
		Prev. Quarter	AR (1)	Nowcast	Actual-PQ	Actual-AR	Actual-Now
2007-Q1	0.01716	0.01741	0.01638	0.01778	**-0.00025**	0.00078	-0.00062
2007-Q2	0.02322	0.01716	0.01621	0.01779	0.00605	0.00701	**0.00542**
2007-Q3	0.01927	0.02322	0.02105	0.02101	-0.00394	-0.00178	**-0.00173**
2007-Q4	0.02379	0.01927	0.01796	0.02130	0.00452	0.00584	**0.00250**

The results, shown in Table 2, indicate that the nowcast outperforms both benchmarks for three of the four quarters, although the differences among them seem to be not significant.

4.2 Out of sample forecast of GDP growth

The second exercise we conduct is to evaluate the out of sample performance of two combinations of forecasts using the models described above and compare their predictive accuracy relative to that of an autoregressive GDP growth model used as benchmark. We combine models using the two previously described weighting criteria: R^2 and the inverse of the *RMSE*. We conduct out of sample forecast for 3, 6 and 12 months horizons.

In *Table 3* we report the performance of each forecast in terms of the *RMSE* which can be compared to those of the AR(1) model. For all horizons, the combination based on out of sample relative performance (*RMSE*) has by far the best forecast accuracy. The R^2 forecast combination only outperforms the AR(1) in the shortest forecast horizon.

Table 3: RMSE of competing GDP growth models

Forecast Horizon	AR(1)	RMSE Pooling	R^2 Pooling
3 months ahead	0.00289	**0.00006**	0.0018
6 months ahead	0.00816	**0.00686**	0.0109
1 year ahead	0.01025	**0.00995**	0.0156

As proposed by Diebold and Mariano (1995), a review of the empirical literature on forecasting reveals that evaluation of the forecasting performance of alternative models is usually based on comparison of specific estimates, without any evaluation of the uncertainty of the sample.

Diebold and Mariano propose a series of tests to evaluate the null hypothesis of equal forecast accuracy of two alternative forecast methods. These tests are based on the evaluation of the presence of significant differences between the models and the data.

We evaluate the significance of the differences in predictive accuracy between RMSE forecast combination and the AR(1) model using the non-parametric sign test which allows working with very few observations, making it possible to work with all horizons.

The test considers the loss differential d_t, between two models i and j, defined as

$$d_t = [g(e_{it}) - g(e_{jt})]$$

the null hypothesis of the test is that the median loss differential is 0

$$med(g(e_{it}) - g(e_{jt})) = 0$$

Assuming that the loss differential is an iid variable , the number of positive differentials in a sample of size T follows a binomial distribution with parameters T, $\frac{1}{2}$, under the null hypothesis. The test statistic is therefore

$$S_1 = \sum_{t=1}^{T} I_+(d_t)$$

where

$$\begin{aligned} I_+(d_t) &= 1 \quad \text{if } d_t \rangle 0 \\ &= 0 \quad \text{otherwise} \end{aligned}$$

The significance of the statistic can be confirmed on the table for the accumulated binomial distribution.

We evaluate the null of equal forecast accuracy of the forecast combination compared to the benchmark model, which is rejected, indicating that RMSE forecast combination outperforms the AR(1).

5 Conclusions

While real time assessment of economic activity is crucial to evaluate the presence of inflationary pressures for monetary policy decisions purpose, GDP figures are produced in a quarterly basis and released with a certain lag.

Recent advances in the forecasting literature, focused on working in a rich-data environment have developed strategies to profit from the availability of a large number of business cycle indicators to improve forecast through the use of factor models and forecast pooling. Both have proved to deliver good results in terms of forecast accuracy.

In terms of producing real time forecast, pooling has the advantage of being flexible to sequentially update forecast at the time new information is released.

Using a large set of daily, weekly and monthly business cycle indicators we construct a pooling and conduct nowcast and forecast of Argentina's GDP growth.

In the case of data based nowcast of contemporaneous GDP growth we asses the information content of these indicators in terms of the improvement they produce in predictive accuracy when they are sequentially added to the information set used to estimate current GDP growth. In this case individual estimations are combined using *Rsquared* values of fitted models, what appears to be the natural weighting method when prediction is based on estimated fitted values.

When we conduct the out of sample forecast exercise we combine the individual forecasts through two weighting criteria: the *R-squared* and the *RMSE*.

The results show that nowcast performs exceptionally well for every quarter. Although the analysis is conducted for only one year, it seems not to be biased to over or under-predict. It can also be noticed that it is not clear that performance improves with the addition of information. In fact, the prediction for the first month outperforms the prediction using the complete set of information for the current quarter.

In order to evaluate the predictive performance of nowcast relative to a benchmark we compare the three months nowcast estimation with forecast one quarter ahead of an AR(1) model for GDP growth for the same quarter. We also use a benchmark the previous quarter actual value of GDP growth as an alternative predictor. The results also indicate that the nowcast outperforms both benchmarks for three of the four quarters, although the differences among them seem to be not significant.

The other exercise we conduct is to evaluate the out of sample predictive performance of the forecast pooling of our wide set of variables compared to a unvariate AR(1) model taken as a benchmark. We find that the forecast combinations using the *RMSE* as a weighting criteria outperforms the benchmark at the 3, 6 and 12 month horizons.

Both nowcast and out of sample forecast combining a large set of business cycle indicators to predict Argentina's GDP quarterly growth perform quite well. The methodology has a potentially broad application to any macro or goal variable of interest and it also represents a potentially valuable approach for providing timely information for policy decision making.

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Appendix I

The series used were seasonally adjusted (when necessary) using the X-12 ARIMA program, and were subsequently standardized either by differentiating them (*diff*) or by substracting a linear trend (*trend*). Table A1 presents the complete series.

Table A.1.: Data Set

Series	**Release**	**estationary**
Group 1: 15 days delay		
Autobile national production - units	monthly	dif
Autobile exports - units	monthly	dif
Autobile sales - units	monthly	dif
Autobile national sales - units	monthly	dif
Portland cement production - thousands of tons	monthly	dif
Income Revenues	monthly	tend
Income Revenues - DGI	monthly	tend
Income Revenues - DGA	monthly	dif
VAT revenue	monthly	tend
VAT revenue -DGI	monthly	dif2
MERVAL stock market index - monthly average*	daily	dif
MERVAL stock market index - at month-end	monthly	dif
Group 2: 1 month delay		
Steel rods for concrete production - tons	monthly	dif
Raw steel production - thousands of tons	monthly	dif
Cold rolled steel production - thousands of tons	monthly	dif
Hot rolled non-flat steel - thousands of tons	monthly	dif
Flat hot rolled steel - thousands of tons	monthly	dif
Energy demand sales - GWh	monthly	dif
Private M2*	daily	tend
Nominal interest rate - 30-59 days - private banks*	daily	dif
Group 3: 2 months delay		
Industrial Survey - industry stock levels manufacturing	monthly	dif
Industrial Survey - non-durable cons. goods stock levels	monthly	dif
Industrial Survey - consumer durables stock levels	monthly	dif
Industrial Survey - capital gods stock levels	monthly	dif
Industrial Survey - intermediate goods stock levels	monthly	dif
Industrial Survey -outlook manufacturing industry	monthly	dif
Industrial Survey -outlook non-durable cons. Goods	monthly	dif
Industrial Survey -outlook consumer durables	monthly	dif

Group 3: 2 months delay (cont.)		
Industrial Survey -outlook capital goods	monthly	dif
Industrial Survey -outlook intermediate goods	monthly	dif
Industrial Survey - general situation manufacturing industry	monthly	dif
Industrial Survey - general situation non-durable consumer goods	monthly	dif
Industrial Survey - general situation consumer durables	monthly	dif
Industrial Survey - general situation capital goods	monthly	dif
Industrial Survey - general situation intermediate goods	monthly	dif
Industrial Survey - manufacturing industry demand trend	monthly	dif
Industrial Survey - non-durable cons. goods demand trend	monthly	dif
Industrial Survey - consumer durables demand trend	monthly	dif
Industrial Survey - capital gods demand trend	monthly	dif
Industrial Survey - intermediate goods demand trend	monthly	dif
Industrial production index (IPI) - general level	monthly	dif
IPI - non-durable consumer goods	monthly	dif
IPI - durable consumer goods	monthly	dif
IPI - intermediate goods	monthly	dif
IPI - capital goods	monthly	dif
IPI - food and beverages	monthly	dif
IPI - cigarettes	monthly	dif
IPI - textiles input	monthly	dif
IPI - pulp and paper	monthly	dif
IPI - fuels	monthly	dif
IPI - chemicals and plastics	monthly	dif
IPI - non-metallic minerals	monthly	dif
IPI - steel	monthly	dif
IPI - metalworking	monthly	dif
IPI - automobiles	monthly	dif

* quartely figures are abtained from averaging dayla data

Table A.2.: Summary of models

Model	Dummies included	R2
variable 1	D1995M1 - D1995M2 - D2000M1 - D2001M3 - D2001M4	0.8325
variable 2		0.6545
variable 3	D2001M3 - D2001M4 - D2002M1	0.7822
variable 4		0.6056
variable 5	D1999M2	0.7443
variable 6		0.6479
variable 7	D1995M2 - D2000M1	0.7883
variable 8		0.6219
variable 9	D1995M2 - D2001M3 - D2003M1 - D2001M4 - D1996M1 - D1996M2	0.8239
variable 10	D1995M2	0.6972
variable 11		0.5798
variable 12		0.5791
variable 13	D1995M1 - D1995M2 - D1996M1 - D1996M2 - D2001M3 - D2004M2	0.8658
variable 14	D1995M1 - D1995M2 - D1996M2 - D2004M2 - D1999M4 - D2001M2	0.7130
variable 15	D1996M1 - D1996M2 - D2001M3	0.7124
variable 16	D2000M1 - D2001M3 - D2002M1	0.8154
variable 17	D2001M3 - D1995M1 - D2002M1 - D1995M2 - D2000M1 - D2001M4 - D2003M - D1996M2 - D2004M2 - D2004M2	0.8911
variable 18		0.5579
variable 19		0.5431
variable 20		0.5493
variable 21		0.6359
variable 22	D1995M1 - D1995M2 - D2001M4	0.7129
variable 23		0.5901
variable 24	D1995M1 - D1995M2 - D2001M3 - D1999M4	0.7268
variable 25	D1995M1 - D1995M2 - D2001M3	0.8158
variable 26		0.6000
variable 27		0.5966
variable 28	D1995M1 - D1995M2 - D2001M3 - D2001M4 - D1996M1 - D1996M2 - D1999M	0.8328
variable 29		0.6227
variable 30		0.5603
variable 31		0.5541
variable 32		0.5697
variable 33		0.5874
variable 34		0.6588
variable 35		0.6285
variable 36	D1995M1 - D1995M2 - D2001M3 - D2001M4 - D1999M4 - D1996M1 - D1996M	0.7877
variable 37		0.5863
variable 38		0.5821
variable 39	D1995M1 - D2001M3 - D2000M1 - D2001M4 - D2003M4	0.9408
variable 40	D1995M1 - D1995M2 - D2001M3 - D2001M4 - D1996M2	0.8089
variable 41	D1996M2 - D2003M4 -	0.8702
variable 42	D1995M1 - D2001M3 - D2000M1 - D1999M2	0.8744
variable 43	D1995M1 - D1995M2 - D2001M4	0.8363
variable 44	D1995M1 - D1995M2 - D2001M3 - D2001M4 - D1999M4 - D1998M3 - D1998M - D1996M2	0.8522
variable 45	D1995M1 - D1995M2 - D2001M3	0.7229
variable 46		0.6442
variable 47	D1995M1 - D1995M2 - D2001M3 - D1996M1 - D1996M2 - D2001M4 - D1998M - D1998M4 - D2003M1 - D2003M1	0.8626
variable 48	D2001M3 - D1996M1 - D1996M2	0.7409
variable 49		0.6701
variable 50		0.6501
variable 51	D1995M1 - D1995M2 - D2000M1 -	0.7597
variable 52		0.6861
variable 53	D1995M1 - D1995M2 - D2001M3 - D2000M1 - D2001M4	0.8336
variable 54	D2002M1-D2003M1-D2004M2-D1999M4	0.7102
variable 55	D200M22	0.7606