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Germán López

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Forecast Accuracy of Small and Large Scale Dynamic Factor Models in Developing Economies*

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Abstract

This paper compares forecast accuracy of two Dynamic Factor Models in a context of constraints in terms of data availability. Estimation technique and properties of the factor decomposition depend on the cross section dimension of the dataset included in each model: a large dataset composed by series belonging to seven broad categories or a small dataset with a few prescreened variables. Short term out-of-sample forecast of GDP growth is carried out with both models reproducing the real time situation of data accessibility derived from the publication lags of the series in six Latin American countries. Results show i) the important role of the inclusion of latest released data in the forecast accuracy of both models, ii) the better precision of predictions based on factors with respect to autoregressive models and iii) identify the most adequate model for each of these six countries in different temporal horizons.

Keywords: Factor models, nowcast, forecast, real time, developing economies.

JEL classification numbers: C32, C53, E37, O54.

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** University of Alicante. Contact information: germanlb@ua.es.

1 Introduction

The information contained in some key macroeconomic aggregates is of crucial relevance for economists. They provide a general assessment about the performance of a given economy, allowing to construct expectations about other specific indicators and to evaluate the results of the strategies deployed by policy makers and central bankers.

The current situation of global uncertainty, the increasing differences in the economic achievement between emerging countries with respect to developed economies and the different trends regarding fiscal and monetary policy in countries with low or negative growth all stress the relevance of early evaluation of such indicators in real time.

Unfortunately, the burdensome accounting task needed for the computation of these key aggregates causes a considerable delay in the release of the data. Let us consider Gross Domestic Product (GDP) as the main indicator of the current economic situation. It is usually published at a quarterly frequency and released with more than two months of delay. However, there are hundreds, or even thousands of more specific indicators that require an easier computation, which are earlier released at a higher frequency.

Dynamic Factor Models (DFMs) take advantage of this increasing availability of data. Given that macroeconomic series are very collinear, it is assumed that they can be decomposed in two orthogonal parts: a reduced set of latent common factors which capture the most of the comovements in the data and an idiosyncratic component that only affects a specific series or a reduced set of them. Besides other applications, this factor decomposition has been implemented with forecasting purposes. Because of the lower number of factors with respect to the amount of available data, factors can be included in a forecast equation for a targeted variable, as GDP, with a reduced set of regressors containing the relevant information while keeping a parsimonious specification.

Recent literature has shown a clear improvement in short term forecasting by using DFMs. They have become a key tool for several public institutions such as the European Central Bank and Federal Reserve among others. However, DFMs have been previously treated separately by two clearly distinguishable streams of literature. Small Scale DFMs (SS-DFMs) where the common factor is estimated from a reduced set of indicators considered as representative of the whole economy or prescreened by the forecaster under some technical criteria and a second type of models known as Large Scale DFMs (LS-DFMs) where factors are estimated from a huge dataset under the premise that there is no reason to discard any information. Depending on the number of series used for the estimation of the factors these two DFMs present different theoretical assumptions, computational limitations and estimation procedures. This paper tries to determine which is the more adequate of these approaches for short-term prediction of GDP. The main characteristics of both methodologies are reviewed next.

The paper by Stock and Watson (1991) is considered as a pioneer work in the application of SS-DFMs. They compute a single factor as an alternative to the Index of Coincident Economic Indicator compiled by the Department of Commerce of the US with a small dataset composed by four macroeconomic monthly series related with demand, supply, employment and income. This initial methodology has been extended by the inclusion of indicators in different frequencies. Mariano and Murasawa (2003) add quarterly GDP to this initial set of indicators for the computation of a latent monthly GDP. Aruoba, Diebold and Scotti (2009) include series at weekly and daily frequency for the estimation of an indicator of the economic activity in continuous time. Camacho and Perez Quiros (2010) combine monthly data with several quarterly early estimations of GDP for the short-term forecast of the euro area GDP growth.

Because of the reduced cross section dimension of the datasets used in these models, the common factor and its loadings are both simultaneously estimated by maximum likelihood via the Kalman filter. However, the number of parameters to be estimated rises considerably with the number of indicators included. Thus, for computational reasons, this technique is able to process a limited amount of series. Moreover, in these models, the part of each series not explained by the factor, the idiosyncratic component, is assumed as non cross-correlated. Obviously, this assumption difficultly holds to the extent to which the number of included series increases. Accordingly with the classification of Chamberlain and Rothschild (1983), models relying on this assumption are known as *exact factor models*.

Because of these caveats, another stream of the literature has recently focused on the LS-DFMs. With a different estimation strategy, these models are able to deal with a bigger amount of indicators and limitations regarding the cross section dimension of the dataset are avoided. Furthermore, the thick assumption about zero cross correlation of the SS-DFMs is relaxed allowing for some degree of cross correlation between the idiosyncratic terms (*approximate factor models*).

A seminal work in the application of this procedure for macroeconomic forecast is Stock and Watson (2002). Giannone, Reichlin and Sala (2004) added to this model a second equation, which specifically characterizes the law of motion of the factors; the innovations of this second equation were successfully related with nominal and real shocks in the US economy. Rünstler et al. (2009) find that this method outperforms prediction based on quarterly data or bridge equations. Giannone, Reichlin and Small (2008) and Angelini et al. (2011) carry out short term forecast of the GDP growth of the US and euro area respectively. Doz, Giannone and Reichlin (2011) show the consistency of this procedure under weak cross correlation of the idiosyncratic component when cross section and time dimensions of the panel tend to infinity.

Unfortunately, this model is not free of drawbacks. The theoretical conditions under which consistency is achieved may be unrealistic in empirical applications with real data. Indeed, Stock and Watson (2002b) find some worsening of the model when the idiosyncratic component presents large serial correlation. Boivin and Ng (2006) point out that the amount of the time series included in the model is not harmless; in order to satisfy the theoretical requirements for consistency of large cross section dimension, forecasters put together all the available information. Up to some point, this may be in direct conflict with the other theoretical requisites about weak idiosyncratic cross correlation; it is because by adding more series to the panel it is more likely to find series belonging to the same broad category which are highly correlated. According to this, Bulligan, Marcellino and Venditti (2012) point out that there might be practical cases where a large number of variables are not sufficient to consider the influence of the idiosyncratic components negligible.

On the other hand, regardless the increasing relevance of developing economies in the global economic scenario, DFMs have been almost uniquely evaluated in advanced economies as the US or EU countries. Clearly, implementation of DFMs in developing countries entails some difficulties since they present more abrupt macroeconomic transitions and constraints in data availability such as lower amount of time series, usually shorter or with missing values in many cases.

To the best of my knowledge, only two articles have applied DFMs for developing economies in the particular case of Latin American countries: Liu, Matheson and Romeu (2012) find a better performance of a LS-DFM at GDP forecasting with respect to other multivariate autoregressive models at quarterly frequency or bridge equations with monthly series for ten Latin American countries and Camacho and Perez Quiros (2011) compute a monthly latent factor for six of those countries with a SS-DFM which, also provides better predictions for GDP than autoregressive specifications.

Unfortunately, up to now, previous literature has not investigated which is the more adequate approach in a real context. As stressed by Aruoba, Diebold and Scotti (2009), a comparative assessment of these two techniques from an empirical perspective is necessary despite the theoretical limitations of both methodologies.

Alvarez, Camacho and Perez Quiros (2012) carry out a first comparison between the two DFMs controlling for the characteristics of the data with Monte Carlo simulations. They find that the SS-DFM outperforms the LS-DFM when the panel contains oversampled categories or with high serial correlation of the idiosyncratic component. As an additional support of their findings based on simulated data, both factor models are applied to a balanced dataset for the US economy between 1959-1998 to forecast two real and two nominal monthly indicators. The real variables were similarly or better predicted in many cases by the SS-DFM. Nominal variables were always more accurately forecasted by the SS-DFM.

The main contribution of this paper is to extend this initial work in three ways:

First, in order to assess the external validity of these previous findings, the forecast accuracy of LS and SS DFMs is compared from a completely empirical point of view. Both DFMs are put at work in a real context through six datasets with actual series from different countries, which are expected to presents heterogeneous characteristics. The selected countries are those Latin American countries commonly analyzed in Liu, Matheson and Romeu (2012) and Camacho and Perez Quiros (2011): Argentina, Brazil, Chile, Colombia, Mexico and

Peru. In this way, models are tested in a context of economic volatility and limitations in the accessible data. These characteristics, common in developing economies, are crucial in the evaluation of the precision of DFMs at short term forecasting because factors have to be estimated from indicators reflecting sharp macroeconomic changes and also because of the small amount of data at hand.

Second, due to its relevance as aggregate macroeconomic indicator, instead of other monthly series with more particular information, the selected variable to be forecasted in this paper is quarterly GDP growth. In order to take advantage of the large amount of specific series available at a monthly frequency for the prediction of GDP, the implementations of the models is carried out with mixed frequencies where the monthly estimations of the latent factors have to be related with quarterly rates of GDP growth through aggregation rules.

Finally, the treatment of the data used every month for the prediction of quarterly GDP growth is considered from a realistic point of view. I develop a pseudo real time out-of-sample forecast exercise where the actual situation faced by the forecaster in terms of data availability is closely reproduced: taking into consideration the calendar of the releases for the indicators in the datasets for each country, every month within the out-of-sample forecast period, panels are updated including all the observations which were already published at that date; once updated, dataset differs for the actual series released at that time because they do not include changes due to data revisions. Because of the differences in the publication lag within the set of indicators, models are modified following Giannone, Reichlin and Small (2006) and Camacho and Perez Quiros (2010) in order to deal with unbalanced panels. Based on all the information published for a given month, I predict the previous quarter rate of growth of GDP which is going to be released in the current quarter, *nowcast*, and quarterly rate of growth of GDP corresponding with the following release in the next quarter, *forecast*. Results will show a general improvement in the precision of the estimates along the quarter, especially at nowcasting. This highlights the relevance of the inclusion of the latest released data, especially at short-term prediction, with respect to out-of-sample forecast based on balanced panel where useful information is discarded.

After the evaluation of both models for a sample of six developing economies, I find that the LS-DFM provides more accurate predictions for the Argentinean GDP at nowcasting and forecasting. On the contrary, in the case of Peru, it is the SS-DFM the model which presents best results for the two temporal horizons.

For Brazil and Mexico nowcasted GDP presents lower RMSE when computed by the LS-DFM while the one quarter ahead forecast is more accurate under the SS-DFM approach. The opposite happens in Colombia where the SS-DFM provides more accurate nowcast and the LS-DFM is better at forecast. Finally, the performance of SS and LS DFMs is very similar in the case of the Chilean GDP.

These mixed results suggest that DFMs should be evaluated taking into consideration their theoretical assumptions but also knowing that none of these limitations are sufficiently unrealistic in order to discard one model in favor of the other when they are applied in an empirical framework.

The remaining of the paper is organized as follows. The next section presents the characteristics of the SS and LS DFMs. Section 3 describes the dataset and the details of the pseudo real time out-of-sample experiment. Section 4 includes the empirical results. Section 5 concludes.

2 The Models

Define y_t as our quarterly aggregate of interest to be forecasted and x_t as a set of n macroeconomic series expressed in a monthly basis and earlier released than y_t. Obviously, monthly and quarterly macroeconomic data are related thus, by taking advantage of such a relationship, one can project the quarterly aggregate on the monthly data once it is available. Regardless their different frequencies, the simple OLS regression of y_t on x_{it} with $i = 1, \ldots, n$ becomes inefficient when the number of monthly predictors, n, is big enough. Moreover, the number of regressors will increase dramatically if the forecast equation includes lags of the explanatory variables.

However, let us consider that the whole economy is driven by a reduced number of unobserved shocks. Under this premise, DFMs assume that series can be decomposed into two orthogonal parts accordingly with the following equation:

$$x_{it} = \lambda_i^1 f_t^1 + \ldots + \lambda_i^r f_t^r + \varepsilon_{it} \tag{1}$$

Where $f_t^1, \ldots, f_t^r = F_t$, with $1 \leq r < n$, is the set of latent factors which explain the most of the variation across the n predictors; $\lambda_i^1, ..., \lambda_i^r = \Lambda_i$ are the factor loading for series i and the product of both, factors and loadings, is known as the common component. Finally, ε_{it} is the idiosyncratic component which specifically affects series i and might be serially correlated itself. In turn, the latent factors are also assumed to present an autoregressive dynamic of degree p.

Thus, if the forecaster is able to estimate these latent factors, they can be included in a forecast equation, as a summary of the relevant information, while preserving a parsimonious specification.

A crucial issue is to distinguish whether the relevant information for the computation of the latent factors is contained in some determining series or it is better subtracted for a large set of data. Depending on this decision, the cross section dimension of x_t will vary and the estimation procedure will present different features. The next two subsections outline the details of both approaches.

2.1 Small Scale Dynamic Factor Model

The SS-DFM analyzed is based on the single factor model of Stock and Watson (1991) where four monthly series, considered of relevance because of its relationship with demand, supply, employment and income, are used for the estimation of the common factor. As in the refined version of Camacho and Perez Quiros (2010), this initial set of indicators is enlarged with quarterly GDP, soft indicators due to its early release and variables which represent specific features of each country. Depending on the kind of each of those indicators they will be related with the unique monthly latent factor in a different way.

GDP is released at a quarterly frequency. Following Mariano and Murasawa (2003), it can be shown that the quarterly rate of growth of a given variable z^q is related with its monthly rate of growth z^m through the following expression: $z^q = \frac{1}{3}z_t^m + \frac{2}{3}z_{t-1}^m + z_{t-2}^m + \frac{2}{3}z_{t-3}^m + \frac{1}{3}z_{t-4}^m$. Thus, the quarterly rate of growth of GDP y^q observed at the last month of each quarter will be related with monthly factor f in such a way. Hard monthly series are introduced in annual growth rate (x^h); therefore, they will depend on the sum of the twelve last monthly growth rates of the factor. Soft indicators (surveys) will be included in level (x^s), however they are also assumed to present the same twelve month lag dependence.

Taking into consideration the factor decomposition described in equation (1) for a single factor ($r = 1$) and the different relationship of the monthly factor with each type of indicator, the main equations of the model are summarized as follows:

$$\begin{pmatrix} y_t^q \\ x_1^m \\ \vdots \\ x_{n^s}^m \end{pmatrix} = \begin{pmatrix} \beta_y(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}) \\ \beta_1 \sum_{j=0}^{11} f_{t-j} \\ \vdots \\ \beta_{n^s} \sum_{j=0}^{11} f_{t-j} \end{pmatrix} + \begin{pmatrix} U_{yt} \\ u_{1t} \\ \vdots \\ u_{n^s t} \end{pmatrix} \tag{2}$$

where $U_{yt} = \frac{1}{3}u_{yt} + \frac{2}{3}u_{yt-1} + u_{yt-2} + \frac{2}{3}u_{yt-3} + \frac{1}{3}u_{yt-4}$ and $x_1^m, ..., x_{n^s}^m$ represents the whole set of soft and hard monthly indicators (x^h, x^s) of size n^s.

The dynamic of the latent factor and the idiosyncratic components are also specifically characterized:

$$f_t = \phi_1^f f_{t-1} + ... + \phi_a^f f_{t-a} + \epsilon_t^f \tag{3}$$

$$u_{yt} = \phi_1^{u_y} u_{yt-1} + ... + \phi_b^{u_y} u_{yt-b} + \epsilon_t^{u_y} \tag{4}$$

$$u_{1t} = \phi_1^{u_1} u_{1t-1} + ... + \phi_c^{u_1} u_{1t-c} + \epsilon_t^{u_1} \tag{5}$$

$$\vdots$$

$$u_{n^s t} = \phi_1^{u_{n^s}} u_{n^s t-1} + ... + \phi_d^{u_{n^s}} u_{n^s t-d} + \epsilon_t^{u_{n^s}} \quad (6)$$

Finally, ϵ_t^f ,$\epsilon_t^{u_y}$, $\epsilon_t^{u_1}$, ... and $\epsilon_t^{u_{n^s}}$ are assumed to be independent and identically normal distributed with zero mean and their covariances assumed to be zero.

Let be $Y_t = (y_t, x_t^h, x_t^s)$ a vector which collects observed data at period t and S_t the state vector equal to

$(f_t, f_{t-1}, \ldots, f_{t-11}, u_{yt}, \ldots, u_{yt-5}, u_{1t}, u_{1t-1}, \ldots, u_{n^s t}, u_{n^s t-1})$. With the necessary definition for the matrices Λ and A, equations (2) to (6) can be included in following the state space representation:

$$Y_t = \Lambda S_t + w_t \quad (7)$$

$$S_t = AS_{t-1} + v_t \quad (8)$$

Because of this representation of the system, the latent factor and parameters can be estimated by maximum likelihood using the Kalman Filter.

Due to the different publication lags of the series the panel presents a “ragged end” where some series are available while others are missing for a given month at the end of the sample period. In order to include all the possible information, the filter is modified to give no weight to missing observations while including the latest releases. It is done by avoiding the part of the Kalman gain matrix which corresponds to these missing observations in the update equation. Besides, the factor and the nowcast and forecast of the targeted variable can be easily projected by extending the end of the panel with missing observations.

2.2 Large Scale Dynamic Factor Model

The LS-DFM corresponds with the model of Doz (2011) where the factors are estimated in two steps.

Let us consider the $T \times n^L$ matrix X_T as a set of monthly data which includes n^L macroeconomic series from moment 1 to T and where $n^L >> n^s$. Under the assumption that these observed data can be decomposed into a common component that captures the bulk of the comovements in a given economy and a idiosyncratic part which affects only a single or a small set of series the model can be directly set in a state space representation:

$$X_t = \Lambda F_t + \xi_t \quad (9)$$

$$F_t = \sum_{s=1}^{p} A_s F_{t-s} + B\eta_t \quad (10)$$

F_t represents the $r \times 1$ vector of common factors with $r \geqslant 1$ for a given period t. They are contemporaneously related with the n^L observed series of X_t

at the same period through the $n^L \times r$ matrix of loadings Λ. The idiosyncratic component ξ_t follows a $N(0, \psi)$ distribution; its potential serial correlation is not specifically characterized since ξ_t becomes negligible as cross section dimension increases. The second equation represents the law motion of the common factors where they are related with their p lags via the $r \times r$ A_s matrices with $s = 1, ..., p$. Innovations of equation (10) are driven by the set of q dynamics factors η_t. The number of the contemporaneous (static) factors, r, is bigger or equal than the number of dynamics factors, q, because F_t consits of current and lagged values of the of the dynamic factors η_t. This is known as the static representation of the DFM (see Bai and Ng ,2007, for further description). Thus, η_t is loaded by the full rank $r \times q$ matrix B. Finally, $\eta_t \sim N(0, I)$.

Due to the different dates in which series are released the panel of data X_T is unbalanced and presents a "ragged end". However, due to large cross section dimension of the panel data, MLE is not directly applied to the equations (9) and (10) via the Kalman filter for the inclusion of the most recent data. Instead the estimation procedure is carried out in two stages. First, the r factors $\tilde{F}$ are obtained by Principal Components Analysis (PCA) from the balanced panel of monthly data. Then, the OLS regression of X on $\tilde{F}$ gives the estimates $\tilde{\Lambda}$ and $\tilde{\psi}$ and the regression of $\tilde{F}$ on its p lags gives $\tilde{A}_1, ..., \tilde{A}_p$. $\tilde{B}$ is estimated applying PCA to the covariance matrix of the error term of the VAR. The second stage provides a reestimation, $\hat{F}$, of the factors: given that the model has a state space representation, the Kalman smoother can be directly applied to the entire unbalanced panel assuming that the matrices linearly estimated in the previous step ($\tilde{\Lambda}, \tilde{\psi}, \tilde{A}_1, ..., \tilde{A}_p$ and $\tilde{B}$) are the correct matrices. Finally, as in the SS-DFM, the filter is modified giving no weight to the missing observations in the update equation.

The forecast equation for a given target variable, GDP in this case, is based on the projection of the factors obtained in the previous part. However, GDP is observed at a quarterly frequency and each of the r estimated factors f_t are obtained from the monthly data. In order to express them at a quarterly frequency, they are transformed, as in Rünstler et al (2009) or Angelini et al. (2011), by the following aggregation rule:

$$f_t^Q = \frac{1}{3}(f_t + f_{t-1} + f_{t-2}) \tag{11}$$

This aggregation rule requires to transform the data in 3-months differences or in 3-month differences of the logarithms. Due to this differentiation, the quarterly aggregates of the monthly factors f_t^Q represent a three month rate of growth and the forecast equation is consequently defined as:

$$y_t^Q = \hat{\alpha} + \hat{\beta} f_t^Q \tag{12}$$

where, in our case, y_t^Q is the quarterly rate of growth of GDP and $\hat{\alpha}$ and $\hat{\beta}$ are estimated by OLS.

Contrary to the SS-DMF where the number of factors is fixed and equal to one due to the technical limitations of its estimation procedure, in the case of the LS-DFM there is uncertainty about the optimal number of factor that must be extracted from the observed data.

The most popular method among practitioners for the selection of the correct number of factors, r, is the information criteria proposed by Bai and Ng (2002). Nevertheless, and as highlighted by Caggiano, Kapetanios and Labhard (2011), this approach is designed in order to determine the optimal amount of factors to summarize a large dataset without take into consideration whether all those factors are relevant for the forecast of a target variable y_t. Thus, following these authors, several specification criteria were evaluated paying attention to their results in the forecast equation (12) instead of to their ability for the description of the explanatory data.

Although the results are broadly similar, the criterion developed by Bai and Ng (2002) produces higher errors in equation (12) since it tends to choose too many factors given the short temporal dimension of the panel. The Bayesian criterion proposed by Stock and Watson (1998) includes a penalty function which has to be minimized jointly with the Mean of the Square Errors of the forecast equation and leads to lower values of r. However, the number of factors was finally recursively determined such that the Root Mean Square Error (RMSE) of the forecast equation is minimized since results were slightly better under this procedure. Lag length for the state equation, p, and the number of pervasive shocks, q, were marginally selected for each value of r using the Schwartz Information Criterion and the criterion proposed by Bai and Ng (2007) respectively. This iterative process was repeated in each out of sample period using only information available at that date as explained in the next section.

3 Data and Pseudo Real Time Out-of-Sample Exercise

The aim of the models is the nowcast and short term forecast of GDP growth rate based on the last available monthly information. However, the publication lag of monthly series differs depending on their categories. Soft and financial indicators are usually earlier released than hard indicators. Due to these discrepancies, the dataset presents a “ragged end” with some observations available while other are missing for a given month at the end of the sample. Moreover, the relevant information for the prediction exercise evolves every month within the quarter to the extent in which new monthly series are released. Obviously, the latest released data will play an important role in the nowcast and forecast accuracy and they must be considered for the assessment of the models. In order to closely mirror the actual availability of data faced by the forecaster in a real-time situation, this changing dataset is replicated every month. This exercise only differs for the actual real time context because the panel does not take into consideration data revisions.

The data were downloaded on November 22^{nd} of 2011. The pattern on the data availability on that date due to the differences in the publication lags for each series is replicated every month within the quarter across the out-of-sample forecast period. Let be X_T the observed data at the end of the sample period T. At that date each monthly series x_i presents its last observation for a month $T - h_i$, where h_i represents the publication lag for series $i = 1, \ldots, n$. Hence, for any month t of the out-of-sample nowcast and forecast exercise, the last observation of series i which will be included corresponds with month $t - h_i$. Thus, the "ragged end" of the dataset used for the estimations every second month of a given quarter will be equal to the pattern observed in November 2011. For the first and third months of every quarter the availability of monthly series will present the same shape while quarterly series include in the dataset of the SS-DFM or in the forecast equation of the LS-DFM will be observed according to their release date within the quarter.

The data were downloaded from Datastream, central banks and offices of statistics of the six analyzed countries. Table 1 briefly classifies the series in seven categories for each country: those series labeled as key monthly indicators by Datastream, activity, trade, salaries and employment, financial, prices and surveys.

Because of the different characteristics of the models, the number of series included in each of them varies. While the LS-DFM includes all the available information in order to satisfy assumptions regarding large cross section and time dimension, the SS-DFM includes a considerably smaller subset of indicators within those contained in the LS-DFM.

Selection of the variables for the SS-DFM is based on Camacho and Perez Quiros (2011). The dataset for each country begins with four indicators as in the basic model of Stock and Watson (1991): industrial production as representative of the general level of production, a sales series for supply, an indicator for the evolution of income and one last indicator for employment. This initial group is enlarged with GDP, a soft indicator about expectations due to its early release, imports and export series to control for the effect of international trade and some specific indicators considered of relevance to capture the particular characteristic of this country or its interdependence with other countries. Following this procedure, series with a factor loading with sign opposite to the expected, non significant indicators or those which reduced the percentage of the variance of the GDP explained by the common component were discarded. Table 2 contains the subset of variables selected for each country under these criteria.

In order to keep this research in line with previous applications in the literature corresponding with the LS and SS DFMs, frequency and interval for the rate of growth of the unobserved factors are distinct in each model. As a consequence, the differentiation of the data and the computation of its quarterly aggregates are carried out in a different manner.

Moreover, this different frequency and interval of the factors used in the previous literature of these two models have some advantages in the particular context of this paper. In the LS-DFM, monthly indicators are introduced in the panel in three month differences as in the papers mentioned above. Accordingly with this transformation, the panel provides the three month rate of growth of the quarterly latent factors once it is aggregated through equation (11). By taking differences with respect to the previous quarter, instead of to the previous year, one is able to save some observations. This becomes a crucial issue given the high constraints in the availability of data for developing economies. Notice that the first step in the estimation strategy of the LS-DFM requires a balanced panel for the application of PCA where temporal dimension of the panel is reduced by eliminating the observations in the "ragged end". Later on, in the forecast equation, the latent factors estimated for each month are transformed into their quarterly aggregates dividing by three the temporal dimension of the observations that will be the regressors for quarterly GDP. For these reasons, the LS-DFM is more affected by the short availability of data and the three-months differentiation is more suitable in this model.

In the SS-DFM, due to the smaller cross section dimension of its dataset, n^s, there is no need of balanced panel since the Kalman Filter is directly applied without previous steps and monthly variables are related with quarterly indicators without split the temporal number of observations. Thus, monthly data is introduced in twelve differences and related to the single latent factor through equation (2) as in Camacho and Perez Quiros (2011) with smaller consequences in the available degrees of freedom. Under this procedure, this model estimates the monthly rate of growth of a monthly factor.

Panel data is updated every month, the parameters of the models and selection criteria are reestimated considering the new arrivals of data and factors are newly projected ahead for the nowcast and forecast of GDP growth.

The out-of-sample exercise starts in September 2009. Decision about this starting date was made judgmentally according to the data availability in each country in order to guarantee a large enough temporal dimension of the panel at the beginning of this exercise.

Due to its publication lag, the GDP of the third quarter, from July to September, will not be published until the end of the fourth quarter. At that date, September, a prediction for the quarterly rate of growth of GDP for the third quarter will be computed based on the available information in this month. Following the notation of Liu, Matheson and Romeu (2012), this projection corresponding with the next release of GDP is called Nowcast 1. With the same information set, the quarterly rate of growth of the GDP for the fourth quarter, which will be released in the next quarter, is also predicted (Forecast 1). These projections are repeated every month of the out-of-sample period corresponding with the end of a quarter reproducing the scheme depicted in the Figure 1.

In the next month, October, the estimation for the rate of growth of GDP for the third quarter which will be released in the current quarter (Nowcast 2) and the rate of growth of GDP for the fourth quarter which will be released in the next quarter (Forecast 2) are computed again based on the new set of information available till this month. Nowcast 2 and Forecast 2 will be computed again every month next to the end of each quarter.

Analogously, the Nowcast 3 and the Forecast 3 corresponding with the releases of GDP in the current and next quarters are computed with the information set available two months after the end of the previous quarter.

4 The models at work

The aim of this paper is to empirically determine the best model for prediction of GDP growth given the intrinsic characteristics and data availability of the six considered economies. This analysis is carried out for several temporal horizons in order to control for the different pattern in the flow of data arrivals in each country. For this purpose, the RMSE of the nowcast and one quarter ahead forecast of GDP growth is computed for every month within the quarter.

Table 3 contains the results for the Large and Small Scale DFMs. To simplify comparisons, the RMSE of the models are presented as a ratio over the RMSE of a benchmark model. This model is an Autoregressive model for quarterly GDP growth with $p \leqslant 4$ lags selected by Schwartz Info Criterion. Since GDP is observed at a quarterly frequency, the nowcast and forecast of this model will be the same during the three months of the quarter. First column of Table 3 presents the RMSE of the AR(p) model for the six countries. The next three couples of columns represent the ratio of the RMSE of the SS-DFM and the LS-DFM over the RMSE of the benchmark model for first, second and third month of each quarter respectively. Thus, an entry lower than one means that the DFM outperforms the AR(p). The last two columns contain the average of the nowcast and forecast relative RMSE of the three months for each country. Notice that the entries for the nowcast corresponding to the third month of Chile are empty. It is because GDP is earlier released in this country and for the date in which third nowcast is computed Chilean GDP is already published.

Factor models based on monthly data clearly outperform the autoregressive benchmark model for quarterly GDP at nowcasting. Exceptionally, the AR(p) provides a lower RMSE for Colombia than for the other five countries. In fact, the results of this benchmark model in this country are only beaten by the SS-DFM in the third month of the quarter. As expected, the errors of the predictions for the GDP which will be published in the current quarter show an overall decrease with the arrival of new data from month to month within the quarter. However, this pattern is less clear for the next quarter ahead forecast. These findings highlight the relevance of the informational content of new releases and its important role in short term prediction.

Accordingly with the relative RMSE of both models applied to Argentinean economy, the LS-DFM presents higher accuracy than the SS-DFM at nowcasting GDP growth during the first two month of the natural quarter (Nowcast 2 and 3). It is during the last month of the quarter (Nowcast 1) when the SS-DFM presents lower errors. However, the average for the relative RMSE of three months remains lower for the LS-DFM. Regarding the one quarter ahead projection of GDP growth (Forecast 1, 2 and 3), it is also the LS-DFM the model which presents a better performance during the three months of the quarter.

For the case of Brazil, the LS-DFM also has the best achievement at nowcasting in every month. Nevertheless, in the forecast at larger horizon, the SS-DFM produces the most accurate estimations at the beginning of each term (Forecast 1 and 2) while the model based on a large dataset of indicators is outperformed by the AR model.

Results corresponding with Chile are mixed. The LS-DFM is more precise than the SS-DFM in the first nowcast while the opposite happens in the second. However, these differences are very small and the averages relative RMSE are almost identical. For the one quarter ahead forecast, the single factor model beats the LS-DFM in the first two projections and presents a clear deterioration in the third forecast. On average, the differences in this case are also small and do not point out a clear winner between both approaches. It is important to notice that standard tests for statistical significance in the differences of the forecast based on each model, as Giacomini and White (2006), are not applicable to these results due to the reduced out-of-sample size. Recall that, because of the small temporal dimension of some series, the starting point for the out-of-sample evaluation of the models was fixed in September 2009. This allows us to produce 8 nowcast and 7 forecast predictions of quarterly GDP until November 2011, date when the dataset was downloaded.

Regarding Colombia, the AR model presents considerably better estimations in comparison with its results for the others five countries. In fact, none of the factor models are able to defeat this naïve model with the exception of the LS-DFM which presents better results in the one quarter ahead projections. Despite its simplicity, forecasts based on AR models have been shown to be rather accurate in previous literature. As highlighted in the results based on simulated data of Banerjee Marcellino and Masten (2008), this simple model may outperform DFMs, especially when the number of factors is large and the temporal dimension small.

Similarly to the results for the Brazilian economy, the nowcast is better estimated during every month by the LS-DFM with data from Mexico. In this case the differences between the RMSE are considerably larger. The RMSE of the multi-factor model is approximately one half of the RMSE corresponding to the SS-DFM. Contrary, it is the single factor model the approach that provides the highest accuracy for the forecasts in every month of the quarter.

Finally, for the projection of Peruvian GDP growth, the SS-DFM presents the lowest RMSE for both nowcasting and forecasting while the model based on the large dataset only outperforms the AR model at nowcasting.

5 Concluding Remarks

This paper provides a comparative assessment of the short-term forecast performance of Small Scale and Large Scale Dynamic Factor Models in an empirical framework. From a cross-country dataset for six developing economies, quarterly growth rate of GDP is predicted every month within the quarter with monthly data released up to each month. In order to closely replicate the information set available for the forecaster, the arrival of data is carefully reproduced considering the publication lag for each series. This out-of-sample pseudo real time exercise uniquely differs for actual forecast that would be made every month because it does not include changes in the series due to data revisions.

Forecast is carried out for two different temporal horizons. A prediction for the immediately following publication of quarterly GDP which will be released, *nowcast*, and a second estimation for next quarter release, *forecast*. Both, nowcast and forecast RMSEs are compared for six Latin American countries.

Factor models based on monthly data show a better performance at the short-term forecast than autoregressive models with quarterly releases of GDP. In addition, the inclusion of the latest available data also improves the accuracy of the models month by month along the quarter.

Within the set of the six analyzed countries, both models present very similar results applied to data from Chilean economy. For the Brazilian, Colombian and Mexican economies, it seems that none of the limitations of one model prevail over the other. In fact, in all these three countries, there is a model that performs better than the other for a given temporal horizon of the projections. The most remarkable case is the nowcast of Mexico where the RMSE of the LS-DFM is around a half of the SS-DFM´s RMSE. This suggests that SS and LS DFMs should be complementarily applied in these economies depending on whether the target is the nowcast or the forecast of GDP growth. In the case of the Peruvian economy, both nowcast and forecast are better produced with a single factor computed by a SS-DFM based on a smaller set of reasonably prescreened series. On the other hand, the Argentinean GDP growth is better nowcasted and forecasted by the factors obtained from the large dataset.

LS-DFMs have recently received growing attention because of their capacity to summarize huge amount of information and also because these models relax the strong assumption of SS-DFMs regarding zero cross correlated idiosyncratic component. Nevertheless, the theoretical requirements of LS-DFMs about big enough cross section dimension of the panel data containing weak cross correlated idiosyncratic components are not necessarily satisfied in applications with real data. The results provided in this paper stress the need of deeper assessment of these methodologies in relation with the context in which they are implemented. None of the theoretical and computational limitations of the models seem to be determinant enough in order to completely discard any of the models in favor of the other in empirical applications. Thus, under the light of these findings, previous results in the literature, where DFMs have been analyzed separately, should be prudently considered. Further research is needed in order to disentangle their causes, the effect of characteristics of the indicators included in the dataset, the ability of the models in correct estimation of the latent factors and the predictive power of the factors for a particular target variable.

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	Key	Activity	Trade	Finance	Employment	Prices	Surveys	TOTAL
ARGENTINA	29	14	23	11	10	23	1	111
BRAZIL	20	0	28	13	36	20	4	121
CHILE	26	0	31	0	8	16	0	81
COLOMBIA	21	9	18	4	11	5	0	68
MEXICO	39	17	31	3	20	27	5	142
PERU	30	23	17	7	10	1	1	89

Table 1. Series per country and category

Argentina	Brazil	Chile
Unemployment	IPI	IPI (Manufacturing)
Industrial Activity Indicator (EMI)	Retail Trade	Retail Trade Volume
Electric Consumption	Employment	Money Supply (M1)
Consumer Confidence Index (ICC)	Imports (Non Energetic)	Civilian Employment
Imports (Non Energetic)	Exports	Imports (Non Energetic)
Exports		Exports

Colombia	Mexico	Peru
IPI	IPI	IPI (Manufacturing)
Money Supply (M1)	Retail Sales Index	Electric Consumption
Manufacturing Wages	Retail Trade Volume	Trade Index
Exports	Workers Affiliated To The IMSS	Exports
Imports	Exports	Imports (Non Energetic)
	Imports (Non Energetic)	3 Months Expectations

Table 2. Data set included in the SS-DFM

	NOWCAST	1st Month NOWCAST		2nd Month NOWCAST		3rd Month NOWCAST		Average NOWCAST	
	AR(p)	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM
ARGENTINA	2,70	0,63	0,69	0,73	0,67	0,86	0,80	0,74	0,72
BRAZIL	3,15	0,74	0,71	0,75	0,69	0,71	0,65	0,73	0,68
CHILE	2,46	0,71	0,68	0,63	0,65	-	-	0,67	0,66
COLOMBIA	0,85	1,15	1,26	1,05	1,36	0,96	1,43	1,05	1,35
MEXICO	3,46	0,61	0,30	0,56	0,22	0,48	0,24	0,55	0,25
PERU	1,99	0,37	1,05	0,33	0,93	0,46	0,76	0,38	0,92

	FORECAST	1st Month FORECAST		2nd Month FORECAST		3rd Month FORECAST		Average FORECAST	
	AR(p)	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM
ARGENTINA	3,11	1,07	0,78	0,99	0,85	0,76	0,72	0,94	0,78
BRAZIL	3,02	0,80	1,55	0,81	1,17	0,94	0,75	0,85	1,16
CHILE	2,06	0,77	0,89	0,88	0,96	1,04	0,98	0,90	0,94
COLOMBIA	0,99	1,11	0,78	1,09	0,85	1,15	0,91	1,12	0,85
MEXICO	3,33	0,53	0,69	0,50	0,61	0,41	0,45	0,48	0,58
PERU	2,04	0,94	1,63	0,91	1,57	0,46	1,26	0,77	1,49

Table 3. Ratio of RMSE of SS and LS DFM over the RMSE of an AR model for nowcast and forecast during the three months of the quarter.

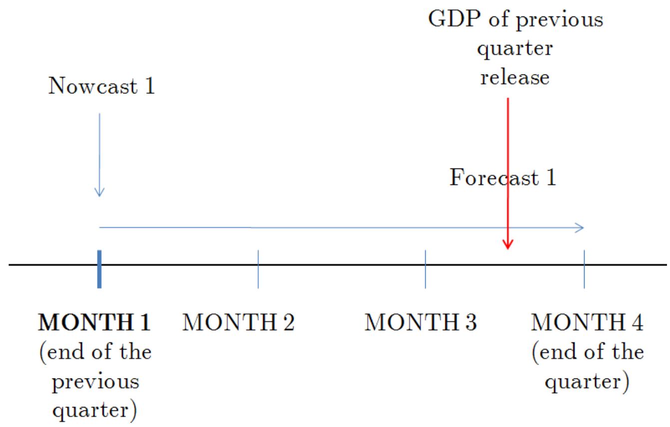


Figure 1. Time Scheme of Nowcast and Forecast 1

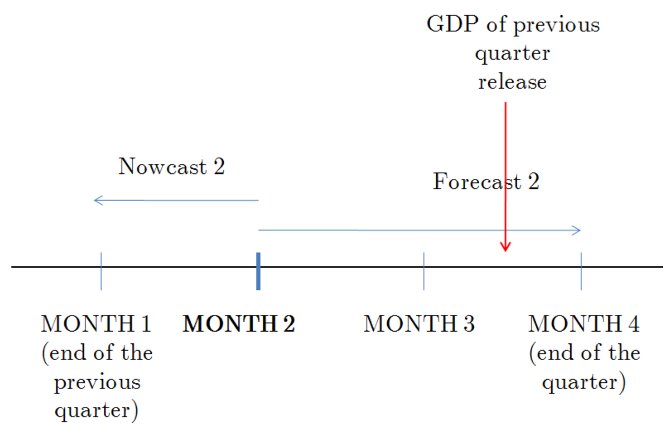


Figure 2. Time Scheme of Nowcast and Forecast 2

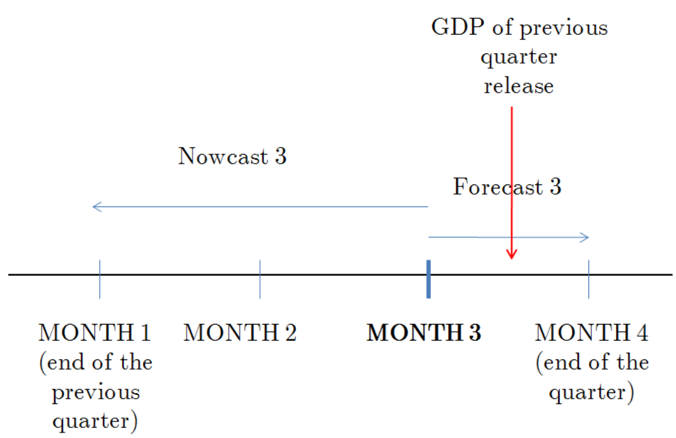


Figure 3. Time Scheme of Nowcast and Forecast 3

Figure 4. Quarterly rate of growth of Argentinean GDP, nowcasted and forecasted quarterly rate of growth of Argentinean GDP by Small Scale and Large Scale DFM for the three months of each quarter.

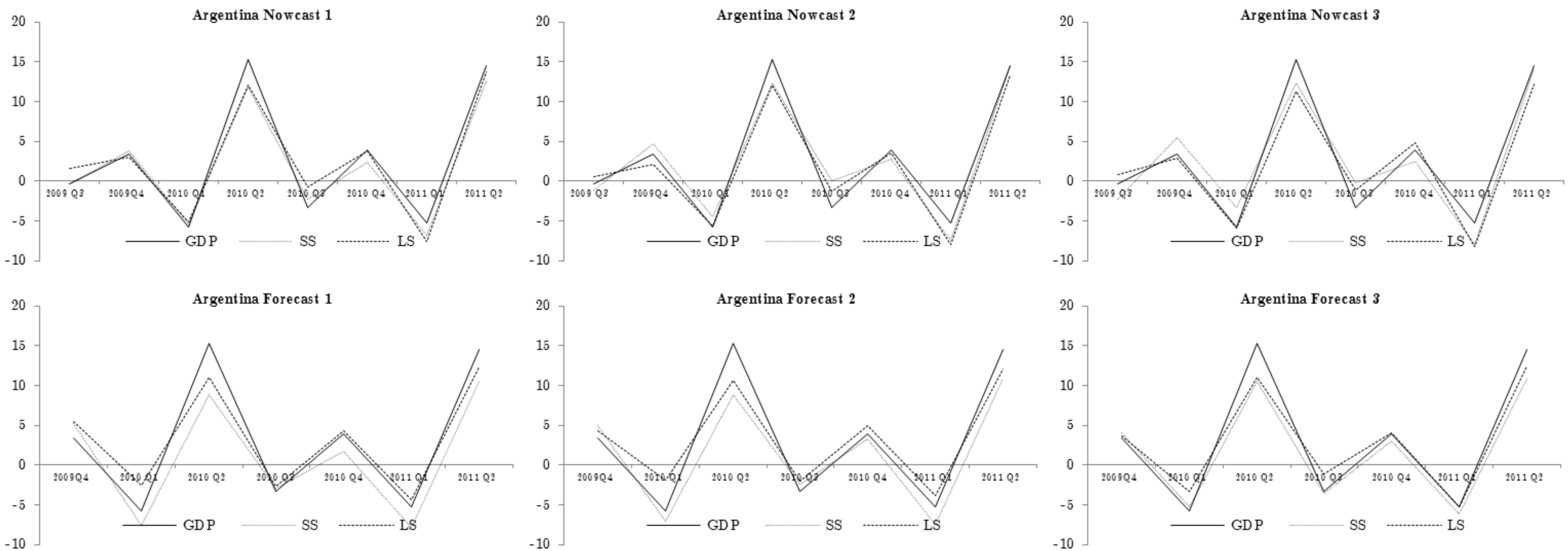


Figure 5. Quarterly rate of growth of Brazilian GDP, nowcasted and forecasted quarterly rate of growth of Brazilian GDP by Small Scale and Large Scale DFM for the three months of each quarter.

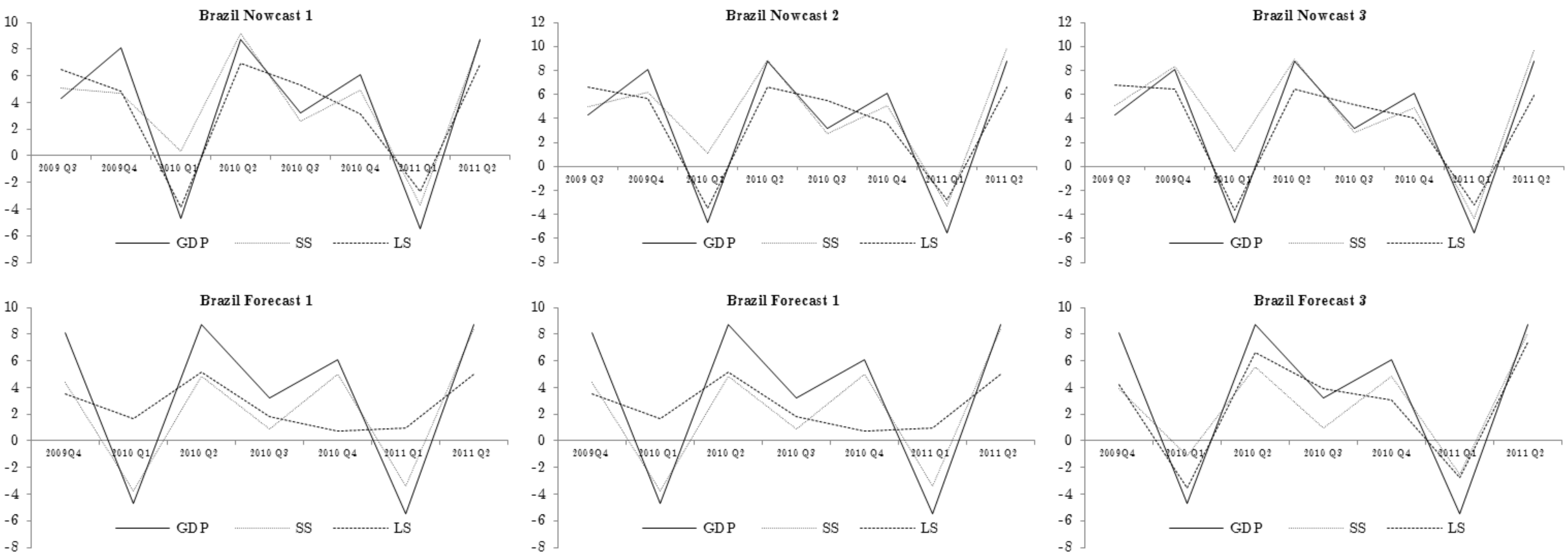


Figure 6. Quarterly rate of growth of Chilean GDP, nowcasted quarterly rate of growth of Chilean GDP for the firsts two months of each quarter and forecasted quarterly rate of growth of Chilean GDP by Small Scale and Large Scale DFM for the three months of each quarter.

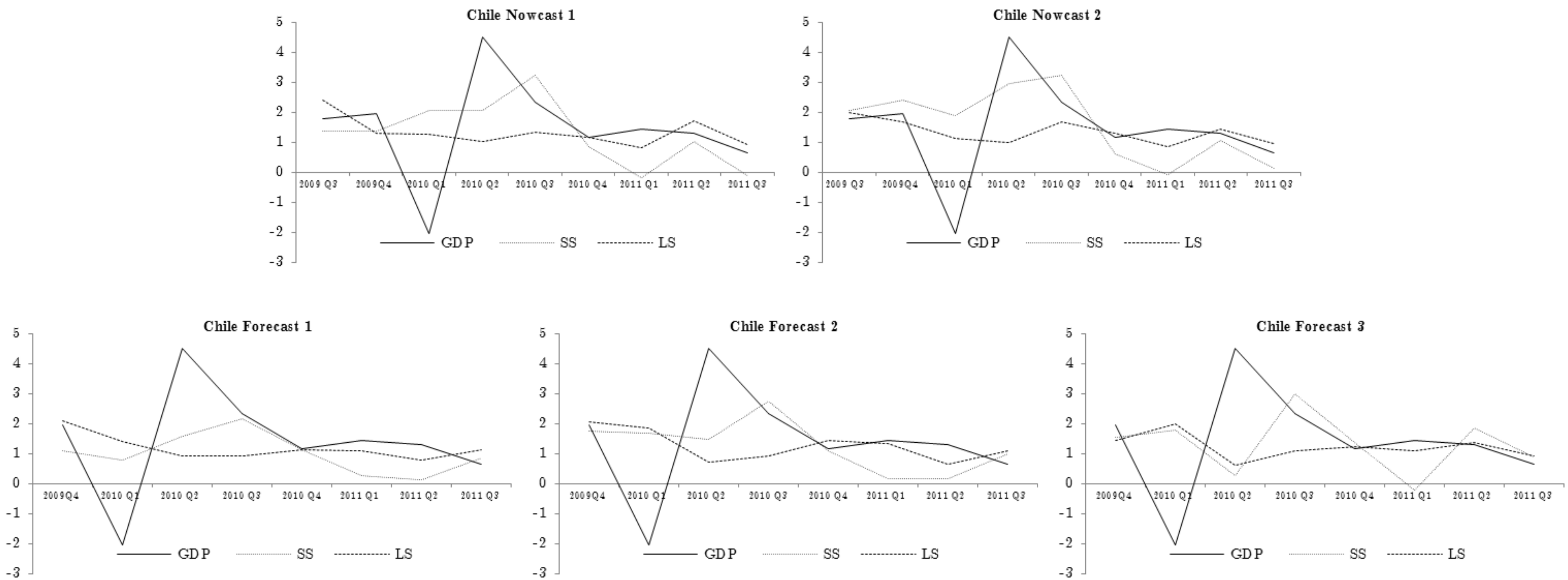


Figure 7. Quarterly rate of growth of Colombian GDP, nowcasted and forecasted quarterly rate of growth of Colombian GDP by Small Scale and Large Scale DFM for the three months of each quarter.

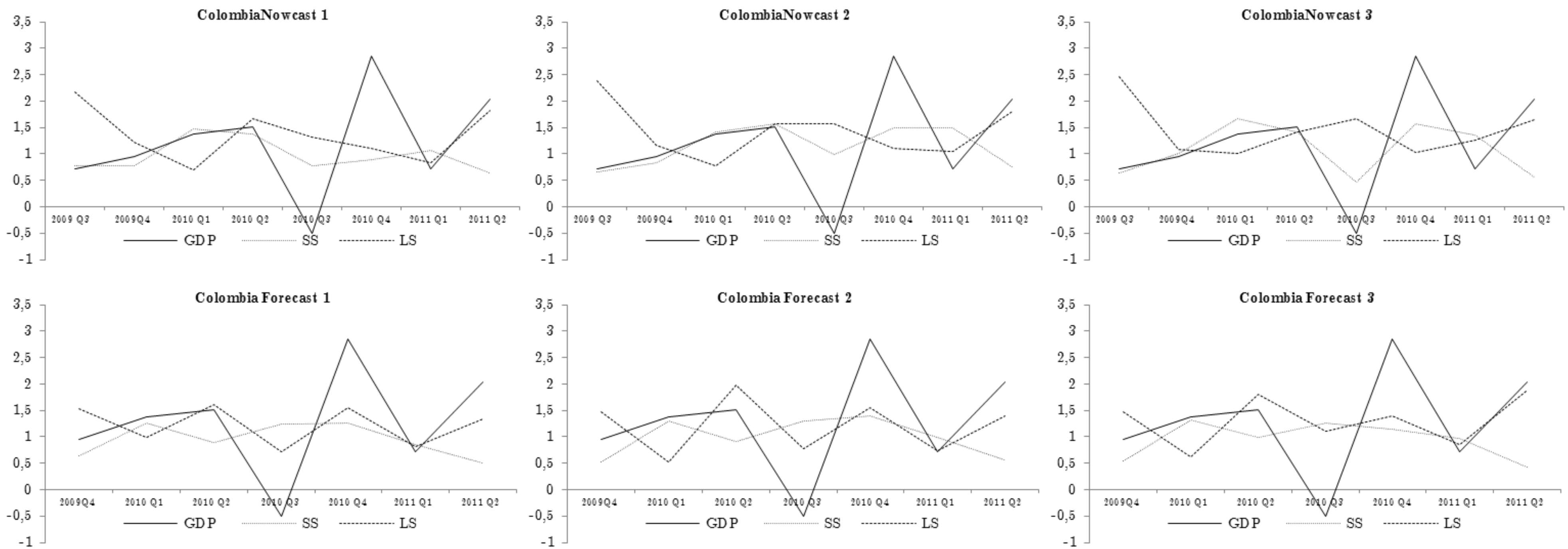


Figure 8. Quarterly rate of growth of Mexican GDP, nowcasted and forecasted quarterly rate of growth of Mexican GDP by Small Scale and Large Scale DFM for the three months of each quarter.

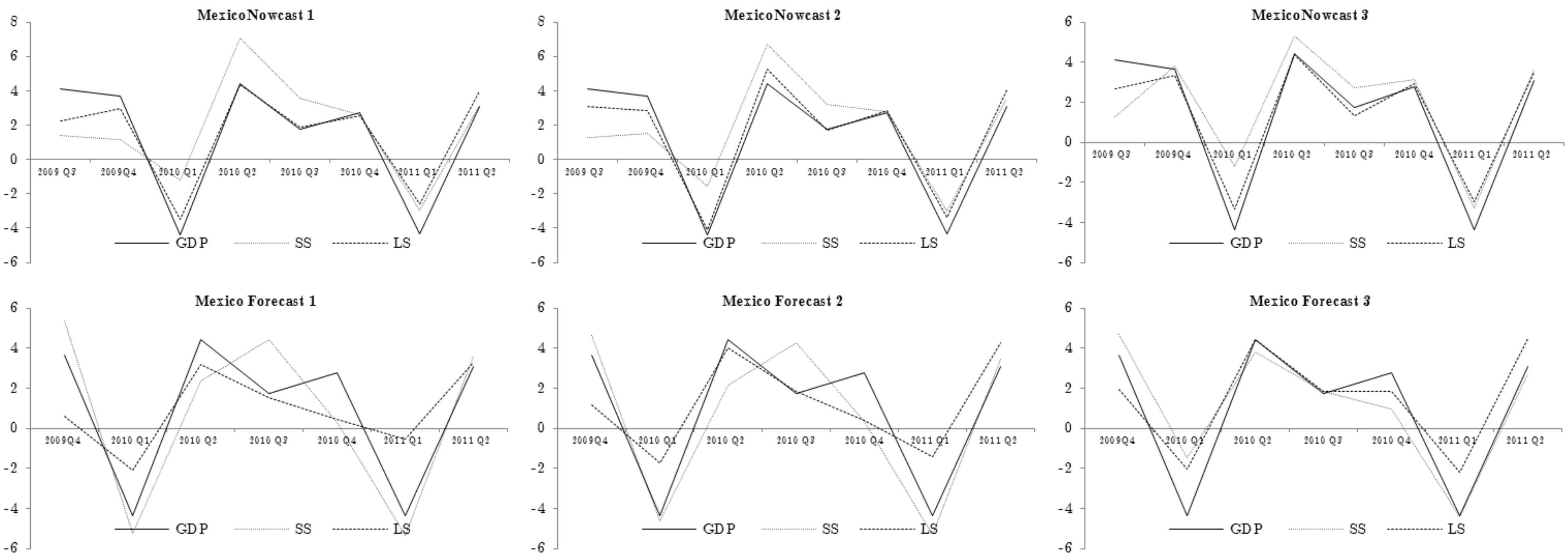
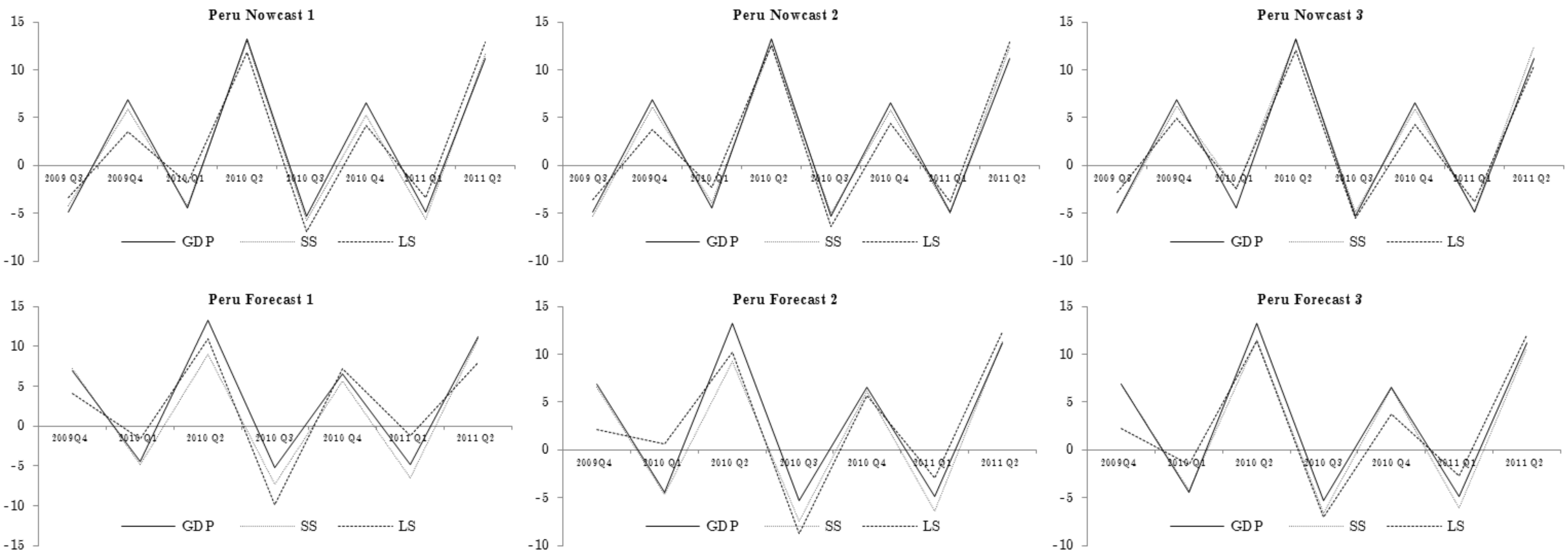


Figure 9. Quarterly rate of growth of Peruan GDP, nowcasted and forecasted quarterly rate of growth of Peruan GDP by Small Scale and Large Scale DFM for the three months of each quarter.



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Ivie

Guardia Civil, 22 - Esc. 2, 1º
46020 Valencia - Spain
Phone: +34 963 190 050
Fax: +34 963 190 055

Website: www.ivie.es
E-mail: publicaciones@ivie.es