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Abstract This paper develops a macroeconomic uncertainty index based on the methodology proposed by Jurado, Ludvigson, and Ng (2015). Our approach streamlines the computation of the macroeconomic uncertainty index by using a state-space model that allows us to obtain the unforecastable component of the macroeconomic variables used to construct the index and the latent factors. Moreover, we estimate this state-space model by maximum likelihood, obtaining the parameters of the model and the latent factors in one step, which is more efficient, by construction, than a multi-stage estimation. Finally, with the forecast errors of the state-space model, we propose to estimate stochastic volatility models also by maximum likelihood, using a density filter that could be faster than a Bayesian estimation. After showing that our methodology produces reasonable results for the United States, we apply it to compute a macroeconomic uncertainty index for Ecuador. Our estimate is the first of this kind for a developing or middle-income country. The results show that the Ecuadorian economy is more volatile and less predictable during recessions. We also provide evidence that macroeconomic uncertainty is detrimental to economic activity, finding that the responses of non-oil GDP, the unemployment rate, and consumer prices to macro uncertainty shocks are sizable and persistent.

JEL classification C32 · D80 · E32

Keywords Macroeconomic uncertainty · state-space model · stochastic volatility · density filter

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The views expressed in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System.

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1 Introduction

Uncertainty is a broad concept that frames several circumstances, whether they are economic-related or not. For instance, there could be uncertainty episodes over the path of macro-level phenomena such as gross domestic product (GDP) growth, micro-level phenomena such as firms' hiring and investment decisions, and non-economic related events such as civil wars, climate, and natural disasters. Uncertainty, then, can be a subjective term, and, as with any subjective concept, measuring it is challenging. Even by narrowing the term's scope into economic uncertainty, it is not an observable phenomenon and has to be inferred. To that end, the empirical literature has relied on proxies of uncertainty, using subjective concepts based on the volatility of stock market returns, dispersion of firms' profits, newspaper coverage, survey-based forecasts, and forecaster disagreement.

Jurado, Ludvigson, and Ng (2015) (JLN hereafter) pioneered the development of an index of macroeconomic uncertainty for the United States. In JLN's framework, what matters for uncertainty is whether the economy has become more or less predictable through the lens of a forecasting model. Importantly, the index is as free as possible from theoretical models and dependence on a single observable economic indicator (e.g., stock market returns). Despite its relevance and usefulness, JLN's macroeconomic uncertainty index has been barely replicated in other economies (especially in the developing world), perhaps because of the lack of data or complications with implementing the procedure. In this paper, we streamline the procedure put forward by JLN to measure macroeconomic uncertainty and apply it to the Ecuadorian economy. Our intention is to offer a framework that can allow policymakers and researchers in general to construct and update a macroeconomic uncertainty index akin to JLN's in a relatively timely and straightforward fashion.

In order to offer a clear understanding of our contribution, we recap the framework proposed by JLN. Their first step is to obtain, using the method of principal components, latent factors from a large data set that includes macroeconomic and financial variables, as well as latent factors from the series in the data set squared. The second step consists of estimating, by ordinary least squares, an autoregressive model for each of the macroeconomic variables in the data set augmented with the latent factors obtained before. The third step involves estimating a stochastic volatility model with Bayesian methods on the regression residuals in the previous step and on those of the latent factors, assuming they have vector autoregressive (VAR) dynamics. The fourth step is to use the VAR structure of the macroeconomic variables and latent factors put together to obtain the h-period-ahead forecast error variance of each variable, assuming a stochastic volatility process on the errors. The final step consists of obtaining an average or common factor of the square roots of the forecast error variances at different forecast horizons, which constitutes the macroeconomic uncertainty index.

Our framework offers two modifications to streamline the approach in JLN. First, by using a state-space model, we estimate by maximum likelihood—in a single step—the latent factors, the coefficients of their VAR dynamics, and the coefficients of the regression used to forecast each of the macroeconomic series. Compared with JLN, this step allows us to gain efficiency both in terms of achieving a smaller variance of the estimates as well as in terms of computational time. Second, we obtain the one-step-ahead forecast errors from the state-space model in the previous step and estimate stochastic volatility models using maximum likelihood through a density filter. This step is computationally more economical than using Bayesian methods, as in JLN. The two last steps of the procedure are the same as in JLN. One additional feature to note is that by using the state-space formulation, one can update the forecast errors, and then their volatility and the macroeconomic uncertainty index itself as soon as new data arrives.

To compare our methodology to that of JLN, we use their same database and obtain the macroeconomic uncertainty indexes for the United States with our proposed approach. Our indexes have broadly similar statistical features compared with those in JLN, although they are somewhat higher because, to offer a more streamlined procedure within the state-space formulation of our model, we use a more parsimonious structure.

Confident that our methodology provides results consistent with our benchmark, we apply the proposed approach to obtain a macroeconomic uncertainty index for Ecuador, a small developing economy highly dependent on oil revenues. Our data set is much smaller than that of JLN, a common feature among developing countries. In total, we consider 24 variables that do not include financial indicators. Our macroeconomic uncertainty index tends to increase significantly before and during recessions and shares some of the JLN index features for the U.S. economy regarding the role of predictors. In addition, we examine the effects of our measure of macroeconomic uncertainty on real GDP, the unemployment rate, and inflation and find that an increase in uncertainty is detrimental to economic activity and employment, and pushes prices down. These results are similar to those obtained if we use the spread of sovereign bonds as our indicator of uncertainty, as it is usually done in developing countries.

This paper is organized as follows. Section 2 presents the related literature on the applications to compute macroeconomic uncertainty using the JLN framework. Section 3 describes the methodology proposed to construct the index. In Section 4, we describe the data sources and variables used. Section 5 presents the results of the macroeconomic uncertainty estimates for the United States and Ecuador and analyzes their properties, as well as the effect of uncertainty on Ecuadorian macroeconomic dynamics. Finally, Section 6 summarizes the main findings of the study.

2 Literature review

This study constitutes the first application of JLN's framework to construct a macroeconomic uncertainty index in a small developing economy, such as Ecuador. To the best of our knowledge, the only applications for developed countries in the literature are Grimme and Stöckli (2018) for Germany and Shin et al. (2018) for South Korea. For larger developing economies, the only references are Huang et al. (2018) for China and Godeiro and Lima (2017) for Brazil. As can be seen, there is only a handful of applications of the JLN macroeconomic uncertainty index for other countries. We hope that our streamlined methodology can allow researchers in other countries to estimate a measure of uncertainty, such as that proposed by JLN.

The uncertainty index obtained by Grimme and Stöckli (2018) is less volatile than commonly used indicators, such as the Expected Stock Market Volatility (VDAX), which is the German equivalent of the U.S. VIX, and the Economic Policy Uncertainty (EPU) index (see Baker et al., 2016). Importantly, the authors find that macroeconomic uncertainty can explain 11 percent of the change in Germany's investment. Their index also reported a significant increase during the financial crisis in 2008, while a downward trend is experienced during the European sovereign debt crises.

Shin et al. (2018) estimate the JLN uncertainty index for South Korea, which has similar dynamics with the Korean analog of the U.S. VIX (denominated VKOSPI), but not with the EPU index. Regarding the effect of macroeconomic uncertainty on economic activity, the Korean indicator of industrial production falls sharply about 1 percent when uncertainty increases. Compared with the effect of the other two indexes (VKOSPI and EPU), the effect of macroeconomic uncertainty is more pronounced in the short run.

For China, Huang et al. (2018) compute the JLN macroeconomic uncertainty index and investigate if there are spillovers with the United States. The results show that the Chinese index reacts significantly to uncertainty increases in the United States, but that the effect in the opposite direction is not significant. In addition, both the Chinese and the U.S. indexes have effects on China's real economy.

Godeiro and Lima (2017) estimate the JLN macroeconomic index for Brazil and show that the level of uncertainty rises during recessions, but there are also rises in uncertainty that do not precede a recession. Additionally, they find that an increase in uncertainty is detrimental to industrial production and employment only when the forecasting horizon is 12 months.

3 Methodology

Our modeling strategy relies on the framework developed by JLN, and we use their notation to facilitate the comparison with our approach. There are two fundamental differences in how we implement JLN's proposal.[1] First, we estimate a dynamic factor model (DFM) by maximum likelihood using the expectations maximization (EM) algorithm (see Watson and Engle, 1983; Banbura and Modugno, 2014, for example), which allows us to gain efficiency compared with the two-step estimator in JLN. Second, we estimate the stochastic volatility processes by maximum likelihood by using a density filter, as in Friedman and Harris (1998) and Kawakatsu (2007), instead of the Bayesian estimation used by JLN, which allows us to implement a more streamlined and expedited coding strategy.

3.1 Modelling macroeconomic uncertainty

We are interested in the h-period-ahead uncertainty of each variable $y_{jt} \in Y_t = (y_{1t}, y_{2t}, \cdots, y_{N_Y t})'$ denoted by $\mathscr{U}^y_{jt}(h)$. This uncertainty represents the conditional volatility of the purely unforecastable

[1] As is prevalent in developing economies due to data availability, in this setup we deal only with a set of macroeconomic variables from which we obtain both the dynamic factors and the macroeconomic uncertainty index. In contrast, JLN dealt with two sets (macroeconomic and financial), excluding the set of financial variables from the uncertainty index's construction.

component of the future value of the series, as follows:

$$\mathcal{U}_{jt}^{y}(h) \equiv \sqrt{E\left(\left(y_{j,t+h} - E\left(y_{j,t+h}|I_t\right)\right)^2 |I_t\right)}, \tag{1}$$

where we assume that the economic agents use all the information available at time t, denoted as I_t.

Under this definition, the measure of macroeconomic uncertainty is constructed by aggregating the individual uncertainties at each date, $\mathcal{U}_{jt}^{y}(h)$, using aggregation weights, w_j, as follows:

$$\mathcal{U}_{t}^{y}(h) \equiv \text{plim}_{N_y \to \infty} \sum_{j=1}^{N_y} w_j \mathcal{U}_{jt}^{y}(h) \equiv E_w\left[\mathcal{U}_{jt}^{y}(h)\right]. \tag{2}$$

To implement the estimation of this model, we replace the conditional expectation $E\left(y_{j,t+h}|I_t\right)$ in (1) with a forecast obtained from a medium-rich model (from here on we use $E_t y_{j,t+h}$ instead of $E\left(y_{j,t+h}|I_t\right)$ for notational convenience). This forecast allows us to obtain the forecast error for each variable, which, in turn, forms the basis of the uncertainty measures. The medium-rich model includes autoregressive components as well as common factors obtained from the macroeconomic variables and is given by the following specification:

$$y_{jt} = \phi_j(L) y_{j,t-1} + \Lambda_j^{YF} \hat{F}_t + \Lambda_j^{YG} \hat{G}_t + v_{jt}^{y}, \tag{3}$$

where $\phi_j(L)$ is a lag polynomial of order 4 in the lag operator, L, Λ_j^{YF}, and Λ_j^{YG} are coefficient vectors of dimension $1 \times N_F$ and $1 \times N_G$, respectively. $\hat{F}_t$ is a $N_F \times 1$ vector that contains the consistent estimators of the common factors for Y_t and $\hat{G}_t$, of dimension $N_G \times 1$, contains consistent estimators of the common factors for the variables in Y_t squared (denoted Y_t^s).

Notice that we do not incorporate lags or leads of the common factors. Following Giannone et al. (2008) and Banbura et al. (2010), we consider only contemporaneous factors, which in turn follow a vector autoregressive structure. In any case, the setup that we propose is flexible enough to allow one to include lags or leads of the common factors. In addition, as opposed to JLN, we do not incorporate the square of the first factor of the series in levels ($\hat{F}_{1t}^2$), so that the state-space model can remain linear.

In order to estimate the macroeconomic uncertainty index, we first estimate the model in equation (3) to obtain the forecast errors, which are the basis for the uncertainty index through their estimated volatility, as indicated previously. The next two sections lay out the estimation strategy.

3.2 Estimation of the forecasting model and the forecast errors

We estimate jointly the coefficients and the factors in (3) using the following state-space representation:

$$\begin{bmatrix} Y_t \\ Y_t^s \end{bmatrix} = \begin{bmatrix} I & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Lambda^{Y^sG} \end{bmatrix} \begin{bmatrix} X_t \\ X_{t-1} \\ X_{t-2} \\ X_{t-3} \\ F_t \\ G_t \end{bmatrix} + \begin{bmatrix} 0 \\ \mathcal{V}_t^{Ys} \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} I & 0 & 0 & 0 & -\Lambda^{YF} & -\Lambda^{YG} \\ 0 & I & 0 & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 & 0 \\ 0 & 0 & 0 & I & 0 & 0 \\ 0 & 0 & 0 & 0 & I & 0 \\ 0 & 0 & 0 & 0 & 0 & I \end{bmatrix} \begin{bmatrix} X_{t+1} \\ X_t \\ X_{t-1} \\ X_{t-2} \\ F_{t+1} \\ G_{t+1} \end{bmatrix} = \begin{bmatrix} \Phi_1^Y & \Phi_2^Y & \Phi_3^Y & \Phi_4^Y & 0 & 0 \\ I & 0 & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \Phi^F & 0 \\ 0 & 0 & 0 & 0 & 0 & \Phi^G \end{bmatrix} \begin{bmatrix} X_t \\ X_{t-1} \\ X_{t-2} \\ X_{t-3} \\ F_t \\ G_t \end{bmatrix} + \begin{bmatrix} \mathcal{V}_{t+1}^Y \\ 0 \\ 0 \\ 0 \\ \mathcal{V}_{t+1}^F \\ \mathcal{V}_{t+1}^G \end{bmatrix}. \tag{5}$$

In the model of equations (4)-(5), Λ^{YF} and Λ^{YG} are the factor loadings ($N_Y \times N_F$ and $N_Y \times N_G$, respectively) of the observable macroeconomic variables, Y_t, on the common factors, F_t and G_t, whereas Λ^{Y^sG} ($N_Y \times N_G$) contains the loading coefficients of the variables squared, Y_t^s, on their common factors, G_t. The $N_Y \times N_Y$ matrices $\Phi_l^Y, l = 1,2,3,4$ are diagonal and contain the autoregressive coefficients of the observable variables, whereas the respective $N_F \times N_F$ and $N_G \times N_G$ matrices Φ^F and Φ^G contain the vector autoregressive coefficients of the factors.[2]

Additionally, each of the elements in the vectors $\mathcal{V}_t^K, K = Y, F, G$ contains stochastic volatility dynamics, as follows:

$$\begin{aligned} v_{jt} &= \sigma_{jt} u_{jt}, & (6)\\ &= \exp\left(\frac{1}{2}\left(\alpha_{0j} + \alpha_{1j} z_{jt}\right)\right) u_{jt}, & (7) \end{aligned}$$

$$z_{j,t+1} = \rho_j z_{jt} + \sqrt{\left(1-\rho_j^2\right)} e_{j,t+1}, \tag{8}$$

for $j = 1,2,\dots,N_Y + N_F + N_G$, where u_{jt} and $e_{j,t+1}$ are independent $N(0,1)$ both across time and variables, $\log\left(\sigma_{jt}^2\right) = \alpha_{0j} + \alpha_{1j} z_{jt}$, $\alpha_{1j} > 0$, and $|\rho_j| < 1$.

We estimate the model in equations (4)-(5) (without taking into account stochastic volatility) by maximum likelihood using the EM algorithm as in Banbura and Modugno (2014) (see also Dempster et al., 1977; Rubin and Thayer, 1982; Watson and Engle, 1983). In this way, we gain efficiency compared with the estimation in JLN because the estimation obtains the loading and autoregressive coefficients as well as the latent factors in one step.

Notice that we can write equation (5) as follows:

$$\mathcal{X}_{t+1} = \Phi^{\mathcal{X}} \mathcal{X}_t + \mathcal{V}_{t+1}^{\mathcal{X}}, \tag{9}$$

[2] We have assumed a first order autoregressive structure in the factors for expositional purposes.

where $\mathscr{X}_t = (X_t, X_{t-1}, X_{t-2}, X_{t-3}, F_t, G_t)'$, $\mathcal{V}_t^{\mathscr{X}} = \left(\mathcal{V}_t^Y, 0, 0, 0, \mathcal{V}_t^F, \mathcal{V}_t^G\right)'$, and $\Phi^{\mathscr{X}}$ is a conformable matrix. Hence, the optimal h-period-ahead forecast is given by the conditional mean

$$E_t \mathscr{X}_{t+h} = \left(\Phi^{\mathscr{X}}\right)^h \mathscr{X}_t, \tag{10}$$

with h-period-ahead forecast error variance given by

$$\Omega_t^{\mathscr{X}}(h) = E_t\left[\left(\mathscr{X}_{t+h} - E_t\mathscr{X}_{t+h}\right)\left(\mathscr{X}_{t+h} - E_t\mathscr{X}_{t+h}\right)'\right]. \tag{11}$$

For $h = 1$, the forecast error variance is

$$\Omega_t^{\mathscr{X}}(1) = E_t\left(\mathcal{V}_{t+1}^{\mathscr{X}} \mathcal{V}_{t+1}^{\mathscr{X}\,\prime}\right), \tag{12}$$

whereas for $h > 1$ it is

$$\Omega_t^{\mathscr{X}}(h) = \Phi^{\mathscr{X}} \Omega_t^{\mathscr{X}}(h-1) \Phi^{\mathscr{X}\,\prime} + E_t\left(\mathcal{V}_{t+h}^{\mathscr{X}} \mathcal{V}_{t+h}^{\mathscr{X}\,\prime}\right). \tag{13}$$

To obtain the expected forecast uncertainty of variable y_{jt} given information at time t, previously denoted as $\mathscr{U}_{jt}^y(h)$, we use a selection vector, 1_j, and take the square root of the appropriate entry of the forecast error variance $\Omega_t^{\mathscr{X}}(h)$, as follows:

$$\mathscr{U}_{jt}^y(h) = \sqrt{1_j' \Omega_t^{\mathscr{X}}(h) 1_j}. \tag{14}$$

As indicated in equation (2), we aggregate the individual uncertainty estimates in (14) using weights w_j to estimate the macroeconomic uncertainty index. In our case, as in the baseline version of JLN, we use uniform weights ($w_j = 1/N_Y$), and consequently the aggregation is a simple average of the individual uncertainties.[3]

We emphasize that the time variation in the h-period-ahead forecast error variance, $\Omega_t^{\mathscr{X}}(h)$—and hence in the expected forecast uncertainty of each variable j, $\mathscr{U}_{jt}^y(h)$—occurs because of the presence of stochastic volatility in the errors $\mathcal{V}_t^{\mathscr{X}}$. In the next section, we propose how to estimate the stochastic volatility processes.

3.3 Estimating the stochastic volatility processes

To estimate the stochastic volatility model in equations (6)-(8) by maximum likelihood, we follow Kawakatsu (2007). In essence, the method entails the use of a density filter in which we use numerical integration to obtain the likelihood function.

[3] In JLN, the factors were obtained from a larger information set that included financial in addition to macroeconomic variables, but the macroeconomic uncertainty index was obtained only from macroeconomic variables. The setup presented in this paper is able to accommodate that possibility by including the additional financial variables in the set of observable variables of the state-space in equations (6)-(8) and by then choosing the desired macroeconomic variables with the appropriate selection vector, 1_j.

We first obtain the filtered disturbances of $\mathcal{V}_t^Y$ and the smoothed disturbances of $\mathcal{V}_t^F$ and $\mathcal{V}_t^G$ by using the forward and backward recursions, respectively, of the Kalman filter and smoother once the state-space model in equations (4)-(5) is estimated as described in the previous section.

The density filter works as follows (we omit the subscript j for convenience of notation, but this description applies to each error of the variables with which the macroeconomic uncertainty index will be constructed, y_{jt}, as well as the common factors F_t and G_t):

$$p(z_t|\mathfrak{F}_{t-1}) = \int p(z_t|z_{t-1})p(z_{t-1}|\mathfrak{F}_{t-1})dz_{t-1}, \qquad \text{prediction step} \tag{15}$$

$$p(z_t|\mathfrak{F}_t) = \frac{p(v_t|z_t)p(z_t|\mathfrak{F}_{t-1})}{c_t}, \qquad \text{updating step} \tag{16}$$

$$c_t = \int p(v_t|z_t)p(z_t|\mathfrak{F}_{t-1})dz_t \tag{17}$$

$$\mathfrak{L}(\theta) = \sum_{t=1}^{T} \ln c_t, \qquad \text{likelihood function} \tag{18}$$

where $\theta = \{\alpha_0, \alpha_1\, \rho\}$ and $\mathfrak{F}_t$ is the σ-field with the information spanned by the sequence $\{v_s\}_{s=1}^{t}$. Notice that the filtered state entering the stochastic volatility process can be obtained by calculating $E(z_t|\mathfrak{F}_t) = \int z_t p(z_t|\mathfrak{F}_t)dz_t$.

We use the Gauss-Legendre quadrature to approximate the above integrals, as follows:

$$\int_a^b f(\tilde{z})d\tilde{z} \approx \sum_{i=1}^{m} w_i f(\tilde{z}_i),$$

where w_i and $\tilde{z}_i$ are the weights and nodes, respectively, of the quadrature and $w(\tilde{z}) = 1$. Appendix B describes the density filter in more detail.

We can get each of the elements in $E_t\left(\mathcal{V}_{t+h}^{\mathcal{X}}\mathcal{V}_{t+h}^{\mathcal{X}\,\prime}\right)$ to compute the h-period-ahead forecast error variance in equations (12) and (13) as follows (once again, we omit the subscript j for notational convenience): Given that $v_{t+h} = \sigma_{t+h}u_{t+h}$ and the normality and independence assumptions of the innovations u_t and e_t, then

$$\begin{aligned}
E_t v_{t+h}^2 &= E_t \sigma_{t+h}^2, \\
&= E_t \exp\left(\alpha_0 + \alpha_1 z_{t+h}\right), \\
&= \exp\left(\alpha_0 + \alpha_1 E_t z_{t+h} + \frac{1}{2}\alpha_1^2 var_t z_{t+h}\right), \\
&= \exp\left(\alpha_0 + \alpha_1 \rho^h z_t + \frac{1}{2}\alpha_1^2\left(1-\rho^2\right)\sum_{s=0}^{h-1}\rho^{2s}\right),
\end{aligned}$$

where we use the one-sided estimate, $E(z_t|\mathfrak{F}_t)$, in place of z_t.

4 Data

This section describes the variables used and the sample as well as the selection of the number of factors of the DFM used to forecast.

4.1 Variables and sample

In order to construct the uncertainty index, we rely on available monthly information from official websites, such as the Central Bank of Ecuador (BCE hereafter), the National Institute of Statistics and Censuses (INEC hereafter), and the Internal Revenue Service (SRI hereafter).

The selected variables reflect the macroeconomic activity of the country and also are frequently updated. These variables are based on the data set collected by González-Astudillo and Baquero (2019) for their nowcasting model for Ecuador's real GDP growth rate. All in all, we used 24 variables grouped into six categories: (i) banking and monetary sector, (ii) international trade, (iii) prices and confidence indexes, (iv) real sectoral indexes, (v) government finances, and (vi) labor market indexes. Appendix A describes the data in more detail.

Given the availability of data, we use a semi-balanced data set that starts in December 2006 and ends in December 2019 (with 1 fewer variable for the initial 6 months). Where needed, we seasonally adjust the series using the X-12 ARIMA multiplicative decomposition method.

4.2 Determining the number of factors

There are several tests and methodologies aimed to determine the optimal number of factors. Cattell (1966) introduces a test that chooses the number of factors based on the eigenvalues of the variance-covariance matrix. The test plots the number of factors on the horizontal axis and the eigenvalues on the vertical axis. The number of factors is chosen at the point where the curve reaches an inflection point.

The test suggested by Liu and Romeu (2012), which consists of adding one additional factor to the DFM to report a marginal increase in the R^2 of the regression in (3). This procedure starts estimating the DFM with only one factor and keeps adding an additional factor as long as the increase in the R^2 is higher than 0.025. Thus, this method stops adding a factor when the marginal increase in the R^2 is lower than 0.025.

This paper employs the statistical procedure proposed by Bai and Ng (2002) that provides accurate results for a sample with a large number of variables and that has good finite-sample properties, which is not necessarily the case in our panel of only 24 variables. In any case, when we test for a consistent number of factors constrained to a maximum of 10, the test suggests to use only one factor. Based on these results, the number of both linear (level) and nonlinear (squared) factors is one-each.

Table 1: JLN versus this paper: Summary statistics

	JLN			This paper		
	$\overline{\mathscr{U}}_t^y(1)$	$\overline{\mathscr{U}}_t^y(3)$	$\overline{\mathscr{U}}_t^y(12)$	$\overline{\mathscr{U}}_t^y(1)$	$\overline{\mathscr{U}}_t^y(3)$	$\overline{\mathscr{U}}_t^y(12)$
AR(1)	0.99	0.99	0.99	0.97	0.98	0.98
Half life	50.28	65.95	123.22	22.11	30.33	42.78
Skewness	1.81	1.74	1.30	1.70	1.57	1.35
Kurtosis	7.06	6.60	4.97	6.72	5.96	4.90
IP-corr(0)	-0.62	-0.61	-0.58	-0.69	-0.68	-0.67
IP-corr(12)	-0.49	-0.52	-0.57	-0.34	-0.37	-0.44
IP-corr(-12)	-0.15	-0.14	-0.16	-0.24	-0.24	-0.27
max IP-corr(k), $k > 0$	-0.70	-0.70	-0.67	-0.70	-0.70	-0.69
At lag $k =$	4	5	5	2	2	2
max IP-corr(k), $k < 0$	-0.59	-0.58	-0.55	-0.68	-0.67	-0.65
At lag $k =$	-1	-1	-1	-1	-1	-1

5 Results

This section lays out the results of our proposed methodology, first comparing it with the results of JLN and then applying it to find a macroeconomic uncertainty index for Ecuador.

5.1 Comparing our procedure to JLN's

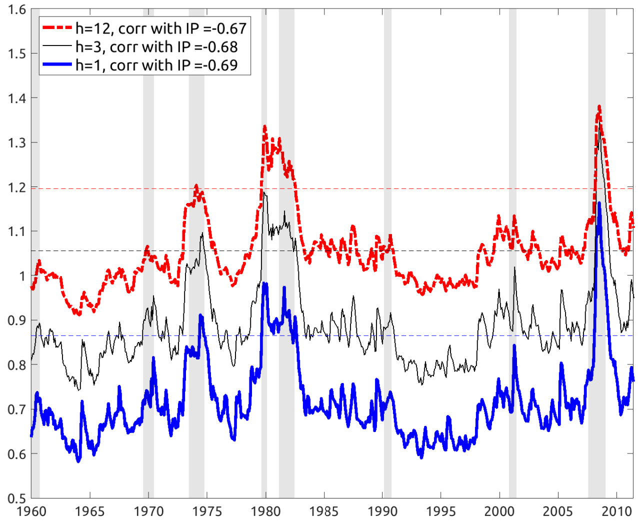
The first step to evaluate our procedure is to compare its results with those of JLN. In this section, we compare the indexes for h =1,3, and 12 along various statistical dimensions.

We use the same sample and variables as in JLN and compute the macroeconomic uncertainty indexes using our methodology. Figure 1a shows our results and Figure 1b reproduces the results in JLN. As can be seen, the dynamics are very similar across forecast horizons. However, there is a difference in the level of the series, with our indexes being higher than those of JLN. In any case, the qualitative features of the indexes are similar. For instance, the average uncertainty increases with the forecasting horizon and our indexes tend to surpass the 1.65 standard deviation threshold during the same recession periods as in JLN.

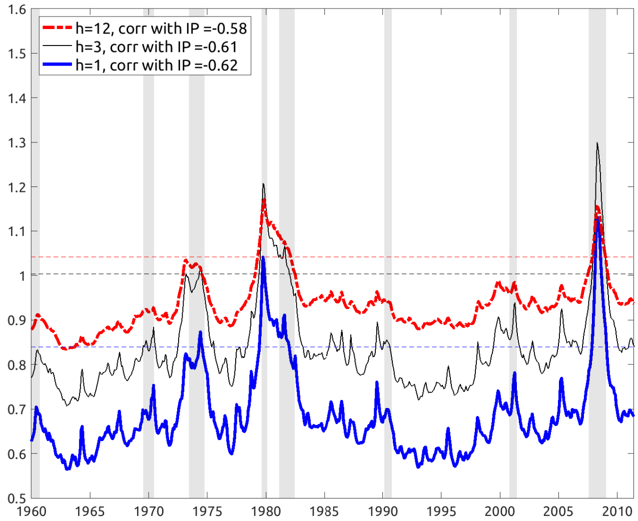
In Table 1, we compute key summary statistics for each macroeconomic index both in JLN and in our paper. In general, the indexes in our paper share the features of those in JLN. For example, the correlations (contemporaneous and lagged) with IP are relatively similar. Even though our indexes are very persistent, the first autocorrelation coefficients are slightly smaller than those in JLN and, hence, our half lives are shorter. In addition, although the asymmetry of the distributions of our indexes is broadly similar to that of the indexes in JLN, theirs have slightly fatter tails than ours. Moreover, the results indicate that the JLN uncertainty indexes around five months earlier tend to correlate the most with IP, whereas in our case that happens only around two months earlier.

Finally, we present the pairwise correlation coefficients between each of the indexes in JLN and our paper, as well as the standardized average difference between them in Table 2. As can be seen,

Fig. 1: Macroeconomic uncertainty indexes



(a) This paper



(b) JLN

Note: The horizontal line correspond to 1.65 standard deviations above the mean of each index. Shaded areas correspond to NBER recession periods.

Table 2: JLN versus this paper: Differences

Correlation coefficient			Standardized mean difference		
$\overline{\mathcal{U}}_t^y(1)$	$\overline{\mathcal{U}}_t^y(3)$	$\overline{\mathcal{U}}_t^y(12)$	$\overline{\mathcal{U}}_t^y(1)$	$\overline{\mathcal{U}}_t^y(3)$	$\overline{\mathcal{U}}_t^y(12)$
0.9386	0.9332	0.9357	0.3342	0.5152	1.8489

the correlation coefficients for all the indexes are greater than 0.93, indicating a great degree of co-movement between our indexes and those in JLN. However, as evidenced in Figure 1, our indexes indicate a somewhat higher degree of macroeconomic uncertainty. In fact, our indexes are roughly within 0.3 and 1.8 standard deviations of the indexes obtained by JLN, on average.

There could be several reasons behind the differences between the results from our approach and those of JLN. For instance, we do not consider the first linear factor squared in the set of explanatory variables to obtain the forecast errors. Neither do we include lags of the factors.[4] One could expect that these additional explanatory variables reduce the variability of the forecast errors. Another possibility is that our more efficient estimation method simply weighs differently the factors to obtain the forecast errors. In any case, we emphasize that our streamlined procedure obtains results very close to those in JLN and could be used to approximate reasonably well their uncertainty measure and to update it swiftly.

5.2 The indexes for Ecuador

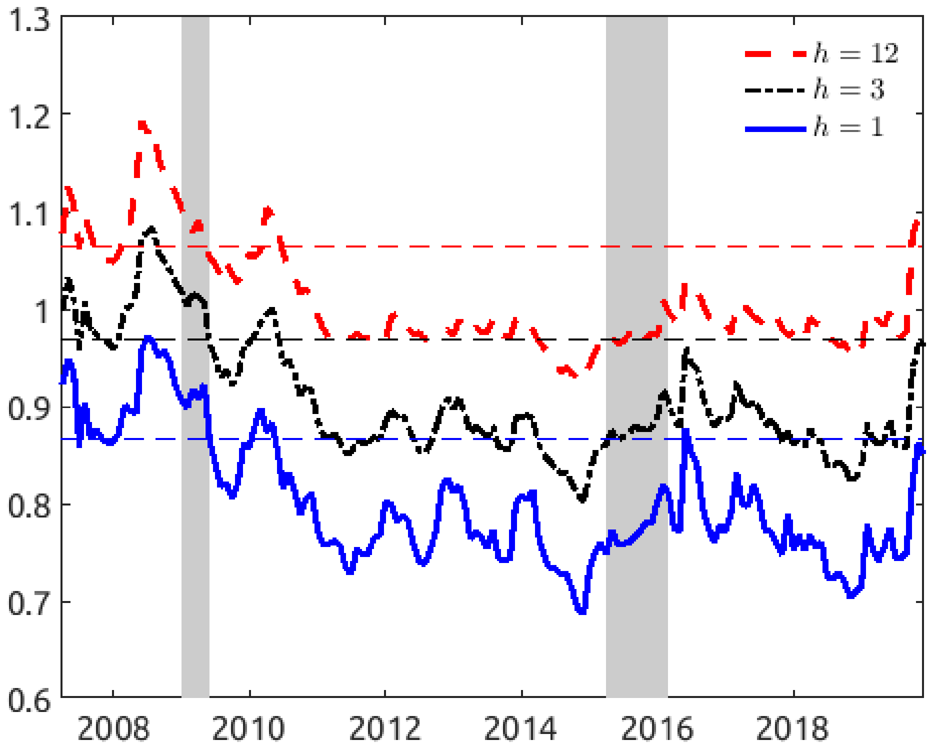
Using our methodology, we estimate the macroeconomic uncertainty index for three different horizons: h =1, 3, and 12 months for the Ecuadorian economy. Figure 2 plots the macroeconomic uncertainty indexes for these three horizons, including recession bars based on official data from the BCE. This graph includes dashed horizontal lines to represent one standard deviation above the mean for each horizon as a benchmark measure of high uncertainty.

The figure shows that, on average, the level of uncertainty increases with the horizon length. Additionally, uncertainty increases during the two recessions in the sample, but there are rises in uncertainty that do not necessarily precede a recession. The behaviors of uncertainty for all the horizons are quite similar. For example, the estimates of macroeconomic uncertainty exceed one standard deviation over its mean three times before 2011. After that, the one-month-ahead macroeconomic uncertainty index surpasses its threshold in mid-2016 and the twelve-month-ahead index exceeds the threshold one more time at the end of 2019. We group these increases of uncertainty into five episodes.

The first episode of high uncertainty happens at the beginning of the sample, through late 2007. The variables that experience the highest levels of uncertainty are the employment in the construction sector and the imports of refined oil products. The second episode occurs from early 2008 through mid-2009. This period coincides with the country's sovereign debt default and the subsequent recession triggered by the fall in oil prices that, in turn, led to lower oil exports and government oil revenues.

[4] As pointed out before, we could actually include lags of the factors in our state-space model structure at the cost of increasing its dimension and overfitting.

Fig. 2: Aggregate uncertainty for *h*=1, 3 and 12



Note: The horizontal lines correspond to one standard deviations above the mean of each index. Shaded areas correspond to recession periods defined as two or more consecutive quarters of declining GDP.

During this period, the variables that experienced the highest levels of uncertainty are the same as in the previous episode. The third episode develops right after the 2009 recession, in mid-2010. This time, in addition to the imports of refined oil products, the income tax receipts experience an increase in uncertainty as well, most likely influenced by the rebound in oil prices. After this episode, macroeconomic uncertainty starts declining relative to its previous levels.

During the fourth episode, in 2016, demand deposits and the index of consumer sentiment experience the highest uncertainties. This period of high uncertainty occurs roughly at the same time of considerable declines in oil prices between late 2014 and early 2016. Finally, the fifth episode occurs at the end of the sample. The variables that experience the highest uncertainty are the extraction of oil (because of disruptions caused by protests in the country) and the employment in the construction sector. As can be seen, the indexes of macroeconomic uncertainty are heavily influenced by swings in oil prices and oil production. The Ecuadorian economy has been historically influenced by fluctuations in oil revenues (see World Bank, 2018).

As defined by JLN, our indexes reflect the volatility of the unforecastable component across many series. Therefore, each series can be affected by its own uncertainty shocks as well as by external macroeconomic uncertainty shocks. To estimate the influence of macroeconomic uncertainty across all series composing the index, we regress the uncertainty of each of the 22 variables on the aggregate macroeconomic uncertainty index for the three different horizons. These regressions enable us to compute the following coefficient of determination, $R^2_{j\tau}(h)$, for each series:

$$R^2_{j\tau}(h) = \frac{var_\tau(\hat{\varphi}_{j\tau}(h)\bar{\mathscr{U}}^y_t(h))}{var_\tau(\hat{\mathscr{U}}^y_{jt}(h))}, \tag{19}$$

where $\hat{\varphi}_{j\tau}(h)$ is the coefficient from a regression of individual uncertainty, $\hat{\mathscr{U}}^y_{jt}(h)$, on macroeconomic uncertainty, $\bar{\mathscr{U}}^y_t(h)$. Similar to JLN, this statistic is estimated for h =1, 3, and 12 months for the full sample, for recession periods, and for non-recession periods. Then, we obtain the average R^2 from the regressions of individual uncertainty on macroeconomic uncertainty for the three different horizons under each scenario, denoted as $R^2_\tau(h)$. In this context, $R^2_\tau(h)$ represents the fraction of total uncertainty that can be explained by macroeconomic uncertainty—the explanatory power of macroeconomic uncertainty increases as $R^2_\tau(h)$ rises.

Table 3 indicates that the forecasting ability of our macroeconomic uncertainty index increases with the horizon length. Moreover, similar to the findings in JLN, our index has, on average, a higher explanatory power during recessions than for the full-sample and non-recession periods. In our case, the explanatory power of macroeconomic uncertainty during recessions is slightly larger than the results obtained by JLN for the United States. However, we must take these results cautiously because there are only two recession periods in our sample.

Table 3: Cross-sectional averages of R^2

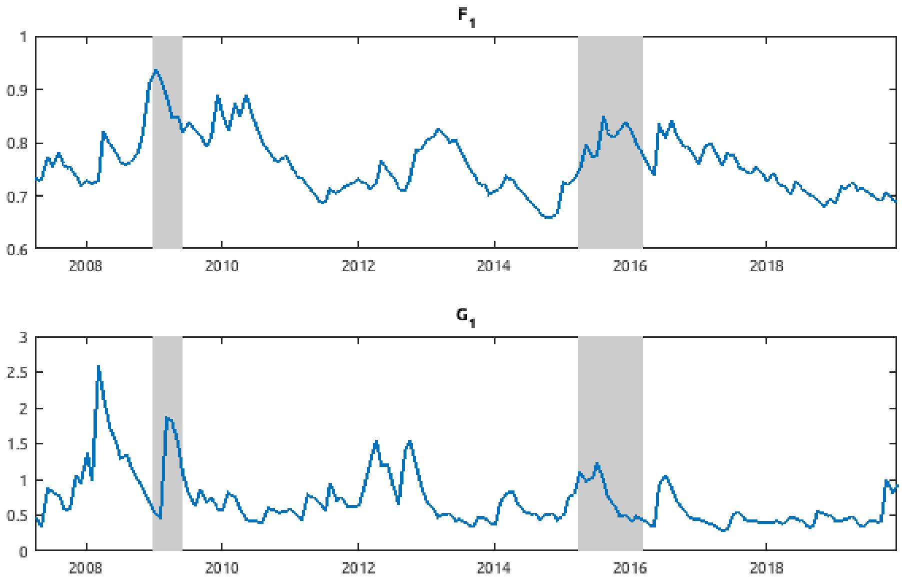
Average R^2 from regressions of individual uncertainty on macroeconomic uncertainty Average: $\bar{\mathscr{U}}^y(h)$			
h	R^2 **full sample**	R^2 **recession**	R^2 **non-recession**
1	0.16	0.23	0.16
3	0.21	0.30	0.21
12	0.26	0.41	0.26

It is also important to highlight that there is substantial variation in the explanatory power of macroeconomic uncertainty among the series composing our index. For example, when the forecast horizon is h =3, $R^2_\tau(h) = 0.21$ for the full sample. However, based on further research not presented in Table 3, this estimate ranges from a level close to zero for demand deposits and the real activity index on services to 0.66 for income tax receipts. The $R^2_{j\tau}(h)$s for this last variable is also the highest during recession periods, indicating the key role of aggregate uncertainty to understand the behavior of this series.

5.3 The role of the predictors

The two factors, F_t and G_t, allow the model to remove some of the predictable components for each variable. We evaluate how important these predictable variations are in our estimates by analyzing the uncertainties of the two factors, which in turn contribute to the h-period-ahead uncertainty of each variable. Figure 3 plots the one-period-ahead uncertainty for each of the two factors. The degree of fluctuations in their uncertainties suggests that the factors contribute importantly to explain the uncertainty in each macroeconomic variable to be forecast.

Fig. 3: Predictor uncertainty



Note: The uncertainty corresponds to $h = 1$. Shaded areas correspond to recession periods defined as two or more consecutive quarters of declining GDP.

The inclusion of these factors can have a strong effect on the level and behavior of the individual uncertainty series. Traditional measures of uncertainty most often neglect this effect. We examine the contribution of these factors by first re-estimating the individual uncertainty series, removing only the unconditional mean of the variables, with a model as follows:

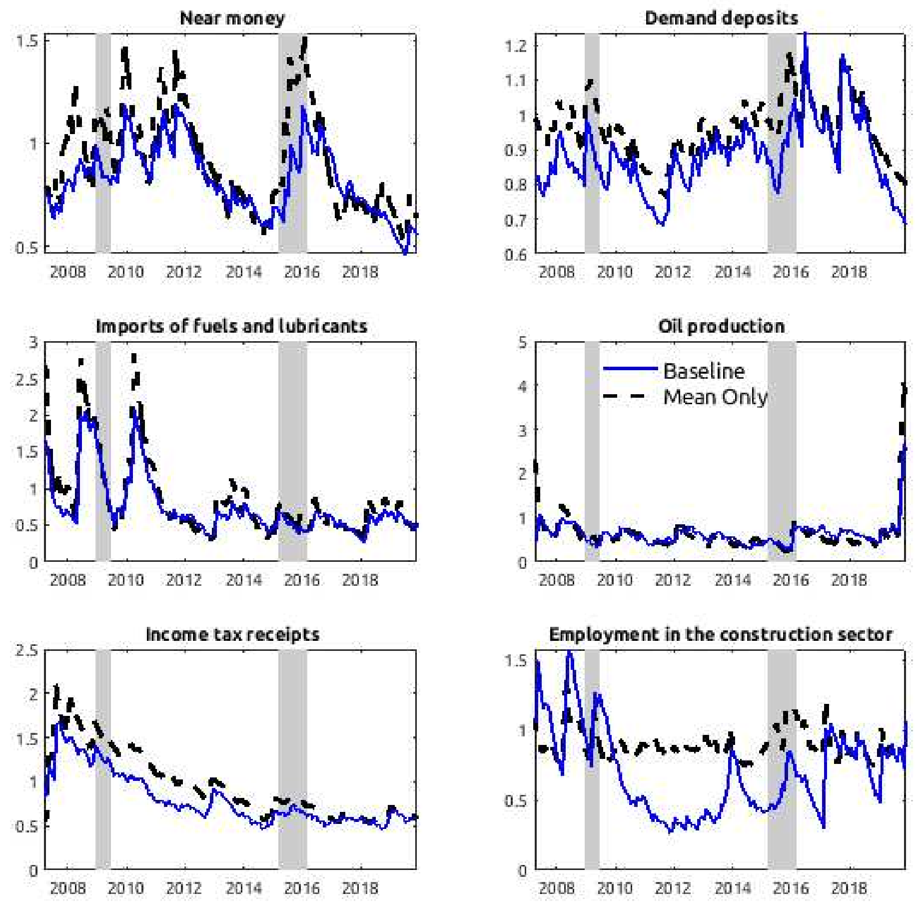
$$y_{jt} = \tilde{\sigma}_{jt} \tilde{u}_{jt}. \tag{20}$$

This model, potentially misspecified, neglects the role of serial correlation in each of the variables as well as the estimated factors as predictors in the multivariate forecasting regression of $y_{i,t+h}$.[5] Figure 4 plots the one-period-ahead uncertainty index using this possibly misspecified model and compares it

[5] Table 2 in Appendix C summarizes the degree to which these factors alter the forecasts. The first factor, F_t, is significant in ten of the forecast regressions and encompasses the banking and monetary sector variables, the import variables, real sectoral indexes, consumer confidence index, the government finances, and labor market outcomes on the construction sector. The

with the baseline case that uses the full set of predictors. The variables chosen are those that are more prominent in the analysis performed so far. As can be seen in the figure, the estimates of uncertainty in these series are significantly influenced by whether or not the forecastable variation is removed before computing uncertainty.

Fig. 4: Role of predictors



Note: The figures show the one-period-ahead uncertainty index for each variable in the baseline case (blue line) and in the case with no predictors (black dashed line). Shaded areas correspond to recession periods defined as two or more consecutive quarters of declining GDP.

Uncertainty tends to be lower when the forecastable component is removed. For example, the level difference between the two estimates of the employment in the construction sector is noticeable.

second factor, G_t, is highly significant in eight of the forecast regressions and complements the first factor on price indexes and the labor market index for the manufacturing sector.

These differences suggest that much of the variation in these series is predictable and should not be attributed to uncertainty.

We further examine how the one-period-ahead uncertainty would perform when allowing for the inclusion of the autoregressive components in the model, but not the factors. This version of the model appears in equation (21) below:

$$y_{jt} = \tilde{\phi}_j(L) y_{j,t-1} + \tilde{\sigma}_{jt} \tilde{u}_{jt}. \tag{21}$$

We compare this model with the baseline model of equation (3) and the vanilla model in equation (20). Figure 5 shows a three-way comparison. As can be seen, the autoregressive components enable us to take into account more available information about the economic outlook, compared with the vanilla model, to abstain from wrongly concluding that forecastable fluctuations are part of the uncertainty in the series. However, as the figure shows, it is the baseline model that provides the lowest average level of uncertainty because the factors indeed help to remove other forecastable fluctuations beyond the autoregressive structure, especially during recession periods.

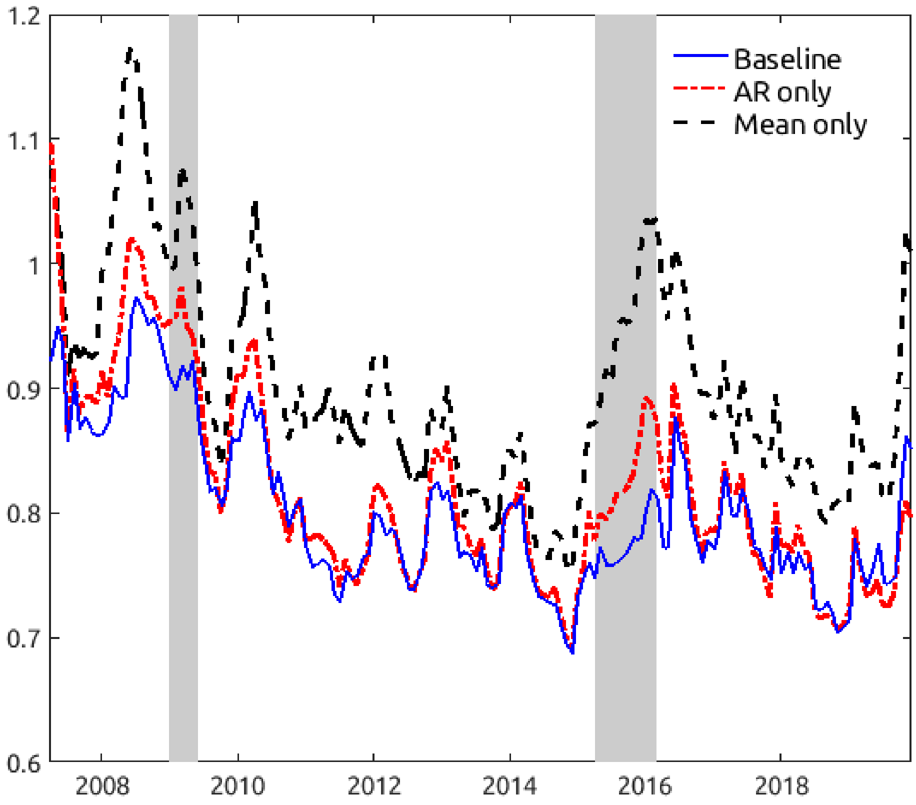
5.4 Sensitivity analysis: Macroeconomic uncertainty index versus J.P. Morgan's Emerging Markets Bond Index

An important analysis done by JLN consists of plotting macroeconomic uncertainty and an indicator of stock market volatility, such as the VXO index. In the context of the Ecuadorian economy, a measure of stock market volatility is not a representative indicator of uncertainty, as the capital markets are not well developed. In fact, the Guayaquil and Quito stock exchanges' trading volumes and market capitalization are small compared with other capital markets in the region.[6] Thus, the J.P. Morgan Emerging Markets Bond Index for Ecuador (EMBI hereafter) is a more suitable variable explaining the level of country risk. The EMBI describes the country's capacity to repay its public debt and it is sometimes used as a measure of uncertainty for the Ecuadorian economy.

Figure 6 plots the (standardized) EMBI for Ecuador as a proxy of uncertainty along with our (standardized) macroeconomic uncertainty index for $h = 3$. The figure also includes a dashed horizontal line corresponding to one standard deviation above the mean for these normalized series. As previously mentioned, our estimate of macroeconomic uncertainty exceeds one standard deviation above its mean three times throughout the sample, while the EMBI exceeds the benchmark measure once. The only period when the EMBI exceeds the benchmark corresponds to Ecuador's 2008 sovereign default followed by the 2009 recession. Moreover, the EMBI reports a higher uncertainty level, on average, than the macroeconomic uncertainty index during the two recessions in our sample. This fact seems to confirm the finding of JLN regarding an overestimation of uncertainty by commonly used proxies during trouble times in financial markets.

[6] For instance, Ecuador's stock market capitalization represented 6.8 percent of its GDP in 2018, while this indicator in Chile reached 84 percent of its GDP.

Fig. 5: Uncertainty under different specifications ($h = 1$)



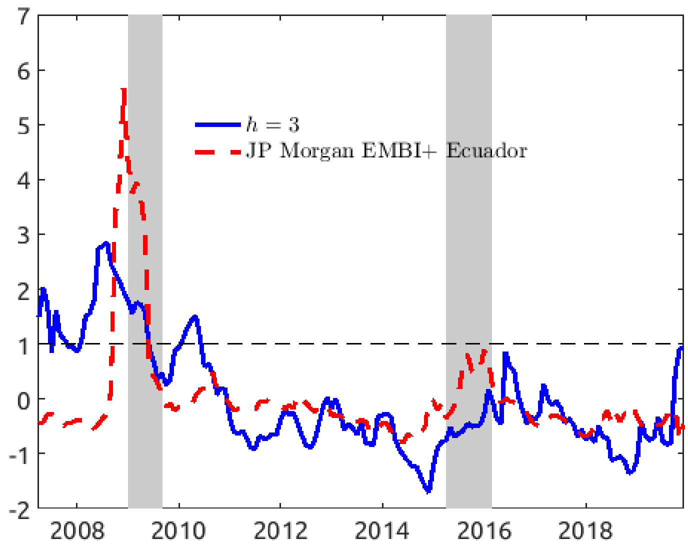
Note: Shaded areas correspond to recession periods defined as two or more consecutive quarters of declining GDP.

Although the indexes can show significant differences during some periods, we note that they tend to move in the same direction, especially before or during recession periods. In fact, the contemporaneous correlation coefficient is 0.44 and, interestingly, our macroeconomic uncertainty index tends to precede the EMBI, as indicated by the lag-lead correlation coefficients between these two series, which reach the highest value (0.58) at a lag (of macroeconomic uncertainty) of four months.

5.5 Uncertainty and macroeconomic dynamics

Consistent with the results of JLN for the United States, our results for Ecuador found interesting dynamic relationships between macroeconomic uncertainty and economic conditions. In particular, we showed that uncertainty increases during recessions. In this section, we use vector autoregressions (VARs) to estimate the dynamic responses of macroeconomic variables to shocks in our uncertainty index for the three horizons, and compare them with the responses to innovations in the EMBI as an

Fig. 6: JP Morgan EMBI+ and uncertainty



Note: Series are standardized. The horizontal line correspond to one standard deviation above the mean of both series. Shaded areas correspond to recession periods defined as two or more consecutive quarters of declining GDP.

alternative indicator of uncertainty. Our VAR is similar to the one studied by Christiano et al. (2005), with an akin identification scheme based on the ordering of the variables but using a smaller set of series (real non-oil GDP, the unemployment rate, and the consumer price index (CPI)).[7] We use a quarterly frequency from 2007:Q2 to 2019:Q4 and treat macroeconomic uncertainty measures for h =1, 3 and 12 as exogenous to determine how uncertainty affects key macroeconomic variables. Our VAR has two lags and we estimate it on the series in levels, including a linear trend, with Bayesian methods using an independent Normal-Inverse Wishart distribution.[8]

Figure 7 shows the impulse-response functions of our VAR for 20 quarters for h =1, 3, and 12 in the first three rows. In all cases, an increase in uncertainty of one standard deviation significantly reduces real GDP and the price level, while the unemployment rate increases, indicating the detrimental effects of macroeconomic uncertainty. The effects on GDP and CPI persist slightly after the 20-quarter horizon. By contrast, the persistence of the unemployment rate response is considerably lower, reaching zero after five quarters. In addition, the effect of uncertainty on GDP and the unemployment rate seems to be slightly stronger as the forecasting horizon lengthens.

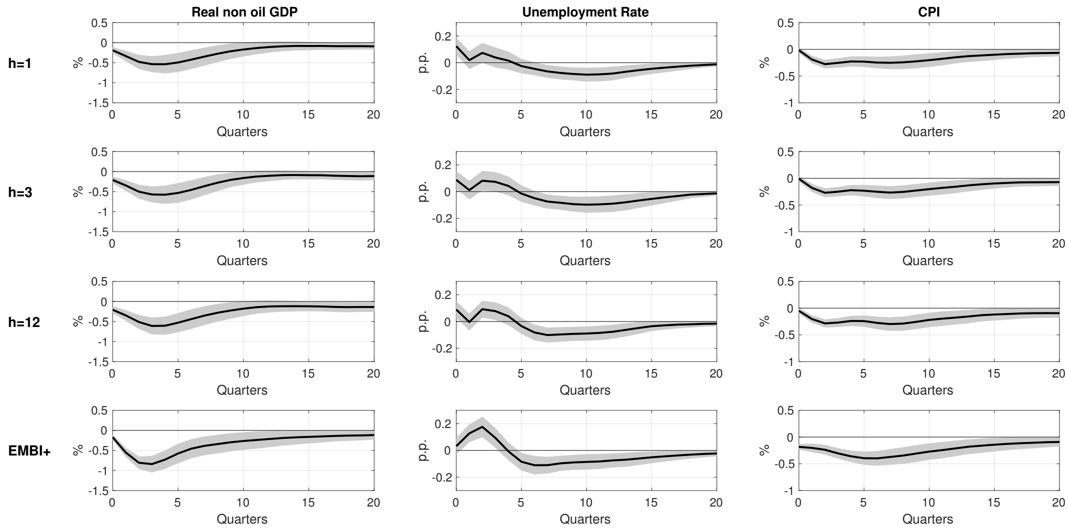
The last row of Figure 7 shows the responses of the same macroeconomic variables when the EMBI is considered as a proxy for uncertainty. In this case, the responses of the macroeconomic variables in terms of magnitude are larger compared with the ones reported with macroeconomic uncertainty, but the persistence does not seem to change significantly.

[7] Recall that a dollarized economy such as Ecuador does not have indicators of monetary policy.

[8] We apply logs to real non-oil GDP and the CPI.

Regarding the EMBI's larger effects, we believe there is at least one reason to expect larger responses of key macroeconomic variables to the EMBI compared with our macroeconomic uncertainty index. JLN uses the VXO index as a proxy for uncertainty, which measures the stock market volatility, while the EMBI is an indicator of the fiscal sustainability conditions of the Ecuadorian economy, which can be fundamental in a dollarized economy. In particular, when the fiscal stance is perceived as unsustainable, several other factors can trigger imbalances in the real and nominal economy that affect production, employment, and prices.

Fig. 7: Dynamic responses of real non-oil GDP, unemployment rate and CPI to the macroeconomic uncertainty index and EMBI+



Note: The shaded bands denote 90 percent credible intervals.

6 Conclusions

In this paper, we propose an alternative method to compute the macroeconomic uncertainty index originally put forward by JLN. Our method is easily implementable and can be more efficient than that of JLN. In addition, because it is easy to implement, our method allows for a frequent update of the macroeconomic uncertainty index than can be useful for public and private decisionmaking. We show that our methodology produces a macroeconomic uncertainty index with very similar dynamics to that of JLN for the United States, although ours indicates a somewhat higher degree of uncertainty.

Our macroeconomic uncertainty index is the first estimate of this kind that is completed for a developing or middle-income country. Ecuador's economic uncertainty index is composed of 24 macroeconomic variables covering the most relevant sectors of the economy. The index shows that uncertainty has declined, on average, over the past ten years, but it has started to increase at the end of 2019.

Our estimates imply that the economy is less predictable during recessions than otherwise. Additionally, our measure of macroeconomic uncertainty is not uniformly important to explain the unforecastable component of each of the 24 variables composing the index during recession and non-recession periods. Moreover, we show through a VAR model that the responses of key macroeconomic variables to uncertainty shocks are sizable and persistent.

The paper confirms the vulnerability of the Ecuadorian economy to oil shocks, as the level of uncertainty increases significantly during sharp swings in oil prices or oil production. The episodes of high uncertainty identified in the data are related with high uncertainty in oil-related and employment variables. Therefore, one possible avenue for policymakers to prevent these fluctuations in uncertainty could be to shield the economy from oil price fluctuations through financial derivatives and a fiscal stabilization fund.

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Conflict of interest

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendices

A Sources of variables

In the banking and monetary dataset, we include 3 variables (a) loans-to-expire to the private sector, (b) near money (M2), and (c) demand deposits. These variables are published monthly by the BCE.

The international trade category clusters seven variables: (a) non-oil exports, (b) oil exports, (c) imports of capital goods, (d) imports of fuels and lubricants, (e) imports of consumer goods, (f) imports of raw materials, and (g) oil production.

The prices and confidence indexes include the following variables: (i) consumer price index (CPI), (ii) CPI without food and energy, (iii) producer price index (PPI), and (iv) consumer confidence measured by the Current Situation Index.

The variables included in the sectoral indexes group come from the Monthly Business Opinion Surveys developed by the BCE. These variables are based on the response of 1,000 large firms regarding the next month expectations of production, construction volumes and sales. The variables refer to the following sectors: (i) commerce, (ii) construction, (iii) manufacturing, and (iv) services.

The government finances category includes two variables: (i) value-added tax receipts, and (ii) income tax receipts (monthly collections). These two items combined have represented, on average, 64 to 68 percent of the government's annual tax revenue for the years 2006-2018.

As the sectoral indexes, the employment indexes come from the Monthly Business Opinion Surveys developed by the BCE. The survey summarizes individual firms changes to employed personnel on a monthly basis. The variables refer to the following sectors: (i) commerce, (ii) construction, (iii) manufacturing, and (iv) services.

B Density Filter

In equations (15)-(18), the following holds:

$$p(z_t|z_{t-1}) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(z_t - z_{t-1})^2\right),$$
$$p(v_t|z_t) = \frac{1}{\sqrt{2\pi \exp(\alpha_0 + \alpha_1 z_t)}} \exp\left(-\frac{1}{2}\frac{v_t^2}{\exp(\alpha_0 + \alpha_1 z_t)}\right).$$

In particular, we use p_1, a vector $m \times 1$, to denote the prediction step density, $p(z_t|F_{t-1})$, and p_0, also a vector $m \times 1$, to denote the updating step density, $p(z_t|F_t)$. We can approximate the filtered state, $E(z_t|F_t)$, by $\sum_{j=1}^m z_j p_0[j]$.

The filter works as follows:

- input: $v_{T\times 1}, \theta_{p\times 1}, m_{1\times 1}, z_{01\times 1}, h_{1\times 1}$
- output: $l_{1\times 1}$
- **Initialization:**
  - z_0
  - z, w Gauss-Legendre quadrature nodes and weights in $(z_0 - h, z_0 + h)$
  - $p_0[i] = w_i p_0(z_i)/w(z_i)$ with $p_0(\cdot)$ being the standard normal density
  - $l = 0$
- **for** $t = 1$ to T
  - $p_1[i] = \sum_{j=1}^m p(z_i|z_j) p_0[j], \qquad 1, \ldots, m$
  - $p_0[i] = p(v_t|z_i) w_i p_1[i]/w(z_i), \qquad 1, \ldots, m$
  - $c_t = \sum_{j=1}^m p_0[j]$
  - $p_0[i] = p_0[i]/c_t, \qquad 1, \ldots, m$

Table 1: Description of variables

			Frequency	Source
Banking and Monetary		Loans to expire	Monthly	BCE
		Near money	Monthly	BCE
		Demand deposits	Monthly	BCE
International Trade	Non-Oil	Non-oil exports	Monthly	BCE
		Imports of capital goods	Monthly	BCE
		Imports of consumer goods	Monthly	BCE
		Imports of raw materials	Monthly	BCE
	Oil	Oil exports	Monthly	BCE
		Imports of fuels and lubricants	Monthly	BCE
		Oil production	Monthly	BCE
Indexes	Confidence	Consumer confidence index	Monthly	INEC
	Prices	CPI	Monthly	INEC
		CPI w/o food and energy	Monthly	INEC
		PPI	Monthly	INEC
Real activity indexes		Manufacturing	Monthly	BCE
		Commerce	Monthly	BCE
		Construction	Monthly	BCE
		Services	Monthly	BCE
Government finances		Value-added tax receipts	Monthly	SRI
		Income tax receipts	Monthly	SRI
Labor market indexes		Manufacturing	Monthly	BCE
		Commerce	Monthly	BCE
		Construction	Monthly	BCE
		Services	Monthly	BCE

INEC is the National Statistics Office, BCE is the Ecuadorian Central Bank, SRI is the Internal Revenue Service, CPI is consumer price index, and PPI is the producer price index.

  - $l = l + \ln(c_t)$
- **end for**

We choose $m = 20$, $z_0 = 0$ and $h = 5$. Choosing more nodes or a wider interval do not change the results significantly.

C Additional results

Table 2: Factor significance in forecast

Variable categories		Variables	Factors 1	Factors 2
Banking and Monetary		Loans to expire	***	
		Near money	***	
		Demand deposits		
International Trade	Non-Oil	Non-oil exports		
		Imports of capital goods	***	
		Imports of consumer goods	***	
		Imports of raw materials	***	***
	Oil	Oil exports		
		Imports of fuels and lubricants		
		Oil production		*
Indexes	Confidence	Consumer confidence index	***	***
	Prices	CPI		***
		CPI w/o food and energy		***
		PPI	*	***
Real activity indexes		Manufacturing	***	
		Commerce	*	
		Construction	**	***
		Services		
Government finances		Value-added tax receipts	***	
		Income tax receipts	***	
Labor market indexes		Manufacturing	*	***
		Commerce		
		Construction	***	***
		Services		

Note that *** 1% significance level; ** 5 percent significance level; and * 10 percent significance level. CPI is consumer price index and PPI is producer price index.

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