ASOCIACION ARGENTINA
DE ECONOMIA POLITICA

ANALES | ASOCIACION ARGENTINA DE ECONOMIA POLITICA

XLIX Reunión Anual

Noviembre de 2014

ISSN 1852-0022
ISBN 978-987-28590-2-2

GDP NOWCASTING: ASSESSING BUSINESS CYCLE CONDITIONS IN ARGENTINA

D'Amato, Laura
Garegnani, Lorena
Blanco, Emilio

GDP Nowcasting: assessing business cycle conditions in Argentina*

Laura D'Amato
BCRA, UBA and UNLP

Lorena Garegnani
BCRA and UNLP

Emilio Blanco
BCRA and UBA

August 2014

Abstract

Having a correct assessment of current business cycle conditions is one of the mayor challenges for monetary policy conduct. Given that GDP figures are available with a significant delay, central banks are increasingly using *Nowcasting* as a useful tool for having an immediate perception of economic conditions. Thus we develop a GDP growth *nowcasting* exercise using two approaches: *bridge equations* and a *dynamic factor model*. Both outperform a typical AR(1) benchmark in terms of forecasting accuracy. Moreover, the factor model outperforms the *nowcast* using bridge equations. Following Giacomini and White (2004) we confirm that these differences are statistically significant.

Keywords: Nowcasting, bridge equations, dynamic factor models
JEL classification: C22, C53, E37

Resumen

Tener una correcta evaluación de las condiciones actuales del ciclo económico es uno de los mayores retos para la conducción de la política monetaria. Teniendo en cuenta que las cifras del PIB están disponibles con un retraso significativo, el uso de *Nowcasting* para tener una percepción inmediata de las condiciones cíclicas de la economía ha sido crecientemente adoptado por los bancos centrales. Desarrollamos un ejercicio de *Nowcast* del crecimiento del PIB utilizando dos enfoques: *bridge equations* y *factor models*. Ambos métodos superan en capacidad predictiva a un *benchmark* AR(1). Adicionalmente, el *Nowcast* basado en un *factor model* supera al de *bridge equations*. Finalmente, Siguiendo a Giacomini y White (2004) confirmamos que estas diferencias son estadísticamente significativas.

*The opinions expressed in this work are those of the authors, and do not necessarily reflect the opinions of the Central Bank of Argentina or its authorities. Email: ldamato@bcra.gov.ar; lgaregnani@bcra.gov.ar; emilio.blanco@bcra.gov.ar

1 Introduction

Having a good assessment of the current cyclical position of the economy is key for monetary policy decision taking. Our knowledge about the current state of the economy is, however, quite imperfect, mainly because Gross Domestic Product (GDP) -the main source of information on economic activity- is released on a quarterly basis and with an important lag. At the same time, a large number of business cycle indicators are available at higher frequencies as monthly or even daily. *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) - has proved to be a useful tool from this valuable but disperse information, to overcome the problem.

Nowcasting -a contraction for *now* and *forecasting*- is a technique mostly applied in meteorology which has been recently introduced in economics. Its basic principle is the exploitation of the valuable information content embodied in a large number of business cycle indicators that are available at high frequencies -daily or monthly- to produce early estimates of a target variable published at a lower-quarterly- frequency. This early estimations can be sequentially update, when new information becomes available. In recent years, the forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. These techniques range from combinations of simple bivariate models known as bridge equations (Kitchen and Monaco, 2003; Drechsel and Maurin, 2008) to factor models (Stock and Watson, 2002, 2010), State Space representations through VARs and dynamic factor models (Evans, 2005; Giannone, Reichlin and Small, 2008; Arouba, Diebold and Scotti, 2009) and Mixed Data Sampling (MIDAS) equations (Ghysels̊, 2004). All of them have proved to be effective in anticipating short-term developments. They also seem to overcame the predictive performance of univariate statistical models, particularly in volatile periods (Bell et al.,, 2014).

Two type of business cycle variables are used to produce *Nowcast:* **(i)** *Hard indicators* of economic activity -such as industrial production and its components, housing indicators, energy consumption and production and financial and monetary time series as money aggregates, interest rates and **(ii)** *Soft indicators* mostly coming from surveys which mainly reflect agents' expectations about economic conditions as consumers confidence indexes.

Giannone et al. (2008) highlight as main advantages of *Nowcasting*: **(i)** The use of a large number of data series, from different sources and frequencies; **(ii)** the updating of estimates when new information becomes available (in accordance with the real-time calendar of data releases) and **(iii)** the fact that it "bridges" monthly data releases with quarterly GDP.

In the case of Argentina, having early predictions of GDP is particularly important, taking into account that official GDP figures are released around 10 weeks after the end of the quarter. 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 and factor models to deal with differences in data frequency. 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) test, that 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. The data set and our empirical approach are presented in section 2. Section 3 describes the results obtained from the Nowcast exercise. In section 4 we evaluate the relative predictive ability of two nowcast exercise using the Giacomini and White (2004) test. Finally, section 5 concludes.

2 Our Nowcast Exercise

Our exercise consists on producing early predictions of GDP growth The initial data set comprises 37 business cycle 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. The variables comprised in the data set are described in Figure 1. The series were seasonally adjusted when needed, de-trended or differentiated to make them stationary and finally log transformed. Using an estimation sample that comprises the period 1993:Q1-2007:Q4, we perform rolling pseudo-real-time one quarter ahead *Nowcast* exercise of GDP growth over the period 2008:Q1-2014:Q1 with a window size of *64 quarters*, using the two methodologies described below: bridge equations and a factor model.

Figure 1: the 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

According to the timing of publication we split the final set of indicators in two group: those series that are available less than 10 days after the end of each month (16 series), and series that are published with a delay raging form 10 to 30 days (21 series). Following this grouping of the series, the Nowcast can be sequentially updated as described in Figure 2.

Figure 2: Sequential updating example

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 (21 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**

As reported by the aforementioned updating scheme, we can obtain 6 early estimations of GDP growth in each quarter.

2.1 The methodological approach

2.1.1 Bridge equations

This is the simplest and earliest approach to Nowcasting (Drechsel and Maurin, 2008). It 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. We choose aggregating 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 to estimate autoregressive distributed bivariate models for each of the corresponding business cycle indicators.

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

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 [1]

Individual-indicator forecasts are can be next aggregated using different weighting criteria to obtain an overall forecast of Y_t^Q for the current period. Weights are supposed to be based on out of sample performance, as for example the root mean square forecasting error *(RMSFE)* We construct the forecast assigning weights which are inversely related to the *RMSFE*.[2]

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

Some of the drawbacks of this methodology have been highligthed in the Nowcasting literature: The potential loss of relevant information by the rudimentary aggregation process applied (i.e.

[1] A summary of the specification of the models is included in Appendix I.

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

discarding any information about the timing of innovations to higher-frequency data), the multi-collinearity problem that can arise when combining equations and the inability to compute a model based *news* or *surprise*Additionally, estimation-based nowcast models are normally estimated using a long history of data, they do not always respond quickly to new information or outbreaks. Additionally, since these models incorporate lags of the dependent and independent variables, they can have a strong dependence on previous values of these variables. This can affect their accuracy in unstable periods. Although we try to deal with this problem using rolling windows and estimating models the most parsimonious as possible, we also use a factor model, another popular approach to nowcasting, that relays on the degree of co-movement among the series, overcoming the problem of dependence on past behavior.

2.1.2 Factor Models

Nowcast can also be conducted through the estimation of common factors from a large set of monthly data and subsequently using them as regressors for GDP -as proposed by Giannone, Reichlin and Small (2005).The idea behind this approach is that the variables in the set of interest are driven by few unobservable factors.

More concretely, the covariance between a large number of n economic time series with their leads and lags can be represented by a reduced number of unobserved q factors, with $n > q$. Disturbances in such factors could in this context represent shocks to aggregate supply or demand.

Therefore, the vector for n observable variables in the cycle can be explained by the distributed lags of q common factors plus n idiosyncratic disturbances which could eventually be serially correlated, as well as being correlated among i.

Given a vector of n stationary monthly indicators time series $x_t = (x_{1t}, ...x_{nt})'$, with $t = 1, ...T$, the vector for n observable variables in the cycle can be explained by the distributed lags of q common latent factors plus n idiosyncratic disturbances which could eventually be serially correlated or correlated among the $i's$

$$X_{it} = \lambda_i(L)'f_t + u_{it} \tag{3}$$

Where f_t is a vector $q\times\ 1$ of unobserved factors, λ is a $q\times\ 1$ vector lag polynomial of *dynamic factor loadings* and the u_{it} are the idiosyncratic disturbances that are assumed to be uncorrelated with the factors in all leads and lags, that is to say $E(f_t u_{it}) = 0\ \forall\ i, s$.

The objective is therefore to estimate $E(y_t \mid X_t)$ modeling y_t according to

$$y_t = \beta(L)'f_t + \varepsilon_t \tag{4}$$

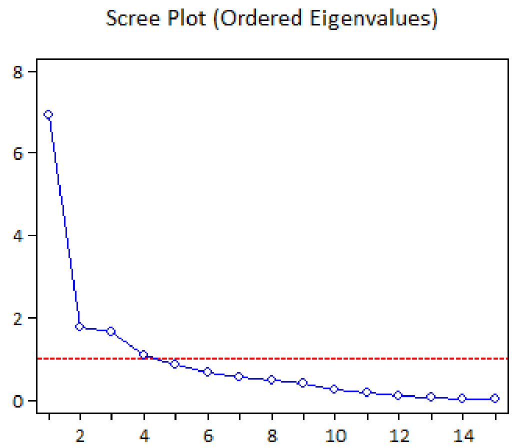
If the lag polynomials $\lambda_i(L)$ in (**??**) and $\beta(L)$ in(**??**) are of finite order p, Stock and Watson (2002a) show that the factors f can be estimated by principal components.

If we define quarterly GDP as the average of monthly latent observations $y_t^Q = (y_t + y_{t-1} + y_{t-2})$ and we obtain quarterly factors f_t^Q from these observations, we can use the following bridge equation to obtain early estimates of GDP:

$$\widehat{y_t}^Q = \beta(L)'f_t^Q \tag{5}$$

To apply the factor model methodology we proceeded in the following way. First, we calculated the correlation coefficient of the n indicators with GDP and selected those with the strongest co-movement with GDP (a correlation coefficient higher than 0.5). This led us with a subset of 15 business cycle indicators.[3] We used this indicators to calculate the factor using the principal component methodology. Then we used the *scree plot*[4] presented in Figure 3 allowed us to determine the number of factors to be used to estimate equation. It can be seen from there that it is up to the fourth factor that the addition of factors contributes to increase the proportion of covariance of the time series explained by the factors. Taking into account this information, we estimated equation (4) using the first four factors.

Figure 3: Scree Plot



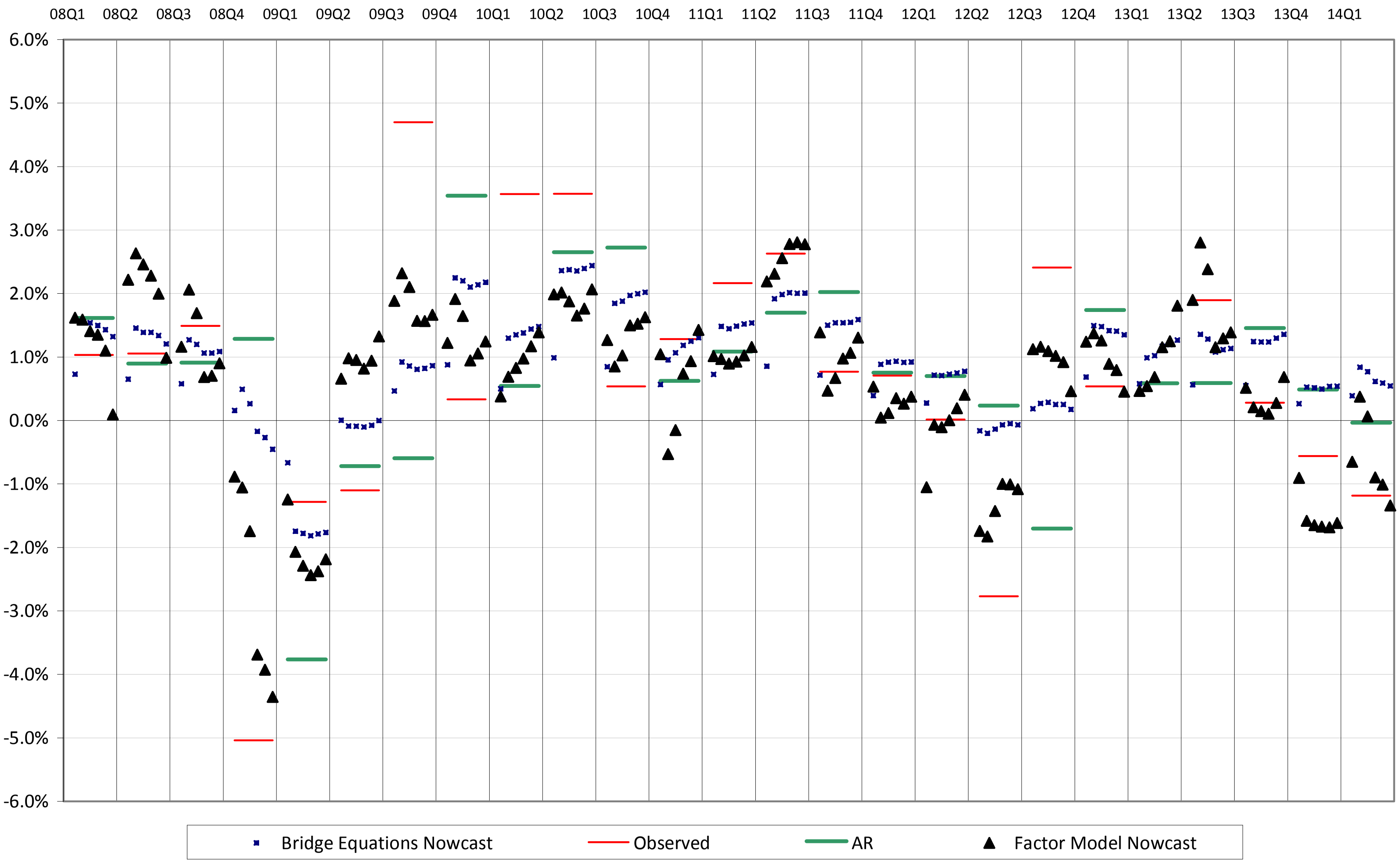
3 Results

In this section we report the results of the two *Nowcasting* exercises using the two methodologies described above: Bridge equations and a factor model Figure 4 presents the sequentially updated predicted values of GDP growth. The outcomes of both exercises are compared to an AR(1) model of GDP growth for the same quarter. It can be seen that both *Nowcast* performs better than the benchmark in almost every quarter. Additionally, the factor model seems to have a systematically better predictive performance relative to the bridge equation methodology, particularly in the last part of the forecasting period.

[3]See Table A.2. in Appendix I.

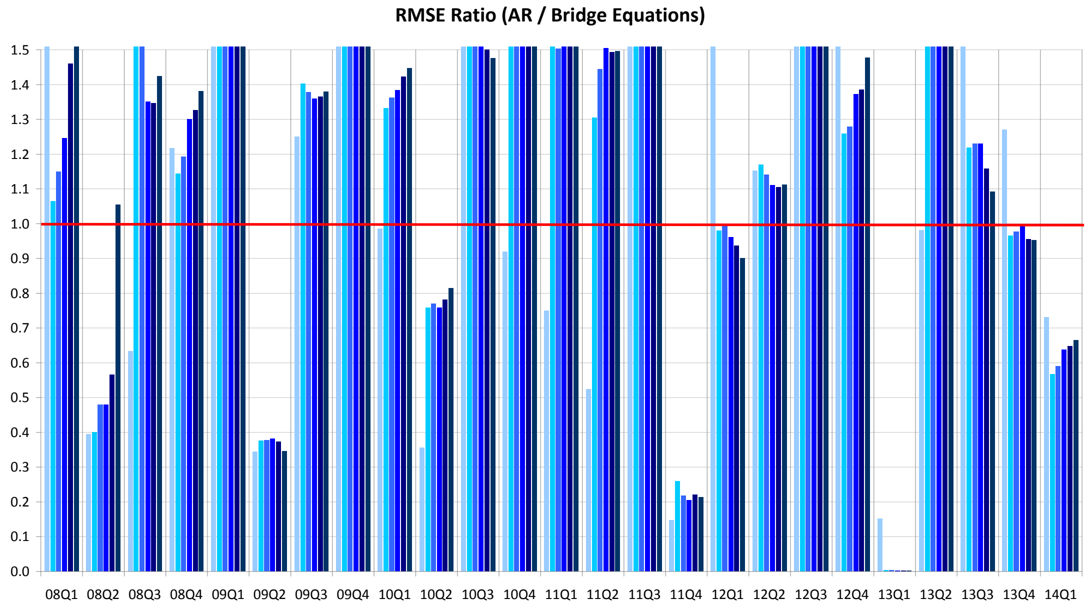
[4]Developed by R B. Cattel in "The scree test for the number of factors", Multivariate Behav. Res. 1:245-76, 1966.University ofillinois, Urbana-Champaign, ILl.

Figure 4: Nowcast performance



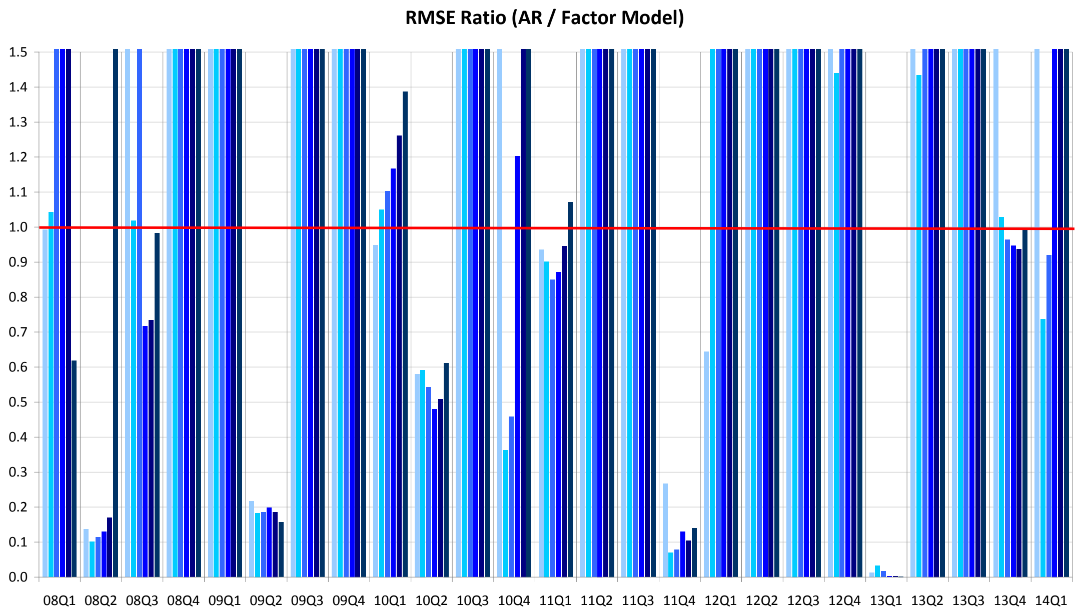
We begin comparing the predictive performance of the two *Nowcast* relative to the benchmark. To compare the relative accuracy, we use the *RMSE* of the 6 within quarter estimations of the nowcast with factors and the bridge equations to the *RMSE* of one quarter ahead forecast of an *AR(1)* model of GDP growth for the same quarter (see Figures 5 and 6). The results suggest that both *nowcast* outperform the *AR(1)* prediction as suggested by Figure 4.

Figure 5: Nowcast using bridge equations relative to benchmark



Note: A value over 1 indicates that the Bridge Equations Nowcast has a better predictive performance
B.E. Nowcast overcomes AR(1) in 67% of the cases

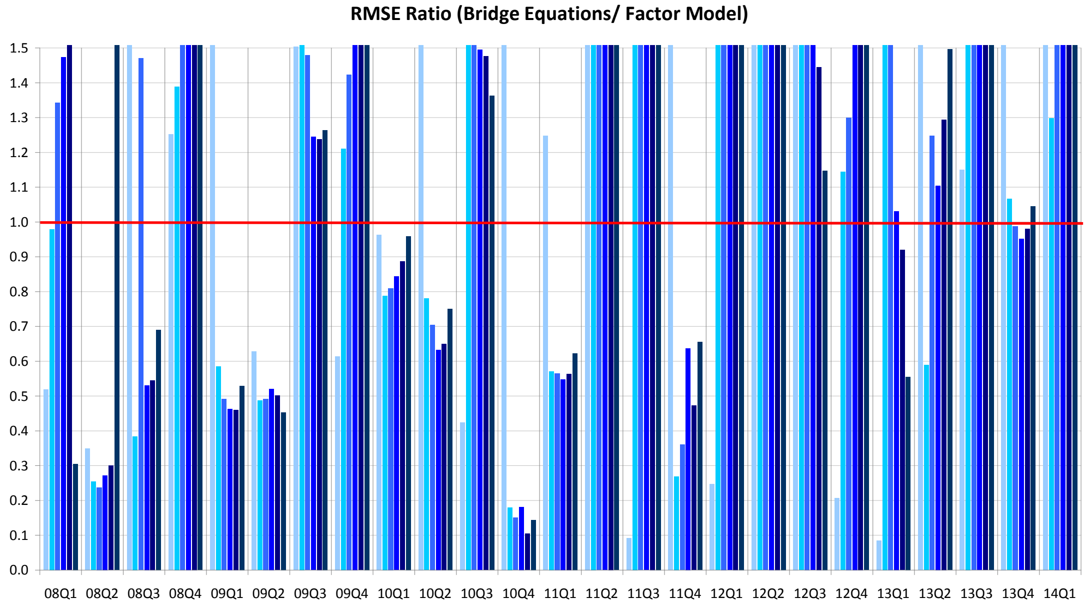
Figure 6: Nowcast using bridge equations relative to benchmark



Note: A value over 1 indicates that the Factor Model Nowcast has a better forecasting performance
Factor Model Nowcast overcomes AR(1) in 66% of the cases

Since the factor model seems to have a better accuracy than the bridge equations (Figure 4), we also compare the *RMSE* of both nowcast approaches. The results confirm our presumption: The factor model outperforms the bridge equation predictions in 59% of the cases.

Figure 7: Nowcast using bridge equations relative to Nowcast using factors



Note: A value over 1 indicates that the Factor Model Nowcast has a better forecasting performance

4 Testing for equal predictive ability

To test if the differences in predictive accuracy found in the previous section are statistically significant we use the Giacomini and White (2004). The Giacomini and White approach differs from that followed by previous tests, as those proposed by Dieblod and Mariano (1995) and West (2003) in what it is based on conditional rather than unconditional expectations. 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 than testing the validity of a theoretical model.[5]

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 non nested 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.

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

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

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 heteroskedasticity and autocorrelation.

The results of applying the Giacomini and White procedure to evaluate the forecasting performance of the two nowcasting methods are shown in Table 1. It can be seen from there that both methodologies outperform the AR(1) (the differences are significant at the 1% level in both cases). Taking into account the findings in the previous section, we also perform the test to compare the relative predictive accuracy of both nowcast methods. The results indicate that the nowcast using a factor model outperforms the bridge equations methodology at the 5% level. Finally, if we restrict the sample to the period 2012Q1-2014Q4 the differences in accuracy are significant at the 1% level. This result is interesting because these last periods includes a turning point, which is usually difficult to capture when using statistical models that are mostly based on past observations.

Table 1: Results of the Giacomini and White test

Sample 2008-2014 (N=150)		
	t-statistic	**p-value**
Bridge Equations Nowcast vs AR	3.390	0.001
Factor Model Nowcast vs AR	2.994	0.003
Factor Model Nowcast vs B.E. Nowcast	2.057	0.042
Sample 2012-2014 (N=53)		
	t-statistic	**p-value**
Factor Model Nowcast vs B.E. Nowcast	3.322	0.002

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, the forecasting literature has developed a series of solutions to deal with this *mixed-frequency problem*. In this paper we develop a nowcasting exercise of GDP growth using two of these methodologies: Bridge equations and a factor model.

The results show that both methodologies outperform the AR(1) as a benchmark and that additionally, the *Nowcast* using factors performs better than that using bridge equations. This is true particularly over the last period, that corresponds to a turning point in GDP. The Giacomini and White (2004) test confirms that these differences in performance are statistically significant.

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] Bell, V. L Co S. Stone and G.Wallis (2014), " Nowcasting UK GDP", Bank of England Quarterly Bulletin Q1.

[7] 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.

[8] 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.

[9] 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.

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

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

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

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

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

[15] 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.

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

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

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

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

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

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

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

[23] 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.

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

[25] 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.

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

[27] 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.

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

Appendix I

Table A.1.: Summary of models

Series N°	Lags		Dummies included (year quarter)
	dependent	independent	
1		t, t-2, t-4	D032, D021, D014, D012, D093, D002, D031, D101
2	t-1		D014, D021, D002, D092, D012, D084, D093, D101
3		t, t-1	D013, D014, D021, D084, D122, D093, D042
4		t, t-1	D993, D013, D014, D021, D084
5		t	D093, D013, D014, D084, D122
6	t-1	t-1, t-2	D021, D014, D084, D013, D122, D093, D002
7		t	D014, D123, D094, D091, D101
8		t, t-1, t-2, t-3	D013, D014, D021, D084, D122, D093, D002
9		t, t-3, t-4	D014, D021, D084, D093, D013, D042
10	t-1	t, t-3	D022, D084, D093, D042, D123, D122, D013
11	t-1	t, t-1, t-3	D013, D122, D084, D093, D042
12	t-1	t, t-1, t-4	D122, D084, D093, D042
13	t-1	t, t-4	D013, D122, D084, D093, D014, D101
14	t-1	t, t-1, t-4	D093, D021, D013, D123, D084, D002
15	t-1	t-1	D013, D122, D043, D084, D094, D042
16		t, t-1, t-3	D013, D014, D092, D093
17	t-1	t	D013, D014, D093, D084, D123, D122
18		t, t-1	D014, D012, D021, D023, D091, D092, D084
19	t-1	t	D013, D092, D123, D122, D093, D084
20		t, t-3	D021, D122, D002
21	t-1	t, t-1	D013, D094, D084, D093, D014
22	t-1	t-1	D013, D123, D043, D084, D093, D014, D122
23	t-1	t, t-1, t-2, t-5	D014, D084, D093, D013
24	t-1	t-2, t-4	D013, D122, D042, D084, D093, D123, D094
25	t-1	t, t-1	D013, D122, D043, D084, D093, D123, D002
26	t-1	t, t-1, t-3	D013, D043, D084, D093, D122
27	t-1	t	D013, D122, D084, D093, D123
28	t-1	t-2	D002, D013, D122, D084, D093, D014
29	t-1	t, t-1, t-4	D013, D022, D043, D084, D093, D122, D123
30	t-1	t, t-2	D014, D084, D093, D031, D094
31	t-1	t-1, t-2	D022, D084, D093, D013, D122, D101
32	t-1	t-2, t-3, t-4	D014, D122, D084, D013
33		t-4	D013, D122, D084, D093, D014
34	t-1	t-1	D013, D122, D084, D093, D014, D021
35	t-1	t	D013, D122, D084, D093, D014, D101
36	t-1	t	D084, D093, D013, D123, D031
37		t	D013, D014, D021, D084, D031, D122, D093

Table A.2.: Ordinary correlations and series selected for Factor

Series No.	Correlation with GDP growth	Order
16	0.7803	1
5	0.7612	2
20	0.7599	3
27	0.7053	4
1	0.6948	5
30	0.6896	6
18	0.6165	7
37	0.5644	8
36	0.5628	9
35	0.5607	10
21	0.5479	11
29	0.5385	12
19	0.5371	13
17	0.5058	14
4	0.5011	15
3	0.4654	16
11	0.4236	17
23	0.4163	18
7	0.4147	19
24	0.4131	20
8	0.4107	21
28	0.4047	22
2	0.4006	23
14	0.3765	24
26	0.2917	25
31	0.2288	28
15	0.2222	29
9	0.1695	30
10	0.1659	31
6	0.1614	32
25	0.1483	33
12	0.1457	34
13	0.0581	35
33	0.0191	36
34	0.0144	37
22	-0.1035	38
32	-0.1322	39