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A Nowcasting Model for the Growth Rate of Real GDP of Ecuador: Implementing a Time-Varying Intercept

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Abstract

This paper proposes a model to nowcast the annual growth rate of real GDP for Ecuador. The specification combines monthly information of 28 macroeconomic variables with quarterly information of real GDP in a mixed-frequency approach. Additionally, our setup includes a time-varying mean coefficient on the annual growth rate of real GDP to allow the model to incorporate prolonged periods of low growth, such as those experienced during secular stagnation episodes. The model produces reasonably good nowcasts of real GDP growth in pseudo out-of-sample exercises and is marginally more precise than a simple ARMA model.

JEL classification: C33, C53, E37

Keywords: Nowcasting model, time-varying coefficients, Ecuador, secular stagnation

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1 Introduction

The Central Bank of Ecuador (Banco Central del Ecuador, BCE) publishes the national accounts from which one can obtain information about the economic growth of the Ecuadorian economy, measured by the growth rate of real GDP, at a quarterly frequency with a publication lag of three months. For example, the growth rate of the economy corresponding to the first quarter of 2018 will not be known until the end of June, according to the publication schedule of the BCE. Given this delay in the release of official information, a real-time estimate of the growth rate of the economy could provide decision makers, at both the private and public levels, with more timely statistics. This situation is especially true given the sharp deceleration and subsequent recession that affected the Ecuadorian economy over 2015 and 2016, which has spurred a debate about how fast the economy has recovered and how sustainable the recovery really is.

One way to obtain an estimate of the growth rate of real GDP in real time is by using nowcasting models. Nowcasting—which is a contraction for *now* and *forecasting*—is defined as the forecast of the present, the very near future, and the most recent past. The aim of a nowcasting model is to use macroeconomic information published at higher frequencies (monthly, for example) than the variable of interest (real GDP, in this case). In this paper, we specify and estimate a nowcasting model of the real GDP growth rate for Ecuador to provide timely estimates of the evolution of its economic activity.

Various institutions around the world—central banks in particular—use nowcasting models to inform their policy decision-making. For instance, nowcasting applications have been used to forecast the growth rate of the economies of Canada (see Chernis and Sekkel, 2017), Spain (see Cuevas and Quilis, 2012), Mexico (see Tirado, Delajara and Alvarez, 2016), and several Latin American countries (see Liu, Matheson and Romeu, 2012), among many others. Of course, nowcasting models are also used for larger economies such as the United States, in which the nowcasts produced by the Federal Reserve Bank of Atlanta (whose model is denominated "GDPNow") (see Higgins, 2014) and the Federal Reserve Bank of New York (see Aarons et al., 2016) are publicly available.

Several variations of nowcasting models exist in the literature, such as Bayesian vector autoregressions, factor-augmented autoregressive models, Bayesian regressions, accounting-based tracking models, and bridge regressions, among others. However, one of the preferred methods in the literature is the use of dynamic factor models (DFMs). DFMs have become popular in macroeconometrics and have been used to analyze business cycles and to forecast and nowcast the state of the economy (see Banbura et al., 2013, for example). To nowcast with DFMs, one gathers information about a broad set of macroeconomic variables and obtains the common factors that explain a good portion of the joint variation of these variables. The factors are later used to forecast in real time the growth rate of the economy.

In the case of Ecuador, Liu, Matheson and Romeu (2012) include the country in the set of analyzed Latin American countries for which their nowcasting models are constructed and estimated. Their DFM includes about 100 macroeconomic and external variables. More recently, Casares (2017) specifies a nowcasting model in which the DFM includes 8 macroeconomic variables. In both cited works, the nowcast is obtained by estimating a bridge regression between real GDP growth and the dynamic factors.

Our nowcasting model considers a DFM with 28 macroeconomic variables at the monthly frequency starting in January 2003. Given the nature of the publication schedule of the BCE, which is the main source of our data, we can provide four nowcasts of the growth rate of real GDP each quarter (the last nowcast is, strictly speaking, a backcast). The main contributions of our modeling strategy are twofold. First, we use the mixed-frequency formulation by Bańbura and Rünstler (2011) to obtain the nowcast; as a result, we avoid having to estimate bridge regressions and, thus, we are able to obtain the nowcast directly from the Kalman filter. Second, we do not demean the growth rate of real GDP, as is usually required in the setup by Bańbura and Rünstler. Instead, we assume that the mean growth rate of real GDP is time varying following a unit root, and we embed this specification in the state-space model along with the dynamic factors. A similar formulation is proposed by Antolin-Diaz, Drechsel and Petrella (2017) to track the slowdown in long-run GDP growth, such as cases in which the features of secular stagnation may be present (see Summers, 2014). The difference lies in how our approach deals with mixed frequencies, which can potentially maintain the state-space at a more manageable scale.

The rest of the paper is organized as follows. Section 2 describes briefly the nowcasting model used, particularly the specification with mixed frequencies and a time-varying mean growth rate. Section 3 illustrates the estimation of the DFM for Ecuador, the variables used, and its results. Section 4 obtains the nowcast of real GDP growth. Section 5 offers a diagnostic of the forecasting abilities of the model relative to an alternative.

2 Nowcasting Model Specification

The nowcasting model we use relies on the dynamic factor structure of the data used to inform the estimation of the growth rate of the economy in real time. As an additional component of our nowcasting model, we introduce a mixed-frequency approach in which the mean growth rate of real GDP varies over time. We present both ingredients in turn below.

The first ingredient is the most common version of a DFM in the context of nowcasting, which specifies a set of macroeconomic variables at the monthly frequency under a factor structure in which the factors follow a VAR process as follows (see Doz, Giannone and Reichlin, 2011, for more details):

$$X_{t_m} = \Lambda F_{t_m} + E_{t_m}, \qquad E_{t_m} \sim \text{i.i.d.} N(0, \Sigma_E), \tag{1}$$

$$F_{t_m} = \Phi(L) F_{t_m} + U_{t_m}, \qquad U_{t_m} \sim \text{i.i.d.} N(0, \Sigma_U), \tag{2}$$

where X_{t_m} is a vector of n monthly macroeconomic variables previously standardized and Λ is a matrix of dimension $n \times p$ that relates the macroeconomic variables with the p monthly factors that appear in the vector F_{t_m}, which follows an autoregressive structure with coefficient matrices $\Phi(\cdot)$. The error terms E_{t_m} and U_{t_m} are normally distributed white noises with variance-covariance matrices Σ_E and Σ_U, respectively, and independent of each other. The fact that the variables X_{t_m} are assumed to have a factor structure is particularly important because both the dynamic properties of these variables, picked up by the dynamics of the factors, and the co-movements among them, picked up by the common factors, are used to inform the nowcast.

This model is proposed by Giannone, Reichlin and Small (2008) to nowcast the real GDP growth rate of the United States based on a significant group of monthly indicators. More specifically, Giannone, Reichlin, and Small estimate the state-space representation (1)-(2) with a two-step procedure. First, the parameters from the state-space representation —μ, Λ, and Σ_E— are obtained by applying principal components analysis (PCA) to a balanced panel that includes the variables in X_{t_m}. The matrices $\Phi(\cdot)$ and Σ_U, meanwhile, are calculated from a VAR with a determined lag length.[1] Second, the factors, F_{t_m}, are re-estimated by applying the Kalman filter and smoother to the state-space model (1)-(2) by taking as given the coefficient matrices calculated in the first step.

The quarterly growth rate of real GDP can be nowcasted by regressing the quarterly GDP growth rate on the monthly factors transformed into their quarterly equivalents in what has been known as "bridging with factors." The equation employed is as follows:

$$y_{t_q} = \mu + \beta' F_{t_q} + e_{t_q}, \qquad e_{t_q} \sim \text{i.i.d.} N(0, \sigma_e^2) \tag{3}$$

where y_{t_q} is the quarterly real GDP growth rate in period t_q, μ is its average, and F_{t_q} are the quarterly aggregated factors in period t_q, which relate to real GDP growth through the regression coefficients β.

We take a somewhat different approach. The second ingredient of our nowcasting model incorporates the growth rate of real GDP at the quarterly frequency in the state-space representation (1)-(2) configuring a mixed-frequency setup as in Bańbura and Rünstler (2011). Moreover, we add the real GDP growth rate without demeaning it and assume that its average growth rate is time varying. More precisely, the mixed-frequency model introduces the real GDP annual growth rate at the monthly frequency, $y^*_{t_m}$, as a latent

[1] A balanced panel is obtained by taking into account only the sample for which all the observations from all the variables considered are available.

variable that is related to the monthly common factors as follows:[2]

$$y^*_{t_m} = \mu_{t_m} + \beta' F_{t_m}, \tag{4}$$

$$\mu_{t_m} = \mu_{t_m - 1} + \nu_{t_m}, \qquad \nu_{t_m} \sim \text{i.i.d.} N(0, \sigma^2_\nu), \tag{5}$$

where μ_{t_m} is the mean annual growth rate of real GDP at the monthly frequency, which we assume changes over time following a random walk process. This formulation allows the model to incorporate periods of output growth that are persistently higher or lower than in other historical episodes.

Summers (2014) argues that the United States and other industrialized economies have been experiencing periods of low rates of estimated potential output growth in recent years, with forecasts that indicate that these low rates will persist in the future for a variety of factors. This phenomenon has been referred to as "secular stagnation." Nowcasting models that do not incorporate the possibility of trend output growth rates that change over time could have difficulty in accurately estimating real GDP growth rates. For that reason, we give our nowcasting model more flexibility than conventional models that assume the mean growth rate of real GDP is constant over time.

In addition to the specification of the annual growth rate of real GDP at the monthly frequency given in (4)-(5), the forecast of the real GDP annual growth rate in the third month of each quarter is written as the quarterly average of those monthly growth rates, as follows:

$$\hat{y}^q_{t_m} = \frac{1}{3}\left(y^*_{t_m} + y^*_{t_m - 1} + y^*_{t_m - 2}\right), \tag{6}$$

whereas the forecast error, $\varepsilon_{t_q} = y_{t_q} - \hat{y}^q_{t_m}$, is assumed to be normally distributed with mean zero and variance σ^2_ε.[3]

In this way, we can obtain a nowcast of the growth rate of the economy consistent

[2] In this setup, the factors are obtained from the macroeconomic variables X_{t_m} transformed to annual figures, either growth rates or averages.

[3] Antolin-Diaz, Drechsel and Petrella (2017) use the approach suggested by Mariano and Murasawa (2003) to deal with mixed frequencies. We believe that our setup is more straightforward as it does not increase the size of the state space, which can be the case under the previously mentioned approach.

with the dynamic factors and with the structural features of the economy regarding trend output. The implied state-space representation is the following (assuming the VAR is of order 1 for expositional purposes):

$$\begin{bmatrix} X_{t_m} \\ y_{t_q} \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_{t_m} \\ y^*_{t_m} \\ \mu_{t_m} \\ \hat{y}^q_{t_m} \end{bmatrix} + \begin{bmatrix} E_{t_m} \\ \varepsilon_{t_q} \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} I_p & 0 & 0 & 0 \\ -\beta & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & -1/3 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_{t_m+1} \\ y^*_{t_m+1} \\ \mu_{t_m+1} \\ \hat{y}^q_{t_m+1} \end{bmatrix} = \begin{bmatrix} \Phi & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & \Xi_{t_m+1} \end{bmatrix} \begin{bmatrix} F_{t_m} \\ y^*_{t_m} \\ \mu_{t_m} \\ \hat{y}^q_{t_m} \end{bmatrix} \begin{bmatrix} U_{t_m+1} \\ 0 \\ \nu_{t_m+1} \\ 0 \end{bmatrix}, \tag{8}$$

where the aggregation rule (6) is implemented in a recursive way from $\hat{y}^q_{t_m} = \Xi_{t_m}\hat{y}^q_{t_m-1} + \frac{1}{3}y^*_{t_m}$ with $\Xi_{t_m} = 0$ in the first month of each quarter and $\Xi_{t_m} = 1$ otherwise. As a result, (6) holds in the third month of each quarter where y_{t_q} has its values—it has missing values everywhere else.

In order to estimate the model, we follow a two-step approach as well. In the first step, we estimate the matrices of the state-space model (1)-(2) by both PCA and the VAR model, as in Giannone, Reichlin and Small (2008). In the second step, we estimate the parameters β, σ^2_ε, and σ^2_ν by maximum likelihood along with the latent variables, including the common factors, by using the Kalman filter and smoother.

3 Nowcasting Model Estimation for Ecuador

This section describes the variables that we use to estimate the dynamic factors and the parameters of the nowcasting model.

3.1 Data

Before selecting the variables, it is important that their time series fulfill two conditions. First, data should be updated frequently (for example, at the monthly frequency) and with a publication delay shorter than the one observed for GDP. Second, the variables need to reflect economic activity in order to be helpful predictors of GDP (see Chernis and Sekkel, 2017). For instance, information on bank loans is more relevant than the interest rate on those operations. While the interest rate is an important variable to determine economic activity, the demand for credit already reflects the degree of economic activity in a sense. In addition, we include variables that summarize economic activity through different indexes, including indexes of aggregate economic activity.

Our main source of information is the Monthly Statistical Information (Información Estadística Mensual, IEM) of the BCE. We also use complementary data from other sources such as the National Institute of Statistics and Censuses (Instituto Nacional de Estadísticas y Censos, INEC), the Agency of Regulation and Control of Electricity (Agencia de Regulación y Control de Electricidad, ARCONEL), and the Internal Revenue Service (Servicio de Rentas Internas, SRI). In the description below, all the variables come from the publications of the BCE, unless otherwise noticed. As the available variables have different characteristics, we have grouped them into 11 categories, as follows:[4]

- Financial
- International trade
- Oil
- Income
- Sales
- Industry

[4] This categorization is roughly based on the Federal Reserve of New York guidelines for its nowcasting model.

- Construction
- Labor market
- Household surveys
- Activity indexes
- Prices

Financial variables include (i) outstanding loans to the private sector, (ii) demand deposits, and (iii) near money. All of these variables correspond to the whole financial sector, which includes private and publicly owned banks.

International trade variables, in turn, contain (i) non-oil exports, (ii) capital goods imports, (iii) consumption goods imports, and (iv) raw materials imports. Oil variables consider (i) oil exports, (ii) oil production, (iii) oil price, and (iv) refined petroleum imports.

The income category includes only the personal income tax reported to the SRI. Meanwhile, sales contains (i) VAT collections reported to the SRI, (ii) survey sales volume in the commercial sector, and (iii) survey sales volume in the service sector. Additionally, the industry and construction categories include volume of production for both variables. Labor market takes into account personnel occupied within four sectors from survey data: (i) industrial, (ii) commercial, (iii) construction, and (iv) services.[5]

Household surveys consider the Current Situation Index (Índice de Situación Presente, ISP), which is a measure of consumer confidence. The activity indexes category, meanwhile, includes (i) the Index of Current Economic Activity (Índice de Actividad Económica Coyuntural, IDEAC), (ii) the Index of the Level of Registered Activity (Índice del Nivel de Actividad Registrada, INA-R) calculated by INEC, and (iii) the national consumption of energy reported by ARCONEL.

[5] The unemployment rate is reported at a quarterly frequency by INEC, so it does not help us much in nowcasting real GDP at a higher frequency.

Finally, the prices category takes into account (i) the consumer price index (CPI), (ii) the consumer price index excluding food and beverages, and (iii) the producer price index (PPI). All of these variables are published by INEC.

Therefore, we use a total of 29 variables, of which only real GDP has a quarterly frequency. The balanced panel of data in this paper starts in January 2008, due to restrictions in the ISP data availability, and ends in January 2018; this balanced data set allows us to perform the PCA. Most of the variables, however, are available from 2003, and we use all this information to estimate the nowcasting model with the use of the Kalman filter.[6]

We work only with variables in constant dollars and use the CPI to deflate the variables in nominal terms. Moreover, we express all the level variables in their year-over-year percent change, whereas those that already represent month-over-month percent variations are expressed in their 12-month moving average. Finally, all the series are seasonally adjusted using the X-12-ARIMA method. A detailed description of the variables used and their adjustments is available in Appendix A.

Finally, we present the evolution of the annual growth rate of real GDP in the sample period. This is the object of interest of the nowcasting model. Figure 1 shows the variable's evolution. From 2004 to 2006, real GDP grows at an annual rate close to 6 percent, on average, after having decelerated in 2003, mainly as a consequence of the drop in private investment due to the finalization of the heavy oil pipeline construction that started in 2000. By 2007, real GDP has decelerated significantly, mainly as a result of the economic uncertainty due to the presidential election of that year. In the following years, real GDP accelerates again until the Global Financial Crisis and the decline of oil prices hit the economy in 2009, when economic activity contracts importantly. From 2010 to 2014, real GDP increases at a sustained annual rate of about 5 percent, on average, although the growth rates show a slight downward trend. The collapse of oil prices since mid-2014

[6] In fact, there is information for most of the variables since January 2000, when the country adopted the U.S. dollar as its official currency. Because the new monetary regime was beginning at that time, we decided to avoid the first three years of the dollarization period due to adjustment in some variables, particularly prices and financial.

Figure 1: Evolution of the Annual Growth Rate of Real GDP

causes the economy to decelerate and later contract significantly until the end of 2016, when it starts to recover slowly. By the end of 2017, the economy returns to positive real GDP growth rates, although lower than the averages experienced in previous years of expansion.

3.2 Stationarity Properties of the Data

It is possible that the balanced panel, which is the basis to obtain the factors through the PCA, may have monthly frequency variables that are not stationary as a result of working with annual growth rates. This could be especially true for series that have a low-frequency component in their growth rates or series that slowly revert to their unconditional mean. Indeed, obtaining factors via PCA from variables whose variances and co-variances are not well defined or change over time, which occur under the presence of series that are nonstationary, can be problematic from a statistical viewpoint.[7]

One way to deal with the possibility of nonstationarity, especially regarding the series in nominal terms, is to deflate these series, which at least removes the trend that prices introduce. This is, in fact, the main reason behind the conversion of the series using the CPI discussed in section 3.1. Nonetheless, we used the Kwiatkowski, Phillips, Schmidt

[7] If the monthly-frequency series are expressed as their monthly or quarterly variations, this may not be a concern because these growth rates usually revert relatively quickly to their unconditional mean.

and Shin (KPSS) (see Kwiatkowski et al., 1992) test of stationarity to check the presence of unit roots. The test was performed on all 28 variables that were used to obtain the dynamic factors.

The test results reveal that the null hypothesis of stationarity can only be rejected at the 1 percent level of significance for two variables —the growth rate of refined oil imports in real terms, and the moving average of the monthly variation in the occupied personnel in the services sector. It is possible that the KPSS test could be producing a type I error. Therefore, we performed the Phillips-Perron's unit root test (see Phillips and Perron, 1988) as an additional check for these two series. The results indicate the rejection of the unit root presence in the case of refined oil imports, but not in the personnel services sector variable. A closer inspection of the latter reveals that its behavior presents a downward trend, making it difficult for the tests to establish whether the series is stationary. However, given that this variable only has data since 2007, the sample size may be affecting the tests' ability to distinguish the nature of the series. Accordingly, we assume that this series is stationary, despite the test results.

3.3 Determining the Number of Factors and the Lag Length of the VAR in the DFM

We proceed with the estimation of the factors, F_{t_m}, using PCA once the database has been constructed and the variables have been seasonally adjusted. There are several procedures to calculate the number of factors. Bai and Ng (2002), for instance, propose a statistical test that performs relatively well under a large sample and number of variables. These assumptions, however, may not necessarily hold in the current case. Bai and Ng's test determines the number of factors following a scheme of model selection. The criteria that the authors propose, therefore, depend on the usual tradeoff between the model's goodness-of-fit and its parsimony. The results of the tests reveal that for our 28-variable database, the number of factors should be either 1 or 28, depending on the criterion employed.

Liu, Matheson and Romeu (2012) argue that the Bai and Ng (2002) test results may lead one to select an excessive number of factors. Thus, they suggest another procedure, which uses the marginal increase in the R^2 of the regression in (3). Accordingly, the procedure first estimates the DFM with only one factor in order to estimate the regression in (3) and its associated R^2. Then, the DFM is estimated again but with an additional factor, which is included in the regression (3). If the R^2 increase is higher than 0.025, it can be concluded that the second factor is important and it is retained. This process continues until the marginal increase in the R^2 is less than 0.025.

In the present paper, however, because we do not use (3) to relate the factors of the DFM to real GDP, we employ the procedure suggested by Cattell (1966), which is usually referred to as the scree test. This test selects the number of factors as the value after which the eigenvalues of the variance co-variance matrix do not present substantial changes. The test is done graphically by plotting the eigenvalues (y-axis) and the number of factors (x-axis), as in Figure 2. Once the curve has reached an inflection point, or elbow, it is possible to choose the number of factors. In our case, as shown in the figure, the number of factors is five. Therefore, this is the number that we select for our model.[8]

We estimate a VAR model using the factors obtained with the PCA to determine the VAR lag length in (2). The specification is a VAR(5), based on the Bayesian Information Criterion (BIC). The results of the estimation appear in Appendix B.[9]

3.4 Results of the Estimation of the DFM

We estimate the DFM in (1)-(2) with information of the 28 variables mentioned before, using five factors and a VAR(5) specification, employing the sample period from January 2003 to January 2018 through the PCA.

[8] As a robustness check, we also performed the exercise proposed by Liu, Matheson and Romeu (2012). The number of factors that resulted from this exercise was also five.

[9] We also examined other information criteria, such as the Akaike and Hannan-Quinn. Both suggested a higher number of lags. However, given that the interest of this paper is not associated with predicting the factors in long-term horizons but with attaining a parsimonious representation within the sample, we take the number of lags suggested by the BIC.

Figure 2: Eigenvalues

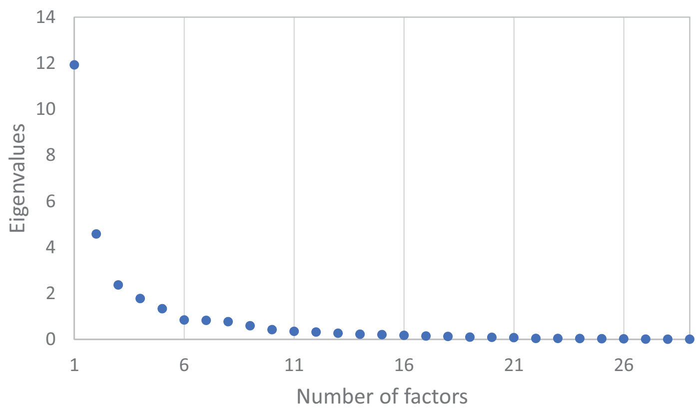


Table 1: Variables with Highest Loadings on the Rotated Factors

First factor	Second factor	Third factor	Fourth factor	Fifth factor
Capital goods imports	Construction volume	Oil production	Oil price	CPI
Consumption goods imports	Personnel occupied in construction	Commercial sales volume	Oil exports	CPI*
Raw materials imports	Current situation index	Industrial production volume		PPI
Outstanding private loans				
Demand deposits				

Note: CPI* is the CPI excluding food and beverages.

The results reveal that the first five factors explain about 80 percent of the joint variation of the 28 variables.[10] In addition, after performing an oblique rotation of the relevant factors, we obtain groups of variables whose loadings are larger for each of the factors.[11] Table 1 presents the variables with the largest loadings for each of the rotated factors.

The first factor seems to be representing the degree of liquidity of the economy, so we call it *liquidity*. The second factor could be referred to as *household pessimism* because it is negatively correlated with its corresponding variables. Negative correlations are also

[10] As a reference, Liu, Matheson and Romeu (2012) reckon that the common component in their model explains 28 percent of the variations in their variables.

[11] An oblique rotation of the factors allows for correlation among them, as should be expected in macroeconomic variables.

present between the variables listed in the third column and the corresponding third factor. We call this factor *firm pessimism*. The fourth factor correlates negatively with variables related to the oil-sector exports, so we refer to it as *oil sector lethargy*. Lastly, the fifth factor seems to represent inflation-related episodes and we call it *inflationary pressures*. These five macroeconomic dimensions, according to the DFM, would have the main effect and, therefore, the greater proportion in explaining the economic activity's evolution. Figure 3 presents the factors obtained from the DFM estimation. The units are standard deviations from each factor's zero mean.

In general, all the factors allow one to create a narrative consistent with the recent developments of the Ecuadorian economy. The most recent years have been characterized by an economic downturn triggered by the fall in oil prices at the end of 2014 and a recovery in relatively early stages considered to be still fragile in 2017. Precisely, the *oil sector lethargy* factor, shown in the middle-right panel of Figure 3, begins to increase in 2014 and reaches a peak in 2015; the lethargy of the oil sector appears to have increased in the last year. The degree of liquidity in the economy, illustrated in the upper-left panel of the figure, declined markedly in 2015 and recovered in 2016 and 2017, although it is showing signs of declining again at the end of the sample period. These developments were accompanied by increases of pessimism in both the household and firm sectors (the upper-right and middle-left panels, respectively), as the evolutions of these factors reveal since 2015. Inflation pressures, shown in the bottom panel, are worryingly low and declining during 2017, possibly reflecting a weak demand and the fragility of the recovery.

The *liquidity* factor (upper-left panel) resembles closely the evolution of the annual growth rate of real GDP shown in Figure 1. We would expect this to be the most relevant factor in informing the nowcast.

4 Nowcasting the Real GDP Growth Rate

Once we have estimated the DFM in (1)-(2), it is possible to use those results to estimate the parameters β, σ_{ε}^2, and σ_{ν}^2 of the state-space model in (7)-(8) to nowcast the

Figure 3: Estimated Dynamic Factors

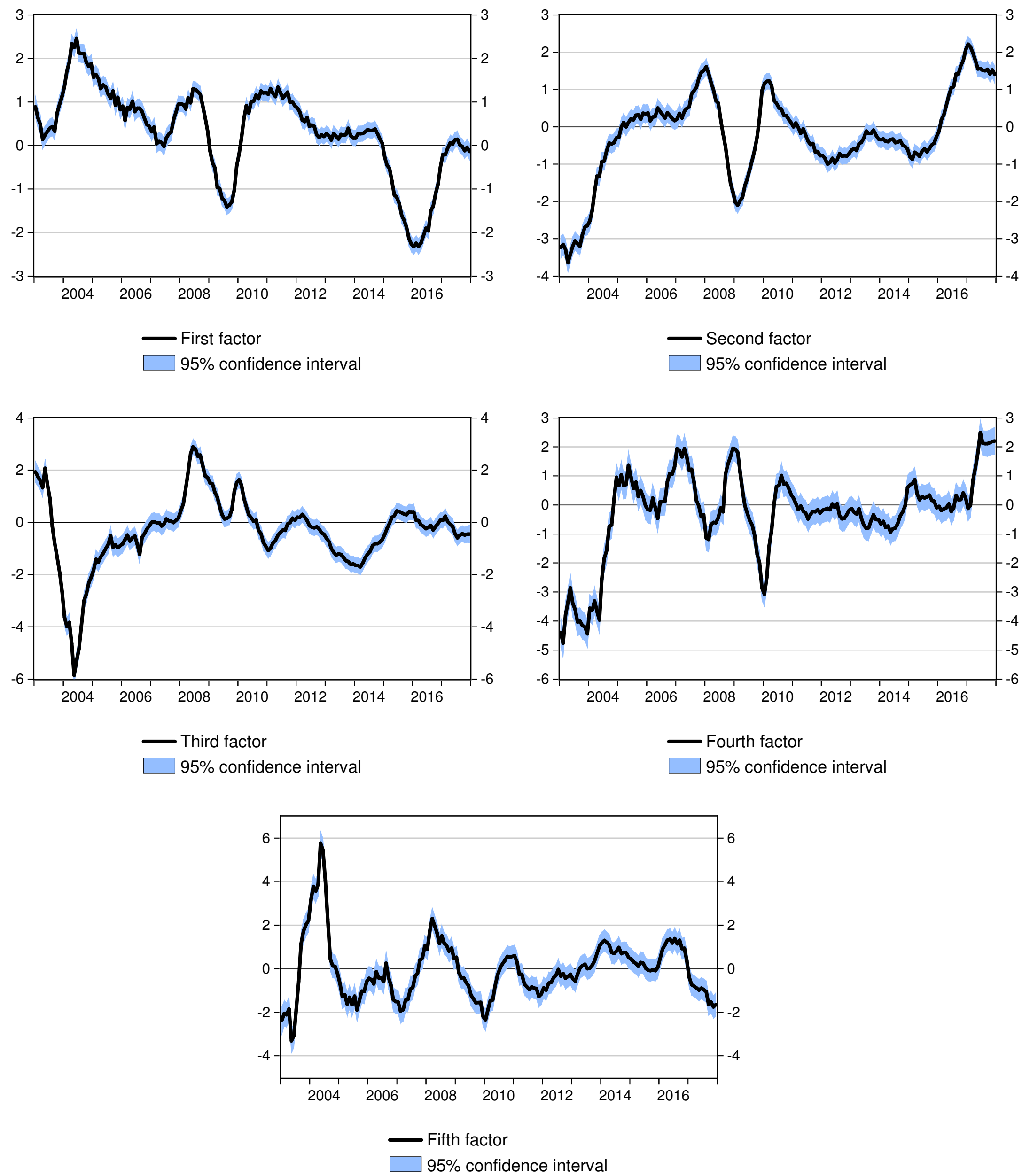
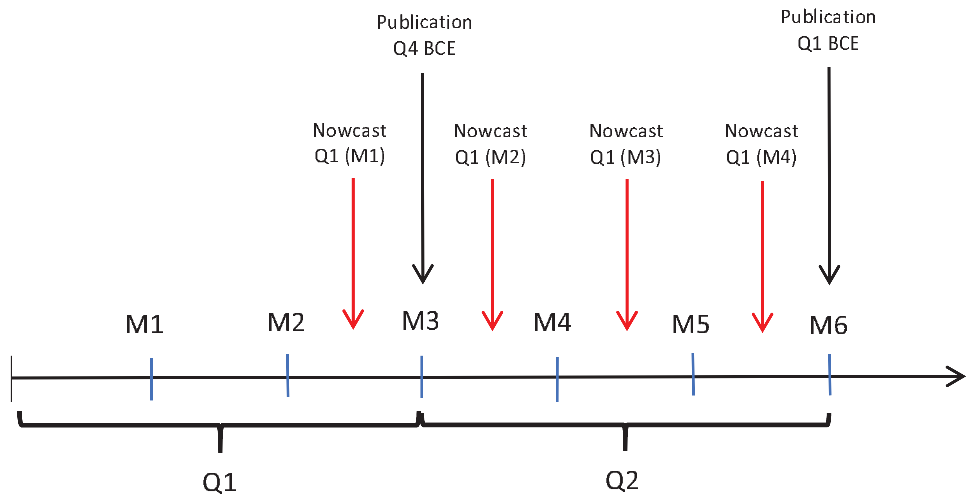


Figure 4: Nowcast Sequence for Any Quarter (Q1)



Note: Q1 represents the current quarter. M1, M2, and M3 denote the three months of the current quarter. Q2 is the next quarter in relation to the current one. M4, M5, and M6 are the months within that next quarter. The blue lines indicate the end of each month. Q4 is the previous quarter to Q1. Finally, months in which there is available information to produce the nowcast appear in parentheses.

real GDP growth rate, as described in Section 2.

4.1 Information Flow

Before presenting the nowcast results and diagnostics, it is necessary to understand the information flow sequence required to estimate the model. Figure 4 presents how information availability evolves and when it is feasible to produce the nowcast for a specific quarter.

The INA-R information is published with a seven-week lag. Thus, only after seven weeks is it possible to produce the nowcast with complete information for the 28 variables. Therefore, the first nowcast of real GDP growth for a given quarter with complete information through the first month could be produced starting in the third week of the third month of the quarter, as is shown in Figure 4.[12] In addition, before the BCE publishes GDP information for a given quarter at the end of that quarter, the model we propose will have provided four nowcasts.

[12]This does not imply that the nowcast cannot be produced as soon as the information of some variables becomes available, owing to the Kalman filter's ability to handle incomplete information.

Another consideration worth taking into account is that the first nowcast of a given quarter must be estimated with GDP information from two quarters ago due to the publication lag of the BCE. Only starting in the second nowcast is it possible to have information from the previous (most recent) quarter. The first nowcast, therefore, would be expected to be the least precise of the four nowcasts that are produced for a given quarter.

4.2 Nowcasting Model Results

Estimation of the state-space model in (7)-(8) yields the following loading coefficients, β, on each of the five factors:

- Liquidity: 2.90
- Household pessimism: negative 0.68
- Firm pessimism: negative 0.12
- Oil sector lethargy: negative 0.24
- Inflation pressures: 0.39

The first factor, which we called *liquidity*, has the highest weight to calculate the nowcast of the real GDP growth rate. As we indicated before, its evolution—plotted in the upper-left panel of Figure 3—is qualitatively very similar to the evolution of the real GDP annual growth rate in Figure 1.

Figure 5 shows the evolution in the sample of the estimated real GDP growth rate using the state-space model in (7)-(8), its associated confidence interval, and the realized series. As the figure illustrates, the estimated growth rate of real GDP (the dashed blue line) is historically close to the observed growth rate (the solid black line). The 95 percent confidence interval (the light blue shaded area), in fact, includes the real GDP growth rate throughout the sample period.

Figure 5: Estimated Growth Rate of Real GDP

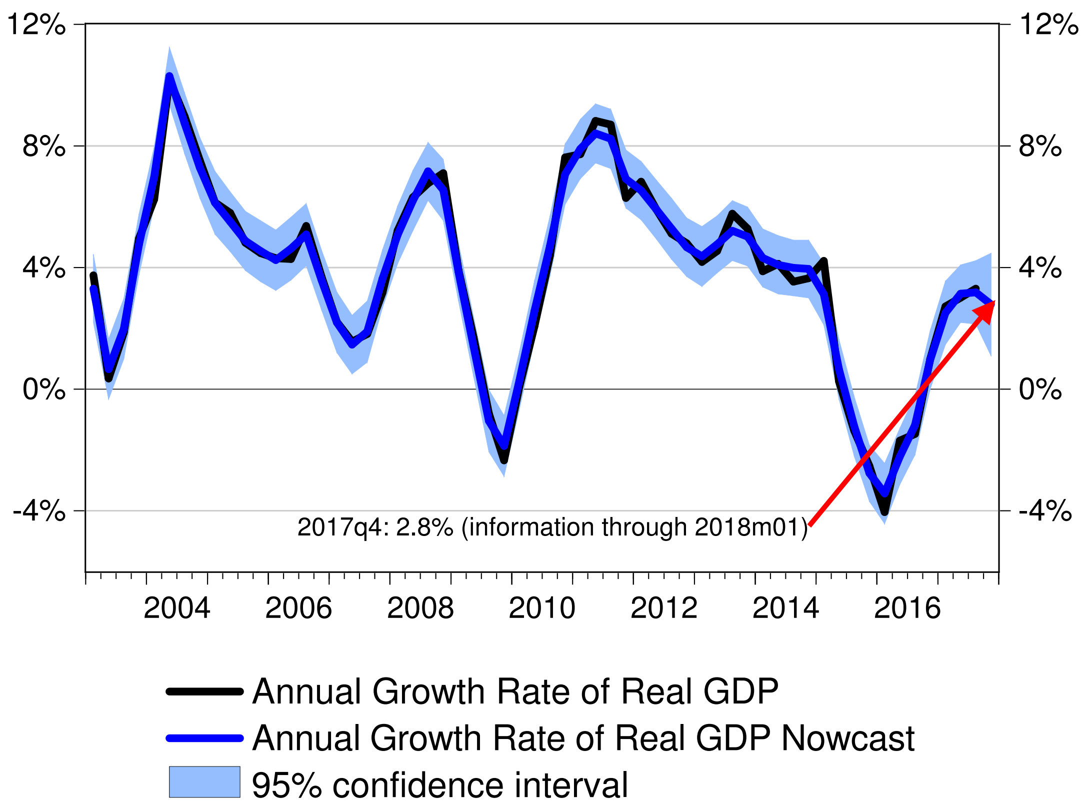
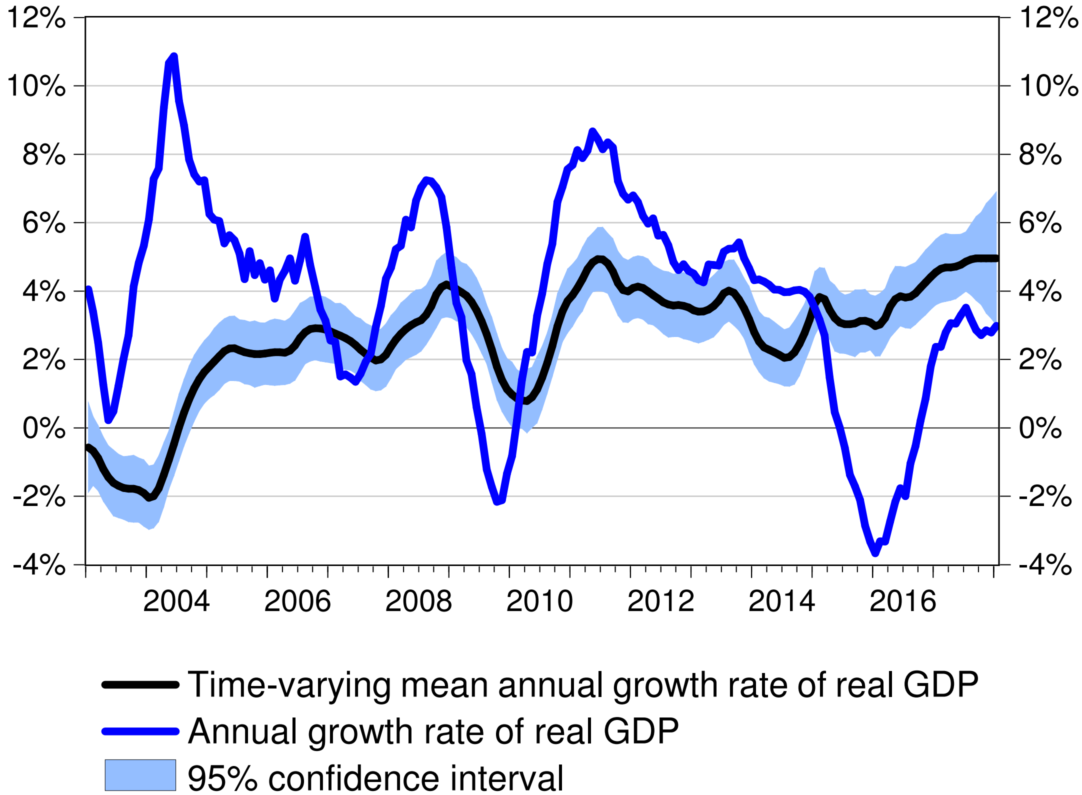


Figure 6: Estimated Mean Growth Rate of Real GDP (μ_t)



The nowcast of the annual growth rate of real GDP for the fourth quarter of 2017 with information through January 2018, according to the estimated model, was 2.8 percent. Its 95 percent confidence interval ranges from 1.1 percent to 4.5 percent.

An additional estimate of the model we propose is the evolution of the average growth rate of real GDP, which we assume is time-varying and have denoted with μ_t in the state-space model (7)-(8). This estimate can be thought of as a proxy for trend output growth, and it becomes important in revealing information about the long-run properties of economic activity and the current cyclical position of the economy. Figure 6 shows the evolution of the estimated time-varying average growth rate of real GDP.

As can be seen in the figure, the Ecuadorian economy has gone through four well-defined periods in terms of the difference between GDP growth and what we call its trend growth rate, μ_t. The first period starts in 2003 and goes through 2006, when the economy was growing faster than its trend. The second period, which starts in 2007 and ends around mid-2010, is somewhat convoluted, with periods of GDP growth higher than its trend analog and other periods with the opposite. The third period (late 2010 to late 2014) is characterized by an economy growing significantly faster than its estimated trend. Finally, starting in 2015, the economy is estimated to be growing significantly slower than its trend.

4.3 Nowcast News Decomposition

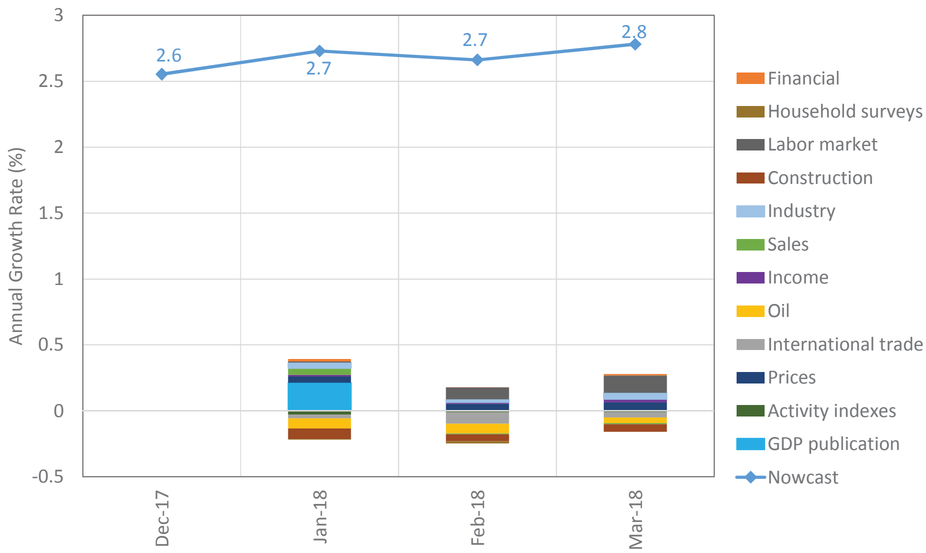
When the second nowcast is produced, we can analyze the sources of news that update the nowcast that was estimated with information until the previous month.[13] In order to understand the mechanism behind this decomposition, it is necessary to realize that, from the second month of a quarter onward, if there are no news-led surprises with respect to what the model expected with the information up to the previous month, the current nowcast of the GDP growth rate would not change with respect to the previous nowcast estimation. The decomposition design is an adaption of the approach proposed by Banbura and Modugno (2014).[14]

Figure 7 shows the nowcast evolution for the fourth quarter of 2017 and the source of revisions between the nowcast produced in December (with information through October) and the one produced in March (with information through January). In this particular case, the revision between the first and second nowcast estimations was 0.17 percentage point, mainly due to the GDP revision of the third quarter of 2017 published at the end of December. In the following months, most of the revisions have come from positive news in the labor market, financial variables, and prices. On the other hand, construction, trade,

[13] This decomposition assumes that there is not parameter uncertainty.

[14] It is worth mentioning that because of revisions to previous GDP figures every time the BCE publishes the national accounts information, the real GDP growth rate is accordingly updated for the second nowcast of a given quarter given this "news." Hence, if there are any updates in the previous GDP information, these surprises are also incorporated in the revision of the first nowcast. For the subsequent nowcast computations, however, this value is not taken into account for the news decomposition.

Figure 7: Evolution of 2017:Q4 Nowcasts and News Decompositions



Note: The 2017:Q4 annual growth rate published by the BCE is 3.0%.

and oil variables have contributed negatively to the revisions. The growth rate of real GDP published by the BCE for 2017:Q4 is currently 3.0 percent.

5 Nowcast Model Diagnostics

This section conducts a diagnostic of the proposed nowcasting model. First, we investigate its performance to nowcast the growth rate of real GDP in a pseudo out-of-sample exercise. Second, we compare the forecasting performance of the model against a simple alternative given by an ARMA model of the annual growth rate of real GDP.

For the first diagnostic, we assume that information is available to the model through October 2014; thus, we start to produce the nowcast from December 2014, rolling in an additional month of information at the time. Therefore, we produce several nowcasts for the GDP growth rate from 2014:Q4 onward with the information flow discussed in Figure 4.

Figure 8 shows the nowcast's historical evolution. The black line is the real GDP annual growth rate reported by the BCE in the most recent national accounts bulletin.

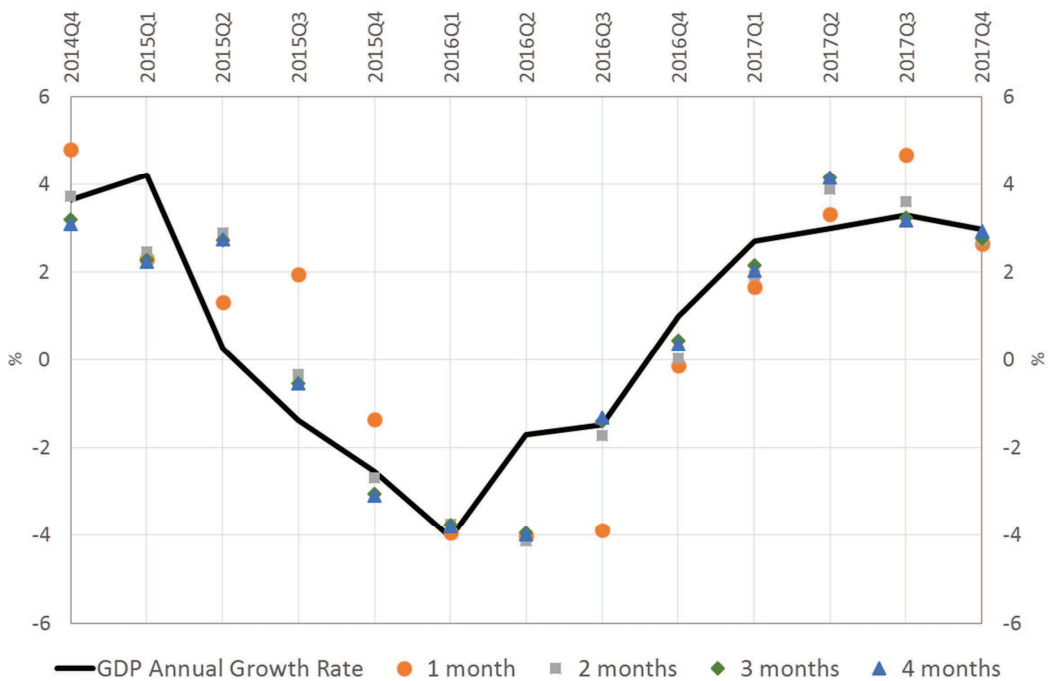
The orange points correspond to the nowcasts produced by the model with one month of information in each quarter. The gray squares, in turn, represent the nowcasts with two months of information in each quarter. Finally, the green rhombus and the blue triangles correspond to estimations with three and four months of information, respectively. As can be seen in the figure, the model features a reasonably good performance in forecasting negative real GDP growth rates during quarters in which the economy experienced important decelerations and contractions (in the period 2015:Q2 to 2016:Q1). Furthermore, as soon as the economy started to experience positive growth rates (in 2016:Q4), the model also begins to forecast positive growth rates, which in fact are fairly close to the ones reported by the BCE, especially when the model incorporates three or more months of information.

The nowcast, as is natural in these type of models, tends to have a lower forecast error, as more information is added during the quarter. The root mean square error of the annual growth rate forecast is 1.62 percent when there is information available for one month within the quarter, and 1.23 percent and 1.18 percent when there is information for two and three months, respectively; this value is 1.21 percent for the backcast when four months of information are available.

The second way to assess the model performance is to compare its accuracy to another forecasting model for the real GDP growth rate. In this case, we compare the nowcasting model with an ARMA(4,1) model for the real GDP annual growth rate in the same pseudo out-of-sample framework. ARMA models tend to be fairly precise at forecasting, especially when they are specified with a rich structure, as the one proposed, which has four lags of the GDP growth rate and one moving average term. The ARMA(4,1) model has a forecast root mean square error of 1.81 percent, which is higher than the ones reported previously for the nowcast model for the same forecast period. This result indicates that, at least with respect to the chosen ARMA model, our nowcasting model has better forecast performance.[15]

[15]The Diebold and Mariano (2002) test does not allow us to conclude that the nowcast model is significantly superior to the ARMA(4,1) at the usual significance levels.

Figure 8: Nowcasts Historical Evolution by Months of Information



Appendix A Variables and Data Processing

The employed variables and their release date, frequency, source, and transformation to estimate the DFM appear in Table 2.

One transformation that is worth describing is related to ISP. The BCE changed the way it constructed this variable in December 2014, thus making comparisons before and after this date impossible. In order to merge both periods, we take the ISP series through November 2014, which uses the previous methodology, and project what would have been the ISP for December 2014. For this purpose, we use the last three months of the ISP average growth rate. Accordingly, beginning in January 2015, the growth rate indicated by the new methodology is applied to our December projection.

Appendix B Estimating the Factor's VAR Lag Length

The DFM requires one to specify the VAR lag length in (2). We obtain it by using information criteria. To that end, we estimate VAR models with the 5 factors obtained with different lag numbers —in this case, a maximum of 10 lags. The number of lags is associated with the minimum value of a chosen information criterion. We consider here the most common ones: Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and Hannan-Quinn Information Criterion (HQ). Table 3 presents the results.

The BIC criterion suggests a lag number of 5, whereas the AIC and the HQ obtain 10 and 8 lags, respectively. The BIC tends to select more parsimonious models to explain the data within the sample. The AIC, on the other hand, leans toward models that produce overfitting of the data and are usually better at predicting. The purpose of our model, however, is not related to predicting the factors over long horizons but rather to find the number of lags that best fits them in sample. Consequently, as the BIC determined, we work with 5 lags.

Table 2: Macroeconomic Variables

Variable	**Synchronization**	**Frequency**	**Source**	**Transformation**
Oil Exports	Week 10	Monthly	BCE	Change % t/t-12
Non-oil Exports	Week 10	Monthly	BCE	Change % t/t-12
Consumption Goods Imports	Week 10	Monthly	BCE	Change % t/t-12
Raw Materials Imports	Week 10	Monthly	BCE	Change % t/t-12
Capital Goods Imports	Week 10	Monthly	BCE	Change % t/t-12
Oil Imports	Week 10	Monthly	BCE	Change % t/t-12
Consumer Price Index	Week 5	Monthly	INEC	Change % t/t-12
Consumer Price Index (excludes foods and beverages)	Week 5	Monthly	INEC	Change % t/t-12
Producer Price Index (includes exports products)	Week 10	Monthly	INEC	Change % t/t-12
Current Situation Index (gross series)	Week 10	Monthly	BCE	Change % t/t-12
Oil Total Exports Average Price	Week 10	Monthly	BCE	Change % monthly
Oil National Production	Week 10	Monthly	BCE	Change % t/t-12
Monthly Income Tax Retentions	Week 8	Monthly	SRI	Change % t/t-12
Monthly Value-Added Tax Collections	Week 8	Monthly	SRI	Change % t/t-12
Occupied Personnel - Industrial Sector	Week 7	Monthly	BCE	12-month moving average
Occupied Personnel - Commercial Sector	Week 7	Monthly	BCE	12-month moving average
Occupied Personnel - Construction Sector	Week 7	Monthly	BCE	12-month moving average
Occupied Personnel - Services Sector	Week 7	Monthly	BCE	12-month moving average
Industrial Volume Production	Week 7	Monthly	BCE	12-month moving average
Sales Volume - Commercial Sector	Week 7	Monthly	BCE	12-month moving average
Construction Volume Production	Week 7	Monthly	BCE	12-month moving average
Sales Volume - Services Sector	Week 7	Monthly	BCE	12-month moving average
Current Situation Index	Week 7	Monthly	BCE	None
Short-term Deposits (Financial Panorama)	Week 10	Monthly	BCE	Change % t/t-12
Narrow Money (Financial Panorama)	Week 10	Monthly	BCE	Change % t/t-12
Outstanding Loans to Private Sector (Financial Panorama)	Week 10	Monthly	BCE	Change % t/t-12
Energy Consumption (National)	Week 10	Monthly	ARCONEL	Change % t/t-12
Index of Level of Registered Activity	Week 11	Monthly	INEC	None
Gross Domestic Product in 2007 Constant Dollars	Week 12	Quarterly	BCE	Change % t/t-4

Table 3: VAR Lag Length and Information Criteria

	Information Criteria		
Lag Length	BIC	AIC	HQ
1	-0.7327	-1.2951	-1.0668
2	-1.9547	-2.9858	-2.5673
3	-1.9879	-3.4877	-2.8789
4	-2.3265	-4.2950	-3.4960
5	-2.3990^{*}	-4.8361	-3.8469
6	-2.3270	-5.2328	-4.0533
7	-2.1218	-5.4962	-4.1265
8	-1.8971	-5.7402	-4.1802^{*}
9	-1.4222	-5.7340	-3.9838
10	-1.1164	-5.8969^{*}	-3.9564

* indicates the lag length selected by each of the information criteria.

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