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Nowcasting GDP in Argentina: Comparing the predictive ability of different models*

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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. We develop a GDP growth Nowcasting exercise using a broad and restricted set of indicators to construct different models including dynamic factor models as well as a FAVAR. We compare their relative forecasting ability using the Giacomini and White (2004) and find no significant difference in predictive ability among them. Nevertheless a combination of them proves to significantly improve predictive performance.

Keywords: Nowcasting, dynamic factor models, forecast pooling
JEL classification: C22, C53, E37

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1 Introduction

Although the assessment of current economic economic conditions is a crucial ingredient of decision making in central banks and other areas of the government, this process has to be conducted in real time based on incomplete information, 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 to overcome this problem. As a result, its use by central banks and other government institutions has been growing rapidly over the recent years. A contraction for *now* and *forecasting,* Nowcasting 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 updated, when new information becomes available.

The most simple and earlier version of Nowcasting is that of bridge equations that consists in combination of simple bivariate models known (Kitchen and Monaco, 2003; Drechsel and Maurin, 2008). Recently new statistical approaches that deal *high dimension* and *mixed-frequency problems* inherent to the Nowcasting technique have been developed. While dynamic factor models (Stock and Watson, 2002, 2006), implemented through the estimation of principal components or a state space representations (Evans, 2005; Giannone et al., 2008; Arouba, et al., 2009) address the *high dimension* problem through the estimation of common factors to large sets of indicators, Mixed Data Sampling (MIDAS) equations (Ghysels et al., 2004) and state space representations of dynamic factor models provide solutions to the *mixed-frequency problem*. 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 environments (Bell et al., 2014).

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.

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' perceptions about economic conditions, as consumers confidence indexes.

In this paper we consider a broad set of different nowcasting models of GDP growth for Argentina and evaluate their relative ability for predict quarterly GDP growth figures in Argentina over the period 2006-Q1 2017Q1. The exercise is particularly challenging because the economy was subject to several shocks over this years, including two sharp depreciations of the currency in January 2014 and December 2015. Since then the economy has been going through major structural reforms including the adoption of a floating exchange regime, the removal of exchange rate controls and the adoption of an inflation targeting scheme to conduct monetary policy.

In this paper we consider a set of different nowcasting models for Argentina's GDP growth and conduct a pseudo-real-time one quarter ahead forecasting exercise of GDP growth to compare their relative predictive ability. To evaluate the potential gain of using a large group vs. a reduced group of business cycle indicators we consider two groups: one that includes 112 indicators and a more restricted subset within them of 30 indicators (those that have the highest contemporaneous correlation with GDP growth) to conduct a pseudo-real-time one quarter ahead forecasting exercise. For these two sets we obtain common factors and estimate the following nowcasting models: (i) a Factor Model, (ii) a Factor Model in which we split the set in three factors (*hard*, *soft* and *price* indicators) and (iii) a Factor augmented VAR (FAVAR). Having estimated the models we evaluate their relative predictive performance using the Giacomini and White test (2004). The finding that none of them outperforms the rest of models leads us to investigate if there is any forecast combination that could perform better than individual models in terms of predictive ability.

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 the *Nowcasting* models 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 based on the sample period 2006:Q1 - 2017:Q1. In Argentina the official GDP figures are released around 10 weeks after the end of the quarter. The initial data set comprises 112 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 car sales. The variables comprised in the data set are described in Annex 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 2006:Q1-2011:Q1, we perform rolling pseudo-real-time one quarter ahead *Nowcast* exercise of GDP growth over the period 2011:Q1-2017:Q1 with a window size of *20 quarters*, using the methodologies described below for two sets of series: A broad one, composed by 112 business cycle indicators and a subset of 30 series that exhibit the highest contemporaneous correlation with GDP growth within the unrestricted set (see Annex 1).

According to the timing of publication we split the final set of indicators in two groups: those series that are available less than 10 days after the end of each month (Group 1), and series that are published with a delay raging form 10 to 30 days (Group 2). Following this grouping of the series, the Nowcast can be sequentially updated as described in Figure 1.

Figure 1: Sequential updating example

Date	02/10/2016	02/28/2016	03/10/2016	03/31/2016	04/10/2016	04/30/2016	05/10/2016	05/31/2016	06/10/2016
Available data									
Group 1:	Jan-16	Jan-16	Feb-16	Feb-16	Mar-16	Mar-16	Apr-16	Apr-16	May-16
Group 2:	Dic-15	Jan-16	Jan-16	Feb-16	Feb-16	Mar-16	Mar-16	Apr-16	Apr-16
Nowcast	I 2016	I 2016	I 2016	I 2016	I 2016	I 2016	II 2016	II 2016	II 2016
Official Releases									**First Official Release I 2016**

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

2.1 The methodological approach: 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 of 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.

A vector X_{it} of n stationary monthly business cycle indicators $x_t = (x_{1t}, ..., x_{nt})'$, with $t = 1, ...T$ can be explained by the distributed lags of q common latent factors plus n idiosyncratic disturbances which could eventually be serially correlated

$$X_{it} = \lambda_i(L)'f_t + u_{it} \tag{1}$$

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

$$y_t = \beta(L)'f_t + \gamma(L)'y_{t-1} + \varepsilon_t \tag{2}$$

If the lag polynomials $\lambda_i(L)$ in (1) and $\beta(L)$ in(2) 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:

$$\widehat{y_t}^Q = \beta(L)'f_t^Q \tag{3}$$

Additionally to estimating models using a single equation approach as in (2), we also estimate a VAR on GDP growth and the factors.[1]

3 Results

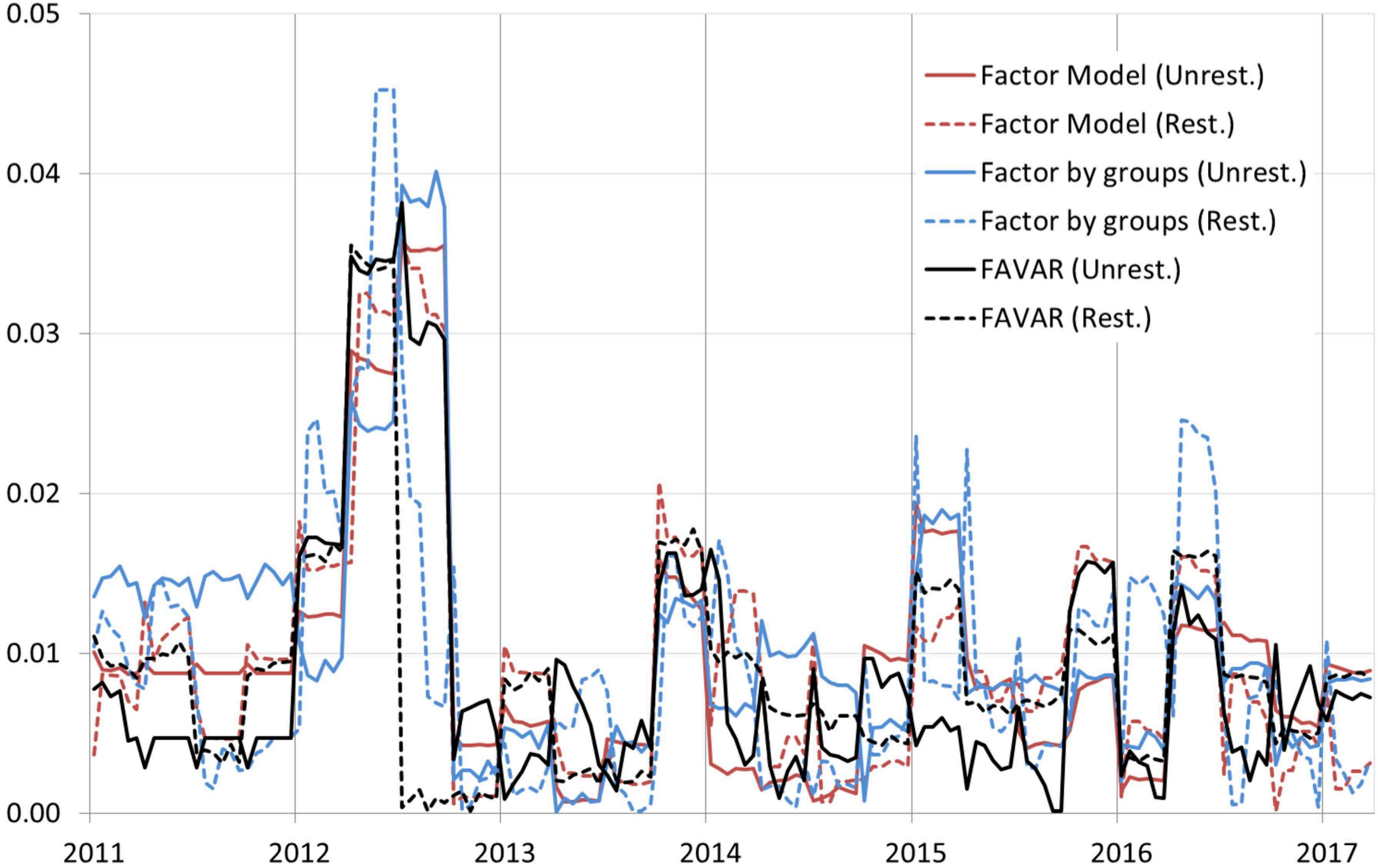
To estimate the factors for both the restricted and unrestricted sets of indicators we proceeded in the following way. We use the two sets of indicators to calculate the factors using the principal component methodology. Then we determine the number of factors to be used to estimate the models using a the *scree plots*[2]. Based on this we use the factors all the models detailed above, from (M1) to (M6) the restricted and the unrestricted sets of indicators.

Based on these estimation we conduct a rolling window Nowcasting exercise for each of the models over the period 2011:Q1-2017:Q1. Figure 2 presents for each quarter of the predictive sample the correspondent loss function for each model, measured by the Root Mean Square Error (RMSE). At first sight it seems that none of the models seems out perform the rest.

[1] Estimation results are available upon request.

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

Figure 2: Nowcast performance (RMSE)



To provide a better insight, Figure 3 shows the frequency at which each model is ranked as first in terms of its forecast accuracy (measured by the RMSE).[3] We calculate these frequencies for the complete sample and then we split it into the pre and post structural break in December 2015. The FAVAR models outperforms the rest of the models for the complete predictive sample, while in the last period (although the sample is quite short) it seems that other models, as the restricted and the unrestricted factor models, have rather the same predictive ability. To verify if the observed difference in predictive ability are statistically significant we conduct the Giacomini White test and find that none of the models outperforms the rest (see Figure 5 in section 5).

Figure 3: Frequency at which models are ranked as first in terms of predictive accuracy (lowest RMSE)

% of periods with lowest RMSE	*Full Sample* 2011q1-2017q1 (150 obs)	1^{st} *Sample* 2011q1-2015q4 (120 obs)	2^{nd} *Sample* 2016q1-2017q1 (30 obs)
M1: Factor Model (Rest.)	13%	9%	**27%**
M2: Factor Model (Unrest.)	17%	17%	20%
M3: Factor by groups (Rest.)	25%	24%	**27%**
M4: Factor by groups (Unrest.)	11%	13%	0%
M5: FAVAR (Rest.)	7%	8%	0%
M6: FAVAR (Unrest.)	**28%**	**28%**	**27%**

4 Pooling of Nowcasts

Since Bates and Granger (1969), the forecasting literature has emphasized that a combination of different forecasts might result in a better performance in comparison with each individual model. This technique is particularly useful in the presence of structural breaks. The pooling or combination of forecasts implies combining two or more forecasts derived from models that use different predictors to produce a forecast. The basic idea is as follows:

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

$$Y_{t+h|t}^{h} = \omega_0 + \sum_{i=1}^{n} \omega_{it} Y_{i,t+h}^{h} \tag{4}$$

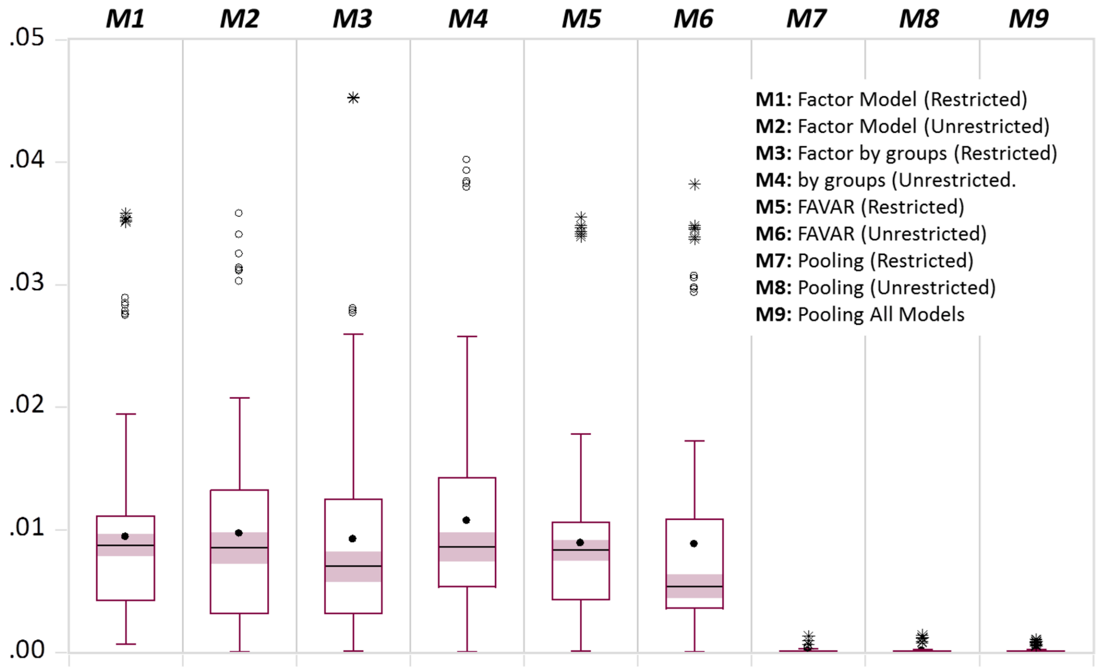
where ω_{it} is the weight of the i^{th} forecast in period t.[4]
Given this general setting, we conduct a pooling exercise of the different forecasting models using equal weights:

- (M7) Combining only Restricted models
- (M8) Combining only Unrestricted models
- (M9) Combining all models

It can be seen from Figure 4, that shows the box-plots of the distribution of the RMSE for all Factor Models and the three forecast combinations described above, that any of the forecast combinations seems to outperform all of the individual models. In the next section we proceed to evaluate the differences in predictive ability of all of the nowcasting exercises reported in Figure 4.

[3] See Annex 2 for a relative position histogram of each of the models for the full sample
[4] See D'Amato et al. (2009) for a brief discussion on different weighting schemes.

Figure 4: Box plots of RMSE



5 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) test. 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**)** it is useful for forecasts based on both nested and non nested models, **(**iii**)** it allows the forecasts to be produced by general estimation methods, and **(**iv**)** it 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

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

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:

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

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 models are shown in Figure 5. They corroborate the intuitions provided by the descriptive analysis in the previous section: While none of the individual models outperforms the rest of them, all the forecast combinations perform much better than individual models, but there is no clear prevalence of any particular combination over the others.

Figure 5: Results of the Giacomini and White test

Difference in RMSE Model in row - Model in Column

G&W test	Factor Model (Rest.)	Factor Model (Unrest.)	Factor by groups (Rest.)	Factor by groups (Unrest.)	FAVAR (Rest.)	FAVAR (Unrest.)	Pooling (Rest.)	Pooling (Urest.)	Pooling All
Factor Model (Rest.)		0.000	0.000	-0.001	0.001	0.001	0.0095	0.0095	0.0095
Factor Model (Unrest.)	-0.0003		0.000	-0.001	0.000	0.001	0.0093	0.0092	0.0092
Factor by groups (Rest.)	-0.0005	0.000		-0.002	0.000	0.002	0.0091	0.0090	0.0091
Factor by groups (Unrest.)	0.0010	0.001	0.002		0.002	0.000	0.0106	0.0105	0.0106
FAVAR (Rest.)	-0.0009	0.000	0.000	-0.002		0.000	0.0088	0.0087	0.0088
FAVAR (Unrest.)	-0.0008	-0.001	0.000	-0.002	0.000		0.0086	0.0086	0.0086
Pooling (Rest.)	-0.0095	-0.0093	-0.0091	-0.0106	-0.0088	-0.0086		0.0000	0.0000
Pooling (Urest.)	-0.0095	-0.0092	-0.0090	-0.0105	-0.0087	-0.0086	0.0000		0.0000
Pooling All	-0.0095	-0.0092	-0.0091	-0.0106	-0.0088	-0.0086	0.0000	0.0000	

Significant at 5%

6 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 - 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.

We conduct a nowcasting exercise for GDP growth in Argentina over the period 2006:Q1 - 2017:Q1 for a bunch of different nowcasting models including a Factor model and a FAVAR for a large and a more restricted set of business cycle indicators. The exercise is quite challenging because the Argentine economy is currently experiencing a structural break. The results indicate that there is no statistically significant prevalence of a model over the others in terms of predictive ability while there seem to be some gains of combining them to produce nowcast.

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Annex 1: Complete Data Set

No	Source	Series	Group	
serie1	ADEFA	Automobile national production - units	1	hard
serie2	ADEFA	Automobile exports - units	1	hard
serie3	ADEFA	Automobile sales - units	1	hard
serie4	ADEFA	Automobile national sales - units	1	hard
serie5	AFCP	Portland cement production	1	hard
serie6	MECON	Ganancias (Total)	1	hard
serie7	MECON	Ganancias DGI	1	hard
serie8	MECON	Ganacias DGA	1	hard
serie9	MECON	Total Income revenues	1	hard
serie10	MECON	Income revenues DGI	1	hard
serie11	MERVAL	Income revenues DGA (customs)	1	prices
serie12	MERVAL	Total VAT revenues	1	prices
serie13	BCRA	VAT revenues DGI	1	prices
serie14	BCRA	Interest rate on Time Deposits - Private Banks	1	prices
serie15	CCA	Used Car Sales	1	hard
serie16	UTDT	Consumer Confidence Index - General - BSAS city	1	soft
serie17	UTDT	Consumer Confidence Index - General	1	soft
serie18	UTDT	ICC-DI	1	soft
serie19	UTDT	ICC-SM	1	soft
serie20	UTDT	ICC-SP	1	soft
serie21	UTDT	ICC-Condiciones Presentes	1	soft
serie22	UTDT	ICC-Expectativas	1	soft
serie23	CIS	Hierro Primario	1	hard
serie24	CIS	Acero Crudo	1	hard
serie25	CIS	Lam. Frío	1	hard
serie26	CIS	Lam. En caliente Total No Planos	1	hard
serie27	CIS	Lam. En caliente Planos	1	hard
serie28	FIEL	Industrial production index (IPI) - general level	2	hard
serie29	FIEL	IPI - nondurable consumer goods	2	hard
serie30	FIEL	IPI - durable consumer goods	2	hard

No	Source	Series	Group	
serie31	FIEL	IPI - intermediate goods	2	hard
serie32	FIEL	IPI - capital goods	2	hard
serie33	FIEL	IPI - food and beverages	2	hard
serie34	FIEL	IPI - cigarettes	2	hard
serie35	FIEL	IPI - textiles input	2	hard
serie36	FIEL	IPI - pulp and paper	2	hard
serie37	FIEL	IPI - fuels	2	hard
serie38	FIEL	IPI - chemicals and plastic	2	hard
serie39	FIEL	IPI - nonmetallic minerals	2	hard
serie40	FIEL	IPI - steel	2	hard
serie41	FIEL	IPI - metalworking	2	hard
serie42	FIEL	IPI - automobiles	2	hard
serie43	Gov. BSAS city - CABA	Gross Revenue Tax Collection - City of Buenos Aires	2	hard
serie44	Gov. BSAS Prov. (State)	Gross Revenue Tax Collection - Buenos Aires province	2	hard
serie46	CAME	Sales - General Level	1	hard
serie47	CAME	Sales - FOOD AND DRINKS	1	hard
serie48	CAME	Sales - BAZAAR AND GIFTS	1	hard
serie49	CAME	Sales - Bijouterie	1	hard
serie50	CAME	Sales - Shoes	1	hard
serie51	CAME	Sales - sports	1	hard
serie52	CAME	Sales - Home appliances	1	hard
serie53	CAME	Sales - Pharmacies	1	hard
serie54	CAME	Sales - Hardware store	1	hard
serie55	CAME	Sales - Candy and Soft Drinks	1	hard
serie56	CAME	Sales - Toy stores	1	hard
serie57	CAME	Sales - Leather Goods	1	hard
serie58	CAME	Sales - Electrical Supplies	1	hard
serie59	CAME	Sales - Construction materials	1	hard
serie60	CAME	Sales - Home furniture	1	hard

No	Source	Series	Group	
serie61	CAME	Sales - Office furniture	1	hard
serie62	CAME	Sales - Perfumery	1	hard
serie63	CAME	Sales - Textile - Clothing	1	hard
serie64	CAME	Sales - Textile - White	1	hard
serie65	CONSTRUYA	Construction Companies Activity Index	1	#N/A
serie66	CONSTRUYA	Construction Companies Activity Index SA	1	hard
serie67	INDEC	Exports - General Level	2	hard
serie68	INDEC	Exports - Q Primary Products	2	hard
serie69	INDEC	Exports - Q manufactures of agricultural origin	2	hard
serie70	INDEC	Exports - Q manufactures of industrial origin	2	hard
serie71	INDEC	Exports - Q Fuels and energy	2	hard
serie72	INDEC	Exports - P General level	2	hard
serie73	INDEC	Exports - P Primary Products	2	prices
serie74	INDEC	Exports - P manufactures of agricultural origin	2	prices
serie75	INDEC	Exports - P manufactures of industrial origin	2	prices
serie76	INDEC	Exports - P Fuels and energy	2	prices
serie77	INDEC	Imports - Q General level	2	hard
serie78	INDEC	Imports - Q capital goods	2	hard
serie79	INDEC	Imports - Q intermediate goods	2	hard
serie80	INDEC	Imports - Q Fuels and energy	2	hard
serie81	INDEC	Imports - Q Parts and Accessories	2	hard
serie82	INDEC	Imports - Q consumer goods	2	hard
serie83	INDEC	Imports - vehicles	2	hard
serie84	INDEC	Imports - P General level	2	prices
serie85	INDEC	Imports - P capital goods	2	prices
serie86	INDEC	Imports - P intermediate goods	2	prices
serie87	INDEC	Imports - P Fuel and energy	2	prices
serie88	INDEC	Imports - P Parts and Accessories	2	prices
serie89	INDEC	Imports - P consumer goods	2	prices
serie90	INDEC	Imports - P vehicles	2	prices

No	Source	Series	Group	
serie91	Ministerio de Agroindustria	Soybean milling	2	hard
serie92	Secretaría de Hacienda	Direct real investment + capital transfers to provinces	2	hard
serie93	Secretaría de Hacienda	Direct real investment	2	hard
serie94	Secretaría de Hacienda	Capital transfers to provinces	2	prices
serie95	Tendencias	Dismissals (1986 = 100)	1	soft
serie96	Tendencias	Suspensions (1986 = 100)	1	soft
serie97	EIL - Ministerio de Trabajo de la Nación	Net employment expectancy	2	soft
serie98	EIL - Ministerio de Trabajo de la Nación	Companies that searched for personnel	2	soft
serie99	BCRA	Multilateral nominal exchange rate index (Dec-15=100)	1	prices
serie100	BCRA	Personal Credits	1	prices
serie101	BCRA	Credit Cards	1	prices
serie102	BCRA	Personal + Cards	1	prices
serie103	GCBA	Vehicule Registrations BSAS city	2	hard
serie104	GCBA	Vehicule Registrations Argentina	2	hard
serie105	GCBA	Tolls (collection)	2	hard
serie106	GCBA	Tolls (vehicle ciculation)	2	hard
serie107	GCBA	Tolls (average vehicles)	2	hard
serie108	GCBA	Stamp duty-BSAS city	2	hard
serie109	GCBA	Passengers transported by rail (in thousands)	2	hard
serie110	Banco Central de BRASIL	Brazil Industrial production s.a.	2	hard
serie111	Banco Central de BRASIL	Brazil Industrial production	2	hard
serie112	Banco Central de BRASIL	Brazil Activity indicator s.o.	2	hard
serie113	Banco Central de BRASIL	Brazil Activity indicator s.a.	2	hard
serie114	Secretaria de energía	Asphalt (in tonnes)	2	hard
serie115	Colegio de escribanos Buenos Aires	BSAS city Scriptures	2	hard

Annex 2: Histogram of relative positions for each model (full Sample)