Forecast Accuracy of Small and Large Scale Dynamic Factor Models in Developing Economies[1]

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Abstract

Developing economies usually present limitations in the availability of economic data. This constraint may affect the capacity of Dynamic Factor Models to summarize large amounts of information into latent factors that reflect macroeconomic performance. This paper addresses this issue by comparing the accuracy of two kinds of Dynamic Factor Models at GDP forecasting for six Latin American countries. Each model is based on a dataset of different dimensions: a large dataset composed of series belonging to several macroeconomic categories (Large Scale Dynamic Factor Model) and a small dataset with a few prescreened variables considered as the most representative ones (Small Scale Dynamic Factor Model). Short- term pseudo real time 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 each country. Results i) confirm the important role of the inclusion of latest released data in the forecast accuracy of both models, ii) show better precision of predictions based on factors with respect to autoregressive models and iii) identify the most adequate model for each country according to availability of the observed data.

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I. 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 expectations about other specific indicators to be constructed and results of strategies deployed by policymakers and central bankers to be evaluated.

The increasing differences between developing and developed economies in economic performance, the recent and unusual monetary and fiscal policies in advanced economies, and their spillover effects on emerging countries all shape a challenging scenario of global uncertainty. In such a context, the policymakers of less developed countries require early evaluation of these key macroeconomic aggregates in real time in order to measure the consequences of these global events and adapt their responses accordingly.

Unfortunately, the burdensome accounting task needed to compute these key indicators causes considerable delay in the release of the data. For instance, Gross Domestic Product (GDP), widely considered to be the main indicator of the current economic situation, is usually published at a quarterly frequency and released with more than two months delay; while, on the other hand, there are hundreds of more specific indicators that involve 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 into two orthogonal parts: a reduced set of latent common factors, which capture most of the co-movements in the data, and an idiosyncratic component that only affects a specific series or a reduced set of them. In addition to 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, such 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 using DFMs. In fact, these models have become a key tool for several economic institutions such as the European Central Bank and the Federal Reserve, among others. However, their implementation and the evaluation of their performance have been carried out mainly in developed economies where a large amount of macroeconomic information is available. It is important to note that the quantity as well as the quality of existing data affects the choice of different DFMs. Depending on the number of series included in the model, DFMs can be classified into two clearly distinguishable strands of the literature: 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 and Small Scale DFMs (SS-DFMs), where the common factor is estimated from a reduced set of indicators prescreened by the forecaster as those with the highest informational content and which are considered as sufficient for a complete characterization of macroeconomic behavior. Depending on the number of series used for estimation of the factors, these two DFMs present different theoretical assumptions, computational limitations and estimation procedures. In this context, the constraints in data availability in developing economies, such as the lower amount of time series, which are usually shorter, later released or with missing values in many cases, play an important role in the performance of DFMs. These limitations can make one of the two models more appealing for the forecaster, depending on the amount, quality and informational content of accessible information. Thus, the main contribution of this paper is to assess which of these two methodologies performs better in the particular context of developing economies. In order to highlight what the effects of the properties of the dataset are on the estimation of the latent factors, we review the main characteristics of both methodologies next.

Stock and Watson (1991) pioneered SS-DFMs literature. In their seminal paper, they use this method to compute a single factor that closely mirrors the Index of Coincident Economic Indicators compiled by the US Department of Commerce with a small dataset composed of four macroeconomic monthly series related to demand, supply, employment and income. This initial methodology has since been extended by inclusion of indicators at different frequencies. Mariano and Murasawa (2003) add quarterly GDP to this initial set of indicators for computation of a latent monthly GDP. Aruoba et al. (2009) include series at weekly and daily frequency to estimate an indicator of the economic activity in continuous time. Camacho and Perez Quiros (2010) combine monthly data with several quarterly early estimations of GDP to provide short-term forecast for the euro area GDP growth, which are shown to be as accurate as predictions made by a set of different professional forecasters. Despite the successful results of these studies, the implementation of SS-DFM presents some limitations. Given the reduced cross-section dimension of the datasets used in these models, the common factor is estimated by maximum likelihood via the Kalman filter. However, the number of parameters which relate the latent factor to the observables increases considerably with the size of the dataset. This implies that, for computational reasons, this estimation technique is only able to process a limited amount of series. Hence, in this context, researchers must find the most representative indicators for a complete characterization of macroeconomic behavior with the resulting variable selection issues. Furthermore, in these models, the part of each series not explained by the factor, the idiosyncratic component, is assumed to be non-cross-correlated. Obviously, this thick assumption does not necessarily hold when the number of included series increases. According to the classification of Chamberlain and Rothschild (1983), the models relying on this assumption are known as *exact factor models*.

Because of these caveats, another strand of the literature has focused on the LS-DFMs. With a different estimation strategy, these models are able to deal with a larger number of indicators, and limitations regarding the cross-section dimension of the dataset are avoided. Additionally, the strong assumption about the 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 that of Stock and Watson (2002a). In their study, they use a large dataset of 215 variables for the prediction of eight monthly series in the US. Giannone et al. (2005) extended the model including a specific description for the law of motion for the factors; innovations of this model successfully capture nominal and real shocks in the US economy. Rünstler et al. (2009) find that this method outperforms predictions based on quarterly data or bridge equations. Giannone et al. (2008) and Angelini et al. (2011) carry out short-term forecast of the GDP growth for the US and euro area respectively. Doz et al. (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 time series included in the model is not harmless; in order to satisfy the theoretical requirements for consistency related to a 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 regarding weak idiosyncratic cross-correlation; this is because by adding more series to the panel it is more likely to find series belonging to the same broad category that are highly correlated. Accordingly, there might be practical cases where a large number of variables is not sufficient to consider the influence of the idiosyncratic components to be negligible.

Despite the theoretical limitations of both methodologies, LS and SS-DFM have both been shown to be a powerful tool for economic analysis and forecasting. However, it must be noted that the two approaches were implemented separately and compared with simpler models. As highlighted by Aruoba et al. (2009), it is necessary to make a comparative assessment of these two techniques from an empirical perspective in order to determine whether economic performance is better summarized by the factors computed using large information sets or, on the contrary, by using a small sample of the most informative series. Alvarez et al. (2015) carry out a first comparison between DFMs with different cross sectional sample size controlling for the characteristics of the data with Monte Carlo simulations. They find that DFMs with a few series from different macroeconomic categories outperforms DFMs based on large sets of disaggregate series when the panel contains oversampled categories or with high cross correlation of the idiosyncratic components. As additional support for their findings based on simulated data, both factor models are applied to a balanced dataset for the US economy between 1959-1998 to forecast monthly indicators. Their results point out that real indicators are in general better predicted by the DFM based on aggregate series.

Furthermore, the aforementioned main studies focusing on DFMs are implemented in an advanced economy taking advantage of high availability of data. To the best of our knowledge, only two articles have applied DFMs to developing economies in the particular case of Latin American countries. Liu et al. (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. Interestingly, 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. Thus, the aim of this study is to provide a detailed comparison of the two distinct methods in this specific context. Such a comparison extends the work of Alvarez et al. (2015) in three ways:

First, in order to assess the external validity of their findings, the forecast accuracy of LS and SS DFMs is compared from a realistic point of view where the presence of restrictions in data availability is taken into account. Both DFMs are put to work in a real context through six datasets with actual series from different developing countries that present heterogeneous characteristics in terms of availability and publication delay. These countries are those Latin American countries analyzed in Liu et al. (2012) and Camacho and Perez Quiros (2011): Argentina, Brazil, Chile, Colombia, Mexico and Peru.

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

Third, given that quarterly GPD forecast is based on monthly data that is progressively released within the quarter, the possible consequences of the delay in the release in the series on the accuracy of the models must be specifically considered. For this reason, we develop a pseudo real time out-of-sample forecast exercise where the actual situation faced by the forecaster in terms of data availability throughout the quarter is closely reproduced. According to 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 to include all the observations that were already published at that date. Once updated, the datasets differ for the actual series released at that time because they do not include changes due to data revisions. To do this, it is important to note that, at the end of the sample, the datasets become unbalanced with missing values for some series not yet released, while others are already available due to their differences in the publication lags. Thus, models are modified following Giannone et al. (2008) and Camacho and Perez Quiros (2010) in order to deal with the presence of missing observations at the end of the sample.

Then, based on all the information published for a given month we predict the previous quarter's GDP rate of growth that is going to be released in the current quarter, nowcast, and the quarterly GDP rate of growth corresponding to the following release in the next quarter, forecast. Results reveal general improvement in precision of the estimates with the arrival of new information during 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 the out-of-sample forecast based on a balanced panel where some useful information is discarded. Following the evaluation of both models for the datasets of the six developing economies, we find an overall better performance of the LS-DFM. For Argentina, Brazil, Colombia, Mexico and Peru, the LS-DFM provides more precise nowcast and one-quarter ahead forecast. In the case of Chile, the SS-DFM produces moderately better results at nowcasting and is more accurate at forecasting.

The remainder 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.

II. 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, we can project the quarterly aggregate on the monthly data once it is available. Regardless of 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 large 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 according to the following equation:

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

where $f_t^1,..., f_t^r = F_t$, with $1 \leq r < n$, is the set of latent factors which explain most of the variation across the n predictors; $\lambda_i^1,...,\lambda_i^r = \Lambda_i$ are the factor loadings 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 if 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 details of both approaches.

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 their 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 their early release and variables that represent specific features of each country. Depending on the type of each of those indicators, they will be related to 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 to 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 to 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 for 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:

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

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

$$u_{1t} = \phi_1^{u_1} u_{1t-1} + ... + \phi_c^{u_1} u_{1t-c} + \xi_t^{u_1} \quad (5)$$

$$\vdots$$

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

Finally, ξ_t^f, $\xi_t^{u_y}$, $\xi_t^{u_1}$, ... and $\xi_t^{u_{n^s}}$ 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 $(f_t, f_{t-1}, ..., f_{t-11}, u_{yt}, ..., u_{yt-5}, u_{1t}, u_{1t-1}, ..., u_{n^s t}, u_{n^s t-1})$. With the necessary definition for the matrices Λ and A, equations (2) to (6) can be included in the following the state space representation:

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

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

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 possible information, the filter is modified to give no weight to missing observations while including the latest releases. This is done by avoiding the part of the Kalman gain matrix that corresponds to these missing observations in the update equation. In addition, 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.

Large Scale Dynamic Factor Model

The LS-DFM corresponds to the model of Doz et al. (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 an idiosyncratic part which affects only a single or a small set of series, the model can be directly set in a state space representation:

$$X_t = \Lambda F_t + \zeta_t \tag{9}$$

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

F_t represents the $r\times 1$ vector of common factors with $r \geq 1$ for a given period t. They are contemporaneously related to 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 ζ_t follows a $N(0,\psi)$ distribution. 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 higher than or equal to the number of dynamic factors, q, because F_t consists of current and lagged values of the dynamic factors η_t. This is known as the static representation of the DFM (see Bai and Ng ,2007 for a 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 the 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 re-estimation, $\hat{F}$, 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 the data to be transformed in 3-month 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.

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 et al. (2011), this approach is designed in order to determine the optimal amount of factors to summarize a large dataset without taking 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 to describe 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 that 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 periods using only information available on that date as explained in the next section.

III. 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 released earlier 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 taken into account to assess the models. In order to closely mirror the actual availability of data confronting the forecaster in a real time situation, this changing dataset is replicated every month. This exercise only differs for the actual real time out-of-sample forecast because the panel does not take into consideration data revisions (Bernanke and Boivin, 2003, and Giannone et al., 2008, have documented the robustness of the forecast results to the use of finally revised data instead of real time data).

The pattern on the data availability 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 X_T be 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 monthly dataset used for the estimations every month within the quarter will present the same shape while quarterly series included 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 statistics offices for the six analyzed countries and classified into several macroeconomic categories: activity, trade, salaries and employment, financial, prices and surveys. Due to the restrictions in data availability in developing economies some series spanned only a few years or presented missing values within the sample period. Hence, those series covering a short period were discarded and missing values within the sample were linearly interpolated. When necessary, data was seasonally adjusted by X-11 and corrected for outliers. The series were also transformed to induce stationarity. Table 1 briefly classifies the series for each country[3]. First column describes the number of series labeled as key monthly indicators by Thomson Reuters Datastream[4]. These economic key indicators are considered by Thomson Reuters as *the most important series for each market* and incorporates series from the different macroeconomics categories previously enumerated. In addition, as detailed in the next columns, more series were included to each category according to their availability. The key indicators also contain exchange rates and dollar prices in national currencies due the relevance of exporting activities of Latin American countries and to their strong financial and trade relationships with the US. For this reason, measurements of US activity were also included to mirror the effects of the economic developments of the US on the analyzed countries. In this regard, we select Industrial Production Index as has been widely considered as a representative indicator of economic activity[5] available at a monthly frequency.

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-

[3] Detailed description of the dataset is available upon request.

[4] They include several series in each country covering National Accounts, Balance of Payments, Merchandise Trade, Monetary Series, Labor Market, Sector Specific Indicators, Public Businesses and Industries.

[5] See Foerster et al. (2011) or Camacho and Palmieri (2017) among others.

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 related to 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. 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 to the LS and SS DFMs, frequency and interval for the rate of growth of the unobserved factors are distinct in each model. Therefore, the differentiation of the data and the computation of its quarterly aggregates are carried out in a different way.

Moreover, this different frequency and interval of the factors used in the previous literature for 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. According to 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 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 the 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-month 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 for a balanced panel since the Kalman Filter is directly applied without previous steps, and monthly variables are related with quarterly indicators without splitting 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 lesser 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 re-estimated 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 and finishes in January 2014. The decision about the 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 et al. (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 to the end of a quarter, reproducing the scheme depicted Figure 1[6].

In the next month, October, the estimation for the GDP rate of growth for the third quarter which will be released in the current quarter (Nowcast 2) and the GDP rate of growth 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 until this month. Nowcast

[6] Publication lag of Chilean GDP varies along time. In this exercise, we follow Liu et al. (2012) and consider that it is released at the end of the next quarter to help the comparability of the results.

2 and Forecast 2 will be computed again every month next to the end of each quarter as described in Figure 2.

Analogously, Nowcast 3 and 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 (Figure 3).

IV. The models at work

The aim of this paper is to determine empirically 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 are 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 $p \leq 4$ 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. The first column of Table 3 presents the RMSE of the AR*(p)* model for the six countries. The next three pairs of columns represent the ratio of the RMSE of the SS-DFM and the LS-DFM over the RMSE of the benchmark model for the first, second and third months 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.

Several conclusions emerge from the results in Table 3. The factor models based on monthly data outperform the short-term predictions of the quarterly autoregressive model for GDP. These findings are in agreement with Camacho and Perez Quiros (2011) for the SS-DFM and with Liu et al. (2012) for the case of the LS-DFM. Exceptionally, the AR*(p)* provides low RMSE for Colombia. The results of this benchmark model in this country are bettered at nowcasting by the LS-DFM while the one-period ahead predictions of the AR improve the results of the DFMs[7]

As expected, the errors of the predictions for the GDP that will be published in the current quarter show an overall decrease with the arrival of new data from month to month within the quarter as the gap between the date of the last released data and the GDP observation to be forecasted decreases[8]. Consequently, we find smaller average relative RMSEs along the quarter (last two columns) at nowcasting than at forecasting. These findings highlight the relevance of the informational content of new monthly releases and the ability of the DFMs to take advantage of it for short-term prediction in this context.

Regarding the comparison between the two DFMs, in general we find a higher accuracy of the LS-DFM with respect to the SS-DFM at nowcasting. The LS-DFM provides more accurate predictions for Argentina, Brazil, Colombia, Mexico and Peru. To a small extend, the SS-DFM shows lower RMSEs along the first two months of the quarter for Chile (one of the countries where Camacho and Perez Quiros, 2011, find a better performance of the SS-DFM).

For the one-period ahead forecast, the SS-DFM has the best achievement at forecasting in every month for Chile. In the remaining five countries, the LS-DFM provides more accurate results for the one-period ahead forecast. The third month forecast for Peruvian GDP is an exception to this. In that month, the SS-DFM shows an improvement with the inclusion of the latest information at the end of the quarter and produces better results than the LS-DFM for this country.

It is worth mentioning that, due to their accessibility, the number of series included in the datasets for the estimation of the LS-DFM along the analyzed countries differs with respect to those in Liu et al. (2012). These differences in the cross-section dimension of the datasets may affect the comparability of the results between both papers. Chile is a remarkable case where we include a considerably smaller number of series and where

7 AR models have been shown to be quite accurate in previous literature and may outperform DFMs. In fact, Liu et al. (2012) also find a good performance of the AR model for the one-quarter ahead predictions of the Colombian GDP.

8 These findings are consistent with the results obtained from previous implementations of DFMs in developed economies. See Giannone et al. (2008) and Banbura and Modugno (2014) for short-term predictions of the GDP in the US and in the euro area respectively.

we find an overall better performance of the SS-DFM. Nevertheless, the LS-DFM for this country estimated here with a smaller number of series provides the same nowcast RMSE relative to the AR(p) than in Liu et al. (2012) (around 0.7 during the three months of the quarter). Thus, we consider that the series in our dataset include enough informational content to provide short-term predictions as accurate as those estimated with a larger dataset.

V. Concluding Remarks

This paper evaluates the effects of constraints in data accessibility usually observed in developing economies on the ability of Dynamic Factors Models to summarize and predict macroeconomic evolution. For this purpose, we perform a comparative assessment of the performance at short-term GDP prediction for Small Scale Dynamic Factor Models based on a reduced amount of representative series, and Large Scale Dynamic Factor Models based on a large set observable data. Using a cross-country dataset for six developing economies, quarterly growth rate of GDP is predicted every month within the quarter, with the monthly data released up to each month. The arrival of data is reproduced considering the publication lag for each series in order to replicate the information set available for the forecaster in these particular countries. This out-of-sample pseudo real time exercise uniquely differs for actual forecasts that would be made every month because it does not include changes in the series due to data revisions.

In order to evaluate which of these DFMs is more appropriate according to data availability and publication lag of the series in each country, both models are compared for two different forecast horizons: a prediction for the immediately following publication of quarterly GDP which will be released in the current quarter (nowcast), and a second estimation for next quarter release (forecast).

From the comparison of both nowcast and forecast RMSEs in the six Latin American countries, it is observed that factor models based on monthly data show better performance at the short-term forecast than autoregressive models with quarterly observations of GDP. In addition, the inclusion of the latest available data improves the accuracy of the models month by month througout the quarter. We also find that the RMSE of the DFMs with respect to quarterly AR models are smaller at nowcasting that at forecasting due to their ability to take advantage of the informational content of the latest released data.

Within the set of the six analyzed countries, we find that for the Argentinean, Brazilian, Colombian, Mexican and Peruvian economies, the LS-DFM performs better than the SS-DFM for the two temporal horizon of the projections. However, in the case of Chile, forecasts are better produced with a single factor computed by a SS-DFM based on a smaller set of reasonably prescreened series.

The results provided in this empirical application show that LS-DFM produces satisfactory results for the short-term prediction of GDP in the analyzed developing economies. Still, we find a few cases where the SS-DFM is able to provide more accurate predictions. Thus, policymakers, central bankers, forecasters and researchers interested in the application of DFMs in countries presenting constraints in data availability, should take into account that the selection of these models should not only be based on the prior comparison of their statistical properties, but also on evaluating the performance of the model depending on the amount and quality of available data. In the light of these findings, and considering that previous literature has analyzed DFMs separately, further research is needed in order to identify the most accurate model for GDP prediction in other countries, to evaluate the effect of the characteristics of the indicators included in the dataset on the ability of the models to estimate the latent factors as well as the adequacy of those factors to predict a particular target variable at a given temporal horizon.

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	Key	Activity	Trade	Finance	Employment	Prices	Surveys	TOTAL
ARGENTINA	27	13	23	11	6	23	1	**104**
BRAZIL	17	0	28	12	36	20	3	**116**
CHILE	30	1	31	1	1	3	0	**67**
COLOMBIA	22	9	18	4	11	5	1	**70**
MEXICO	37	17	30	1	20	24	5	**134**
PERU	28	22	16	6	11	12	2	**97**

Table 1: Dataset per country and category

Argentina	Brazil	Chile
Unemployment	IPI	IPI (Manufacturing)
Industrial Activity Indicator (EMI)	Retail Trade	Retail Trade
Electric Consumption	Employment	Money Supply (M1)
Consumer Confidence Index	Imports (Non Energetic)	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	Trade Index
Exports	Workers Affiliated to IMSS	Exports
Imports	Exports	Imports (Non Energetic)
	Imports (Non Energetic)	3 Months Expectations

Table 2: Subset of indicators included in the SS-DFM

	AR(p)	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM	SS-DFM	LS-DFM
ARGENTINA	3.68	0.78	0.68	0.82	0.67	0.80	0.67	0.80	0.67
BRAZIL	1.27	0.98	0.86	0.94	0.84	0.90	0.81	0.94	0.84
CHILE	1.10	0.68	0.69	0.67	0.69	0.73	0.71	0.69	0.70
COLOMBIA	0.70	1.23	0.98	1.07	0.99	1.03	0.97	1.11	0.98
MEXICO	1.20	0.90	0.59	0.89	0.49	0.78	0.35	0.86	0.48
PERU	1.03	0.98	0.93	0.98	0.89	0.91	0.90	0.96	0.91
	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	2.62	0.93	0.83	0.90	0.79	0.80	0.75	0.88	0.79
BRAZIL	1.31	0.86	0.85	0.90	0.84	0.90	0.82	0.89	0.84
CHILE	0.95	0.89	1.04	0.77	1.02	0.76	0.81	0.81	0.96
COLOMBIA	0.69	1.20	1.01	1.18	1.04	1.23	1.07	1.20	1.04
MEXICO	1.04	0.90	0.79	0.86	0.78	0.76	0.69	0.84	0.75
PERU	0.87	1.23	0.89	1.23	1.01	1.13	1.23	1.20	1.04

Table 3: Ratio of RMSE of SS and LS DFM over the RMSE of an AR model for nowcast and forecast

FIGURE 1 Nowcast 1 and Forecast 1 time scheme

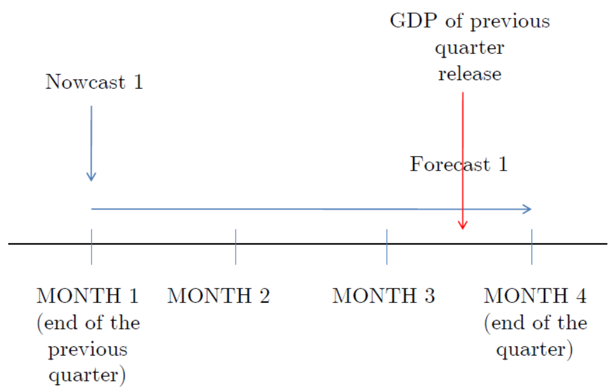

FIGURE 2 Nowcast 2 and Forecast 2 time scheme

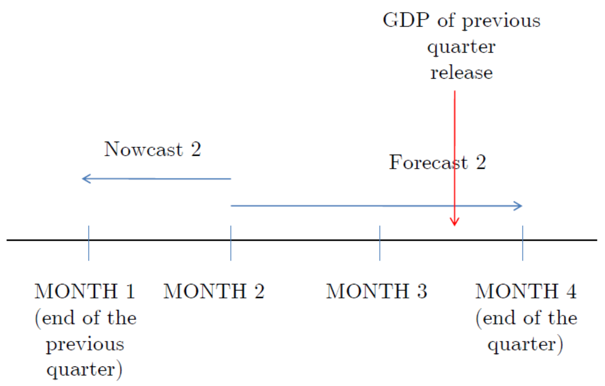

FIGURE 3 Nowcast 3 and Forecast 3 time scheme