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 30 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 more precise than a nowcasting model that assumes a constant mean real GDP growth rate and an 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.\(^1\) The aim of a nowcasting model is to take advantage of 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. The approach we propose can be useful to nowcast the economic activity of other small developing economies in which the availability of macroeconomic data is not as rich and opportune as in more advanced economies.

Our nowcasting model is based on a dynamic factor model (DFM) estimated with 30 macroeconomic variables at the monthly frequency starting in January 2004. Among the several variations of nowcasting models that exist in the literature (Bayesian vector autoregressions, factor-augmented autoregressive models, Bayesian regressions, accounting-based tracking models, and bridge regressions, for instance), DFMs have become popular in macroeconometrics to analyze business cycles and to forecast and nowcast the state of

\(^1\)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.
Institutions around the world—central banks in particular—use nowcasting models to inform their policy decision-making. For instance, nowcasting applications with DFMs exist for Spain (see Cuevas and Quilis, 2012), Mexico (see Tirado, Delajara and Alvarez, 2016), Canada (see Chernis and Sekkel, 2017), and the U.S. (see Higgins, 2014; Aarons et al., 2016, whose nowcasts are publicly available), among many others. In the case of Ecuador, there are two proposals of nowcasting models in the literature. Liu, Matheson and Romeu (2012) incorporate the country in the set of analyzed Latin American countries for which they construct and estimate nowcasting models. 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.

The main contributions of our modeling strategy are threefold. First, we use the mixed-frequency formulation by Bańbura and Rünstler (2011) to obtain the nowcast directly from the Kalman filter; as a result, we avoid having to estimate bridge regressions as is the case in Liu, Matheson and Romeu (2012) and Casares (2017). Second, we do not demean the growth rate of real GDP, as is usually required in the setup by Bańbura and Rünstler and in most nowcasting applications that use DFMs. 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 (using the Bańbura and Rünstler setup), which maintains the state-space at a more manageable scale with respect to the approach in Antolin-Diaz, Drechsel, and Petrella. Third, because employment statistics are released only at the quarterly frequency in the case of Ecuador, we use employment growth survey data with monthly frequency at the firm level to obtain a monthly counterpart of aggregate employment. In a similar vein, because key economic
activity index data are released with a four-month lag, we employ output growth survey
data at the firm level to obtain the updated economic activity indexes. We use these
estimated series to inform our nowcasting model.

We estimate our model in two stages. In the first stage, we obtain the parameters of the
DFM using the method of principal components and its dynamic structure by estimating
a vector autoregressive (VAR) model. In the second stage, we estimate the parameters
that link output growth to the dynamic factors within the mixed-frequency specification,
as well as the time-varying mean growth rate of real GDP, by maximum likelihood and
the use of the Kalman filter. 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). Because the
approach we use is easily implementable, the model we propose can be used not only for
small developing economies but also for more advanced economies with macroeconomic
data more readily available to estimate the DFM.

We find that our nowcasting model with a time-varying real GDP mean growth rate
delivers a lower root-mean-square forecast error in pseudo out-of-sample exercises com-
pared with a nowcasting model with a constant mean growth rate and an ARMA(4,1)
model, although the differences do not seem to be statistically significant. The model also
allows one to obtain a smoothed estimate of the mean growth rate of real GDP which
we refer to as “trend GDP growth.” The results show that the Ecuadorian economy was
growing at about the same pace compared with its estimated trend growth rate, which is
close to one percent, in the second quarter of 2018.

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 two alternatives.
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):

\[
\begin{align*}
X_{tm} &= \Lambda F_{tm} + E_{tm}, \quad E_{tm} \sim \text{i.i.d.} \mathcal{N}(0, \Sigma_E), \\
F_{tm} &= \Phi(L)F_{tm} + U_{tm}, \quad U_{tm} \sim \text{i.i.d.} \mathcal{N}(0, \Sigma_U),
\end{align*}
\]

where \(X_{tm}\) is a vector of \(n\) monthly macroeconomic variables previously standardized and \(\Lambda\) is a matrix of dimension \(n \times p\) that relates the macroeconomic variables with the \(p\) monthly factors that appear in the vector \(F_{tm}\), which follows an autoregressive structure with coefficient matrices \(\Phi(\cdot)\). The error terms \(E_{tm}\) and \(U_{tm}\) are normally distributed white noises with variance-covariance matrices \(\Sigma_E\) and \(\Sigma_U\), respectively, and independent of each other. The fact that the variables \(X_{tm}\) 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 \(-\mu, \Lambda, \text{ and } \Sigma_E\) are obtained by applying principal components analysis (PCA) to a
balanced panel that includes the variables in $X_{tm}$. The matrices $\Phi(\cdot)$ and $\Sigma_U$, meanwhile, are calculated from a VAR with a determined lag length.\(^2\) Second, the factors, $F_{tm}$, 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:

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

(3)

where $y_{tq}$ is the quarterly real GDP growth rate in period $t_q$, $\mu$ is its average, $F_{tq}$ are the quarterly aggregated factors in period $t_q$, which relate to real GDP growth through the regression coefficients $\beta$, and $e_{tq}$ is an error.

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, $y^*_{tm}$, as a latent variable that is related to the monthly common factors as follows:\(^3\)

$$y^*_{tm} = \mu_{tm} + \beta' F_{tm},$$

(4)

$$\mu_{tm} = \mu_{tm-1} + \nu_{tm}, \quad \nu_{tm} \sim \text{i.i.d. } N(0, \sigma_\nu^2),$$

(5)

where $\mu_{tm}$ 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

\(^2\)A balanced panel is obtained by taking into account only the sample for which all the observations from all the variables considered are available.

\(^3\)In this setup, the factors are obtained from the macroeconomic variables $X_{tm}$ transformed to annual figures, either growth rates or averages.
the model to incorporate periods of output growth that are persistently higher or lower than in other historical episodes.

Summers (2014) argues that the U.S. 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 in real time. 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:

\[ \hat{y}^q_{tm} = \frac{1}{3} \left( y^*_{tm} + y^*_{tm-1} + y^*_{tm-2} \right), \]  

whereas the forecast error, \( \varepsilon_{tq} = y_{tq} - \hat{y}^q_{tm} \), is assumed to be normally distributed with mean zero and variance \( \sigma^2_\varepsilon \).

In this way, we can obtain a nowcast of the growth rate of the economy consistent 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):
The dynamic factors appear in the state-space model (7) of Bańbura and Rünstler. This approach implies adding lags of monthly growth rates, where the aggregation rule follows the specification (8) of the DFM and use the approach suggested by Mariano and Murasawa (2003) to deal with mixed frequencies. This approach implies adding lags of the latent variables, in particular the dynamic factors, which already appear with lags in the observation equation (9) of the DFM and use the approach suggested by Antolin-Díaz, Drechsel and Petrella (2017) to deal with mixed frequencies. This approach implies adding lags of the latent variables, in particular the dynamic factors, which already appear with lags in the specification (1)-(2), to the state space with mixed frequencies. In contrast, our setup follows Bańbura and Rünstler (2011) which is more straightforward as it does not increase the size of the state space. The dynamic factors appear in the state-space model (7)-(8) only with the number of lags needed for specifying their vector autoregressive structure. This simplification can be particularly useful to estimate the parameters of the model and

\[
\begin{align*}
\begin{bmatrix}
X_{tm} \\
y_{tq}
\end{bmatrix}
&= \begin{bmatrix}
\Lambda & 0 & 0 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
y^*_{tm} \\
\mu_{tm} \\
\hat{y}^q_{tm}
\end{bmatrix}
+ \begin{bmatrix}
E_{tm} \\
\varepsilon_{tq}
\end{bmatrix},
\end{align*}
\]

(7)

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

(8)

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

Antolin-Díaz, Drechsel and Petrella (2017) also introduce time-varying intercepts in the observation equation (1) of the DFM and use the approach suggested by Mariano and Murasawa (2003) to deal with mixed frequencies. This approach implies adding lags of the latent variables, in particular the dynamic factors, which already appear with lags in the specification (1)-(2), to the state space with mixed frequencies. In contrast, our setup follows Bańbura and Rünstler (2011) which is more straightforward as it does not increase the size of the state space. The dynamic factors appear in the state-space model (7)-(8) only with the number of lags needed for specifying their vector autoregressive structure. This simplification can be particularly useful to estimate the parameters of the model and

\[
y^q_{tm} = \frac{1}{3}y^*_{tm} + \frac{2}{3}y^*_{tm-1} + y^*_{tm-2} + \frac{2}{3}y^*_{tm-3} + \frac{1}{3}y^*_{tm-4},
\]

(9)

where \(y^*_{tm}\) has the factor structure (1)-(2). One needs to substitute the corresponding line of equation (1) into equation (9) to incorporate the mixed frequencies.

\footnote{Under this approach, the observed quarterly growth rate of real GDP, \(y^q_t\), is related to the unobserved monthly growth rates, \(y^*_{tm}\), and its lags using a weighted mean, as follows:}

\[
y^q_{tm} = \frac{1}{3}y^*_{tm} + \frac{2}{3}y^*_{tm-1} + y^*_{tm-2} + \frac{2}{3}y^*_{tm-3} + \frac{1}{3}y^*_{tm-4},
\]

(9)

\footnote{The key is the use of the aggregation rule given by \(\hat{y}^q_{tm} = \Xi_{tm}\hat{y}^q_{tm-1} + \frac{1}{3}y^*_{tm}\).}
to obtain the smoothed estimates of the latent variables with less computational burden.

In order to estimate the model, we follow a two-step approach. In the first step, we estimate the matrices of the state-space model (1)-(2) by PCA while the embedded VAR model is estimated by ordinary least squares, as in Giannone, Reichlin and Small (2008). In the second step, we estimate the parameters $\beta$, $\sigma^2_\varepsilon$, and $\sigma^2_\nu$ 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 indexes of economic activity by industry.

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) 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 10 categories, as follows.\textsuperscript{6}

- Financial
- International trade
- Oil
- Income
- Sales
- Industry
- Construction
- Labor market
- Household surveys
- 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, 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) the retail goods sales index constructed by the SRI, and (ii) the retail services sales index constructed by the same institution. The industry and construction categories include the respective index

\textsuperscript{6}This categorization is roughly based on the Federal Reserve of New York guidelines for its nowcasting model.
constructed by the SRI for each variable. We update these indexes with output growth survey data by industry, namely from retail goods sales, retail services sales, manufacturing, and construction.

Labor market takes into account our monthly estimates of the quarterly urban adequate employment and unemployment rates published by INEC, which are constructed using monthly employment growth survey data by industry. Household surveys consider the Current Situation Index (Índice de Situación Presente, ISP), which is a measure of consumer confidence. 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 23 variables in our nowcasting model, 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 July 2018; this balanced data set allows us to perform the PCA. Most of the variables, however, are available from January 2004, and we use all this information to estimate the nowcasting model with the use of the Kalman filter.

All the series are seasonally adjusted using the X-12-ARIMA method and we express 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 averages. A detailed description of the variables used and their adjustments is available in Appendix B.

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7For more information on these indexes, see Servicio de Rentas Internas (2017 (Accesed: 2018-09-12).
8Strictly speaking, we use eight additional variables, which involve employment growth and output growth for each industry (retail goods sales, retail services sales, manufacturing, and construction) in estimating our monthly employment indicators and our updated economic activity indexes by industry. Appendix A describes the models used to obtain our estimated employment data and activity indexes.
9In 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.
10There is a fundamental reason to work with the series in their year-over-year percent change. The reason is that the real GDP figures published by the BCE may not be free of seasonality. This situation implies that working with the quarter-over-quarter percent variation may be subject to seasonal factors that cannot be picked up by the state-space model we consider in this paper.
To conclude the description of the data, 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 briskly at an annual rate close to 6 percent, on average. 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 causes the economy to decelerate and later contract significantly until the end of 2016, when it starts to recover slowly. By early 2017, the economy has already returned to positive real GDP growth rates around 3 percent and is showing signs of deceleration in the first quarter of 2018, which is the most recent available information.

3.2 Stationarity Properties of the Data

It is possible that the monthly variables from which we obtain the factors through the PCA may not be 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.\footnote{If the monthly-frequency series were expressed as their monthly or quarterly percent variations, this would not be a concern because these growth rates usually revert relatively quickly to their unconditional mean.}

We used sequentially the Kwiatkowski, Phillips, Schmidt, and Shin (see Kwiatkowski et al., 1992) test of stationarity and the Phillips-Perron’s unit root test (see Phillips and Perron, 1988) to check for nonstationarity. The tests were performed one at the time on all 22 variables that were used to obtain the dynamic factors. The results reveal that there is evidence of nonstationarity at the five percent level of significance in three of the variables: the indexes of retail goods sales, retail services sales, and manufacturing output. A closer inspection of these series reveals that other unit root tests, such as the Elliott, Rothenberg, and Stock (see Elliott, Rothenberg and Stock, 1996) test, rejects the null of a unit root for the retail goods sales and manufacturing output indexes at the ten percent level of significance. The only series for which it is not possible to rule out statistically its nonstationarity is the year-over-year percent change of the index of retail services sales, which shows a downward trend in the sample period. In fact, the Phillips-Perron test rejects strongly the presence of a unit root in favor of stationarity with trend. Because we do not expect the annual growth rate of the index of retail services sales to trend downward permanently, we assume that this series is stationary, despite the results of the tests.

### 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, $F_{tm}$, using PCA once the database has been constructed. 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 22-variable database, the number of factors should be 22 regardless of the criterion employed, which is not a very useful result.

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 three. Therefore, this is the number that we select for our model.\(^\text{12}\)

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(1), based on the Bayesian Information Criterion (BIC).\(^\text{13}\)

\(^{12}\)If we use the Bai and Ng (2002) test setting the maximum number of common factors to seven, the Akaike criterion results in 3 common factors.

\(^{13}\)We also examined other information criteria, such as the Akaike and Hannan-Quinn. Both suggested a higher number of lags (7 and 2, respectively). 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.
3.4 Results of the Estimation of the DFM

We estimate the DFM in (1)-(2) with information of the 22 variables mentioned before, using three factors and a VAR(1) specification, employing the sample period from January 2004 to July 2018 through the PCA.

The results reveal that the first three factors explain about 72 percent of the joint variation of the 22 variables.\textsuperscript{14} 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.\textsuperscript{15} Table 1 presents the variables with the largest loadings for each of the rotated factors.

The first factor seems to be representing the dynamism of economic activity, so we call it \textit{economic activity}. The second factor seems to represent inflation-related episodes and we call it \textit{inflationary pressures}. Lastly, the third factor summarizes a combination

\textsuperscript{14}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.

\textsuperscript{15}An oblique rotation of the factors allows for correlation among them, as should be expected in macroeconomic variables.
Table 1: Variables with Highest Loadings on the Rotated Factors

| First factor                      | Second factor | Third factor     |
|-----------------------------------|---------------|------------------|
| Current situation index CPI*      | Adequate employment | CPI* Manufacture |
| CPI                               | Adequate employment | CPI Oil production |
| Oil production index              | CPI           | Oil production   |
| Refined petroleum imports         | CPI           | Oil production   |
| Raw materials imports             | CPI           | Oil production   |
| Demand deposits                   | CPI           | Oil production   |
| Oil exports                       | CPI           | Oil production   |
| Retail goods sales index          | CPI           | Oil production   |
| VAT collections                   | CPI           | Oil production   |
| Consumption goods imports         | CPI           | Oil production   |

Note: CPI* is the CPI excluding food and beverages. The cutoff value for the loadings of the variables that appear in the table is 0.7.

of formal labor market- and oil production-related variables, so we denominate it *formal employment*. These three macroeconomic dimensions, according to the DFM, would have the main effect and, therefore, the greater proportion in explaining the evolution of real GDP growth. Figure 3 presents the factors obtained from the estimation. The units are standard deviations from each factor’s zero mean.

In general, considering the factors jointly allows one to create a narrative consistent with the latest 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 2018. Precisely, the *economic activity* factor, shown in the upper panel of Figure 3, begins to decline in early 2015 and reaches a trough in early 2016. The *formal employment* factor (third panel of Figure 3) also evidences a sharp decline in 2016, consistent with the evolution of the *economic activity* factor. The *inflationary pressures* factor, shown in the second panel of Figure 3, has declined in a sustained way since 2015 and remains in negative territory in 2018, when annual inflation rates have averaged negative $\frac{1}{2}$ percent. In line with this deflation scenario, both the *economic activity* and the *formal employment* factors have declined in 2018 after showing a recovery during 2017.

We notice that the *economic activity* factor resembles closely the evolution of the annual growth rate of real GDP shown in Figure 1. We would expect this to be the most
Figure 3: Estimated Dynamic Factors

First factor
95% confidence interval

Second factor
95% confidence interval

Third factor
95% confidence interval
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.

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 $\beta$, $\sigma^2$, and $\sigma^2$ of the state-space model in (7)-(8) to nowcast the 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 first nowcast of real GDP growth for a given quarter with complete information through the first month could be produced starting in the second week of the third month
of the quarter, as is shown in Figure 4. In addition, before the BCE releases GDP information for a given quarter at the end of that quarter, the model we propose will have provided four nowcasts.

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. In addition, the release of GDP data between the first and second quarters is likely to influence the estimate of the time-varying intercept because the model informs the estimation of this latent variable on GDP data almost exclusively; the estimated time-varying intercept should not change significantly from the third nowcast onwards.

### 4.2 Nowcasting Model Results

Estimation of the state-space model in (7)-(8) yields the following loading coefficients, $\beta$, on each of the three factors:

- Economic activity: 2.38
- Inflationary pressures: 0.32
- Formal employment: 1.05

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

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16This 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.
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.

The nowcast of the annual growth rate of real GDP for the second quarter of 2018 with information through July 2018, according to the estimated model, was 1.2 percent. Its 95 percent confidence interval ranges from negative 1.2 percent to 3.7 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 $\mu_t$ 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
Figure 6: Estimated Mean Growth Rate of Real GDP ($\mu_t$)

The Ecuadorian economy has gone through four well-defined periods in terms of the difference between real GDP growth and what we call its trend growth rate, $\mu_t$. The first period starts in 2004 and goes through 2008, when the economy was growing faster than its trend. The second period, which starts in 2009 and ends around mid-2010, indicates real GDP growth rates below its trend. This period coincides with the recession that hit the economy during the Global Financial Crisis and the subsequent collapse of oil prices. The third period (late 2010 through 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 or at about
the same pace than its trend, whose growth rate has declined to just above 1 percent.

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.\textsuperscript{17} 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).\textsuperscript{18}

Figure 7 shows the nowcast evolution for the second quarter of 2018 and the source of revisions between the nowcast produced in June (with information through April) and the one produced in September (with information through July). In this particular case, the revision between the first and second nowcast estimations was negative 1.46 percentage points, mainly due to the GDP release for the first quarter of 2018 that implied an annual growth rate about 1 percentage point lower than the average in 2017. In the following months, most of the revisions have come from negative news in the international trade (in particular lower imports) and oil (in particular oil production) variables. The growth rate of real GDP released by the BCE for 2018:Q2 is currently x.x percent.

\textsuperscript{17}This decomposition assumes that there is no parameter uncertainty.

\textsuperscript{18}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” through the effect on $\mu_t$, as indicated before. 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 2018:Q2 Nowcasts and News Decompositions

Note: The 2018:Q2 annual growth rate released by the BCE is x.x percent.
5 Nowcasting Model Diagnostics

This section conducts a diagnostic of the proposed nowcasting model. We investigate its performance to nowcast the growth rate of real GDP in a pseudo out-of-sample exercise comparing it with the performance of a nowcasting model in which the mean growth rate is constant. We also compare the forecasting performance of the model against a simple alternative given by an ARMA model of the annual growth rate of real GDP.

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 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 contractions (in the period 2015:Q3 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.

Figure 9, in contrast, depicts the evolution of the nowcast in history produced by a model that assumes a constant average real GDP growth rate. This model seems to have serious problems nowcasting the magnitude of the trough of the recession in the first quarter of 2016.

One way to assess the benefit to introduce a time-varying mean growth rate to nowcast real GDP growth is to compute the root-mean-square forecast error (RMSFE) for each model and for each of the four nowcasts produced each quarter. Table 2 shows the statistics. The nowcasts, as is natural in these type of models, tend to have a lower RMSFE as more information is added during the quarter. For the model with time-varying mean,
Figure 8: Nowcasts Historical Evolution by Months of Information (Time-Varying Intercept)

Figure 9: Nowcasts Historical Evolution by Months of Information (Constant Intercept)
Table 2: Root-Mean-Square Forecast Errors From Different Models (in percent)

| Model             | First nowcast | Second nowcast | Third nowcast | Fourth nowcast |
|-------------------|---------------|----------------|---------------|----------------|
| Time-varying mean | 1.62          | 1.26           | 1.13          | 1.15           |
| Constant mean     | 2.10          | 1.97           | 1.81          | 1.80           |
| ARMA(4,1)         |               |                | 1.80          |                |

The RMSFE of the annual growth rate forecast is 1.62 percent when there is information available for one month within the quarter, and 1.26 percent and 1.13 percent when there is information for two and three months, respectively; this value is 1.15 percent for the backcast when four months of information are available. The same feature—a declining RMSFE as more information becomes available—is present for the model with a constant mean, but its RMSFE is higher than the model’s with time-varying mean.

Finally, we compare the nowcasting models 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 in the short run, 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 RMSFE of 1.80 percent for the one-quarter-ahead forecast, which is higher than the one reported previously for the nowcasting model with time-varying intercept, but lower than the one for the model with a constant real GDP growth rate mean. Hence, to summarize, the nowcasting model that we propose with a time-varying mean growth rate of real GDP dominates a nowcasting model with a constant mean and a simple time series model.\(^{19}\)

\(^{19}\)The Harvey, Leybourne and Newbold (1997) test (known as the modified Diebold and Mariano (1995) test) does not allow us to conclude that our nowcasting model is superior to the other two models at the usual significance levels, although the test statistics at each of the four nowcasts are the highest when we compare the nowcasting models with time-varying and constant intercepts. Unfortunately, the size of the sample can be problematic to test statistically the forecasting performance of the model at this stage.
Appendix A  Obtaining the Monthly Employment Data and Updating the Economic Activity Indexes

We use state-space models and the Kalman filter to obtain monthly equivalents of the urban adequate and total employment rates as well as the missing values at the end of the sample of the sectoral production indexes.

The model for the employment rates is as follows:

\[
\begin{align*}
    e_t &= \mu^e_t + \alpha_1 x^d_t + \alpha_2 x^s_t + \nu^e_t, \\
    \tilde{e}_t &= \mu^\tilde{e}_t + \tilde{\alpha}_1 x^d_t + \tilde{\alpha}_2 x^s_t + \nu^\tilde{e}_t, \\
    n^r^g_t &= \theta^r^g_t + \theta^r^g x^s_t + \nu^r^g_t, \\
    n^r^s_t &= \theta^r^s_t + \theta^r^s x^s_t + \nu^r^s_t, \\
    n^c_t &= \theta^c_t + \theta^c x^s_t + \nu^c_t, \\
    n^m_t &= \theta^m_t + \theta^m x^s_t + \nu^m_t, \\
    \mu^e_t &= \mu^e_{t-1} + \eta^e_t, \\
    \mu^\tilde{e}_t &= \mu^\tilde{e}_{t-1} + \eta^\tilde{e}_t, \\
    x^d_t &= \phi^d x^d_{t-1} + \phi^d x^d_{t-2} + \varepsilon^d_t, \\
    x^s_t &= \phi^s x^s_{t-1} + \phi^s x^s_{t-2} + \varepsilon^s_t,
\end{align*}
\]

where \( e_t \) is the year-over-year variation in the quarterly urban adequate employment rate, \( \tilde{e} \) is the year-over-year variation in the quarterly urban total employment rate defined as 100 minus the unemployment rate, \( n^j_t \) is the year-over-year percent variation of employment in economic industry \( j \), for \( j = \) retail goods sales, retail services sales, construction, and manufacturing reported in the Monthly Business Opinion Survey (Encuesta Mensual de Opinión Empresarial, EMOE) of the BCE. The error terms are assumed to be white noise normally distributed and independent of each other. Figure 10 compares the quarterly
series with their monthly estimates. As the figure shows, the model does a very good job at fitting the variation in the quarterly employment rates.

The model to update the sectoral production indexes is as follows:

\[
\begin{align*}
y_{tg}^t &= \mu_{tg}^t + \gamma_{1tg}^t x_{tg}^t + \gamma_{2tg}^t x_{td}^t + u_{tg}^t, \\
y_{ts}^t &= \mu_{ts}^t + \gamma_{1ts}^t x_{ts}^t + \gamma_{2ts}^t x_{td}^t + u_{ts}^t, \\
y_{tc}^t &= \mu_{tc}^t + \gamma_{1tc}^t x_{tc}^t + \gamma_{2tc}^t x_{td}^t + u_{tc}^t, \\
y_{tm}^t &= \mu_{tm}^t + \gamma_{1tm}^t x_{tm}^t + \gamma_{2tm}^t x_{td}^t + u_{tm}^t, \\
q_{rg}^t &= \delta_{1rg}^t + \delta_{2rg}^t x_{rg}^t + \delta_{3rg}^t x_{rs}^t + v_{rg}^t, \\
q_{rs}^t &= \delta_{1rs}^t + \delta_{2rs}^t x_{rs}^t + \delta_{3rs}^t x_{ts}^t + v_{rs}^t, \\
q_{c}^t &= \delta_{1c}^t + \delta_{2c}^t x_{c}^t + \delta_{3c}^t x_{ts}^t + v_{c}^t, \\
q_{m}^t &= \delta_{1m}^t + \delta_{2m}^t x_{m}^t + \delta_{3m}^t x_{ts}^t + v_{m}^t, \\
\mu_{tg}^t &= \mu_{tg}^{t-1} + \eta_{tg}^t, \\
\mu_{ts}^t &= \mu_{ts}^{t-1} + \eta_{ts}^t, \\
\mu_{tc}^t &= \mu_{tc}^{t-1} + \eta_{tc}^t, \\
\mu_{tm}^t &= \mu_{tm}^{t-1} + \eta_{tm}^t, \\
x_{td}^t &= \phi_{1td} x_{td}^{t-1} + \phi_{2td} x_{td}^{t-2} + \varepsilon_{td}^t, \\
x_{ts}^t &= \phi_{1ts} x_{ts}^{t-1} + \phi_{2ts} x_{ts}^{t-2} + \varepsilon_{ts}^t, \\
x_{c}^t &= \phi_{1c} x_{c}^{t-1} + \phi_{2c} x_{c}^{t-2} + \varepsilon_{c}^t, \\
x_{m}^t &= \phi_{1m} x_{m}^{t-1} + \phi_{2m} x_{m}^{t-2} + \varepsilon_{m}^t,
\end{align*}
\]

where \( y_{j}^t \) is the annual growth rate of the index of industry \( j \), for \( j = \) retail goods sales, retail services sales, construction, and manufacturing, whereas \( q_{j}^t \) is the respective counterpart for industry \( j \) from the EMOE. The error terms are assumed to be white noise normally distributed and independent of each other.
Figure 10: Estimates of the Variation in Monthly Employment Rates
Appendix B  Variables and Data Processing

The employed variables and their release date, frequency, source, and transformation to estimate the DFM appear in Table 3. The synchronization column shows the number of weeks after the beginning of a quarter when the information is first released.

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.
| Variable                                           | Synchronization | Frequency | Source | Transformation            |
|----------------------------------------------------|-----------------|-----------|--------|---------------------------|
| Oil Exports                                        | Week 10         | Monthly   | BCE    | Annual % change           |
| Non-oil Exports                                    | Week 10         | Monthly   | BCE    | Annual % change           |
| Consumption Goods Imports                          | Week 10         | Monthly   | BCE    | Annual % change           |
| Raw Materials Imports                              | Week 10         | Monthly   | BCE    | Annual % change           |
| Capital Goods Imports                              | Week 10         | Monthly   | BCE    | Annual % change           |
| Oil Imports                                        | Week 10         | Monthly   | BCE    | Annual % change           |
| Consumer Price Index                               | Week 5          | Monthly   | INEC   | Annual % change           |
| Consumer Price Index (excludes foods and beverages) | Week 5          | Monthly   | INEC   | Annual % change           |
| Producer Price Index (includes exports products)   | Week 5          | Monthly   | INEC   | Annual % change           |
| Current Situation Index (gross series)             | Week 10         | Monthly   | BCE    | Annual % change           |
| Oil National Production                            | Week 10         | Monthly   | BCE    | Annual % change           |
| Monthly Income Tax Collections                     | Week 6          | Monthly   | SRI    | Annual % change           |
| Monthly Value-Added Tax Collections                | Week 6          | Monthly   | SRI    | Annual % change           |
| Occupied Personnel - Industrial Sector             | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Occupied Personnel - Commercial Sector             | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Occupied Personnel - Construction Sector           | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Occupied Personnel - Services Sector               | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Sales Volume - Industrial Sector                   | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Sales Volume - Commercial Sector                   | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Sales Volume - Construction Sector                 | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Sales Volume - Services Sector                     | Week 8          | Monthly   | BCE    | 12-month moving average   |
| Demand Deposits (Financial Panorama)               | Week 10         | Monthly   | BCE    | Annual % change           |
| Narrow Money (Financial Panorama)                  | Week 10         | Monthly   | BCE    | Annual % change           |
| Outstanding Loans to Private Sector (Financial Panorama) | Week 10   | Monthly | BCE    | Annual % change           |
| Urban Unemployment Rate                            | Week 13         | Quarterly  | INEC   | Annual change             |
| Urban Adequate Employment Rate                     | Week 13         | Quarterly  | INEC   | Annual change             |
| Index of Retail Goods Sales                        | Week 16         | Monthly   | SRI    | Annual % change           |
| Index of Retail Services Sales                     | Week 16         | Monthly   | SRI    | Annual % change           |
| Index of Construction Sales                        | Week 16         | Monthly   | SRI    | Annual % change           |
| Index of Manufacturing Sales                       | Week 16         | Monthly   | SRI    | Annual % change           |
| Gross Domestic Product in 2007 Constant Dollars    | Week 24         | Quarterly  | BCE    | Annual % change           |
References

Aarons, Grant, Daniele Caratelli, Matthew Cocci, Domenico Giannone, Argia Sbordon, and Andrea Tambalotti. (2016) “Just Released: Introducing the FRBNY Nowcast.” http://libertystreeteconomics.newyorkfed.org/2016/04/just-released-introducing-the-frbny-nowcast.html.

Agencia de Regulación y Control de Electricidad. (2017 (Accessed: 2017-10-29)) Demanda Mensual de Energía Eléctrica, http://www.regulacionelectrica.gob.ec/estadistica-del-sector-electrico/demanda-mensual/.

Antolin-Diaz, Juan, Thomas Drechsel, and Ivan Petrella. (2017) “Tracking the Slowdown in Long-Run GDP Growth.” The Review of Economics and Statistics, 99, 343–356.

Bai, Jushan and Serena Ng. (2002) “Determining the Number of Factors in Approximate Factor Models.” Econometrica, 70, 191–221.

Banbura, Marta, Domenico Giannone, Michele Modugno, and Lucrezia Reichlin. (2013) “Now-Casting and the Real-Time Data Flow.” in Handbook of Economic Forecasting, 2: Elsevier, Chap. Chapter 4, 195–237.

Banbura, Marta and Michele Modugno. (2014) “Maximum Likelihood Estimation of Factor Models on Data Sets with Arbitrary Pattern of Missing Data.” Journal of Applied Econometrics, 29, 133–160.

Bańbura, Marta and Gerhard Rünstler. (2011) “A Look into the Factor Model Black Box: Publication Lags and the Role of Hard and Soft Data in Forecasting GDP.” International Journal of Forecasting, 27, 333–346.

Banco Central del Ecuador. (2017 (Accessed: 2017-10-29)a) Índice de Actividad Económica Coyuntural, https://www.bce.fin.ec/index.php/component/k2/item/313- indice-de-actividad-econ- A~3mica-coyuntural-ideac.
Banco Central del Ecuador. (2017 (Accessed: 2017-10-29)b) Índice de Confianza del Consumidor, https://www.bce.fin.ec/index.php/component/k2/item/320-~A
discretionary-~indice-de-confianza-del-consumidor.

Casares, Félix Francisco. (2017) “Nowcasting: Modelos de Factores Dinámicos y Ecua-
cciones Puente para la Proyección del PIB del Ecuador.” COMPENDIUM: Cuadernos de 
Economía y Administración, 4, 25–46.

Cattell, Raymond B. (1966) “The Scree Test for the Number of Factors.” Multivariate 
Behavioral Research, 1, 245–276, PMID: 26828106.

Chernis, Tony and Rodrigo Sekkel. (2017) “A dynamic factor model for nowcasting Cana-
dian GDP growth.” Empirical Economics, 53, 217–234.

Cuevas, Angel and Enrique M. Quilis. (2012) “A Factor Analysis for the Spanish Economy.”
SERIEs, 3, 311–338.

Diebold, Francis X. and Roberto S. Mariano. (1995) “Comparing Predictive Accuracy.” 
Journal of Business & Economic Statistics, 13, 253–263.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin. (2011) “A Two-Step Estima-
tor for Large Approximate Dynamic Factor Models based on Kalman Filtering.” Journal 
of Econometrics, 164, 188 – 205, Annals Issue on Forecasting.

Elliott, Graham, Thomas J Rothenberg, and James Stock. (1996) “Efficient Tests for an 
Autoregressive Unit Root.” Econometrica, 64, 813–36.

Giannone, Domenico, Lucrezia Reichlin, and David Small. (2008) “Nowcasting: The Real-
Time Informational Content of Macroeconomic Data.” Journal of Monetary Economics, 
55, 665–676.

Harvey, David, Stephen Leybourne, and Paul Newbold. (1997) “Testing the equality of 
prediction mean squared errors.” International Journal of Forecasting, 13, 281–291.
Higgins, Patrick. (2014) “GDPNow: A Model for GDP *Nowcasting*.” FRB Atlanta Working Paper 2014-7, Federal Reserve Bank of Atlanta.

Instituto Nacional de Estadística y Censos. (2017 (Accessed: 2017-10-29)) Índice de Nivel de Actividad Registrada, http://www.ecuadorencifras.gob.ec/indice-de-nivel-de-la-actividad-registrada/.

Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. (1992) “Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are we that Economic Time Series Have a Unit Root?” *Journal of Econometrics*, 54, 159 – 178.

Liu, Philip, Troy Matheson, and Rafael Romeu. (2012) “Real-time Forecasts of Economic Activity for Latin American Economies.” *Economic Modelling*, 29, 1090–1098.

Mariano, Roberto and Yasutomo Murasawa. (2003) “A new coincident index of business cycles based on monthly and quarterly series.” *Journal of Applied Econometrics*, 18, 427–443.

Phillips, Peter C. B. and Pierre Perron. (1988) “Testing for a Unit Root in Time Series Regression.” *Biometrika*, 75, 335–346.

Servicio de Rentas Internas. (2017 (Accessed: 2018-09-12)) Índice de Actividad Empresarial No Petrolera, https://cef.sri.gob.ec/mod/page/view.php?id=10260.

Summers, Lawrence. (2014) “U.S. Economic Prospects: Secular Stagnation, Hysteresis, and the Zero Lower Bound.” *Business Economics*, 49, 65–73.

Tirado, Abel Rodriguez, Marcelo Delajara, and Federico Hernandez Alvarez. (2016) “Nowcasting Mexico’s Short-Term GDP Growth in Real-Time: A Factor Model versus Professional Forecasters.” *Economia Journal of the Latin American and Caribbean Economic Association*, 17, 167–182.