Short-Run Forecasting of Argentine GDP Growth*

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Abstract

We propose a small-scale dynamic factor model for monitoring Argentine GDP in real time using economic data at mixed frequencies (monthly and quarterly) which are published with different time lags. Our model not only produces a coincident index of the Argentine business cycle in striking accordance with professional consensus and the history of the Argentine business cycle, but also generates accurate short-run forecasts of the highly volatile Argentine GDP growth. By using a pseudo real-time empirical evaluation, we show that our model produces reliable backcasts, nowcasts and forecasts well before the official data is released.

Keywords: Real-time forecasting, Argentine GDP, business cycles, state-space models, mixed frequencies.

JEL Classification: C22, C53, E27, E32, E37.

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1 Introduction

Gross Domestic Product (GDP) is the most important measure of the aggregate state of economic activity in any market economy. As such, it should be the most relevant business cycle indicator for policymakers and economic agents who are constantly making relevant real-time economic decisions. However, the quarterly GDP figures are typically published with significant time lag, which constitutes a major problem for economic agents who need updated information in order to make a proper assessment of current and future macroeconomic conditions. Needless to say, such problem is particularly acute in emerging countries, which usually face longer publication delays for the relevant economic indicators than developed countries.

In Argentina, for instance, the GDP data for a given quarter is published about 10 weeks after the end of the corresponding quarter, clearly too late to be a useful indicator for real-time decisions. Economic agents (investors, policymakers, consumers) are therefore forced to rely on other economic series available throughout the quarter to track the evolution of current GDP. However, those series correlate with partial aspects of economic activity, they are usually more volatile than the GDP, and they often yield contradictory insights about how the GDP is evolving over a given quarter. Moreover, it is difficult to use monthly series to forecast quarterly GDP since the models need to process data with different frequencies. Hence, having an econometric model that can combine monthly and quarterly economic series to obtain a real-time measure of economic activity as an updating assessment tool for tracking quarterly GDP is of the utmost interest. As a result, it comes as no surprise that research economists devote increasing time and effort to develop econometric techniques in order to address those shortcomings.

In this context, a very useful small-scale factor model for building a coincident index of business cycle which handles mixing monthly and quarterly series, and unbalanced panels of data, was developed by Mariano and Murasawa (2003) for the US economy. It was later on refined for specific forecasting purposes by Camacho and Perez-Quiros (2010) with regard to the eurozone. They treat the unobserved cells - that appear when mixing frequencies and dealing with different reporting lags - as missing observations, and replace them with independent realizations of a standard normal distribution, which is independent of the model parameters. Then, they rewrite the state-space model accordingly, so that they can apply the Kalman filter to evaluate the likelihood function. Therefore, they follow the lines initiated by Kohn and Ansley (1983) and Harvey and Pierse (1984) who handle the shortcomings of dealing with missing observations by setting up the models in state-space form and by applying the Kalman filter with minor modifications of the standard cases.[1]

Mariano and Murasawa (2003), Camacho and Perez-Quiros (2010), and a small but growing literature that follows them (see Section 2 below), analyze only advanced regions or countries. However, to the best of our knowledge

[1] Among others, see also Bernanke et al. (1997), Nunes (2005), and Aruoba et al. (2009).

this is the first attempt to apply such methodology for developing countries. This is particularly relevant as developing countries usually face much more volatile business cycles than advanced economies.[2] For instance, the variance of Argentine real GDP fluctuations between 1993 and 2012 is eight times higher than that of the USA (see Figure 1).[3] It is hence very interesting to test whether this methodology can be successfully applied to a middle-income developing country as Argentina. In this work, we tackle this question. In particular, we extend those seminal works and use their setup to produce backcast, nowcast and short-run forecast estimates of Argentine real GDP growth. Thus, our model uses partial information on the current economic situation of Argentina, mixing just a few monthly and quarterly indicators with differing lengths to obtain an accurate assessment of current and future Argentine real GDP growth.

[Insert Figure 1 here]

Our main results can be summarized as follows. First, the coincident indicator has a strong performance as a business cycle indicator for Argentina since it is in striking accordance with professional consensus and the history of the Argentine business cycle. Second, the percentage of the variance of the very volatile Argentine real GDP growth that is explained by the model is above 89%, indicating the high potential ability of the indicators used to explain Argentine growth. Third, our pseudo real-time analysis shows that dynamic factor models clearly outperform univariate forecasts, especially when forecasting the next unavailable figure of Argentine GDP growth. This encourages real-time forecasters to back-check the bulk of monthly real and survey data which are published in the respective quarter before the next GDP release. Against this backdrop, our model is able to produce accurate forecasts, leading us to strongly consider our model a valid tool to be used for short-term analysis.

This paper is organized as follows. The related literature is briefly reviewed in Section 2. Section 3 presents an outline of the model, indicates how to mix frequencies, describes its dynamic properties, along with the state-space representation, and demonstrates its estimation process. Section 4 contains data description and highlights the main empirical results, both in- and out-of-sample. Finally, conclusions and some proposals for future lines of research are presented in Section 5.

2 Brief review of relevant related literature

For the sake of brevity, we focus this review on recent advances on small-scale dynamic factor models and on the papers that have recently examined the em-

[2] See Lane (2003) and Aguiar and Gopinath (2007). Also, Alper (2002) presents a detailed study for Mexico and Turkey.

[3] However, it is important to note that in spite of its high volatility, the Argentine GDP growth does not follow an ARCH process. We carry out ARCH tests for the residual from an AR(1) specification of Argentine real GDP growth and were not able to reject the null of no-presence of ARCH in the residuals at usual significance levels. These results are available from the authors upon request.

pirical performance of some models to forecast Argentine GDP. The modern literature on business cycle estimation starts with the Stock and Watson (1989, 1991) coincident index. They estimate a monthly coincident index of economic activity as the unobservable factor in a dynamic factor model for four coincident indicators: industrial production, real disposable income, hours of work and sales, with the aim of providing a formal probabilistic basis for the Burns and Mitchell (1946) coincident and leading indicators. However, the dynamic factor model advocated by these authors exhibits two important drawbacks when it is used to monitor economic activity in real time. First, their method requires balanced panels, which precluded them from using data with mixed frequency or indicators with different publication delays. Therefore, their model ignores the information contained in quarterly indicators such as real GDP, which is likely the most important business cycle indicator. Second, the index they obtain is computed as linear combinations of meaningful economic indicators; the fact that it is not related to a particular variable of interest makes it difficult to find an economic interpretation of its level or its reactions to shocks.

To address those drawbacks, Mariano and Murasawa (2003) proposed a coincident index of business cycles with the distinctive characteristic of blending indicators published both at monthly and quarterly frequencies. They also incorporate a maximum likelihood factor analysis to the four monthly indicators, but since their methodology is able to handle mixing frequencies, they can also include real GDP as an additional fifth coincident indicator. Moreover, they can include series of differing lengths. Their coincident index accurately captures the NBER business cycle reference dates and presents a very high statistical correlation with the Stock and Watson (1991) coincident index. Moreover, their index has an economic interpretation as the common factor component in a (latent) monthly real GDP. One drawback of Mariano and Murasawa (2003) is that they do not explore the forecasting properties of their model.

The forecasting analysis of this model is tackled later on by Camacho and Perez-Quiros (2010), who successfully modified Mariano and Murasawa's model to compute short-term forecasts of the eurozone real GDP growth in real time.[4] Their small-scale dynamic factor model is able to forecast eurozone real GDP growth at least as well as (and usually better than) professional forecasters. Further developments of their work are Camacho and Perez-Quiros (2011) and Camacho and Domenech (2012) for Spain, Camacho and Martinez-Martin (2013) for the USA, and Camacho and Garcia-Serrador (2013) for the euro area.[5]

This recent literature on short-run real GDP growth forecasting is almost exclusively focused on developed economies. The related literature is very scarce for emerging countries in general, and especially for Argentina. To the best of our knowledge, there are only three attempts similar to ours in the literature, but

[4] Aruoba and Diebold (2010) also build on Stock and Watson (1989, 1991) and Mariano and Murasawa (2003) and examine the real-time performance of the common factor as a business cycle indicator, but their focus is on the assessment of current economic activity and not on forecasting.

[5] This econometric model is, however, quite flexible. For an application to a very different field, FX rate forecasting, see Dal Bianco et al. (2012).

using different approaches. The first is Simone (2001), who constructs coincident and leading indicators of economic activity in Argentina. Although he proposes a useful contribution, he only uses quarterly data and does not attain a reliable leading indicator for Argentine real GDP. Second, two recent works by D'Amato et al. (2011a, 2011b) employ two techniques to produce predictions of current real GDP growth within the quarter, referred to as "nowcasting," and one-quarter ahead forecast of real GDP growth.[6] Third, Liu et al. (2011) estimate a large-scale factor model based on monthly data for nowcasting and forecasting. However, the related RMSE show only traces of weak forecasting capacity.

3 The econometric model

3.1 Mixing frequencies

We use data at two frequencies: monthly and quarterly. To mix them, we consider all series as being of monthly frequency and treat quarterly data as monthly series with missing observations. In this case, the quarterly series are observed in the last month of the quarter, and exhibit missing observations in the first two months of each quarter.

In particular, let G_t be the level of a quarterly flow variable that can be decomposed as the sum of three (usually unobserved) monthly values G_t^*. To avoid using a non-linear state-space model, we follow Mariano and Murasawa (2003) and approximate the arithmetic mean with the geometric mean.[7] Hence, the level of the variable can be written as

$$G_t = 3(G_t^* G_{t-1}^* G_{t-2}^*)^{1/3}. \tag{1}$$

Taking logs on both sides of this expression and computing the three-period differences for all t, we obtain

$$\triangle_3 \ln G_t = \frac{1}{3}(\triangle_3 \ln G_t^* + \triangle_3 \ln G_{t-1}^* + \triangle_3 \ln G_{t-2}^*). \tag{2}$$

Denoting the quarter-on-quarter growth rate $\triangle_3 \ln G_t = g_t$ the monthly-on-monthly growth rate $\triangle \ln G_t^* = g_t^*$ and applying algebra, we obtain

$$g_t = \frac{1}{3}g_t^* + \frac{2}{3}g_{t-1}^* + g_{t-2}^* + \frac{2}{3}g_{t-3}^* + \frac{1}{3}g_{t-4}^*. \tag{3}$$

Accordingly, we express the quarter-on-quarter growth rate (g_t) as a weighted average of the past monthly-on-monthly growth rates (g_{t-i}^* , $i = 0, ..., 4$) of the monthly series.

[6] They do not present "backcasting" results, which are the estimation on a given quarter of the previous quarter rate of growth *before* they are published by the statistical agency, i.e., within the ten weeks of delay.

[7] Aruoba et al. (2009) extended this analysis to include high frequency data using an exact algorithm, as opposed to the approximate algorithm of Mariano and Murasawa (2003). However, Aruoba et al. (2009) face the cost of assuming deterministic trends in the series.

3.2 Dynamic properties

We use the common assumption in factor modelling literature that the time series used in the model are the sum of two orthogonal components: a common component, x_t, which represents the overall business cycle conditions, and an idiosyncratic component, which refers to the particular dynamics of the series. The underlying business cycle conditions are assumed to evolve with $AR(p_1)$ dynamics:

$$x_t = d_1^x x_{t-1} + ... + d_{p1}^x x_{t-p_1} + \varepsilon_t^x, \tag{4}$$

where $\varepsilon_t^x = iN(0, \sigma_x^2)$.

Let us consider k_1 quarterly indicators and k_2 monthly indicators. For each of the quarterly indicators, g_t, we assume that the evolution of its underlying monthly growth rates, g_t^*, depends linearly on x_t and on the idiosyncratic dynamics, u_t^g, which evolve as an $AR(p_2)$:

$$g_t^* = \beta_g x_t + u_t^g, \tag{5}$$

$$u_t^g = d_1^g u_{t-1}^g + ... + d_{p2}^g u_{t-p_2}^g + \varepsilon_t^g, \tag{6}$$

where $\varepsilon_t^g = iN(0, \sigma_g^2)$. In addition, the evolution of each of the monthly indicators, z_t, depends linearly on x_t and on the idiosyncratic component, whose dynamics can be expressed in terms of autoregressive processes of p_3 orders:

$$z_t = \beta_z x_t + u_t^z, \tag{7}$$

$$u_t^z = d_1^z u_{t-1}^z + ... + d_{p2}^z u_{t-p_3}^z + \varepsilon_t^z, \tag{8}$$

where $\varepsilon_t^z = iN(0, \sigma_z^2)$. Finally, the shocks of the common component and all the idiosyncratic shocks are assumed to be mutually uncorrelated in cross-section and time-series dimensions.[8]

Using the assumptions described below, this model can be easily stated in state-space representation and estimated – as further developed in the following section – by using the Kalman filter.

3.3 State-space representation and estimation

Let us start by assuming that all variables are always observed at a monthly frequency. The state-space model represents a set of observed time series, Y_t, as linear combinations of a vector of auxiliary variables, which are collected on the state vector, ξ_t. This relation is modelled by the *measurement equation*

$$Y_t = H\xi_t + E_t, \tag{9}$$

with $E_t \sim i.i.d.N\left(0, R\right)$. The dynamics of the sate vector is modelled by the *transition equation*

$$\xi_t = F\xi_{t-1} + W_t, \tag{10}$$

[8] We could consider time-varying parameters. However, it is out of the scope of this paper and is left for further research.

with $W_t \sim i.i.d.N(0, Q)$. In addition, it is assumed that the measurement equation errors independent of the transition equation errors.[9]

The estimation of the model would be by standard maximum likelihood and using the Kalman filter if all series were observable at the monthly frequency, as we assume so far. However, this assumption is quite restrictive since we are using time series of different length and different reporting lags and we are mixing monthly data with quarterly data.

Among others, Mariano and Murasawa (2003) describe a framework to easily handle this issue. Following these authors, the unobserved cells can be treated as missing observations and maximum likelihood estimation of a linear Gaussian state-space model with missing observations can be applied straightforwardly after a subtle transformation of the system matrices. The missing observations can be replaced with random draws ϑ_t, whose distribution must not depend on the parameter space that characterizes the Kalman filter.[10] Thus, the likelihood function of the observed data and that of the data whose missing values are replaced by the random draws are equivalent up to scale. In particular, we assume that the random draws come from $N(0, \sigma_\vartheta^2)$. In addition, the measurement equation must be transformed conveniently in order to allow the Kalman filter to skip the missing observations when updating.

Let Y_{it} be the i-th element of the vector Y_t and R_{ii} be its variance. Let H_i be the i-th row of the matrix H which has ς columns and let $0_{1\varsigma}$ be a row vector of ς zeroes. The measurement equation can be replaced by the following expressions

$$Y_{it}^{+} = \begin{cases} Y_{it} & \text{if } Y_{it} \text{ observable} \\ \vartheta_t & \text{otherwise} \end{cases}, \tag{11}$$

$$H_{it}^{+} = \begin{cases} H_i & \text{if } Y_{it} \text{ observable} \\ 0_{1\varsigma} & \text{otherwise} \end{cases}, \tag{12}$$

$$E_{it}^{+} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \vartheta_t & \text{otherwise} \end{cases}, \tag{13}$$

$$R_{iit}^{+} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \sigma_\vartheta^2 & \text{otherwise} \end{cases}. \tag{14}$$

According to this transformation, the time-varying state space model can be treated as having no missing observations so the Kalman filter can be directly applied to Y_t^+, H_t^+, E_t^+, and R_t^+.

The estimation of the model's parameters can be developed by maximizing the log-likelihood of $\left\{Y_t^+\right\}_{t=1}^{t=T}$ numerically with respect to the unknown parameters. Let $\xi_{t|\tau}$ be the estimate of ξ_t based on information up to period τ. Let $P_{t|\tau}$ be its covariance matrix. The prediction equations are

$$\xi_{t|t-1} = F\xi_{t-1|t-1}, \tag{15}$$

[9] A description of how these equations look like for an illustrative simplified model is set out in the Appendix.

[10] Note that replacements by constants would also be valid.

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q. \tag{16}$$

Hence, the predicted value of Y_t with information up to $t-1$, denoted by $Y_{t|t-1}$, is

$$Y_{t|t-1} = H^{+}\xi_{t|t-1}, \tag{17}$$

and the prediction error is

$$\eta_{t|t-1} = Y_t^{+} - Y_{t|t-1} = Y_t^{+} - H^{+}\xi_{t|t-1}, \tag{18}$$

with covariance matrix:

$$\nu_{t|t-1} = H^{+}P_{t|t-1}H^{+} + R_t^{+}. \tag{19}$$

The way missing observations are treated implies that the filter, through its implicit signal extraction process, will put no weight on missing observations in the computation of the factors.

In each iteration, the log-likelihood can be computed as

$$\log L_{t|t-1} = -\frac{1}{2}\ln\left(2\pi\left|\nu_{t|t-1}\right|\right) - \frac{1}{2}\eta'_{t|t-1}\left(\nu_{t|t-1}\right)^{-1}\eta_{t|t-1}. \tag{20}$$

It is worth noting that the transformed filter to handle missing observations has no impact on the model estimation. In that sense, the missing observations simply add a constant to the likelihood function of the Kalman filter process. Hence, the parameters that maximize the likelihood are achieved as if all the variables were observed.

The updating equations are:

$$\xi_{t|t} = \xi_{t|t-1} + P_{t|t-1}H_t^{+\prime}\left(\nu_{t|t-1}\right)^{-1}\eta_{t|t-1}, \tag{21}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H_t^{+\prime}\left(\nu_{t|t-1}\right)^{-1}H_t^{+}P_{t|t-1}. \tag{22}$$

Therefore, the missing observations are skipped from the updating recursion.

4 Empirical Results

4.1 Preliminary analysis of the data

The data employed in this paper, which was collected on September 15, 2012, spans the period from January 1993 to August 2012. Regarding the relatively wide potential set of indicators that could be used in the analysis, we only chose those that satisfy the following four properties. First, they must exhibit high statistical correlation with the real GDP growth rate, which is the target series to be estimated and predicted. Second, for a given quarter they should refer to data of that quarter, which implies that they must be published before the GDP figure becomes available in the respective quarter. Third, they must be relevant in the model from both theoretical and empirical (statistical) points of view. Finally, they must be available in at least one third of the sample.

We started the analysis with the Argentine version of the set of coincident economic indicators used in Mariano and Murasawa (2003): real quarterly GDP, monthly industrial production, quarterly employment, monthly real personal income, and real trade sales, which exhibit a strong (statistical) link with the GDP cycle. However, income was discarded because its loading factor was not statistically significant and was replaced with a Synthetic Indicator of Construction Activity, which exhibits higher correlation with GDP and a statistically significant loading factor. The potential enlargements of the data set were sequentially tested by including additional indicators such as the Consumer Confidence Index. However, the loading factors were not statistically significant and they were not included in the model.

The five indicators used in the empirical analysis and their respective publication delay are summarized in Table 1. All the variables are seasonally adjusted and are (weakly) stationary or transformed to be stationary.[11] Accordingly, the quarterly indicators enter the model in quarterly growth rates while the monthly indicators enter in monthly growth rates. Before estimating the model, the variables are standardized to have zero mean and variance equal to one. Therefore, the final forecasts are computed by multiplying the initial forecasts of the model by sample standard deviation, and then adding the sample mean.

[Insert Table 1 here]

4.2 In-sample analysis

In this section we present the results obtained in the estimation of the model outlined in Section 3. In Table 2 we present the estimated values for the factor loadings which reflect the degree to which variations in each observed variable are correlated with the latent factor. As observed, all variables show statistically significant loading factors.[12] Notably, Table 2 also shows that the percentage of variance of the actual Argentine real GDP growth that is explained by the factor is very high, reaching about 90%.

[Insert Table 2 here]

The empirical reliability of the inferred factor as an Argentine business cycle indicator is examined in Figure 2. Together with this series, the figure plots the corresponding growth rates of the Monthly Estimator of Economic Activity (EMAE from its acronym in Spanish), which is a widely accepted monthly proxy of Argentine real GDP. You can see in this graph that the evolution of the inferred factor is in striking accordance with that of EMAE.

[11] In particular, if the log of a variable appears as non-stationary according to Ng and Perron (2001) unit root tests, then the data are used in growth rates. To save space, the results are not presented but they are available from the authors upon request.

[12] The lag lengths used in the empirical exercise were always set to 2 since the AR(2) specification is able to model very rich dynamics in the time series. However, we perform several exercises to check that our results were robust to other reasonable choices of the lag lengths.

[Insert Figure 2 here]

With the aim of meticulously checking the accuracy of the common factor as a real-time business cycle indicator, we assume that the indicator is subject to regime switches.[13] For this purpose, we assume that the switching mechanism of the common factor at time t, x_t is controlled by an unobservable state variable, s_t which is allowed to follow a first-order Markov chain.[14] Following Hamilton (1989), a simple regime-switching model can be specified as:

$$x_t = c_{s_t} + \sum_{j=1}^{p} \alpha_j x_{t-j} + \varepsilon_t, \tag{23}$$

where $\varepsilon_t \sim iidN(0, \sigma^2)$.[15] The nonlinear behavior of the time series is governed by c_{s_t}, which is allowed to change within each of the two distinct regimes $s_t = 0$ and $s_t = 1$. The Markov-switching assumption implies that the transition probabilities are independent of the information set at $t-1$, x_{t-1}, and of the business cycle states prior to $t-1$. Accordingly, the probabilities of remaining in each state are:

$$p(s_t = i \mid s_{t-1} = j, s_{t-2} = h, ..., x_{t-1}) = p(s_t = i \mid s_{t-1} = j) = p_{ij}. \tag{24}$$

Taking the maximum likelihood estimates of parameters, as reported in Table 3, we observe that in the regime represented by $s_t = 0$ the intercept is positive and statistically significant, while in the regime represented by $s_t = 1$, it is negative and statistically significant. Hence, we can associate the first regime with expansions and positive values of the indicator, and the second regime with recessions and negative values of the indicator. In line with the related literature, expansions in Argentina are more persistent than downturns (estimated p_{00} and p_{11} of about 0.97 and 0.87, respectively). These estimates are in line with the well-known fact that expansions are longer than contractions, on average. Using the transition probabilities, one can derive the expected number of months that the business cycle phases prevail as $(1 - p_{ii})^{-1}$. Conditional on being in $s_t = 0$ the expected duration of a typical Argentine expansion is 33 months, and the expected duration of recession is approximately 8 months.

[Insert Table 3 here]

Finally, to check empirically whether the business cycle information that can be extracted from the common factor is in line with the historical consensus, we

[13] Camacho et al. (2013) show that although the fully Markov-switching dynamic factor model is generally preferred to the shortcut of computing inferences from the common factor obtained from a linear factor model, its marginal gains rapidly diminish as the quality of the indicators used in the analysis increases. This is precisely our case.

[14] Recently, Male (2011), Altug and Bildirici (2012) and Camacho and Perez-Quiros (2014) have also used nonlinear models in Latin American Countries.

[15] Based on Camacho and Perez-Quiros (2007), we did not include any lags in the factor. We checked that the resulting model is dynamically complete in the sense that the errors are white noise.

plot in Figure 3 the probabilities of being in recession (i.e., to be in state $s_t = 1$) extracted from our coincident indicator along with shaded areas that refer to recessionary periods according to the reference works of Jorrat and Cerro (2000) and Jorrat (2005, 2012).

[Insert Figure 3 here]

The figure shows the strong performance of the coincident indicator as a business cycle indicator for Argentina since it is in striking accord with previous estimates of turning points for the Argentine cycle. During the periods classified as recessions by this related literature, our estimated smoothed probabilities of being in recession are usually high. The only recession identified by Jorrat (2012) which is not reflected in a high probability of recession in our model is the one that appears to start in November 2011. However, Jorrat's dating of this last recession was tentative as his methodology defines a recession as a period of five consecutive monthly falls of his Economic Activity Index and in Jorrat (2012) there is only four consecutive monthly falls.[16] Hence, this recession could not be confirmed with additional information in future updates of Jorrat's business cycle dating, which would be consistent with our results. Lastly, bearing in mind Figure 2, it shows that there is a high commonality in switch times of probabilities with Argentine business cycle phases as identified by both the common factor and EMAE.[17]

4.3 Pseudo real-time analysis

To begin with, it is worth mentioning that we could not perform the forecast evaluation in real-time, i.e., by using only the information that would have been available at the time of each forecast. The reason is that the historical records of the time series used in the analysis are not available so we cannot construct the real-time vintages for all the indicators in the panel.

One feasible alternative, employed for example by Stock and Watson (2002), is to develop an out-of-sample analysis. The method consists of computing forecasts from successive enlargements of a partition of the latest available data set. It begins with data of all the time series from the beginning of the sample until one predefined period. Using this sample, the model is estimated and the h-period-ahead forecasts are computed. Then, the sample is updated by one period of each indicator, the model is reestimated and the forecasts are computed again. The forecasting procedure continues iteratively until the final forecast.

One key characteristic of this procedure is that the forecasts are computed from balanced panels of data as if all the data releases were synchronous. Therefore, this evaluation procedure would miss the fact that the data flows of the

[16] That is why the last shaded month in the graph is March 2012 which corresponds with the last data analyzed by Jorrat (2012), but this does not imply that this apparent recession ended on that month, as it could have lasted longer.

[17] It validates the interpretation of state $s_t = 1$ as recession and the probabilities plotted in Figure 2 as probabilities of being in recession.

variables involved in the forecasting analysis do not occur at the same time and the fact that some indicators exhibit longer reporting lags than others. In our context, if the evaluation process did not consider that data are reported in an asynchronous manner, it would diminish the usefulness of the early available monthly indicators to compute forecasts of Argentine GDP.

To overcome this drawback, we follow the pseudo real-time forecasting evaluation used, among others, by Giannone et al. (2008). Since the Argentine statistical agencies release economic data with a relatively stable calendar, we constructed data sets as successive enlargements of a partition of the latest available data set that replicate the pattern of data availability implied by the stylized calendar of the data releases outlined in Table 1. The first data set uses data from the beginning of the sample until April 1, 2002. It assumes that the latest available figures of GDP is December 2001, of IPI is February 2002, of Employment is January 2002, of Sales is February 2002 and of ISAC is February 2002. With this data set, the model is estimated and nine-month blocks of forecasts of GDP growth are computed. The first three forecasts (January, February and March) are labelled as backcasts since they actually refer to a past value of GDP, although it is not reported until May. The next three forecasts (April, May and June) are labelled as nowcasts since they refer to current values of GDP. The last three forecasts (July, August and September) refer to future values of GDP.

Using again the latest available data, the sample is updated by a period of 15 days of each indicator by preserving the structure of the data availability described below. Then, the model is reestimated and the nine-month block of GDP forecasts is computed again. Following this method, the forecasting procedure continues iteratively each 15 days until the final forecast, which is computed from a model that uses the latest available data in September 15, 2012, leading to 246 different blocks of forecasts. Therefore, the pseudo real-time analysis is conducted from the latest available data but on the basis of data sets that, due to the different publication lags that characterize the real-time forecasts, are unbalanced at the end of each partition of the data set.

The predictive accuracy of our model is examined in Table 4. The table shows the mean-squared forecast errors (MSE), which are the average of the deviations of the predictions from the final releases of GDP available in the data set. Results for backcasts, nowcasts and forecasts appear in the second, third and fourth columns of the table, respectively. In addition to the factor model described in Section 3, two benchmark models are included in the forecast evaluation. The former is an autoregressive model of order two (AR), which is estimated by following the pseudo real-time method and producing iterative forecasts. The latter is a random walk (RW) model whose forecasts are equal to the average latest available observations.

The MSE leads to a ranking of the competing models according to their forecasting performance. However, it is advisable to test whether the forecasts obtained with the dynamic factor model are significantly superior to the others models' forecasts. To analyze whether empirical loss differences between two or more competing models are statistically significant, the last three rows of the table shows the pairwise test introduced by Diebold and Mariano (1995).

The immediate conclusion obtained when comparing the forecasts is that the dynamic factor model unequivocally outperforms the alternative forecasting models, although the magnitude of these gains depend on the forecast horizon. In the backcasting exercise, the differences between the MSE results using the factor model and the benchmark models are noticeable. The relative MSE of the dynamic factor model versus RW and AR are 0.368 to 0.350. According to the p-values of the Diebold and Mariano test, the differences are statistically significant (p-values of 0.001 in both cases). The relative gains diminishes with the forecasting horizon, reducing to 0.742 and 0.709 in nowcasting and to 0.880 and 0.866 in forecasting. This result is quite intuitive because the backcasts and nowcasts are computed immediately before the end of the quarter, which allow the model to use the latest available information of the respective quarter from the early available indicators. Notably, although the gains diminish, they are still statistically significant, according to the p-values of the Diebold and Mariano test reported in the bottom panel of this table.

[Insert Table 4 about here]

5 Conclusions

In this paper, we propose a small-scale factor model with mixed frequencies to produce accurate backcasts, nowcasts and short-run forecasts of Argentine real GDP growth. Our model is successful not only in computing a coincident indicator, which is in striking accord with the actual history of Argentine business cycle, but also in explaining a very high percentage of the variance of actual GDP growth. Moreover, our pseudo real-time analysis shows that our dynamic factor model clearly outperforms univariate forecasts, especially when forecasting the next unavailable figure of GDP growth. This encourages real-time forecasters to back-check the bulk of monthly real and survey data which are published in the respective quarter before the next GDP release. Therefore, we strongly consider that it is a valid tool to be used to monitor the business cycle and to compute short-term forecasts of Argentine GDP growth.

Several other alternatives of short-term forecasting in real time have recently emerged from the literature. An interesting alternative is the mixed-frequency VAR model used in Mariano and Murasawa (2010) and its extension to a Markov-switching context by Camacho (2013). These models, as ours, rely on the Kalman filter that depends on Gaussians errors, stationarity and a correct specification of the models. Other alternative is the MIDAS model, initially proposed by Ghysels et al. (2004) and its extension to account for Markov-switching dynamics by Guerin and Marcellino (2013). Although MIDAS is a direct multi-step forecast device and the models based on Kalman filters typically perform iterated forecasts, a further comparison of their relative performance is in our research agenda

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Appendix

To illustrate what the matrices stated in the measurement and transition equations look like, let us assume that there are only one quarterly indicator, g_t, and only one monthly indicator, z_t, and that $p_1 = p_2 = p_3 = 1$. In this simplified version, the *measurement equation,* $Y_t = H\xi_t + E_t$,with $E_t \sim i.i.d.N\left(0, R\right)$, can be stated by defining

$$
\begin{aligned}
Y_t &= \left(g_t, z_t\right)', && \text{(A1)}\\
H &= \begin{pmatrix} \frac{\beta_g}{3} & \frac{2\beta_g}{3} & \beta_g & \frac{2\beta_g}{3} & \frac{\beta_g}{3} & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 \\ \beta_z & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}, && \text{(A2)}\\
\xi_t &= \left(x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, u_t^g, u_{t-1}^g, u_{t-2}^g, u_{t-3}^g, u_{t-4}^g, u_t^z\right)', && \text{(A3)}\\
E_t &= \left(0, 0\right)', && \text{(A4)}\\
R &= 0_{2\times 2}. && \text{(A5)}
\end{aligned}
$$

In the same way, the *transition equation,* $\xi_t = F\xi_{t-1} + W_t$, with $W_t \sim i.i.d.N\left(0, Q\right)$ can be stated by defining

$$
\begin{aligned}
F &= \begin{pmatrix} F_1 & 0_{5\times 5} & 0_{5\times 1} \\ 0_{5\times 5} & F_2 & 0_{5\times 1} \\ 0_{1\times 5} & 0_{1\times 5} & d_1^z \end{pmatrix}, && \text{(A6)}\\
F_1 &= \begin{pmatrix} d_1^x & 0_{1\times 4} \\ I_4 & 0_{4\times 1} \end{pmatrix}, && \text{(A7)}\\
F_2 &= \begin{pmatrix} d_1^g & 0_{1\times 4} \\ I_4 & 0_{4\times 1} \end{pmatrix}, && \text{(A8)}\\
\xi_t &= \left(\varepsilon_t^x, 0, 0, 0, 0, \varepsilon_t^g, 0, 0, 0, 0, \varepsilon_t^z\right)', && \text{(A9)}\\
Q &= diag\left(\sigma_x^2, 0, 0, 0, 0, \sigma_g^2, 0, 0, 0, 0, \sigma_z^2\right)'. && \text{(A10)}
\end{aligned}
$$

The identifying assumption implies that the variance of the common factor, σ_x^2, is normalized to a value of one. This is a very standard assumption in factor models.

Table 1: Final variables included in the model

	Series	Sample	Source	Publication delay	Data transformation
1	Real Gross Domestic Product (GDP, SAAR, Mil.1993 ARS)	1993.1 2012.3	INDEC	2.5 to 3 months	QGR
2	Industrial Production Index (IPI) (SA, 1993=100)	1993.01 2012.07	FIEL	25 days	MGR
3	All Employees: Total Urban Population (Empl, SA, Thous)	1993.1 2012.2	INDEC	1.5 to 2 months	QGR
4	Real Retail Sales: Total Supermarket Sales (Sales, SA, CPI deflated, constant. ARS)	1997.06 2012.06	INDEC/ Census	25-30 days	MGR
5	Synthetic Indicator of Construction Activity (ISAC, SA)	1993.01 2012.07	INDEC	30 days	MGR

Notes: SA means seasonally adjusted. MGR and QGR mean monthly growth rates, quarterly growth rates and levels, respectively. INDEC: National Institute of Statistics and Census; FIEL: Latin American Foundation of Economic Investigations; CPI: Consumer Price Index; SAAR: Seasonally Adjusted Annual Rate; ARS: Argentine pesos.

Table 2: Loading factors

GDP	IP	Empl	ISAC	Sales	% Var
0.28 (0.05)	0.41 (0.09)	0.28 (0.12)	0.35 (0.07)	0.16 (0.08)	89.9%

Notes: The first five columns show the estimated loading factors and (in brackets) their standard errors. The last column refers to the percentage of the variance of GDP that is explained by the common factor. See Table 1 for a description of these indicators.

Table 3. Markov-switching estimates

c_0	c_1	σ^2	p_{00}	P_{11}
1.09 (0.15)	-5.39 (0.43)	3.45 (0.32)	0.97 (0.01)	0.87 (0.06)

Notes: The estimated model is $x_t = c_{s_t} + \varepsilon_t$, where x_t is the common factor, s_t is an unobservable state variable that governs the business cycle dynamics, $\varepsilon_t \sim iidN(0,\sigma)$, and $p(s_t = i/s_{t-1} = j) = p_{ij}$.

Table 4: Predictive accuracy

	Backcasts	Nowcasts	Forecasts
	Mean Squared Errors		
Our model	1.049	1.552	1.884
RW	2.851	2.090	2.139
Our model/RW	0.368	0.742	0.880
AR	2.999	2.189	2.174
Our model/AR	0.350	0.709	0.866
	Equal predictive accuracy tests		
Our model vs RW	0.001	0.032	0.041
Our model vs AR	0.001	0.015	0.021

Notes. The forecasting sample is 2002.1-2012.1, which implies comparisons over 246 forecasts. The top panel shows the Mean Squared Errors (MSE) of our dynamic factor model, a random walk (RW), an autoregressive model of order two (AR), along with the relative MSEs over that of our model. The bottom panel shows the *p*-values of the Diebold-Mariano (DM) test of equal predictive accuracy.

Figure 1. Argentina and USA, real GDP growth (var. % q/q, S.A., 1993:1-2012:4)

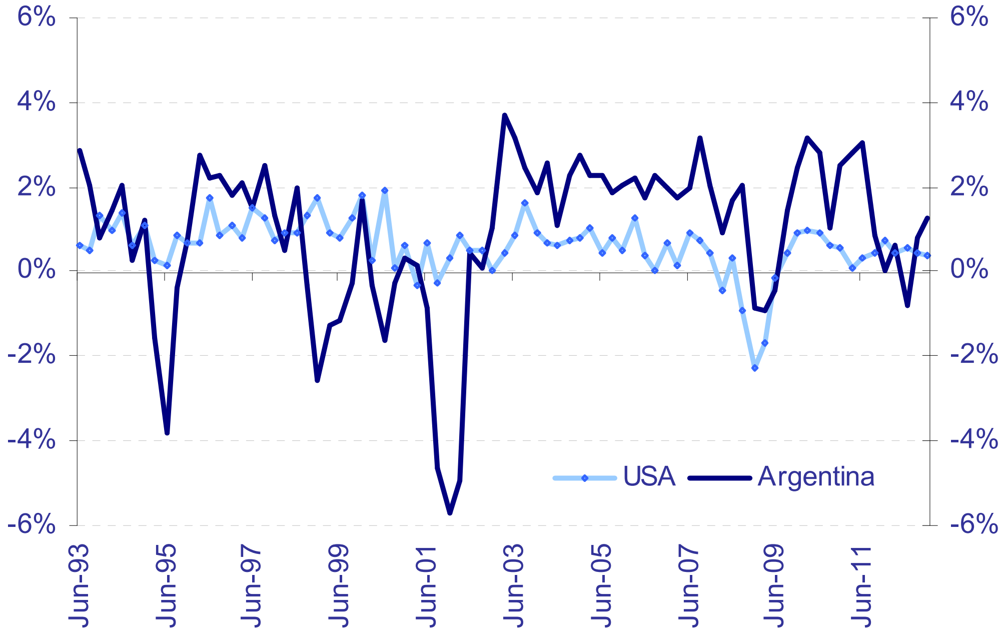
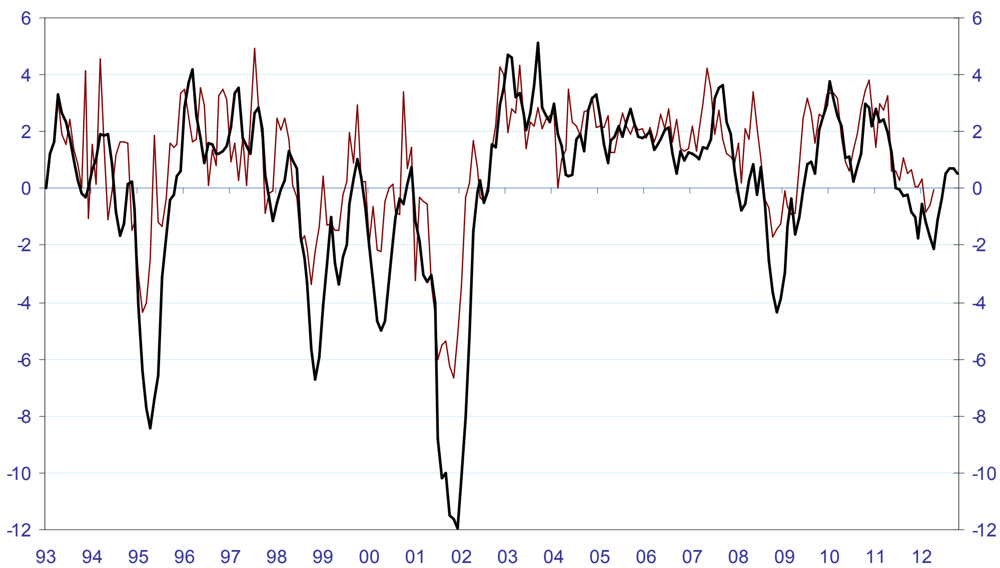


Figure 2. Common factor and EMAE (var. % 3M-3M)



Notes. Black line refers to the common dynamic factor (1993.03-2012.12). Red line refers to EMAE (1993.06-2012.06).

Figure 3. Probability of recession from our factor and periods of recession (shaded) according to Cerro and Jorrat (2000), and Jorrat (2005,12)