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USING A NOWCAST APPROACH TO ASSES BUSSINESS CYCLE CONDITIONS IN ARGENTINA

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Using a Nowcast approach to assess business cycle conditions in Argentina[*†]

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Abstract

Real-time judgment of current and future business cycle conditions is one of the mayor challenges monetary policy conduct faces. GDP *Nowcasting* has been increasingly taken into account by central banks as a measure of immediate perception of economic conditions.

We conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations. Comparing forecasting performance our results to the typical AR(1) benchmark, we conclude that the Nowcasts is superior in almost 74% of the cases. Using the Giacomoni and White (2004) test, we also concude this dfferences are statistically significant.

Resumen

Evaluar en tiempo real las condiciones económicas actuales y futuras es uno de los mayores retos a los que se enfrenta la política monetaria. El *Nowcasting* de actividad representa una potencial medida con la cual los bancos centrales pueden estudiar percepciones inmediatas de las condiciones económicas.

Realizamos un pronóstico de crecimiento del PIB de un trimestre adelante en pseudo-tiempo real mediante *bridge equations*. Comparando la capacidad predictiva de nuestro ejercicio con un benchmark AR(1), concluimos que el *Nowcast* es superior en el 74% de los casos. Usando el test de Giacomini y Whte (2004), comprobamos que estas diferencias son significativas.

Keywords: Nowcasting, bridge equations, mixed-frequency data
JEL classification: C22, C53, E37

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1 Introduction

One of the main concerns of monetary policy should be taking decisions based on *real-time* assessment of current and future business cycle conditions. Nevertheless in practice, Gross Domestic Product (GDP) -released on a quarterly basis and with an important lag- is still the main source of information on economic activity. *Nowcasting* -defined as the prediction of the present, the very near future and the very recent past (Giannone et al. (2008), Banbura et al. (2012)) - might be useful to overcome this problem.

Nowcasting, a contraction for *now* and *forecasting,* is a technique mostly applied in meteorology which has been recently introduced in economics. Basically it involves working with high frequency data from different sources to attain early estimations of a lower frequency target variable (for instance GDP). A mayor dilemma faced is that data are not all sampled at the same frequency. In recent years, forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. Following Foroni and Marcellino (2013), we will focus on one of the most common, bridge equations (Kitchen and Monaco (2003); Drechsel and Maurin (2008)), and discuss other two approaches: Mixed Data Sampling (MIDAS) equations (Ghysels et al. (2004)) and State Space representations through VARs and dynamic factor models (Arouba, Diebold and Scotti (2009)). All of them have proven effective to use mixed-frequency data and anticipate short-term developments.

In the case of Argentina, early forecast of GDP is particularly important taking into account that official GDP figures for a specific quarter are released around 10 weeks after it ends. Thus using a large set of daily and monthly business cycle indicators we conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations to deal with differences in data frequency. This framework contains three of the main aspects of Nowcasting as described by Giannone et al. (2008): (i) First it uses a large number of data series, from different sources and frequencies; (ii) it updates nowcasts and measures of their accuracy when new information becomes available (in accordance with the real-time calendar of data releases) and (iii) finally it "bridges" monthly data releases with quarterly GDP applying an out of sample performance weighted pooling to obtain a nowcast.

We compare the performance of our Nowcast against an AR(1) model used as a benchmark. Additionally, we evaluate the out of sample predictive performance compared to the AR(1) model using the Giacomini and White (2004) approach. This test focuses on conditional predictive ability, comparing rival forecasting methods in terms of today´s accuracy to produce forecast for the near future.

The paper is organized as follows. Section 2 briefly describes the developments in the forecasting literature related to working on a rich data environment and dealing with the mixed frequency issue. Our empirical approach and the results obtained from the Nowcast exercise are presented in section 3. We conduct an out of sample forecast exercise in section 4. Finally, section 5 concludes and presents future research agenda.

2 Different approaches to Nowcasting in a mixed frequency environment

Nowcast of a given economic indicator Y_t implies conducting contemporaneous assessment of incoming information to produce continuous updates of forecast -as flows of conjuntural information become available. It can be performed linking a wide variety of high frequency X_t indicators and their bivariate relationships with the low frequency target variable Y_t. In the particular case of GDP, one might then relate daily data $X^D_{j,t}$ (with $j = 1, \ldots, N_D$ being a specific day of a quarter, where

1 is the first day and N_D is the number of trading days within a quarter -assumed constant for simplicity) released within the quarter with national accounts quarterly data Y_t^Q.

Bridge equations

This first conventional approach is the simplest one and basically involves "pre-filtering" the high frequency series to match the frequency of the target variable (GDP): averaging (stocks), adding (flows) or perhaps choosing the last observation. For example, we could aggregate the daily data at the quarterly frequency using averages (thus giving implicitly each observation the same weight) to obtain:

$$X_t^Q = \frac{X_{N_D,t}^D + X_{N_{D-1},t}^D + \ldots + X_{1,t}^D}{N_D} \tag{1}$$

The next step is estimating individual autoregresive distributed lag models (DL) for each indicator:[1]

$$Y_t^Q = \mu + \beta\left(L\right) X_t^Q + u_t \tag{2}$$

where μ is an unknown parameter, $\beta\left(L\right)$ is a lag polynomial of length k and u_t is an error term.

Individual-indicator forecasts might be latter aggregated using different weighting criteria to obtain an overall forecast of Y_t^Q for the current period. The main drawback here are the potential loss of relevant information by the rudimentary aggregation process applied (i.e. discarding any information about the timing of innovations to higher-frequency data) and the misspecification problems that might arise.

An alternative to (2) could be

$$Y_t^Q = \mu + \alpha Y_{t-1}^Q + \sum_{j=0}^{N_{D-1}} \beta_j\left(L\right) X_{N_D-j,t}^Q + u_t \tag{3}$$

(3) would also be not attractive because of a parameter proliferation problem: if one has 66 working days it would be necessary to estimate $66 * k$ parameters β_j (plus μ and α). Mixed Data Sampling (MIDAS) equations are useful in this respect.

Mixed Data Sampling (MIDAS) equations

Ghysels et al. (2004)[2] propose an approach related to distributed lags models that not only is suited to deal with diverse data frequency but also is parsimonious (avoiding parameter proliferation) and enables data to govern the high frequency information weighting process. In this case the lower frequency dependent variable Y_t^Q is regressed on a distributed lag of X_t^D, which is sampled at a higher-frequency. For instance

$$Y_t^Q = \mu + \beta \sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^D\right) X_{D-j,t}^D + u_t \tag{4}$$

where $\omega N_{D-j}\left(\theta^D\right)$ a polynomial function that determines the weights for temporal aggregation, also known as the **Midas term**.

[1] Note that both the left and right hand side of the equation are sampled at the sample (low) frequency.
[2] See also Clements and Galvao 2008 and 2009

(4) gives us a linear projection of high frequency data $X_{j,t}^{D}$ in Y_t. Assuming $\sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^{D}\right) = 1$, parameters $\left(\mu, \beta, \theta^{D}\right)$ might be estimated using Non-linear least squares. The weighting function $\omega N_{D-j}\left(\theta^{D}\right)$ can have different parametrical specifications of functional forms; there is however a trade-off between flexibility and parsimony. For a simple set of experiments, Armesto et al. (2010) found that the performances of different time-aggregation approaches vary and there does not appear to be a golden rule. Some commonly use are: U-MIDAS, Almon Lag Polynomial, Beta Polynomial Weighting Function.

Note that the Midas term in (4) can be written as

$$\sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^{D}\right) X_{D-j,t}^{D} = \frac{1}{N^{D}}\left(X_{N_D,t}^{D} + X_{N_{D-1},t}^{D} + \ldots + X_{1,t}^{D}\right) + \ldots \tag{5}$$

$$\ldots + \left(\omega_0 - \frac{1}{N_D}\right) X_{N_D,t}^{D} + \left(\omega_1 - \frac{1}{N_D}\right) X_{N_{D-1},t}^{D} + \ldots$$

$$\ldots + \left(\omega_{N_D-2} - \frac{1}{N_D-2}\right) X_{2,t}^{D} + + \left(\frac{N_D-1}{N_D} - \omega_0 - \omega_1 - \ldots - \omega_{N_D-2}\right) X_{1,t}^{D}$$

substituting (5) in (4)

$$Y_t^{Q} = \mu + \beta X_t^{Q} + \beta \sum_{j=0}^{N_{D-1}} \left(\omega N_{D-j}\left(\theta^{D}\right) - \frac{1}{N_D}\right) \Delta^{N_D-j} X_{D-j,t}^{D} + u_t \tag{6}$$

(6) shows that the traditional approach to temporal aggregation, which imposes equal weights $\omega_j = \frac{1}{N_D}$ and only considers X_t^{Q} results in an omitted variable in equation (3).

State Space Representation

State Space representations treats the low-frequency variable as a high-frequency one with "missing observations", using the Kalman filter to extract the missing data. Two main approaches have been used: VAR and Factor Models. 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, a large set of business cycle indicators is considered, and by means of multivariate statistical techniques, a reduced number of factors -that explain a significant portion of their variability- underlying those series is extracted. Empirical evidence indicates that these variables add relevant information to explain the variability of the predicted variable.[3]

One the main advantages of this procedure is the use of statistically optimal techniques that do not involve any sort of approximation. Besides, the Kalman filter not only generates projections of all the variables in the model but also allows to calculate the effect of data updates (as forecasting errors). Thus a complete assessment of the role each type of economic indicator has in economic activity may be performed.

[3] Banbura et al. (2012) following Giannone, Reichlin and Small (2008) extend the forecast equation for quarterly GDP introducing the forecast of monthly GDP growth as a latent variable, related to the common factors by the static equation. Arouba, Diebold and Scotti (2009) work with a dynamic factor model treating business conditions as a unoberserved variable, related to a series of observed daily, weekly and monthly indicators, thus explicitly incorporating indicators measured at different high frequencies.

This method has been widely used in central banks (Fed, ECB) given its good predictive *performance* -in comparison with traditional forecasting methods- in the very short run. One of the conclusions different studies arrive at is that *Nowcast* are more accurate when mew information is added. *Soft* indicators turn out to be important at the beginning of each quarter but then become less relevant towards the end, when *hard* indicators are published.

3 Our exercise: Nowcast using bridge equations

Our *Nowcast* procedure using bridge equations and pooling works as follows:

(i) selects the most recent data available by indicator, using simple averages to obtain a quarterly figure

(ii) estimates the bivariate equation based on the last data available by indicator

(iii) produces a forecast by indicator and

(iv) combines the individual forecasts according to their past forecasting performance (inversely related to individual forecast *RMSFE)*

Following Drechsel and Maurin (2008), we estimate autoregressive distributed bivariate models with up to four lags of GDP for each of the corresponding business cycle indicators.[4]

$$Y_t^Q = \alpha_0 + \sum_{i=1}^{4} \alpha_i Y_{t-i}^Q + \sum_{i=0}^{4} \beta_i X_{jt-i}^Q + u_t$$

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.

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

Regarding the pooling or combination of individual models, we chose *weights based on out of sample performance (RMSFE)*. In this case the combined forecast is constructed assigning weights which are inversely related to individual forecast *RMSFE*.[5]

$$w_i = \frac{m_i^{-1}}{\sum\limits_{j=1}^{n} m_j^{-1}}, \ where \ m_i = \sqrt{\frac{\sum\limits_{t=T+1}^{T+h} \left(\hat{y}_{i,t} - y_t\right)^2}{h}}$$

3.1 Data set

The initial data set comprises a broad 37 economic indicators, including *hard* and *soft* business cycle time series, ranging from financial indicators to tax collection data, disaggregated data on industrial production, consumer confidence surveys and cars sales. Series were seasonally adjusted when neded, de-trended or differentiated to make them stationary and finally log transformed. We first define

[4]This procedure helps to reduce the problem of over-fitting and poor forecast performance.

[5]One important feasture of the weights is that they are not time-varying. Further research agenda includes exploring non fixed weighting schemes.

and estimate distributed lags models applied throughout the whole exercise[6]. The sample used to estimate models is 1993:Q1-2009:Q4. Afterwards, we perform a rolling pseudo-real-time one quarter ahead *Nowcast* exercise of GDP growth for the period 2010:Q1-2012:Q4 (window size of 64 quarters). Finally, we selecte from the initial set of indicators those that outperforme the average in terms of predictive performace, measured by the *RMSE*. This led us with a group of 20 series to construct a pooling of nowcast..In Figure 1 we provide a detailed description of both, the complete and the final set of business cycle indicators considered.

According to the timming of publication we split the the final set of indicators tin two group: those series that are available less than 10 days after the end of each month (X series), and X series that are published with a delay raging form 10 to 30 days (X series). According to this grouping of the series, the Nowcast can be sequentially updated as described in Figure 2

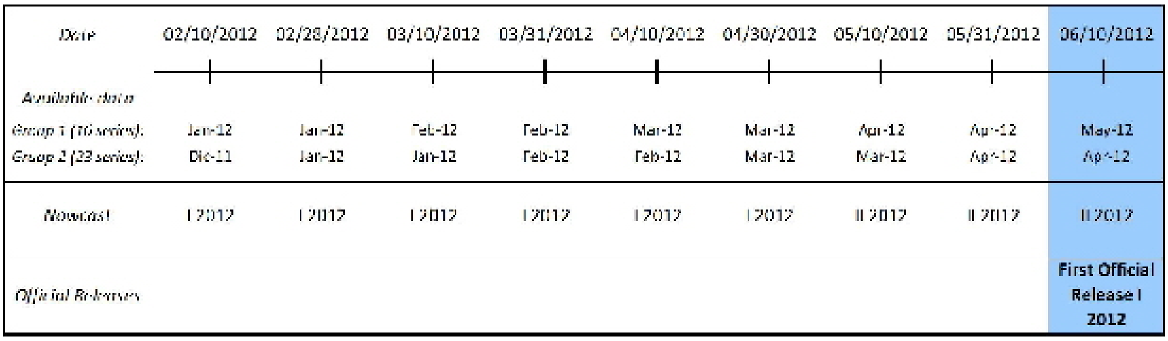
Figure 1: Data set

	Series	freq.	Source	group	SA	Stacionary
1	Automobile national production - units	monthly	ADEFA	1	si	diff
2	Automobile exports - units	monthly	ADEFA	1	si	diff
3	Automobile sales - units	monthly	ADEFA	1	si	diff
4	Automobile national sales - units	monthly	ADEFA	1	no	diff
5	Portland cement production	monthly	AFCP	1	si	diff
6	Steel rods for concrete production	monthly	CIS	2	no	diff
7	Raw steel production	monthly	CIS	2	si	diff
8	Hot rolled nonflat steel production	monthly	CIS	2	si	diff
9	Total Income revenues	monthly	MECON	1	si	trend
10	Income revenues DGI	monthly	MECON	1	si	trend
11	Income revenues DGA (customs)	monthly	MECON	1	si	diff
12	Total VAT revenues	monthly	MECON	1	si	trend
13	VAT revenues DGI	monthly	MECON	1	si	trend
14	MERVAL stock market index	daily	MERVAL	1	no	diff
15	MERVAL stock market index e.o.m.	monthly	MERVAL	1	no	diff
16	Industrial production index (IPI) - general level	monthly	Fiel	2	si	diff
17	IPI - nondurable consumer goods	monthly	Fiel	2	si	diff
18	IPI - durable consumer goods	monthly	Fiel	2	si	diff
19	IPI - intermediate goods	monthly	Fiel	2	si	diff
20	IPI - capital goods	monthly	Fiel	2	si	diff
21	IPI - food and beverages	monthly	Fiel	2	si	diff
22	IPI - cigarettes	monthly	Fiel	2	no	diff
23	IPI - textiles input	monthly	Fiel	2	si	diff
24	IPI - pulp and paper	monthly	Fiel	2	si	diff
25	IPI - fuels	monthly	Fiel	2	si	diff
26	IPI - chemicals and plastic	monthly	Fiel	2	si	diff
27	IPI - nonmetallic minerals	monthly	Fiel	2	si	diff
28	IPI - steel	monthly	Fiel	2	si	diff
29	IPI - metalworking	monthly	Fiel	2	si	diff
30	IPI - automobiles	monthly	Fiel	2	si	diff
31	Private M2* (includes foreign currency deposits)	daily	BCRA	1	si	trend
32	Interest rate on Time Deposits - Private Banks	daily	BCRA	1	no	diff
33	Gross Revenue Tax Collection - City of Buenos Aires	monthly	Min. Hacienda CABA	2	si	diff
34	Gross Revenue Tax Collection - Buenos Aires province	monthly	Min. Economía BSAS	2	no	diff
35	Poultry Production	monthly	CEPA	2	si	diff
36	Used Car Sales	monthly	CCA	1	si	diff
37	Consumer Confidence Index	monthly	UTDT	1	no	diff

Selected Series

[6]i.e. chose the lags of the dependent and indepent variables, add dummy variables if necessary and check the statistical properties of the residuals of each regression. A summary of the specification of the models is included in the Appendix.

Figure 1: Sequential updating



Date	02/10/2012	02/28/2012	03/10/2012	03/31/2012	04/10/2012	04/30/2012	05/10/2012	05/31/2012	06/10/2012
Available data									
Group 1 (16 series):	Jan-12	Jan-12	Feb-12	Feb-12	Mar-12	Mar-12	Apr-12	Apr-12	May-12
Group 2 (23 series):	Dic-11	Jan-12	Jan-12	Feb-12	Feb-12	Mar-12	Mar-12	Apr-12	Apr-12
Nowcast	I 2012	I 2012	I 2012	I 2012	I 2012	I 2012	II 2012	II 2012	II 2012
Official Releases									First Official Release I 2012

According to the sequential updating of the data, we can obtain 6 early estimations of GDP growth in each quarter. The results of our *Nowcast* exercise are presented in the next section.

3.2 Results

Figure 2 presents the sequentially updated predicted values of GDP growth. It can be seen that *Nowcast* performs better than the benchmark in almost every quarter. One of the main conclusions of the exercise is 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 some quarters.

In order to evaluate the predictive performance of the *Nowcast* relative to a benchmark we compare the RMSE of the 6 within quarter estimations with one quarter ahead forecast of an *AR(1)* model of GDP growth for the same quarter. Figure 3 shows the *Nowcast* performance measured by ratio of the RMSE of the Nowcasts relative to the RMSE of the *AR(1)* fitted values. The results, indicate that the nowcast outperforms the *AR(1)* in most of the cases.(74 % of them). Although the differences are important, one must ensure these are statistically significative.

Figure 2: Nowcast performance

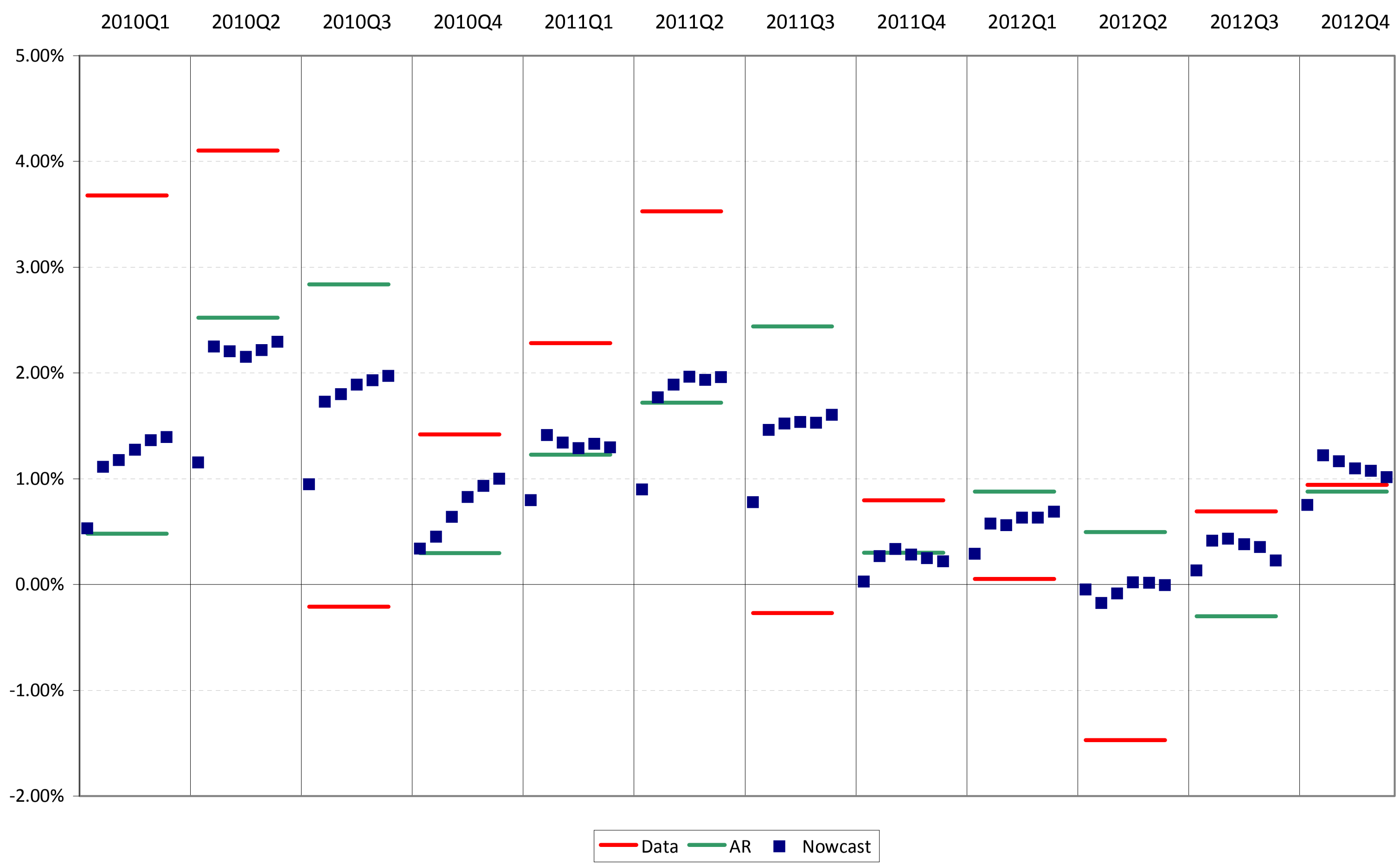
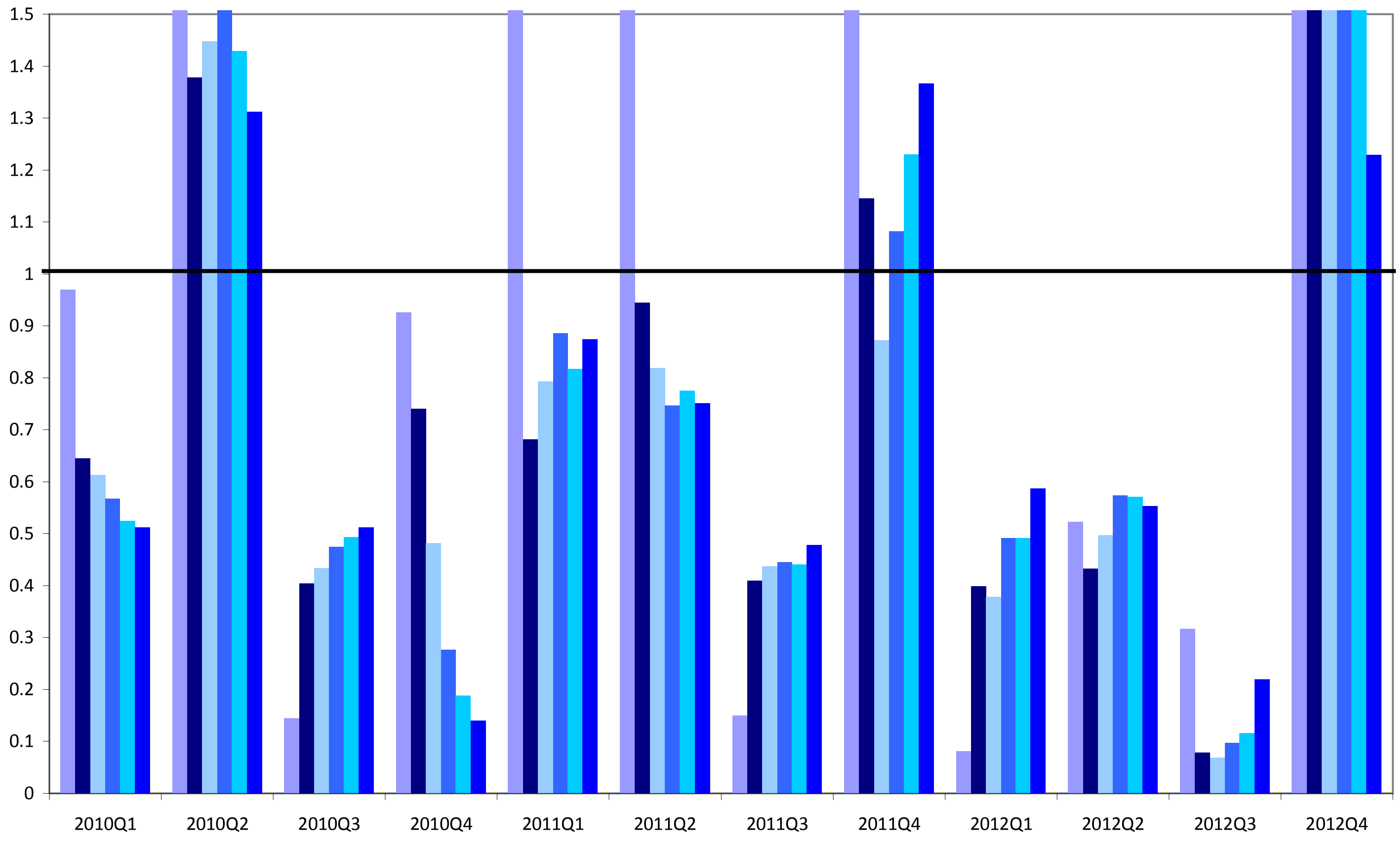


Figure 3: Nowcast relative to benchmark



Note: A number below 1 indicates that the Nowcast has a better predictive performance

4 Testing for equal predictive ability

As usual in forecast comparison, we also evaluate the out of sample forecasting performance of the *Now-casting* relative to that of the autoregressive GDP growth model used as benchmark. For this we conduct an out of sample forecast for 1 quarter ahead horizon for the period 1999Q1-2012Q4.

In this case we compare the predictive accuracy of the two previous forecasting methods: The *AR(1)* and the *Nowcast,* using the methodology developed by Giacomini and White (2004).[7] The Giacomini and White approach differs from that followed by previous accuracy evaluation methodologies, as those proposed by Dieblod and Mariano (1995) and West (2003) in what it is based on conditional rather than unconditional expectations, as it is the case of the tests proposed by the latter. In this regard, the Giacomini and White approach focuses on finding the best forecast method for the following relevant future. Their methodology is relevant for forecasters who are interested in finding methodologies that improve predictive ability of forecast, rather that testing the validity of a theoretical model.

The test has many advantages: **(i)** it captures the effect of estimation uncertainty on relative forecast performance, **(ii)** is useful for forecasts based on both nested and nonnested models, **(iii)** allows the forecasts to be produced by general estimation methods, and **(iv)** is quite easy to be computed. Following a two-step decision rule that uses current information it allows to select the best forecast for the future date of interest.

The testing methodology of Giacomini and White consists on evaluating forecast by conducting an exercise using rolling windows. That is, using the R sample observations available at time t, estimates of y_t are produced and used to generate forecast τ step ahead. The test assumes that there are two methods, f_{Rt} and g_{Rt} to generate forecasts of y_t using the available set of information $\mathcal{F}_t$. Models used are supposed to be parametric.

$$\begin{aligned} f_{Rt} &= f_{Rt}(\widehat{\gamma}_{R,t}) \\ g_{Rt} &= g_{Rt}(\widehat{\theta}_{R,t}) \end{aligned}$$

A total of P_n forecasts which satisfy $R + (P_n - 1) + \tau = T + 1$ are generated. The forecasts are evaluated using a loss function $L_{t+\tau}(y_{t+\tau}, f_{R,t})$, that depends on both, the realization of the data and the forecasts. The hypothesis to be tested is:

$$\begin{aligned} H_0 &: E\left[h_t\left(L_{t+\tau}(y_{t+\tau}, f_{R,t}) - L_{t+\tau}(y_{t+\tau}, g_{R,t})\right) \mid \mathcal{F}_t\right] = 0 \\ & \quad \text{or alternatively} \\ H_0 &: E\left[h_t \Delta L_{t+\tau} \mid \mathcal{F}_t\right] = 0 \ \ \forall\ t \geqslant 0 \end{aligned}$$

for all $\mathcal{F}_t$ -measurable function h_t.

In practice, the test consists on regressing the differences in the loss functions on a constant and evaluating its significance using the t statistic for the null of a 0 coefficient, in the case of $\tau = 1$. When τ is greater than one, standard errors are calculated using the Newey-West covariances estimator, that allows for heteroksedasticity and autocorrelation.

The results of applying the Giacomini and White procedure to evaluate the forecasting performance of the pooling relative to the *AR(1)* are shown in the next table.

[7] See Pincheira (2006) for a nice description and aplication of the test.

Table 2: Results of the Giacomini and White test

Giacomini and White test	
$n = 72$	
t- statistic	**p-value**
-4.6605	0.000

According to the test (sample 2010Q1:2012Q4) forecasts using Nowcast through *bridge equations* outperforms the *AR(1)* at the very short horizons of one quarter. Thus, it seems that rich data set can provide valuable predictions about GDP behavior in the immediate future.

5 Conclusions

One of the main concerns of monetary policy should be taking decisions based on *real-time* assessment of current and future business cycle conditions. Nevertheless in practice, Gross Domestic Product (GDP) -released on a quarterly basis and with a 10 week lag- is still the main source of information on economic activity in Argentina.

Nowcasting -defined as the prediction of the present, the very near future and the very recent past (Giannone et al. (2008), Banbura et al. (2012)) - might be useful to overcome this problem. However, a mayor dilemma faced when working in a rich-data environment is that data are not all sampled at the same frequency. In recent years, forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. On this paper we focus on one of the most used: *bridge equations*. Albeit simple, this framework contains three of the main aspects of nowcasting as described by Giannone et al. (2008): it uses a large number of data series, from different sources and frequencies; it updates nowcasts and measures of their accuracy when new information becomes available (in accordance with the real-time calendar of data releases) and finally it "bridges" monthly data releases with quarterly GDP applying an out of sample performance weighted pooling to obtain a nowcast.

Thus using a large set of daily and monthly business cycle indicators we conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations to deal with differences in data frequency. The results show that the *Nowcast* performs well, although it is not clear that the performance improves with the addition of new information along a quarter.

In order to evaluate the predictive performance of our bridge equations *Nowcast* we use an AR(1) model as a benchmark. Results indicate that the Nowcast outperforms the AR(1) model in almost 74% of the cases considered. Additionally, we evaluate the statistical significance of this differences using the Giacomini and White (2004) approach. This is a promising fact given that the AR(1) is the usual model chosen in the literature for short term forecasting.

Further research agenda includes applying more complex methods to deal with mixed frequency data. Mixed Data Sampling (MIDAS) equations and State Space representations are two of the most effective to anticipate short-term developments and enabling data to govern the high frequency information weighting process.

References

[1] Andreou, E., Ghysels, E. and A. Kourtellos (2012). *Forecasting with mixed-frequency data*. Chapter prepared for *Oxford Handbook on Economic Forecasting* edited by Michael P. Clements and David F. Hendry.

[2] Angelini, E., G. Camba-Méndez, D. Gianonni, G. Rünsler, and L. Reichlin (2008). "Short-term forecast of Euro Area GDP", European Central Bank Working Paper No. 949.

[3] Armesto, Engemann and Owyang (2010). "Forecasting with Mixed Frequencies". *Federal Reserve Bank of St. Louis Review*, November/December 2010, 92(6), pp. 521-36.

[4] Aruoba, S., Diebold, F. and C. Scotti (2009). "Real-Time Measurement of Business Conditions", *Journal of Business and Economic Statistics* 27:4 (October 2009), pp. 417-27.

[5] Banbura, Giannone, Modugno and Reichlin. (2012) "Now-casting and the real-time data flow", ECARES working paper 2012-0026.

[6] Clark, T. and K. West, (2007). "Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics*, Vol. 138, Issue 1, pp. 291-311.

[7] Clements, M. and D. Hendry (2006). "Forecasting with breaks" in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 12, Vol. 1, North-Holland.

[8] Croushore, D. (2006). "Forecasting with real-time macroeconomic data", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 17, Vol. 1, North-Holland.

[9] D'Amato, L., L. Garegnani and E. Blanco (2008). "Forecasting Inflation in Argentina: Individual Models or Forecast Pooling?", BCRA working Paper No. 35.

[10] Diebold, F. and R.S. Mariano (1995)."Comparing Predictive Accuracy", *Journal of Business & Economic Statistics*, No.13, pp. 253-263.

[11] Drechsel, K. and L.Maurin (2008). "Flow of Conjuntural Information and Forecast of Euro Area Economic Activity", ECB WP No. 925, August.

[12] Giacomini, R. and H. White, (2004). "Tests of conditional predictive ability", *Econometrica*, Vol 74 N^o 6, 1545-1578.

[13] Foroni and Marcellino (2013). "A Survey of Econometric Methods for Mixed-Frequency Data", EUI Working Paper ECO 2013/02.

[14] Giannone, D., Reichlin, L. and D. Small (2005). "Nowcasting GDP and Inflation: The Real Time Informational Content of Macroeconomic Data Releases", *CEPR Discussion Papers* 5178, C.E.P.R. Discussion Papers.

[15] Giannone, Reichlin and Small (2008). "Nowcasting: The real-time informational content of macroeconomic data". *Journal of Monetary Economics* 55 (2008) 665– 676.

[16] Ghysels, Santa-Clara and Valkanov (2004). "The MIDAS Touch: Mixed Data Sampling Regression Models", CIRANO Working Papers 2004s-20, CIRANO.

[17] Granger, C. and R. Ramanathan (1984). "Improved methods of forecasting", *Journal of Forecasting*, Vol. 3, pp. 197-204.

[18] Hendry, D. and M. Clements, (2002). "Pooling of forecasts", *Econometrics Journal*, Vol. 5, pp. 1-26.

[19] Kitchen, J. and R. Monaco (2003). "Real-Time Forecasting in Practice", Business Economics, Department of the US Treasury, October.

[20] Marcellino, M. (2002). "Forecasting pooling for short time series of macroeconomic variables", *Oxford Bulletin of Economics and Statistics* No. 66, pp. 91-112.

[21] Pincheira, P. (2006). "Conditional evaluation of exchange rate predictive abilityin long run regressions", Central Bank of Chile, Working Paper No. 378.

[22] Rünstler, G. and F. Sèdillot (2003). "Short-term estimates of Euro Area real GDP by means of monthly data", European Central Bank Working Paper No. 276.

[23] Stock, J. and M. Watson (2002a), "Macroeconomic Forecasting using diffusion indexes", *Journal of Business and Economic Statistics*, Vol. 20, pp. 147-162.

[24] Stock, J. and M. Watson (2006). "Forecasting with many predictors", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 10, Vol. 1, North-Holland.

[25] Timmermann A. (2006). "Forecast Combination", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 4, Vol. 1, North-Holland.

[26] Watson, M. (2001). "Macroeconomic Forecasting Using Many Predictors", in Advances in Economics and Econometrics: Theory and Applications, Eight World Congress, Vol. III, Chapter 3, Econometric Society.

[27] West, K. (2006). "Forecast Evaluation", , in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 3, Vol. 1, North-Holland.

Table A.2.: Summary of models

Series N°	dependent lag	independent	Dummies included (year quarter)
1	no	t	D032,D021,D014,D031,D092
2	no	t	D014,D021,D002,D092,D012,D084
3	no	t , t-1	D013,D014,D021,D084,D042
4	no	t , t-1	D993,D013,D014,D021,D084
5	t-1	t	D093,D084,D013
6	t-1	t	D014,D013,D084
7	t-1	t	D952,D014,D021,D084,D013,D951
8	t-1	t	D952,D013,D014,D021,D084
9	t-1	t	D014,D021,D084,D013
10	t-1	t , t-3	D084,D093,D013,D014,D042
11	t-1	t	D013,D08,D093,D042
12	t-1	t , t-1	D084,D031,D952
13	t-1	t , t-1	D952,D013,D084,D093,D031,D001
14	t-1	t , t-1 , t-2	D021,D952,D094
15	t-1	t , t-1	D013,D021,D043,D084,D094,D042,D002
16	no	t , t-1	D013,D014,D092
17	t-1	t	D013,D014,D093,D952,D084,D031
18	no	t , t-1	D092,D023,D034,D024,D012,D021,D084
19	t-1	t	D013,D092,D951,D992,D042
20	no	t	D014,D021,D002
21	t-1	t	D013,D084,D093,D014,D952
22	t-1	t-1	D013,D014,D043,D084,D093,D951
23	t-1	t	D084,D013,D031,D014,D952
24	t-1	t	D013,D084,D014,D952
25	t-1	t-1	D084,D014,D013,D952,D021
26	t-1	t	D013,D084,D014,D042,D093
27	t-1	t	D084,D993,D093,D013,D951
28	t-1	t	D014,D021,D952,D102,D013,D084,D031
29	t-1 , t-2	t	D014,D084,D093,D022,D103,D013
30	t-1	t	D094,D012
31	t-1	t	D084
32	t-1	t-1	D084
33	t-1	t , t-2	D013,D022,D084,D093
34	t-1	t	D084
35	t-1	t	D013,D084,D014,D093
36	t-1	t	D084,D013,D093,D021,D014
37	no	t	D014,D084,D013,D093,D031,D021

Using a Nowcast approach to asses bussiness cycle conditions in Argentina*†

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Abstract

Real-time judgment of current and future business cycle conditions is one of the mayor challenges monetary policy conduct faces. GDP *Nowcasting* has been increasingly taken into account by central banks as a measure of immediate perception of economic conditions.

We conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations. Comparing forecasting performance our results to the typical AR(1) benchmark, we conclude that the Nowcasts is superior in almost 74% of the cases. Using the Giacomoni and White (2004) test, we also concude this dfferences are statistically significant.

Resumen

Evaluar en tiempo real las condiciones económicas actuales y futuras es uno de los mayores retos a los que se enfrenta la política monetaria. El *Nowcasting* de actividad representa una potencial medida con la cual los bancos centrales pueden estudiar percepciones inmediatas de las condiciones económicas.

Realizamos un pronóstico de crecimiento del PIB de un trimestre adelante en pseudo-tiempo real mediante *bridge equations*. Comparando la capacidad predictiva de nuestro ejercicio con un benchmark AR(1), concluimos que el *Nowcast* es superior en el 74% de los casos. Usando el test de Giacomini y Whte (2004), comprobamos que estas diferencias son significativas.

Keywords: Nowcasting, bridge equations, mixed-frequency data
JEL classification: C22, C53, E37

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1 Introduction

One of the main concerns of monetary policy should be taking decisions based on *real-time* assessment of current and future business cycle conditions. Nevertheless in practice, Gross Domestic Product (GDP) -released on a quarterly basis and with an important lag- is still the main source of information on economic activity. *Nowcasting* -defined as the prediction of the present, the very near future and the very recent past (Giannone et al. (2008), Banbura et al. (2012)) - might be useful to overcome this problem.

Nowcasting, a contraction for *now* and *forecasting,* is a technique mostly applied in meteorology which has been recently introduced in economics. Basically it involves working with high frequency data from different sources to attain early estimations of a lower frequency target variable (for instance GDP). A mayor dilemma faced is that data are not all sampled at the same frequency. In recent years, forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. Following Foroni and Marcellino (2013), we will focus on one of the most common, bridge equations (Kitchen and Monaco (2003); Drechsel and Maurin (2008)), and discuss other two approaches: Mixed Data Sampling (MIDAS) equations (Ghysels et al. (2004)) and State Space representations through VARs and dynamic factor models (Arouba, Diebold and Scotti (2009)). All of them have proven effective to use mixed-frequency data and anticipate short-term developments.

In the case of Argentina, early forecast of GDP is particularly important taking into account that official GDP figures for a specific quarter are released around 10 weeks after it ends. Thus using a large set of daily and monthly business cycle indicators we conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations to deal with differences in data frequency. This framework contains three of the main aspects of Nowcasting as described by Giannone et al. (2008): (i) First it uses a large number of data series, from different sources and frequencies; (ii) it updates nowcasts and measures of their accuracy when new information becomes available (in accordance with the real-time calendar of data releases) and (iii) finally it "bridges" monthly data releases with quarterly GDP applying an out of sample performance weighted pooling to obtain a nowcast.

We compare the performance of our Nowcast against an AR(1) model used as a benchmark. Additionally, we evaluate the out of sample predictive performance compared to the AR(1) model using the Giacomini and White (2004) approach. This test focuses on conditional predictive ability, comparing rival forecasting methods in terms of today´s accuracy to produce forecast for the near future.

The paper is organized as follows. Section 2 briefly describes the developments in the forecasting literature related to working on a rich data environment and dealing with the mixed frequency issue. Our empirical approach and the results obtained from the Nowcast exercise are presented in section 3. We conduct an out of sample forecast exercise in section 4. Finally, section 5 concludes and presents future research agenda.

2 Different approaches to Nowcasting in a mixed frequency environment

Nowcast of a given economic indicator Y_t implies conducting contemporaneous assessment of incoming information to produce continuous updates of forecast -as flows of conjuntural information become available. It can be performed linking a wide variety of high frequency X_t indicators and their bivariate relationships with the low frequency target variable Y_t. In the particular case of GDP, one might then relate daily data $X^D_{j,t}$ (with $j = 1, \ldots, N_D$ being a specific day of a quarter, where

1 is the first day and N_D is the number of trading days within a quarter -assumed constant for simplicity) released within the quarter with national accounts quarterly data Y_t^Q.

Bridge equations

This first conventional approach is the simplest one and basically involves "pre-filtering" the high frequency series to match the frequency of the target variable (GDP): averaging (stocks), adding (flows) or perhaps choosing the last observation. For example, we could aggregate the daily data at the quarterly frequency using averages (thus giving implicitly each observation the same weight) to obtain:

$$X_t^Q = \frac{X_{N_D,t}^D + X_{N_{D-1},t}^D + \ldots + X_{1,t}^D}{N_D} \tag{1}$$

The next step is estimating individual autoregresive distributed lag models (DL) for each indicator:[1]

$$Y_t^Q = \mu + \beta\left(L\right) X_t^Q + u_t \tag{2}$$

where μ is an unknown parameter, $\beta\left(L\right)$ is a lag polynomial of length k and u_t is an error term.

Individual-indicator forecasts might be latter aggregated using different weighting criteria to obtain an overall forecast of Y_t^Q for the current period. The main drawback here are the potential loss of relevant information by the rudimentary aggregation process applied (i.e. discarding any information about the timing of innovations to higher-frequency data) and the misspecification problems that might arise.

An alternative to (2) could be

$$Y_t^Q = \mu + \alpha Y_{t-1}^Q + \sum_{j=0}^{N_{D-1}} \beta_j\left(L\right) X_{N_D-j,t}^Q + u_t \tag{3}$$

(3) would also be not attractive because of a parameter proliferation problem: if one has 66 working days it would be necessary to estimate $66 * k$ parameters β_j (plus μ and α). Mixed Data Sampling (MIDAS) equations are useful in this respect.

Mixed Data Sampling (MIDAS) equations

Ghysels et al. (2004)[2] propose an approach related to distributed lags models that not only is suited to deal with diverse data frequency but also is parsimonious (avoiding parameter proliferation) and enables data to govern the high frequency information weighting process. In this case the lower frequency dependent variable Y_t^Q is regressed on a distributed lag of X_t^D, which is sampled at a higher-frequency. For instance

$$Y_t^Q = \mu + \beta \sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^D\right) X_{D-j,t}^D + u_t \tag{4}$$

where $\omega N_{D-j}\left(\theta^D\right)$ a polynomial function that determines the weights for temporal aggregation, also known as the **Midas term**.

[1] Note that both the left and right hand side of the equation are sampled at the sample (low) frequency.

[2] See also Clements and Galvao 2008 and 2009

(4) gives us a linear projection of high frequency data $X_{j,t}^{D}$ in Y_t. Assuming $\sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^{D}\right) = 1$, parameters $\left(\mu, \beta, \theta^{D}\right)$ might be estimated using Non-linear least squares. The weighting function $\omega N_{D-j}\left(\theta^{D}\right)$ can have different parametrical specifications of functional forms; there is however a trade-off between flexibility and parsimony. For a simple set of experiments, Armesto et al. (2010) found that the performances of different time-aggregation approaches vary and there does not appear to be a golden rule. Some commonly use are: U-MIDAS, Almon Lag Polynomial, Beta Polynomial Weighting Function.

Note that the Midas term in (4) can be written as

$$\sum_{j=0}^{N_{D-1}} \omega N_{D-j}\left(\theta^{D}\right) X_{D-j,t}^{D} = \frac{1}{N^{D}}\left(X_{N_D,t}^{D} + X_{N_{D-1},t}^{D} + \ldots + X_{1,t}^{D}\right) + \ldots \tag{5}$$

$$\ldots + \left(\omega_0 - \frac{1}{N_D}\right) X_{N_D,t}^{D} + \left(\omega_1 - \frac{1}{N_D}\right) X_{N_{D-1},t}^{D} + \ldots$$

$$\ldots + \left(\omega_{N_D-2} - \frac{1}{N_D-2}\right) X_{2,t}^{D} + + \left(\frac{N_D-1}{N_D} - \omega_0 - \omega_1 - \ldots - \omega_{N_D-2}\right) X_{1,t}^{D}$$

substituting (5) in (4)

$$Y_t^{Q} = \mu + \beta X_t^{Q} + \beta \sum_{j=0}^{N_{D-1}} \left(\omega N_{D-j}\left(\theta^{D}\right) - \frac{1}{N_D}\right) \Delta^{N_D-j} X_{D-j,t}^{D} + u_t \tag{6}$$

(6) shows that the traditional approach to temporal aggregation, which imposes equal weights $\omega_j = \frac{1}{N_D}$ and only considers X_t^{Q} results in an omitted variable in equation (3).

State Space Representation

State Space representations treats the low-frequency variable as a high-frequency one with "missing observations", using the Kalman filter to extract the missing data. Two main approaches have been used: VAR and Factor Models. 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, a large set of business cycle indicators is considered, and by means of multivariate statistical techniques, a reduced number of factors -that explain a significant portion of their variability- underlying those series is extracted. Empirical evidence indicates that these variables add relevant information to explain the variability of the predicted variable.[3]

One the main advantages of this procedure is the use of statistically optimal techniques that do not involve any sort of approximation. Besides, the Kalman filter not only generates projections of all the variables in the model but also allows to calculate the effect of data updates (as forecasting errors). Thus a complete assessment of the role each type of economic indicator has in economic activity may be performed.

[3] Banbura et al. (2012) following Giannone, Reichlin and Small (2008) extend the forecast equation for quarterly GDP introducing the forecast of monthly GDP growth as a latent variable, related to the common factors by the static equation. Arouba, Diebold and Scotti (2009) work with a dynamic factor model treating business conditions as a unoberserved variable, related to a series of observed daily, weekly and monthly indicators, thus explicitly incorporating indicators measured at different high frequencies.

This method has been widely used in central banks (Fed, ECB) given its good predictive *performance* -in comparison with traditional forecasting methods- in the very short run. One of the conclusions different studies arrive at is that *Nowcast* are more accurate when mew information is added. *Soft* indicators turn out to be important at the beginning of each quarter but then become less relevant towards the end, when *hard* indicators are published.

3 Our exercise: Nowcast using bridge equations

Our *Nowcast* procedure using bridge equations and pooling works as follows:

(i) selects the most recent data available by indicator, using simple averages to obtain a quarterly figure

(ii) estimates the bivariate equation based on the last data available by indicator

(iii) produces a forecast by indicator and

(iv) combines the individual forecasts according to their past forecasting performance (inversely related to individual forecast *RMSFE)*

Following Drechsel and Maurin (2008), we estimate autoregressive distributed bivariate models with up to four lags of GDP for each of the corresponding business cycle indicators.[4]

$$Y_t^Q = \alpha_0 + \sum_{i=1}^{4} \alpha_i Y_{t-i}^Q + \sum_{i=0}^{4} \beta_i X_{jt-i}^Q + u_t$$

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.

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

Regarding the pooling or combination of individual models, we chose *weights based on out of sample performance (RMSFE)*. In this case the combined forecast is constructed assigning weights which are inversely related to individual forecast *RMSFE*.[5]

$$w_i = \frac{m_i^{-1}}{\sum\limits_{j=1}^{n} m_j^{-1}}, \;\; where \;\; m_i = \sqrt{\frac{\sum\limits_{t=T+1}^{T+h} \left(\hat{y}_{i,t} - y_t\right)^2}{h}}$$

3.1 Data set

The data comprises a broad set of 37 economic indicators ranging from financial indicators to tax collection data, disaggregated data on industrial production, consumer surveys and cars sales. Series were seasonally adjusted when needed, de-trended or differentiated to make them stationary and finally log transformed. We first define and estimate distributed lags models applied throughout the

[4] This procedure helps to reduce the problem of over-fitting and poor forecast performance.

[5] One important feasture of the weights is that they are not time-varying. Further research agenda includes exploring non fixed weighting schemes.

whole exercise[6]. The sample used to estimate models is 1993:Q1-2009:Q4. Afterwards we perform a rolling pseudo-real-time one quarter ahead *Nowcast* exercise of GDP growth for the period 2010:Q1-2012:Q4 (window size of 64 quarters). The data set at this point was divided into two groups: the first includes series which are available less than 10 days after the end of a certain month (16 series), the second one covers series published with a delay raging form 10 to 30 days (21 series). The description of the series is included in the table 1 below., where as the explanatory scheme of the data updating process is depicted in figure 1.

Table 1: Data set

	Series	freq.	Source	group	SA	Stacionary
1	Autobile national production - units	monthly	ADEFA	1	si	diff
2	Autobile exports - units	monthly	ADEFA	1	si	diff
3	Autobile sales - units	monthly	ADEFA	1	si	diff
4	Autobile national sales - units	monthly	ADEFA	1	no	diff
5	Portland cement production	monthly	AFCP	1	si	diff
6	Steel rods for concrete production	monthly	CIS	2	no	diff
7	Raw steel production	monthly	CIS	2	si	diff
8	Hot rolled nonflat steel production	monthly	CIS	2	si	diff
9	Total Income revenues	monthly	MECON	1	si	trend
10	Income revenues DGI	monthly	MECON	1	si	trend
11	Income revenues DGA (customs)	monthly	MECON	1	si	diff
12	Total VAT revenues	monthly	MECON	1	si	trend
13	VAT revenues DGI	monthly	MECON	1	si	trend
14	MERVAL stock market index	daily	MERVAL	1	no	diff
15	MERVAL stock market index e.o.m.	monthly	MERVAL	1	no	diff
16	Industrial production index (IPI) - general level	monthly	Fiel	2	si	diff
17	IPI - nondurable consumer goods	monthly	Fiel	2	si	diff
18	IPI - durable consumer goods	monthly	Fiel	2	si	diff
19	IPI - intermediate goods	monthly	Fiel	2	si	diff
20	IPI - capital goods	monthly	Fiel	2	si	diff
21	IPI - food and beverages	monthly	Fiel	2	si	diff
22	IPI - cigarettes	monthly	Fiel	2	no	diff
23	IPI - textiles input	monthly	Fiel	2	si	diff
24	IPI - pulp and paper	monthly	Fiel	2	si	diff
25	IPI - fuels	monthly	Fiel	2	si	diff
26	IPI - chemicals and plastic	monthly	Fiel	2	si	diff
27	IPI - nonmetallic minerals	monthly	Fiel	2	si	diff
28	IPI - steel	monthly	Fiel	2	si	diff
29	IPI - metalworking	monthly	Fiel	2	si	diff
30	IPI - automobiles	monthly	Fiel	2	si	diff
31	Private M2* (includes foreign currency deposits)	daily	BCRA	1	si	trend
32	Interest rate on Time Deposits - Private Banks	daily	BCRA	1	no	diff
33	Gross Revenue Tax Collection - City of Buenos Aires	monthly	Min. Hacienda CABA	2	si	diff
34	Gross Revenue Tax Collection - Buenos Aires province	monthly	Min. Economía BSAS	2	no	diff
35	Poultry Production	monthly	CEPA	2	si	diff
36	Used Car Sales	monthly	CCA	1	si	diff
37	Consumer Confidence Index	monthly	UTDT	1	no	diff

[6] i.e. chose the lags of the dependent and indepent variables, add dummy variables if necessary and check the statistical properties of the residuals of each regression. A summary of the specification of the models is included in the Appendix.

Figure 1: Sequential updating

Date	02/10/2012	02/28/2012	03/10/2012	03/31/2012	04/10/2012	04/30/2012	05/10/2012	05/31/2012	06/10/2012
Available data									
Group 1 (16 series):	Jan-12	Jan-12	Feb-12	Feb-12	Mar-12	Mar-12	Apr-12	Apr-12	May-12
Gruop 2 (23 series):	Dic-11	Jan-12	Jan-12	Feb-12	Feb-12	Mar-12	Mar-12	Apr-12	Apr-12
Nowcast	I 2012	I 2012	I 2012	I 2012	I 2012	I 2012	II 2012	II 2012	II 2012
Official Releases									**First Official Release I 2012**

According to the sequential updating of the data, we can obtain 6 early estimations of GDP growth in each quarter, results of the exercise are presented in the next section.

3.2 Results

Figure 2 presents the sequentially updated predicted values of GDP growth. It can be seen that *Nowcast* performs better than the benchmark in almost every quarter. One of the main conclusions of the exercise is 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 some quarters.

In order to evaluate the predictive performance of the *Nowcast* relative to a benchmark we compare the RMSE of the 6 within quarter estimations with one quarter ahead forecast of an *AR(1)* model of GDP growth for the same quarter. Figure 3 shows the *Nowcast* performance measured by ratio of the RMSE of the Nowcasts relative to the RMSE of the *AR(1)* fitted values. The results, indicate that the nowcast outperforms the *AR(1)* in most of the cases.(74 % of them). Although the differences are important, one must ensure these are statistically significative.

Figure 2: Nowcast performance

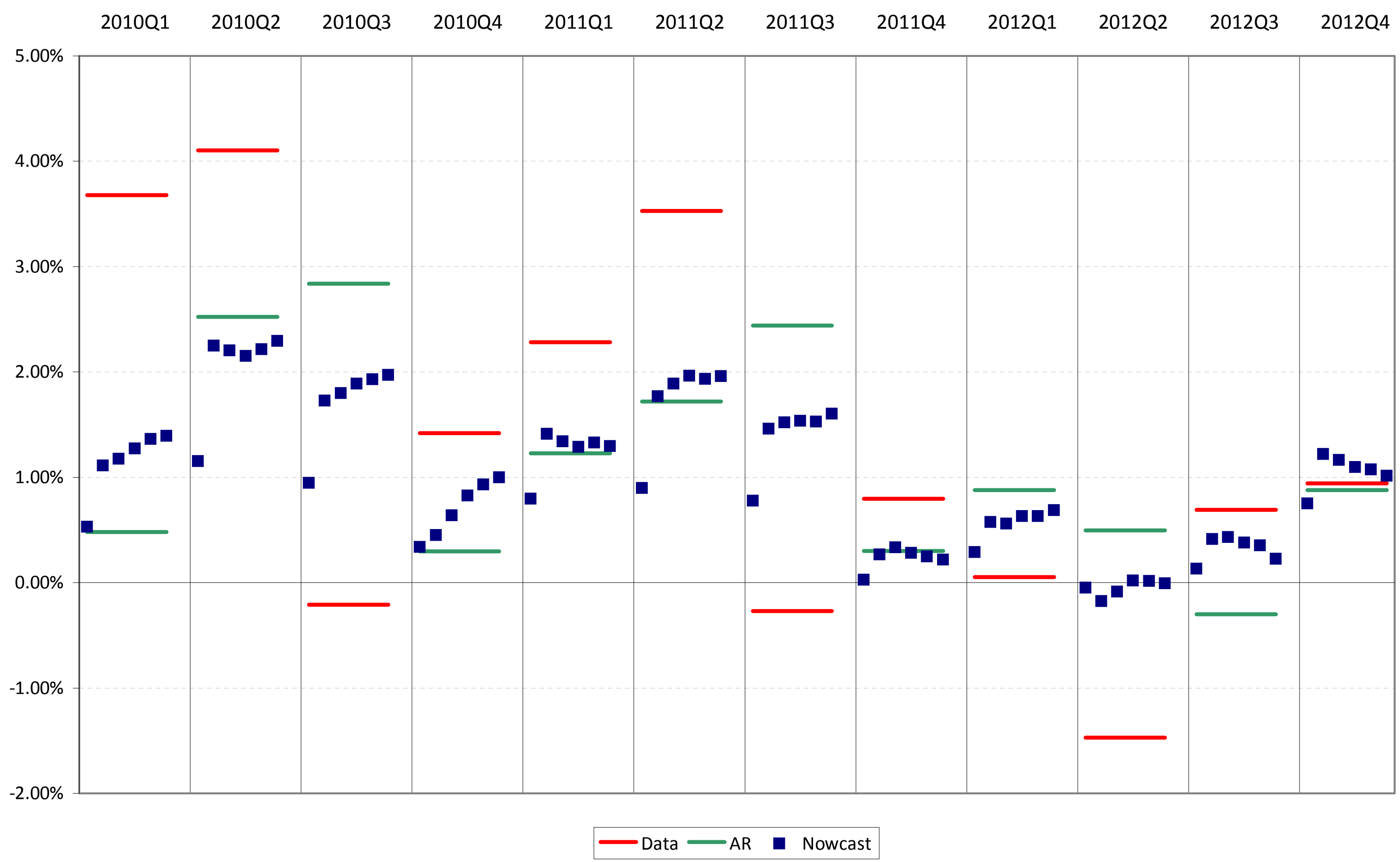
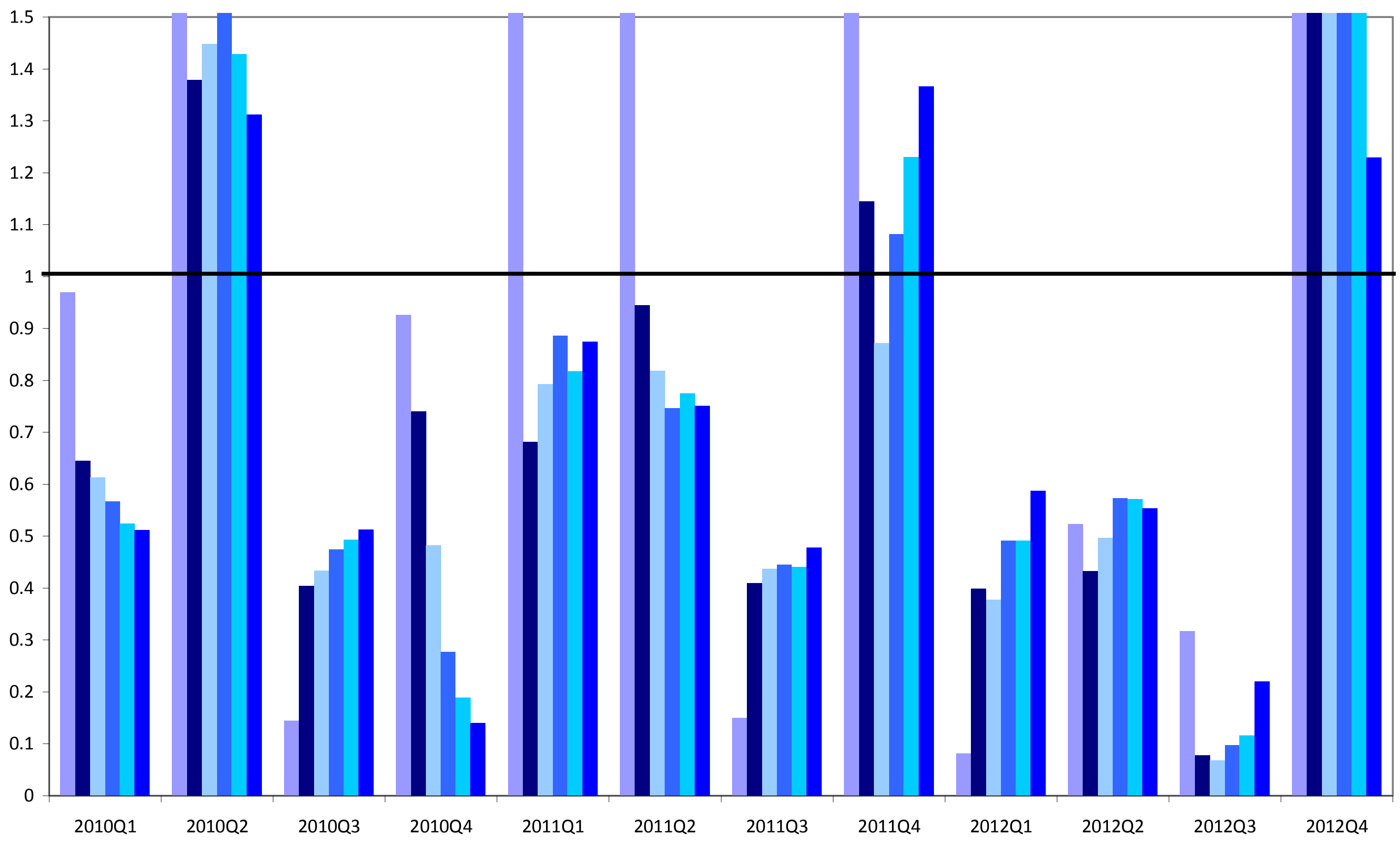


Figure 3: Nowcast relative to benchmark



Note: A number below 1 indicates that the Nowcast has a better predictive performance

4 Testing for equal predictive ability

As usual in forecast comparison, we also evaluate the out of sample forecasting performance of the *Now-casting* relative to that of the autoregressive GDP growth model used as benchmark. For this we conduct an out of sample forecast for 1 quarter ahead horizon for the period 1999Q1-2012Q4.

In this case we compare the predictive accuracy of the two previous forecasting methods: The *AR(1)* and the *Nowcast,* using the methodology developed by Giacomini and White (2004).[7] The Giacomini and White approach differs from that followed by previous accuracy evaluation methodologies, as those proposed by Dieblod and Mariano (1995) and West (2003) in what it is based on conditional rather than unconditional expectations, as it is the case of the tests proposed by the latter. In this regard, the Giacomini and White approach focuses on finding the best forecast method for the following relevant future. Their methodology is relevant for forecasters who are interested in finding methodologies that improve predictive ability of forecast, rather that testing the validity of a theoretical model.

The test has many advantages: **(i)** it captures the effect of estimation uncertainty on relative forecast performance, **(ii)** is useful for forecasts based on both nested and nonnested models, **(iii)** allows the forecasts to be produced by general estimation methods, and **(iv)** is quite easy to be computed. Following a two-step decision rule that uses current information it allows to select the best forecast for the future date of interest.

The testing methodology of Giacomini and White consists on evaluating forecast by conducting an exercise using rolling windows. That is, using the R sample observations available at time t, estimates of y_t are produced and used to generate forecast τ step ahead. The test assumes that there are two methods, f_{Rt} and g_{Rt} to generate forecasts of y_t using the available set of information $\mathcal{F}_t$. Models used are supposed to be parametric.

$$\begin{aligned} f_{Rt} &= f_{Rt}(\widehat{\gamma}_{R,t}) \\ g_{Rt} &= g_{Rt}(\widehat{\theta}_{R,t}) \end{aligned}$$

A total of P_n forecasts which satisfy $R + (P_n - 1) + \tau = T + 1$ are generated. The forecasts are evaluated using a loss function $L_{t+\tau}(y_{t+\tau}, f_{R,t})$, that depends on both, the realization of the data and the forecasts. The hypothesis to be tested is:

$$\begin{aligned} H_0 &: E\left[h_t\left(L_{t+\tau}(y_{t+\tau}, f_{R,t}) - L_{t+\tau}(y_{t+\tau}, g_{R,t})\right) \mid \mathcal{F}_t\right] = 0 \\ & \quad \text{or alternatively} \\ H_0 &: E\left[h_t \Delta L_{t+\tau} \mid \mathcal{F}_t\right] = 0 \;\; \forall\, t \geqslant 0 \end{aligned}$$

for all $\mathcal{F}_t$ -measurable function h_t.

In practice, the test consists on regressing the differences in the loss functions on a constant and evaluating its significance using the t statistic for the null of a 0 coefficient, in the case of $\tau = 1$. When τ is greater than one, standard errors are calculated using the Newey-West covariances estimator, that allows for heteroksedasticity and autocorrelation.

The results of applying the Giacomini and White procedure to evaluate the forecasting performance of the pooling relative to the *AR(1)* are shown in the next table.

[7]See Pincheira (2006) for a nice description and aplication of the test.

Table 2: Results of the Giacomini and White test

Giacomini and White test	
$n = 72$	
t- statistic	**p-value**
-4.6605	0.000

According to the test (sample 2010Q1:2012Q4) forecasts using Nowcast through *bridge equations* outperforms the *AR(1)* at the very short horizons of one quarter. Thus, it seems that rich data set can provide valuable predictions about GDP behavior in the immediate future.

5 Conclusions

One of the main concerns of monetary policy should be taking decisions based on *real-time* assessment of current and future business cycle conditions. Nevertheless in practice, Gross Domestic Product (GDP) -released on a quarterly basis and with a 10 week lag- is still the main source of information on economic activity in Argentina.

Nowcasting -defined as the prediction of the present, the very near future and the very recent past (Giannone et al. (2008), Banbura et al. (2012)) - might be useful to overcome this problem. However, a mayor dilemma faced when working in a rich-data environment is that data are not all sampled at the same frequency. In recent years, forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. On this paper we focus on one of the most used: *bridge equations*. Albeit simple, this framework contains three of the main aspects of nowcasting as described by Giannone et al. (2008): it uses a large number of data series, from different sources and frequencies; it updates nowcasts and measures of their accuracy when new information becomes available (in accordance with the real-time calendar of data releases) and finally it "bridges" monthly data releases with quarterly GDP applying an out of sample performance weighted pooling to obtain a nowcast.

Thus using a large set of daily and monthly business cycle indicators we conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth using bridge equations to deal with differences in data frequency. The results show that the *Nowcast* performs well, although it is not clear that the performance improves with the addition of new information along a quarter.

In order to evaluate the predictive performance of our bridge equations *Nowcast* we use an AR(1) model as a benchmark. Results indicate that the Nowcast outperforms the AR(1) model in almost 74% of the cases considered. Additionally, we evaluate the statistical significance of this differences using the Giacomini and White (2004) approach. This is a promising fact given that the AR(1) is the usual model chosen in the literature for short term forecasting.

Further research agenda includes applying more complex methods to deal with mixed frequency data. Mixed Data Sampling (MIDAS) equations and State Space representations are two of the most effective to anticipate short-term developments and enabling data to govern the high frequency information weighting process.

References

[1] Andreou, E., Ghysels, E. and A. Kourtellos (2012). *Forecasting with mixed-frequency data*. Chapter prepared for *Oxford Handbook on Economic Forecasting* edited by Michael P. Clements and David F. Hendry.

[2] Angelini, E., G. Camba-Méndez, D. Gianonni, G. Rünsler, and L. Reichlin (2008). "Short-term forecast of Euro Area GDP", European Central Bank Working Paper No. 949.

[3] Armesto, Engemann and Owyang (2010). "Forecasting with Mixed Frequencies". *Federal Reserve Bank of St. Louis Review*, November/December 2010, 92(6), pp. 521-36.

[4] Aruoba, S., Diebold, F. and C. Scotti (2009). "Real-Time Measurement of Business Conditions", *Journal of Business and Economic Statistics* 27:4 (October 2009), pp. 417-27.

[5] Clark, T. and K. West, (2007). "Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics*, Vol. 138, Issue 1, pp. 291-311.

[6] Clements, M. and D. Hendry (2006). "Forecasting with breaks" in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 12, Vol. 1, North-Holland.

[7] Croushore, D. (2006). "Forecasting with real-time macroeconomic data", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 17, Vol. 1, North-Holland.

[8] D'Amato, L., L. Garegnani and E. Blanco (2008). "Forecasting Inflation in Argentina: Individual Models or Forecast Pooling?", BCRA working Paper No. 35.

[9] Diebold, F. and R.S. Mariano (1995)."Comparing Predictive Accuracy", *Journal of Business & Economic Statistics*, No.13, pp. 253-263.

[10] Drechsel, K. and L.Maurin (2008). "Flow of Conjuntural Information and Forecast of Euro Area Economic Activity", ECB WP No. 925, August.

[11] Giacomini, R. and H. White, (2004). "Tests of conditional predictive ability", *Econometrica*, Vol 74 N^o 6, 1545-1578.

[12] Giannone, D., Reichlin, L. and D. Small (2005). "Nowcasting GDP and Inflation: The Real Time Informational Content of Macroeconomic Data Releases", *CEPR Discussion Papers* 5178, C.E.P.R. Discussion Papers.

[13] Granger, C. and R. Ramanathan (1984). "Improved methods of forecasting", *Journal of Forecasting*, Vol. 3, pp. 197-204.

[14] Hendry, D. and M. Clements, (2002). "Pooling of forecasts", *Econometrics Journal*, Vol. 5, pp. 1-26.

[15] Kitchen, J. and R. Monaco (2003). "Real-Time Forecasting in Practice", Business Economics, Department of the US Treasury, October.

[16] Marcellino, M. (2002). "Forecasting pooling for short time series of macroeconomic variables", *Oxford Bulletin of Economics and Statistics* No. 66, pp. 91-112.

[17] Pincheira, P. (2006). "Conditional evaluation of exchange rate predictive abilityin long run regressions", Central Bank of Chile, Working Paper No. 378.

[18] Rünstler, G. and F. Sèdillot (2003). "Short-term estimates of Euro Area real GDP by means of monthly data", European Central Bank Working Paper No. 276.

[19] Stock, J. and M. Watson (2002a), "Macroeconomic Forecasting using diffusion indexes", *Journal of Business and Economic Statistics*, Vol. 20, pp. 147-162.

[20] Stock, J. and M. Watson (2006). "Forecasting with many predictors", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 10, Vol. 1, North-Holland.

[21] Timmermann A. (2006). "Forecast Combination", in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 4, Vol. 1, North-Holland.

[22] Watson, M. (2001). "Macroeconomic Forecasting Using Many Predictors", in Advances in Economics and Econometrics: Theory and Applications, Eight World Congress, Vol. III, Chapter 3, Econometric Society.

[23] West, K. (2006). "Forecast Evaluation", , in Handbook of Economic Forecasting, Elliot, G., C. Granger and A. Timmermann, eds., Chapter 3, Vol. 1, North-Holland.

Table A.1.: Summary of models

Series N°	dependent lag	independent	Dummies included (year quarter)
1	no	t	D032,D021,D014,D031,D092
2	no	t	D014,D021,D002,D092,D012,D084
3	no	t , t-1	D013,D014,D021,D084,D042
4	no	t , t-1	D993,D013,D014,D021,D084
5	t-1	t	D093,D084,D013
6	t-1	t	D014,D013,D084
7	t-1	t	D952,D014,D021,D084,D013,D951
8	t-1	t	D952,D013,D014,D021,D084
9	t-1	t	D014,D021,D084,D013
10	t-1	t , t-3	D084,D093,D013,D014,D042
11	t-1	t	D013,D08,D093,D042
12	t-1	t , t-1	D084,D031,D952
13	t-1	t , t-1	D952,D013,D084,D093,D031,D001
14	t-1	t , t-1 , t-2	D021,D952,D094
15	t-1	t , t-1	D013,D021,D043,D084,D094,D042,D002
16	no	t , t-1	D013,D014,D092
17	t-1	t	D013,D014,D093,D952,D084,D031
18	no	t , t-1	D092,D023,D034,D024,D012,D021,D084
19	t-1	t	D013,D092,D951,D992,D042
20	no	t	D014,D021,D002
21	t-1	t	D013,D084,D093,D014,D952
22	t-1	t-1	D013,D014,D043,D084,D093,D951
23	t-1	t	D084,D013,D031,D014,D952
24	t-1	t	D013,D084,D014,D952
25	t-1	t-1	D084,D014,D013,D952,D021
26	t-1	t	D013,D084,D014,D042,D093
27	t-1	t	D084,D993,D093,D013,D951
28	t-1	t	D014,D021,D952,D102,D013,D084,D031
29	t-1 , t-2	t	D014,D084,D093,D022,D103,D013
30	t-1	t	D094,D012
31	t-1	t	D084
32	t-1	t-1	D084
33	t-1	t , t-2	D013,D022,D084,D093
34	t-1	t	D084
35	t-1	t	D013,D084,D014,D093
36	t-1	t	D084,D013,D093,D021,D014
37	no	t	D014,D084,D013,D093,D031,D021