ASOCIACION ARGENTINA DE ECONOMIA POLITICA

LV REUNIÓN ANUAL| NOVIEMBRE DE 2020

Nowcasting Macroeconomic Aggregates in Argentina: Comparing the predictive ability of different models

D´Amato, Laura
Blanco, Emilio
Dogliolo, Fiorella
Garegnani, María Lorena

ISSN 1852-0022 / ISBN 978-987-28590-8-4

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

Emilio Blanco — BCRA and UBA
Laura D'Amato — IIEP UBA
Fiorella Dogliolo — BCRA and UNLP
Lorena Garegnani — BCRA and UNLP

August 2020

Abstract

Monetary policy making requires a correct and timely assessment of current macroeconomic conditions. While the main source of macroeconomic data is quarterly National Accounts, often published with a significant lag, higher frequency business cycle indicators are increasingly available. Taking this into account, central banks have adopted nowcasting as a useful tool for having an immediate and more accurate perception of economic conditions. In this paper, we extend the use of nowcasting tools to produce early indicators of the evolution of two components of aggregate domestic demand: consumption and investment. The exercise uses a broad and restricted set of indicators to construct different dynamic factor models, as well as a pooling of models in the case of investment. Finally, we compare different approaches in a pseudo-real time out-of-sample exercise and evaluate their predictive performance.

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

* The opinions expressed in this work are those of the authors, and do not necessarily reflect those of the Central Bank of Argentina or its authorities. Email: emilio.blanco@bcra.gob.ar; laura.damato@gmail.com; fiorella.dogliolo@bcra.gob.ar lgaregnani@bcra.gob.ar

1 Introduction

Although the assessment of current 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. However, more timely business cycle indicators providing quantitative information on observed spending decisions (hard indicators) as well as qualitative information provided by different surveys (soft indicators) are usually available. In fact, this indicators are the ones usually used by market analysts to track the evolution of domestic spending and are available at the monthly frequency.

The use of these indicators by means of nowcasting techniques to asses business cycle conditions by central banks and other government institutions has been growing rapidly over the recent years. Although initially the target variable was real GDP growth, nowcasting tools are currently used to predict other relevant business cycle indicators as CPI inflation or consumption (see for example, Modugno, 2011, Veerban et al., 2017; Gil et al. 2018) .

In this paper we use different sets of business cycle indicators to produce Nowcast of private sector consumption and investment (Dogliolo, 2018). In doing so, we are extending the use of nowcasting tools for real GDP (D'Amato, Garegnani and Blanco, 2015; Blanco, D'Amato, Dogliolo and Garegnani, 2017) to the prediction of two relevant components of aggregate demand for which there are no monthly updates of official figures in Argentina.

The high macroeconomic instability that characterizes the business cycle in Argentina, makes nowcasting a particularly attractive predictive tool, since it is well known that in the context of high volatility and structural breaks, autoregressive models have a poor predictive performance (Bank of England, 2014).

We construct different unrestricted and restricted sets of business cycle indicators to estimate underlying factors for consumption and investment using Principal Component Analysis (Stock and Watson, 2002a). Based on these factors, we estimate models to produce nowcast of the two target variables.

The exercise is particularly challenging because the Argentine economy was subject to several shocks over the sample period we consider for estimation and prediction purpose, which comprises, broadly, the period 2009-2018. These shocks include two sharp currency depreciation episodes in January 2014 and December 2015, relevant structural reforms in early 2016, including the adoption of a floating exchange regime joint with an inflation targeting scheme and the removal of exchange rate controls and later on, in 2018, and a few episodes of financial stress and currency depreciation.

The paper is organized as follows. In section 2 we present a general description of our empirical approach. The Nowcasting exercise developed for private sector consumption, including the obtained results and the comparison of models in terms of relative predictive ability are described in section 3. In the same manner, section 4 presents the results for investment. Finally, section 5 concludes.

2 Our Methodological approach

The basic principle of nowcasting is the exploitation of the valuable information 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.

Bridge equations is the most simple and earlier version of nowcasting, consisting in combination of simple bivariate models (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).

The excercise we develop here is conducted through the estimation of common factors from a large set of monthly data and subsequently using them as regressors for our two target variables: consumption and investment -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 consumption/investment as the average of monthly latent observations $y_t^Q = (y_t + y_{t-1} + y_{t-2})/3$ and we obtain quarterly factors f_t^Q from these observations, we can use the following bridge equation to obtain early estimates of consumption/investment:

$$\widehat{y_t}^Q = \beta(L)' f_t^Q + \gamma(L)' y_{t-1}^Q$$

2.1 Data treatment

Our exercise consists on producing early predictions of quarterly private sector consumption and investment using different wide sets of business cycle indicators, including *hard* and *soft* business cycle time series. Those series range from financial indicators to tax collection data, data on sales, industrial production, imports or consumer confidence surveys. The series were seasonally adjusted when needed, detrended or differentiated to make them stationary and finally log transformed and standarized.

As highlighted by Giannone et al (2008) one of the advantages of nowcasting is that it allows updating estimates when new information becomes available. To exploid this advantage we split the sets of indicators included in the models according to the timing of publication 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 the example shown in Figure 1.

Figure 1: Sequential updating example

Date	15/2/2019	28/2/2019	15/3/2019	31/3/2019	15/4/2019	30/4/2019	15/5/2019	31/5/2019	15/6/2019
Available data									
Group 1	Jan-19	Jan-19	Feb-19	Feb-19	Mar-19	Mar-19	Apr-19	Apr-19	May-19
Group 2	Dec-18	Jan-19	Jan-19	Feb-19	Feb-19	Mar-19	Mar-19	Apr-19	Apr-19
Nowcast	I 2019	I 2019	I 2019	I 2019	I 2019	I 2019	II 2019	II 2019	II 2019
Official Releases									**Official Release I 2019**

As reported by the aforementioned updating scheme, we can obtain 6 early estimations of our two target variables within each quarter.

2.2 Evaluating models' relative predictive ability

The criteria for deciding which model is best to nowcast our two target variables is predictive ability. To inform this decision, we use the Giacomini and White (2006) test, which allows us to evaluate if the differences in predictive accuracy between models are statistically significant. The Giacomini and White approach differs from that followed by previous tests, as those proposed by Dieblod and Mariano (1995) and West (2003) in that 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.[1]

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.

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

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

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.

3 Nowcasting private consumption

3.1 Data Description

Our first target variable is private sector consumption. This variable accounts for approximately 60% of quarterly GDP released by the National Institute of Statistics of Argentina (INDEC). More precisely, we will generate early estimations of the percentage change in seasonally adjusted quarterly private sector consumption. In this case our target variable is private sector consumption, that accounts for approximately 60% percent of GDP, according to the National Accounts, that are produced at a quarterly frequency by the National Institute of Statistics of Argentina (INDEC). More precisely, we will generate early estimation of the percentage change in seasonally adjusted quarterly private sector consumption.

In performing this exercise we consider an initial set of 112 high frequency indicators including those that provide quantitative information on observed spending decisions or indicators that are related to those decisions (as for example the change in the M2 money aggregate), as well as qualitative information provided by households' surveys on consumer sentiment and consumption plans ("soft" indicators). Many of those are the monthly leading indicators of private consumption usually followed by practitioners and market analysts and are typically available in a real-time basis (1 to 2 months delay).Within these wide set of time series, we consider three groups. In doing so we select those that have a statistically significant correlation with private sector consumption and form two groups: G1, containing a restricted group of 20 indicators and G2, which includes a broader group of 32 indicators. The other other group, G3, is composed by those indicators that are the mostly followed by market analysts when tracking Private Sector Consumption. Table 1 presents the business cycle indicators included in each group.

Table 1: Consumption: Monthly business cycle indicators

Series	Source	Group 1	Group 2	Group 3
Car sales	ADEFA			X
Car Sales - Domestic Productio	ADEFA			X
Brasil Economic Activity Index	Banco Central de Brasil		X	
M2	BCRA	X	X	X
Credit Card loans	BCRA	X	X	X
Retail sales	CAME	X	X	
Retail sales -shoes	CAME		X	
Retail sales - sports	CAME	X	X	X
Retail sales-home appliances	CAME	X	X	X
Retail sales-Hardware	CAME	X	X	X
Retail sales - Candies and soda	CAME		X	
Retail sales - Leather goods	CAME	X	X	X
Retail sales - Electricity appliances	CAME		X	
Retail sales - Construction materials	CAME		X	
Retail sales - Furniture	CAME		X	X
Retail sales - Furniture Office	CAME	X	X	X
Retail sales - Clothing	CAME		X	X
Retail sales - Linens	CAME		X	X
Used car sales	CCA	X	X	X
House deeds - Buenos Aires City	Association of Notaries - City of Buenos Aires	X	X	X
Financial Conditions Index	Econviews Consulting	X		X
Industrial production - Durable goods	FIEL			X
Industrial production - Non durable goods	FIEL		X	X
Industrial production - Textil inputs	FIEL		X	
Industrial production - Cars	FIEL		X	
Car patenting - Argentina	GCBA			X
Car patenting City - of Buenos Aires	GCBA			X
Export Prices Agriculture Manufactures	INDEC	X	X	
Imports - Total	INDEC	X	X	X
Imports - Intermediate Goods	INDEC	X	X	
Imports - Machinery Accesories	INDEC	X	X	
Imports - Consumption goods	INDEC		X	X
Imports - Cars	INDEC			X
Income Tax Collection	MECON			X
Value Added Tax Collection	MECON			X
Employement Expectations	Ministry of Labor	X	X	X
Personnel Search	Ministry of Labor		X	X
Consumer Confidence Index - Buenos Aires	UTDT	X	X	X
Consumer Confidence Index - Argentina	UTDT	X	X	X
Consumer Confidence Index - Durable Goods and Houses	UTDT			X
Consumer Confidence Index - Personal Conditions	UTDT	X	X	X
Consumer Confidence Index - Current Conditions	UTDT	X	X	X

Source: INDEC

Both, the factors and the nowcasting models are estimated for the sample period 2009:Q1 - 2018:Q4. Based on the estimated factor models for the three sets of indicators (G1, G2 and G3) we conduct a rolling window pseudo-out of sample nowcasting exercise over the period 2016:Q1-2018:Q4.

Figures 2 and 3 present for each quarter of the predictive sample the correspondent loss function for each model, measured by the Root Mean Square Error (RMSE) calculated with respect to the initial and the final releases of the National Accounts respectively. As a benchamark, following the standard procedure in the literature, we estimate an autoregressive model for private consumption.

Figure 2: RMSE: Estimated values vs. private sector consumption Q/Q % change (initial release)

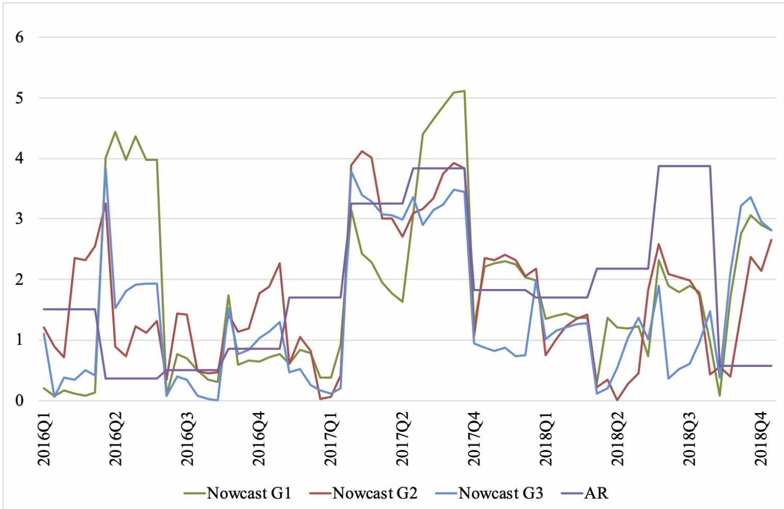
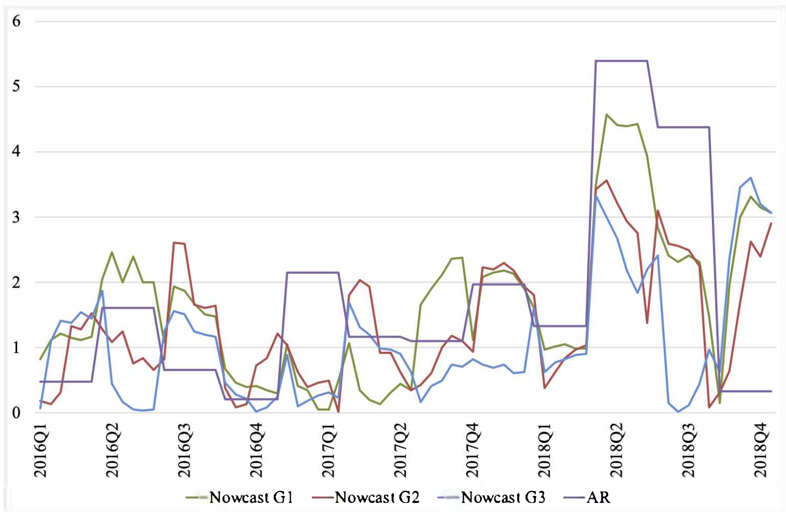


Figure 3: RMSE: Estimated values vs.private sector consumption Q/Q % change (final release)



Looking at the two figures it is difficult to identify at first sight the superiority of any of the three models relative to the others in terms of predictive ability, neither for the case of the initial release of Private Consumption figures or the final release. We thus proceed to compare the relative predictive ability of the three models using the Giacomini and White test, as described in section 2. Tables 2 and 3 present the results of performing the test for the initial and the final release of the National Accounts, respectively. In Table 1 models are first compared relative to a benchmark autoregressive model (AR) and between each other. It can be seen from there that only the G3 model, including the business cycle indicators used by market analysts, outperforms the AR. The comparison of the three models, shown in the second part of Table 2 indicates the G3 exhibits a significantly better performance relative to its competitors, G1 and G2.

Table 2: Results: Giacomini and White Test - Initial release of consumption figures

Sample: Q1 2016 - Q4 2018		
	coefficient	t statistic
Nowcast G1 vs AR	-0.08	-0.50
Nowcast G2 vs AR	0.06	0.45
Nowcast G3 vs AR	-0.25	-1.81
	coefficient	t statistic
Nowcast G3 vs G1	-0.17	-1.72
Nowcast G3 vs G2	-0.31	-3.22
Nowcast G2 vs G1	0.14	1.01

Turning to the performance of the nowcasting models in predicting the final release of the private sector consumption figures, Table 3 shows that again, it is the factor model including the set of business cycle indicators used by market analysts to track the evolution of private sector consumption, the one that outperforms the AR model and in this case the difference is statistically more significant than in the case of the initial release. Also, when comparing between nowcasting factor models, model G3 the difference in predictive performance of the G3 model relative to the other two models out-stands as more significantly that for the case of the initial release.

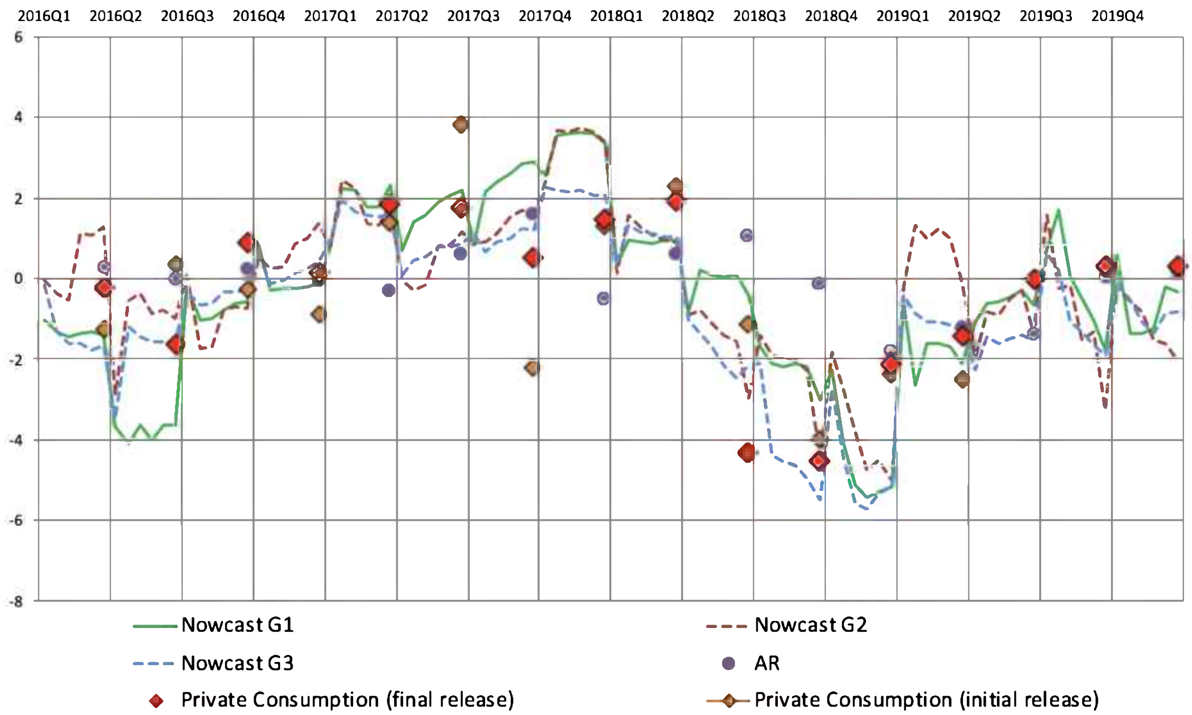
Table 3: Results: Giacomini and White Test - Final release of private sector consumption

Sample Q1 2016 - Q4 2018		
	coefficient	t statistic
Nowcast G1 vs AR	-0.04	-0.29
Nowcast G2 vs AR	-0.09	-0.62
Nowcast G3 vs AR	-0.42	-2.64

	coeficiente	estadístico t
Nowcast G3 vs G1	-0.39	-3.82
Nowcast G3 vs G2	-0.33	-3.53
Nowcast G2 vs G1	-0.06	-0.58

Figure 4 shows the predictions of our selected Nowcasting Factor Model (G3), compared to the AR and the initial and final release of the Private Consumption figures from the National Accounts for an extended period, up to the fourth quarter of 2019.

Figure 4: Private sector consumption Q/Q percentage change s.a.



Source: INDEC

Summing up, we find that a nowcasting factor model including those indicators used by market analysts to track the evolution of private sector consumption significantly outperforms the autoregressive benchmark model as well as other factor models using different sets of business cycle indicators.

4 Nowcasting investment

The use of nowcasting models to asses the evolution of the business cycle has recently extended to the case of consumption (see Verban et al 2017 and Gil et al., 2018). In the case of investment, other relevant component of aggregate domestic demand we did't find any nowcasting exercise developed in the nowcasting literature, except for the work of Dogliolo (2018), for the Argentine case, in which we base the exercise developed here.

Our target variable in this case is the quarter over quarter change in seasonally adjusted investment, according to the figures of the National Accounts. Within a wide set of 99 monthly business cycle that are related to expenditure on investment goods or investment decisions, we select three increasingly restricted subset, according to their correlation with the investment figures: (i) the **G1** group of indicators that have a contemporaneous correlation with the change in Q/Q investment (s.a) higher than 30%, (ii) the **G2** group, composed by 26 indicators with a correlation higher than 35% and (iii) the **G3**, including 19 indicators with correlation higher than 40%.

These three sets include hard and soft indicators, which are described in detail in Table 4.

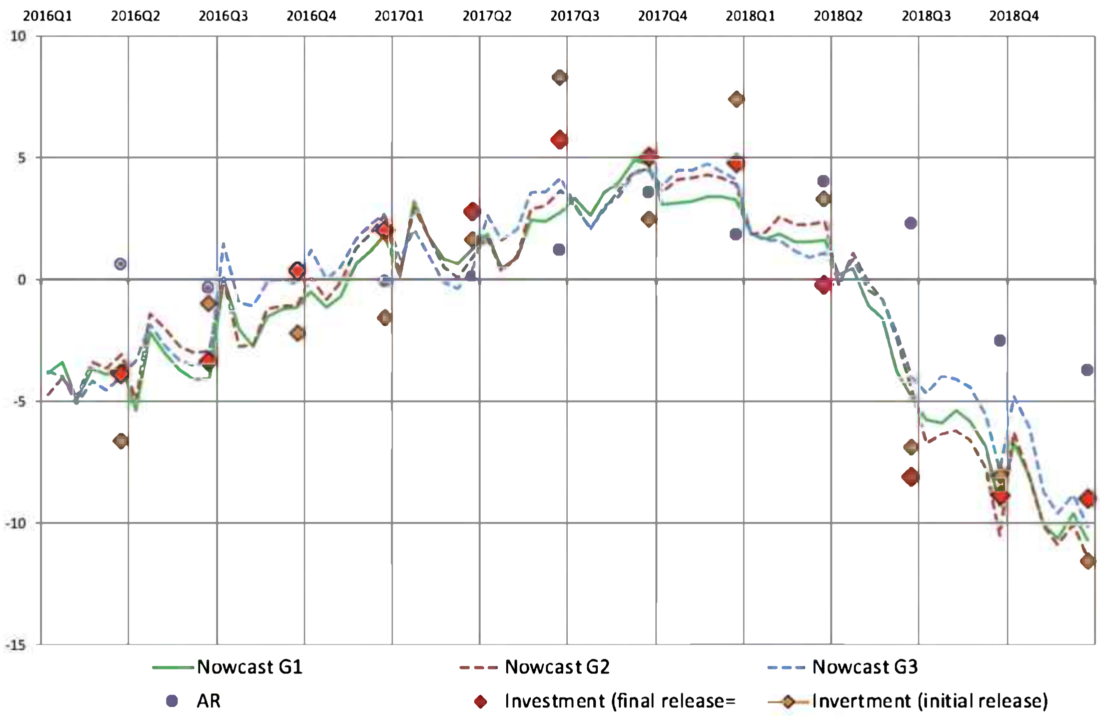
Table 4: Investment: Monthly business cycle indicators

Series	Source	Group 1	Group2	Group3
Car production	ADEFA	×	×	×
Car sales	ADEFA	×	×	
Industrial Production Index - Brasil	Central Bank of Brazil	×	×	×
Economic Activity Index - Brasil	Central Bank of Brazil	×		
M2 Private sectorAmplio Privado Nominal	BCRA	×	×	×
Credit card loans	BCRA	×	×	
Hot rolled steel production	Chamber of the steel industry	×	×	
Cold rolled steel production	Chamber of the steel industry	×		
Flat steel rolling production	Chamber of the steel industry	×		
Retail sales - Hardware	CAME	×	×	×
Retail sales - Office furniture	CAME	×	×	×
Retail sales - Home appliances	CAME	×	×	×
Retail sales - Construction materials	CAME	×		
Retail sales - Electricity materials	CAME	×		
House deeds - City of Buenos Aires	Association of Notaries	×	×	
Industrial Production Index - Investment goods	FIEL	×	×	×
Industrial Production Index - Cars	FIEL	×	×	×
Industrial Production Index - Durable goods	FIEL	×	×	
Total imports	INDEC	×	×	×
Imports - Intermediate goods	INDEC	×	×	×
Imports - Machinery accesories	INDEC	×	×	×
Imports - Consumption goods	INDEC	×	×	×
Export Prices - Primary goods	INDEC	×	×	×
Export Prices - Agroindustry goods	INDEC	×	×	×
Export Prices - Total	INDEC	×	×	×
Car imports	INDEC	×	×	
Exports - Agroindustrial goods	INDEC	×		
Income Tax Collection	MECON	×		
Employement expectations	Ministry of Labor	×	×	
Presonnel search	Ministry of Labor	×		
Consumer Confidence Index - Current conditions	UTDT	×	×	×
Consumer Confidence Index -Personal conditions	UTDT	×	×	×
Consumer Confidence Index - City of Buenos Aires	UTDT	×	×	×
Consumer Confidence Index - Expected conditions	UTDT	×	×	×
Consumer Confidence Index - Durable goods and houses	UTDT	×		
Consumer Confidence Index - Total	UTDT	×		

Source: INDEC

The models were estimated over the period 2008:Q1-2018:Q4. The predictive sample for the nowcasting exercise was initially the period 2016:Q1-2018:Q4. In this case we prefer to show the predicted and released figures because they provide a good insight into the models performance relative to the benchmark. Figure 5 shows the predicted values generated by our three nowcasting model as well as those generated by an autoregressive (AR) model for investment, as a benchmark, for the entire predictive sample: 2011:Q1-2018Q4. When comparing with the Investment figures of the National Accounts for both, the initial and the final releases, several findings are worth noting. First, the revisions between the initial can be quite large (note for example 2016:Q2 or 2017:Q3). Second, the performance of the autoregressive model seems to be very poor, for both the initial and final release of the National Account figures. Third, it is difficult to choose between the three nowcasting models and it also good to notice that for some quarter the performance of the three models is notably poor. Observations 1 and 3 are in line with our knowledge about the volatile behavior of investment over the business cycle across developed and developing countries and its dependence on agents expectations about business cycle conditions.

Figure 5: Investment Q/Q % change s.a.



Source: INDEC

We thus conduct the Giacomini and White test in order to use a statistical criteria to select, within the nowcasting models, the best performing in terms of predictive ability. First we compare models relative to the AR benchmark. The results, shown in Tables 5 and 6 confirm the insight provided by Figure 5. That is, the three models outperform the AR, for both the initial and the final investment figures.

Table 5: Results: Giacomini and White Test - Initial release of the National Accounts

Sample: Q1 2011 - Q4 2018		
	coefficient	t - statistic
Nowcast G1 vs AR	-1.02	-5.22
Nowcast G2 vs AR	-1.15	-5.78
Nowcast G3 vs AR	-0.87	-4.42
Sample Q1 2016 - Q4 2018		
	coefficient	t - statistic
Nowcast G1 vs AR	-1.54	-5.23
Nowcast G2 vs AR	-1.71	-5.95
Nowcast G3 vs AR	-1.37	-4.94

Table 6: Results: Giacomini and White Test - Final release of investment figures

Sample Q1 2011 - Q4 2018		
	coefficient	t - statistic
Nowcast G1 vs AR	-1.41	-8.93
Nowcast G2 vs AR	-1.46	-9.24
Nowcast G3 vs AR	-1.34	-8.54
Sample Q1 2016 - Q4 2018		
	coefficient	t - statistic
Nowcast G1 vs AR	-2.02	-7.90
Nowcast G2 vs AR	-1.97	-7.64
Nowcast G3 vs AR	-1.93	-9.35

We then compare within nowcasting factor models. In this case we consider two predictive samples: the extended one which is 2011:Q1-2018:Q4 and restricted sample: 2016:Q1-2018:Q4, with the purpose of evaluating if the elimination of exchange rate restriction could have had an impact on the models performance, taking into account the strong empirical correlation found in the Argentine data between investment and imports of machinery and tools, which in fact are incorporated within the sets of monthly business cycle. First, the results for the initial release, which are shown in Table 7 indicate that G2 model outperforms the rest in predicting the initial release of investment figures and the differences in predictive performance are statistically more significant for the extended sample.

Table 7: Results: Giacomini and White Test - Initial release of investment figures

Sample: Q1 2011 - Q4 2018		
	coefficient	t - statistic
Nowcast G2 vs G1	-0.13	-3.32
Nowcast G3 vs G2	0.28	4.19
Nowcast G3 vs G1	0.15	2.10
Sample: Q1 2016 - Q4 2018		
	coefficient	t - statistic
Nowcast G2 vs G1	-0.17	-2.45
Nowcast G3 vs G2	0.34	3.09
Nowcast G3 vs G1	0.17	1.44

Table 8 presents the results for the final release of the investment figures in the National Accounts. In this case the results are not clear. Given that we also tried for a more restricted sample, to only consider the last period between 2017:Q1 and 2018:Q4, characterized by a high exchange rate volatility. It can be seen that for all the selected predictive samples the three models are indistinguishable in terms of predictive ability.

Table 8: Results: Giacomini and White Test - Final release of investment figures

Sample: Q1 2011 - Q4 2018		
	coefficient	t - statistic
Nowcast G2 vs G1	-0.05	-1.25
Nowcast G3 vs G2	0.12	1.74
Nowcast G3 vs G1	0.07	1.02
Sample: Q1 2016 - Q4 2018		
	coefficient	t - statistic
Nowcast G2 vs G1	0.05	0.80
Nowcast G3 vs G2	0.04	0.37
Nowcast G3 vs G1	0.10	0.84
Sample: Q1 2017 - Q4 2018		
	coefficient	t - statistic
Nowcast G2 vs G1	0.05	0.58
Nowcast G3 vs G2	0.29	2.04
Nowcast G3 vs G1	0.34	2.63

Taking into account this result we decided to explore the possibility that a pooling of models could outperform any of the individual ones. When pooling models, we decided to use equal weights. Table 9 presents the results of the test comparing the three nowcasting models with the pooling. The results are not very clear in terms of the pooling outperforming the rest of the models, but there is some evidence that the pooling does a better job than the G3 model in terms of predictive ability. In practical terms, these result led us to choose the pooling and the G2 model as the ones selected to track the evolution of investment over the business cycle.

Table 9: Results: Giacomini and White Test - Final release of investment figures

Sample Q1 2011 - Q4 2018		
	coefficient	t - statistic
Pooling vs G1	-0.04	-1.11
Pooling vs G2	0.01	0.42
Pooling vs G3	-0.11	-2.36
Sample Q1 2016 - Q4 2018		
	coefficient	t - statistic
Pooling vs G1	-0.01	-0.27
Pooling vs G2	-0.07	-1.24
Pooling vs G3	-0.11	-1.44
Sample Q1 2017 - Q4 2018		
	coefficient	t - statistic
Pooling vs G1	0.07	1.21
Pooling vs G2	0.02	0.34
Pooling vs G3	-0.27	-3.01

5 Conclusions

We conduct a nowcasting exercise for two relevant components of domestic aggregate demand: consumption and investment, using different sets of high frequency commonly used business cycle indicators to extract the common factors behind them, possibly related to the dynamics of aggregate expenditure shocks. Using these common factors we construct different models and use them to conduct a rolling windows estimation and prediction exercise to obtain early estimates of consumption and investment figures. We then compare the relative predictive performance of the different models using the Giacomini and White (2006) of conditional predictive ability for model selection.

In the case of consumption, factors extracted from a set of indicators commonly used by market analysts perform better than the AR benchmark and the rest of the other models, and it does so for early and final figures of consumption.

Investment, being more volatile and subject to large revisions, reveals harder to predict than consumption. We try evaluating the model for different predictive samples taking into account the macroeconomic uncertainty and structural breaks that prevailed in Argentina over the predictive sample we analyze. However, all nowcasting models prove to outperform the AR model. For the early release of investment, a model using a relatively restricted set of monthly business cycle indicators outperforms the other models.Finally, a pooling of the nowcasting models tracks quite well the final release figures of investment, outperforming in some cases the individual models

References

[1] Andreou E., E. Ghysels 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. Gianonne, G. Rünsler, and L. Reichlin (2008). "Short-term forecast of Euro Area GDP", European Central Bank Working Paper No. 949.

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

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

[5] Banbura M., D. Giannone, M. Modugno and L. Reichlin. (2013) "Now-casting and the real-time data flow", *Handbook of Economic Forecasting*, Elliot G. and A. Timmermann, eds., Chapter 4, Vol. 2, North-Holland.

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

[7] Blanco, E., L. D'Amato, F. Dogliolo and L. Garegnani,(2017). "Nowcasting GDP in Argentina: Comparing the predictive ability of different models", Economic Research Working Papers 2017 N 74, BCRA.

[8] 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.

[9] 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.

[10] 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.

[11] D'Amato, L., L. Garegnani and E. Blanco (2009). "Forecasting Inflation in Argentina: Individual Models or Forecast Pooling?", *Monetaria*, Centro de Estudios Monetarios Latinoamericanos, vol. 0(2), pp. 151-179, apr-jun.

[12] D'Amato L. , L. Garegnani and E. Blanco, (2015). "GDP Nowcasting: Assessing business cycle conditions in Argentina". Estudios BCRA, Working Paper 2015 nro. 69.

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

[14] Dogliolo, F. (2018). "Nowcasting de Inversión. Una estimación en tiempo real con indicadores de alta frecuencia", Documentos de trabajo 2018 N 78, Investigaciones Económicas BCRA.

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

[16] Evans, M. (2005). "Where are we now? Real-time Estimates of the Macro Economy", The International Journal of Central Banking, Vol. 1, 2, pp. 127-175.

[17] Giacomini, R. and H. White, (2006). "Tests of conditional predictive ability", *Econometrica*, Vol 74 N^o 6, 1545-1578.

[18] Ghysels, E. (2013). "MATLAB Toolbox for Mixed Sampling Frequency Data Analysis Using MIDAS Regression Models." Available on MATLAB Central at http://www.mathworks.com/matlabcentral/fileexchange/45150-midas-regression.

[19] Ghysels E., Kvedaras V., Zemlys V. (2016). "Mixed Frequency Data Sampling Regression Models: The R Package midasr." R package version 0.6, URL https://CRAN.R-project.org/ package=midasr.

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

[21] Giannone, D., L. Reichlin 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.

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

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

[24] Ghysels E., Kvedaras V., Zemlys V. (2016). "Mixed Frequency Data Sampling Regression Models: The R Package midasr." Journal of Statistical Software, Volume 72, Issue 4. https://www.jstatsoft.org/article/view/v072i04

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

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

[27] Jansen W. J., X. Jin and J M.de Winter, (2016). "Forecasting and nowcasting real GDP: Comparing statistical models and subjective forecasts", International Journal of Forecasting 32, pp 411-436.

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

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

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

[31] 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.

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

[33] 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.

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

[35] 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.

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