MACROECONOMIC POLICY RESPONSES TO COVID-19

A BVAR TOOLKIT TO ASSESS MACROFINANCIAL RISKS IN BRAZIL AND MEXICO

By Erik Andres-Escayola, Juan Carlos Berganza, Rodolfo G. Campos and Luis Molina

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A BVAR toolkit to assess macrofinancial risks in Brazil and Mexico*

Erik Andres-Escayola, Juan Carlos Berganza,
Rodolfo G. Campos and Luis Molina†

European Central Bank and Banco de España

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Abstract

This paper describes the set of Bayesian vector autoregression (BVAR) models that are being used at Banco de España to project GDP growth rates and to simulate macrofinancial risk scenarios for Brazil and Mexico. The toolkit consists of large benchmark models to produce baseline projections and various smaller satellite models to conduct risk scenarios. We showcase the use of this modeling framework with tailored empirical applications. Given the material importance of Brazil and Mexico to the Spanish economy and banking system, this toolkit contributes to the monitoring of Spain's international risk exposure.

JEL Codes: C32, C53, F44, F47.

Keywords: Macroeconomic projections, risk scenarios, Bayesian vector autoregressions.

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†E-mails: erik.andres_escayola@ecb.europa.eu, jcberganza@bde.es, rodolfo.campos@bde.es, lmolina@bde.es.

1 Introduction

The analysis of the Latin American economies has a long tradition at the Banco de España, as evidenced by the continued publication of a half-yearly report on the region since September 2003. Over time, the analysis has become more sophisticated which has led to the use of macroeconometric tools tailored for each country. Among the new tools in use, vector autoregression (VAR) models have proved to be a suitable and flexible kit to study the co-movement of macroeconomic variables in these economies. Starting with the half-yearly report of 2020 (Banco de España 2020), VAR models have been used to guide and inform forecasts for the two largest economies of the region: Brazil and Mexico. In this paper, we describe the suite of Bayesian VAR (BVAR) models that are currently in use to inform those projections.[1] These two countries are the only countries—other than Spain—for which Banco de España publishes regular forecasts. The advantage of these models over global structural models such as NiGEM or the Global Economic Model[2] is that they are better adapted to the characteristics of the economies of the region and allow for an introduction of relevant idiosyncratic variables. Further, this flexibility and empirical nature of BVARs makes them better suited for designing adequate and reasonable risk scenarios.

There have been prior in-house efforts of using macroeconometric tools to study Latin American economies. For example, Estrada et al. (2020) describe BVAR models that were estimated for Brazil, Mexico, Turkey, Chile, and Peru. However, these prior models did not closely tie the forecasts to the technical assumptions that are used for producing forecasts within the Eurosystem. Therefore, their results were difficult to square with the forecasts for Brazil and Mexico in the (Broad) Macroeconomic Projections Exercise (B/MPE) of the Eurosystem[3] and the forecasts obtained from their use were also not compatible with assumptions underlying the forecasts for the Spanish economy that are regularly published by Banco de España. The current methodology solves this problem by conducting conditional forecasts based on the Eurosystem's technical assumptions. Moreover, from a modeling point of view, the current BVAR toolkit for Brazil and Mexico follows closely the approach of Leiva-Leon (2017) where a suite of BVAR satellite models is presented for the Spanish economy to better identify structural shocks using sign restrictions.

The toolkit for Brazil and Mexico consists of a large benchmark model used to determine the baseline projection for GDP growth and a set of satellite models used to predict the impact of risk scenarios. These models are characterized by key macrofinancial vari-

[1] We consider these two Latin American economies as they are of major importance for the Spanish economy and they represent the largest exposure of the Spanish banking system among emerging economies, see Box 2 in Banco de España (2020).

[2] These are two popular models used in central banks from the National Institute of Economic and Social Research and Oxford Economics.

[3] For details on the Eurosystem's projection exercises please refer to the website here.

ables for Brazil and Mexico and technical assumptions from the Eurosystem's B/MPE. Including these technical assumptions ensure that the baseline projections are conducted within the Eurosystem's framework and makes it possible to deviate from such technical assumptions or the steady-state to simulate scenarios on growth forecast profiles. We define several satellite models for Brazil and Mexico that capture the mechanisms of the particular risk scenario to be simulated. The satellite models used for scenarios concerning deviations in the technical assumptions are structurally identified via sign restrictions, as described by Uhlig (2005). For the satellite model that simulates changes in the steady-state of GDP growth, we use an additional auxiliary model to estimate potential output using a production function. In this paper, we simulate scenarios related to fluctuations in foreign demand, changes in the commodity prices, shifts in domestic economic policy uncertainty and financial tensions, and long-term effects on output as we could witness with the COVID-19 pandemic.

The rest of the paper is structured as follows: in section 2 we explain the methodological framework, the details of the theoretical BVAR models used to carry out the baseline projections and the risk scenarios, and the data used for the empirical exercise. In section 3 we present the estimation results and discuss our findings, and in section 4 we conclude.

2 Methodology

In this section, we define the framework and models of the toolkit used for producing baseline projections and risk scenarios. We also describe the data included in the models for the empirical results.

2.1 Framework

Our modeling strategy to conduct growth projections and simulate risk scenarios entails two steps. The first step consists of defining a benchmark model capturing most of the fundamental macrofinancial relations of the economies of Brazil and Mexico. We then run conditional forecasts where the conditions are anchored to the technical assumptions of the Eurosystem's B/MPE.[4] This benchmark model is used to carry out the baseline projection of GDP growth. Then, four satellite models are defined with a smaller set of variables in some cases. Fewer variables enable for better identification of structural shocks and to focus on the transmission mechanisms for the particular scenario considered. For each of the satellite models, we first simulate a central forecast that includes the same technical assumptions or steady-state as the benchmark model. The risk scenario then

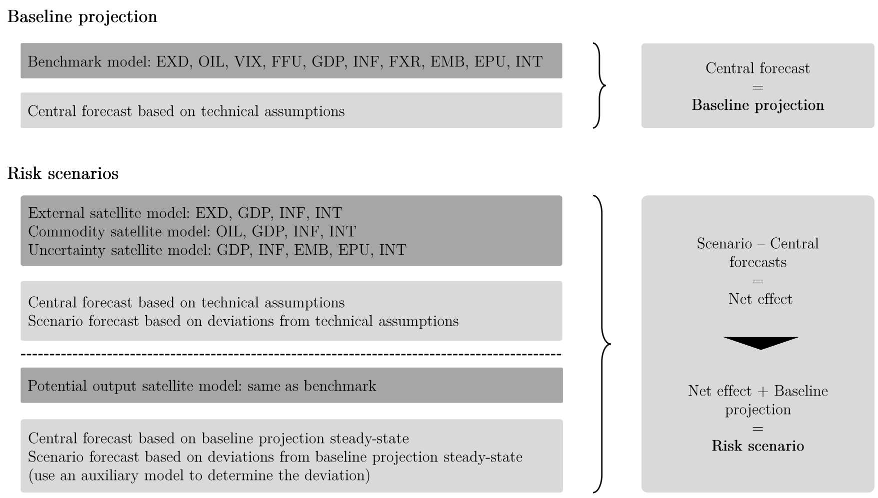
[4]For more details on how we adopt the B/MPE technical assumption to our projection exercises at the Banco de España, see Box 3 in the report on the Latin American economy, Banco de España (2020).

includes deviations of the technical assumptions for some specific variables or a different steady-state. Finally, we compute the difference between the central and the scenario forecasts in the satellite model to obtain the net effect that we add to the baseline projection. By isolating this effect, and integrating it into the baseline projection, we measure the impact of each scenario separately and shed light on the sensitivity of our projections.

The ten model variables are split up into four global and six local ones. For the group of global variables, we construct a measure of foreign demand (EXD) for each country as a weighted average of real imports from the main trade partners. The weights are based on bilateral exports. Further, we include oil prices to proxy commodity prices (OIL), a measure for global financial turbulences (VIX) and the US short-term interest rate to proxy foreign monetary policy (FFU). We assume that global variables affect local variables, but not the other way around (i.e., we assume block exogeneity). In this way, we can better capture the international spillover effects that potentially affect the growth projections of Brazil and Mexico. The local variables for the two Latin American countries are real GDP growth (GDP), core CPI inflation (INF), bilateral exchange rate vis-à-vis the USD (FXR), the EMBI+ as a measure of the sovereign spread that proxies external financing costs (EMB), a measure of economic policy uncertainty (EPU), and the interest rate (INT) being SELIC for the case of Brazil and TIIE for Mexico.

In Figure 1 we illustrate our approach to producing the baseline projections and the risk scenarios.

Figure 1: Summary of the modeling framework



Notes: The benchmark model is used for the baseline projection which is conditioned on technical assumptions. The different satellite models are used to produce a central and a scenario forecast that makes up the net effect of the risk scenario at hand. This net effect is added to the baseline projection to measure the impact of the risk scenario. The variables for the models are: foreign demand (EXD), oil prices (OIL), the VIX (VIX), the US short-term interest rate (FFU), real GDP (GDP), core CPI inflation (CPI), exchange rate with respect to the USD (FXR), the EMBI+ (EMB), the economic policy uncertainty (EPU), and the interest rate (INT).

2.2 General Models

For the projection exercises we estimate large VARs using Bayesian inference. These models have become an essential empirical tool for central banks to conduct macroeconomic analysis. As explained in detail in Bańbura et al. (2010) and Giannone et al. (2015) larger systems and Bayesian estimation are extremely appealing for forecasting applications. Based on the Deviance information criterion (DIC) we select models with four lags, which are then capturing the dynamism of one year for our quarterly model specifications.[5] We choose Minnesota-type priors which are the most common ones used in the literature and they assume that the VAR coefficients behave according to a normal distribution.[6] Then, it is left to the researcher to specify the values for the characterizing parameters of the distribution (i.e., the mean and covariance of the normal distribution), known as the hyperparameters. For the Minnesota-type prior the hyperparameter values follow a certain rationale.[7]

Finally, Bayes' formula is applied to combine information of the prior distribution and the likelihood function, resulting in a posterior distribution. From this latter distribution one obtains draws to compute the functions and estimates of interest (i.e., impulse response functions (IRFs) and forecasts).[8] In practical terms, the estimation is implemented using Markov chain Monte Carlo (MCMC) algorithms (i.e., Gibbs sampling).[9]

The multivariate time-series model for periods $t = 1, \ldots, T$ consists of a $n \times 1$ vector of variables $\{y_t\}_{t=1}^{T}$, $n \times n$ matrices of coefficients $A_i, i = 1, \ldots, p$ capturing the dynamics of the pth lagged system, a $n \times 1$ vector of constants C and a $n \times 1$ vector of error terms ε_t with zero-mean and positive-definite $n \times n$ covariance matrix Σ. This data generating process is assumed to evolve according to the following VAR(p):

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t, \quad \text{with } \varepsilon_t \sim \mathcal{N}(0, \Sigma). \tag{1}$$

[5] The DIC is a popular model selection criterion in the context of Bayesian estimation because it resembles the Aikaike information criterion (AIC), which is widely used in the context of frequentist inference.

[6] In contrast to the frequentist approach, Bayesian inference treats the data as deterministic and the parameter space as stochastic. This type of inference has become increasingly popular as a shrinkage method to resolve overparameterization issues, often encountered in empirical macroeconomics. Given that the time series in Brazil and Mexico are relatively short compared to advanced economies, the use of a shrinkage method is particularly appropriate in our application.

[7] Litterman (1986) describes the specific structure of hyperparameters in the Minnesota prior. They are applied to the whole block of coefficients and are therefore a global shrinkage method to reduce overfitting. Furthermore, for the Minnesota prior, the error covariance matrix is estimated from the model via OLS, whereas other approaches treat is as unknown, and assume an inverse Wishart distribution as the prior. We determine the hyperparameters of the VAR coefficients by running a grid search algorithm that selects the combination of hyperparameters that maximizes the marginal likelihood. Then, we partly adjust the hyperparameter values based on this information.

[8] Usually, the median of the posterior is reported and used as the point estimate. Note that under Bayesian inference the model uncertainty is much better captured since one computes an entire distribution for the parameters.

[9] For the computational implementation of the models we used the developer version of the BEAR toolbox. Refer to Dieppe et al. (2016) for further details.

The open-economy model contains variables for the global block (G) and for the local block (L) consisting of variables for Brazil (BR) and Mexico (MX). Hence, $y_t = \{y_t^G, y_t^L\}$, with $L = (BR, MX)$. Each superscript indicates a group of variables (10 variables in total, 4 in the G group and 6 in the L group). In particular we have $y_t^G = (EXD_t, OIL_t, VIX_t, FFU_t)^\top$ and $y_t^L = (GDP_t, INF_t, FXR_t, EMB_t, EPU_t, INT_t)^\top$ in the case of the benchmark model and subsets from both blocks in the case of the satellite models. The block exogeneity assumption entails imposing zero-restrictions on the coefficient matrices so to cancel out past effects[10] of y_t^L on y_t^G:

$$\begin{pmatrix} y_t^G \\ y_t^L \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} a_{11,i} & 0 \\ a_{21,i} & a_{22,i} \end{pmatrix} \begin{pmatrix} y_{t-i}^G \\ y_{t-i}^L \end{pmatrix} + \begin{pmatrix} \varepsilon_t^G \\ \varepsilon_t^L \end{pmatrix}. \tag{2}$$

One might be interested in having an economic interpretation of the shocks, and for this, one needs to define the contemporaneous relationships between variables. Let $D_j, j = 0, \ldots, p$ capture such structural relationships, K be the constants and η_t be the structural innovations with zero-mean and structural covariances Γ. Therefore, the structural VAR(p) is given by:

$$D_0 y_t = K + D_1 y_{t-1} + D_2 y_{t-2} + \cdots + D_p y_{t-p} + \eta_t, \quad \text{with } \eta_t \sim \mathcal{N}(0, \Gamma). \tag{3}$$

As a result, the link between the reduced-form VAR and the structural counterpart[11] is established by $A_i = DD_i$, $C = DK$, $\varepsilon_t = D\eta_t$ and $\Sigma = D\Gamma D^\top$, with $D = D_0^{-1}$. To recover the structural model from its reduced-form or disentangle η_t from ε_t, one needs to adopt an identification strategy to restrict the contemporaneous matrix D.

2.3 Conditional Forecasts

Note that the baseline projection and the risk scenarios are carried out through conditional forecasts in terms of sequences of observables. This means that the conditional forecasts describe the most likely future path of the unconditioned variable given conditions imposed for the rest of variables (i.e., the likely future path of GDP growth given the assumed path of the rest of variables). The conditioning paths are given by the technical assumptions for the baseline projections. However, for the scenarios, alternative paths are designed which deviate from these technical assumptions. Importantly, imposing conditions (like the deviations for scenario simulations) implies constraining the

[10] This restriction implies that local variables are not Granger causing global variables. Accordingly, we assume that Brazil and Mexico are small open economies when compared to the US and the global variables considered in the models.

[11] The key difference between equation 1 and 3 is that the reduced-form VAR is a mere statistical model, for which estimation is possible. Conversely, the structural augmentation makes the model economically interpretable but not feasible for estimation. These types of models are the workhorse for empirical macroeconomics since their introduction by Sims (1980).

future values of structural shocks.[12] Accordingly, structural identifications defined in the satellite models provide insights for the interpretation of "what if" scenarios for GDP growth profiles because the structural shocks generate the conditioning paths.

As a result, for the benchmark model we run the central forecasts based on the technical assumptions and obtain the baseline projection without giving an economic interpretation to the structural identification (i.e., we use Cholesky factorization as a technical requirement to orthogonalize the responses and to construct the conditioning paths based on the technical assumptions but remain silent on the economic intuition). Contrary, for the satellite models used for simulating risk scenarios, we provide an economic rationale for the structural shocks to gain additional insights regarding the impact of the scenarios on the baseline projections.

2.4 Satellite Models

We partially set-identify some of the satellite models using sign restrictions.[13] For conducting the sign restriction identification, one needs to focus on $\varepsilon_t = D\eta_t$ to restrict the contemporaneous impact matrix D. For the case of sign-identified models we have $D = PQ$, where P is the Cholesky decomposition of Σ and Q is a $n \times n$ orthogonal matrix such that $QQ^\top = I_n$, with I_n being the n-dimensional identity matrix. Then, to achieve identification rewrite the vector of structural impulse responses as $\Xi = f(A, \Sigma, Q)$, where $f(\cdot)$ is a non-linear function, $A = (A_1, A_2, \ldots, A_n)$ contains the coefficient matrices, Σ is the covariance of reduced-form errors, and Q is the matrix from which to obtain candidate draws that satisfy the imposed sign restrictions. Refer to Kilian & Lütkepohl (2017) for an extensive discussion about the identification and estimation of sign-restricted models and to Arias et al. (2018) for the practical implementation we use for this class of models.

Moving to the details of the specification of the satellite models, each one of them contains a set of core variables shared across all satellite models and then additional variables included explicitly for the risk scenario. The core variables are GDP growth, inflation, and interest rates. As is common in the literature, these three variables are used to identify demand, cost-push, and monetary policy shocks. Then, we augment this core setup with scenario-specific variables to identify additional structural shocks. We specify the following satellite models: (i) the external model with $y_{external,t} = (EXD_t, GDP_t, INF_t, INT_t)^\top$ where we identify an external shock, (ii) the commodity model with $y_{commodity,t} = (OIL_t, GDP_t, INF_t, INT_t)^\top$ where we identify a commodity shock, and (iii) the uncertainty model with $y_{uncertainty,t} = (GDP_t, INF_t, EMB_t, EPU_t, INT_t)^\top$

[12] To be able to draw from the restricted disturbances we rely on an algorithm similar to the one described in Waggoner & Zha (1999). For a detailed discussion on the derivations and implementation of this conditional forecasting technique refer to the technical guide of the BEAR toolbox.

[13] There is an ongoing discussion about how appropriate this identification strategy is, see Fry & Pagan (2011), Baumeister & Hamilton (2015), Uhlig (2017), Inoue & Kilian (2020). Yet for the purpose of our analysis this identification scheme is flexible and well-established.

where we identify an economic policy risk shock.[14] In the fourth scenario concerning the long-term effects of output, we use (iv) the potential output satellite model which has the same ten variables as the benchmark model $y_{potential,t} = y_t$. Given that in this particular scenario we are concerned with deviations from the steady-state and not in deviations from the technical assumptions, we implement an alternative modeling strategy detailed later.

Partly following the literature described in Leiva-Leon (2017) we establish the structural identification schemes for the satellite models (i) - (iii):

External:

$$\begin{pmatrix} \varepsilon_{exd,t} \\ \varepsilon_{gdp,t} \\ \varepsilon_{inf,t} \\ \varepsilon_{int,t} \end{pmatrix} = \begin{pmatrix} + & 0 & 0 & 0 \\ + & + & - & - \\ * & + & + & - \\ * & + & + & + \end{pmatrix} \begin{pmatrix} \eta_{external,t} \\ \eta_{demand,t} \\ \eta_{cost-push,t} \\ \eta_{monetary,t} \end{pmatrix}. \tag{4}$$

Commodity:

$$\begin{pmatrix} \varepsilon_{oil,t} \\ \varepsilon_{gdp,t} \\ \varepsilon_{inf,t} \\ \varepsilon_{int,t} \end{pmatrix} = \begin{pmatrix} + & 0 & 0 & 0 \\ + & + & - & - \\ + & + & + & - \\ * & + & + & + \end{pmatrix} \begin{pmatrix} \eta_{commodity,t} \\ \eta_{demand,t} \\ \eta_{cost-push,t} \\ \eta_{monetary,t} \end{pmatrix}. \tag{5}$$

Uncertainty:

$$\begin{pmatrix} \varepsilon_{gdp,t} \\ \varepsilon_{inf,t} \\ \varepsilon_{emb,t} \\ \varepsilon_{epu,t} \\ \varepsilon_{int,t} \end{pmatrix} = \begin{pmatrix} + & - & * & - & - \\ + & + & * & * & - \\ * & * & * & + & * \\ * & * & * & + & * \\ + & + & * & 0 & + \end{pmatrix} \begin{pmatrix} \eta_{demand,t} \\ \eta_{cost-push,t} \\ \eta_{emb,t} \\ \eta_{pol-risk,t} \\ \eta_{monetary,t} \end{pmatrix}. \tag{6}$$

Each entry in the D matrix describes how the responses to the structural shocks will be restricted in relation to the observables. That is, the candidate draws from Q have to satisfy the positive, negative, and zero restrictions in order to be accepted and they are then used to obtain Ξ from the posterior distribution. The symbol "*" denotes that the entry in the matrix is left unrestricted. With these sign-identified satellite models, we run the central forecasts following the technical assumptions and the scenario forecasts based on deviations from the technical assumptions for some variables. The difference between these two forecasts results in the net effect that is added to the baseline projection and measures the impact of the risk scenario.

[14]Note that the EMBI+ is only included in this specification to better identify the economic policy risk structural shock. Hence, $\eta_{emb,t}$ has no economic interpretation and is not a structural shock.

2.5 Auxiliary Models

Lastly, for the scenario on the long-term effects on output we use the potential output satellite model which is based on an alternative BVAR model. Specifically, since our goal is to impose a different steady-state than the one from the baseline projection we decide to depart from the standard BVAR described above and use the mean-adjusted BVAR of Villani (2009). In this alternative representation of the model, the unconditional mean of the vector of variables is $\mathbb{E}(y_t) = \mu$, where μ is an $n \times 1$ vector of constants with the steady-state values.[15] Hence, we can now include information on the steady-state through the prior mean of μ.

Next, we obtain potential output for Brazil and Mexico using an auxiliary model. Using historical data, we fit a calibrated Cobb-Douglas production function and apply the Hodrick-Prescott (HP) filter with smoothing parameter $\lambda = 1600$ to the production factors to compute the long-run trend of output. As explained by Tóth (2021), this is a common approach used by international organizations to obtain a measure of potential output. Assuming that the time-series considered can be decomposed into a cycle and a trend component, we specify a production function with constant returns to scale:

$$Y^* = A^* K^{*\alpha} L^{*1-\alpha}, \tag{7}$$

where the asterisk denotes the trend component of a variable, and Y_t refers to output, A_t to Total Factor Productivity (TFP), K_t to capital, and L_t to labor. The parameter α is the share of capital in output.

We first construct the capital series using the perpetual inventory method, that is, iteratively applying the law of motion of capital:

$$K_t = (1-\delta)K_{t-1} + I_t, \quad t \geq 1, \tag{8}$$

where I_t denotes investment and δ is the depreciation rate of capital. We initialize K_0 in (8) with the pre-sample historical average. We compute TFP by the Solow residual:

$$A_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}}. \tag{9}$$

The series for the labor input is observable, but we need to pin down values for α and δ to determine the evolution of capital and TFP. Following the common practice in neoclassical growth models we calibrate these parameters by computing the averages of

[15] This relation is straight forward because the only exogenous component of our model is the vector of constants C, for the full derivation of the model refer to Villani (2009).

the right-hand side terms in the following equations:

$$\alpha = 1 - \frac{w_t L_t}{Y_t}, \tag{10}$$

$$\delta = \frac{\frac{I_t}{Y_t}\left(\frac{1}{\beta} - 1\right)}{\alpha \frac{I_t}{Y_t}}, \tag{11}$$

$$\beta = \frac{1}{1 + r_t}, \tag{12}$$

where w_t is the real wage rate and r_t is the real rental rate of capital. For the forecasting periods, we iterate forward the series of each factor input using long-term growth rates proxied by historical averages. Subsequently, we apply the HP filter to the factor input series and substitute their trend components into the Cobb-Douglas production function (7). In this way, we obtain potential output Y^* for both countries over the historical and forecasting periods.

Using this auxiliary model, we calculate steady-states as the average of potential output growth rates over all periods. To compute an alternative steady-state for simulating a scenario, we assume that factor inputs evolve at different long-term growth rates than the ones assumed initially. This results in different trend components of the factor inputs and therefore yields an alternative potential output series. The differences between these averages determine the deviation of the steady-state from the baseline projection. We introduce it into the mean-adjusted BVAR through alternative priors for μ.

2.6 Data

We use quarterly data from 2000Q1 to 2020Q4, but the estimation sample runs until 2019Q4 and the year 2020 is included as conditional paths for the forecasting exercises. We do so to avoid problems in the estimation process and the stability of the parameters in the model due to outliers in most variables during the COVID-19 period.[16] Given that the focus of the paper is to illustrate the functionalities of the toolkit and the simulation of risk scenarios rather than accurately forecasting GDP during current times, this approach is the most appealing for our applications. Yet in our half-yearly reports of Banco de España (2020) and Banco de España (2021), we explicitly deal with this current issue because there our growth projections reflect our most updated stance on the future evolution of the Brazilian and Mexican economies. For details on how we do this, refer to the reports.

Data included have the following features. We took seasonally adjusted real GDP, as published by the respective statistics offices. To obtain seasonally adjusted core CPI

[16]For a more thorough treatment on how to perform estimation and forecasts with VARs in the context of the COVID-19 pandemic see Lenza & Primiceri (2020) and Primiceri & Tambalotti (2020).

we use the `X-13-ARIMA-SEATS` procedure from `JDemetra+`.[17] For other high-frequency variables, daily or monthly data are averaged to get quarterly series. The growth rates are expressed as quarter-on-quarter percentages. Moreover, we test for stationarity using the augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests and in the latter, there is enough empirical evidence to reject the hypothesis of unit roots at a 5% significance level.

Our data is downloaded from international sources as well as national sources. Starting with the global variables, for the foreign demand, we use real imports of goods and services from national sources. The bilateral exports data to construct the weights in the foreign demand measure come from the IMF's Direction of Trade Statistics (DOTS). We consider the following main trade partners for both countries: in Brazil we take the US, Euro Area, and China whereas in Mexico it suffices to consider the US only as it makes up most of the total exports. Brent oil prices are taken from Bloomberg and the US 3-months interest rate from national sources. The VIX is the volatility of options on S&P 500 as calculated by the Chicago Board Options Exchange (CBOE). For the local variables, we obtain real GDP growth, core CPI inflation, the bilateral exchange rate vis-à-vis the USD, and the interest rates from national sources. The EMBI+ comes from JP Morgan Chase and the EPU comes from Ghirelli et al. (2020).

Finally, for constructing the series of potential output and calibrating the production function we use data from national sources and the Penn World Table (PWT) version 10.0 from Feenstra et al. (2015) between 1960 and 2020. A summary of the data's descriptive statistics, correlation heatmaps, and the corresponding codebooks are in the appendix D.

3 Empirical Results

In this section, we evaluate the performance of the benchmark model in terms of its forecast accuracy and go over a few stylized empirical applications that showcase the use of satellite models to construct risk scenarios.

3.1 Validations

To assess the performance of the benchmark model, we evaluate the model's ability to forecast GDP growth in a historical out-of-sample exercise over the period 2015–2019. For each quarter, we generate unconditional forecasts for annual GDP growth rates over a 2-year forecasting horizon using only data available at the time of the forecast. We proceed iteratively until 2019, and then compare the quarterly baseline projections to two possible targets: the range of forecasts of private analysts compiled by Consensus

[17] This software is a tool specifically designed for the seasonal adjustment of time-series and has been officially recommended by the European Commission. For more details visit the website here.

Forecasts and published data produced by the respective national statistics office. Our evaluation of the benchmark model is not a real-time exercise because we use revised GDP series. These were not available to private analysts at the time of their forecasts and would also not have been available to the model. Contrary to private analysts, the model does not use high-frequency indicators or analyst judgement to inform the projections, like nowcast estimations, monthly GDP, or industrial production data. As shown in Figures A.1 through A.5, our baseline projections compare favorably to the Consensus Forecasts ranges in most of the cases. Whenever the model's projection departs from the consensus of private analysts, it does so in the direction of the actual data.[18]

After validating the use of the benchmark model for the projections we turn our attention to the satellite models used to simulate the risk scenarios. In the external, commodity, and uncertainty models, structural shocks are identified using sign restrictions. For these satellite models, GDP growth can be decomposed in terms of structural shocks. To validate the satellite models, we verify whether historical decompositions of GDP growth are coherent with economic events in each country. As explained in the previous section, the sign-restricted satellite models share a common core of variables that make up the demand, cost-push, and monetary policy shocks. We focus on the decomposition of the shock of the particular satellite model relative to the remainder of shocks (i.e., shocks of the core variables, unidentified shocks, and exogenous shocks). For the external model, the external shock is identified as a positive co-movement of GDP growth and foreign demand, leaving the rest of the variables unrestricted. In the commodity model, we restrict oil prices to move in the same direction as GDP growth and inflation,[19] leaving the rest undetermined. For the external and commodity models there are additional zero-restrictions to capture the exogeneity assumption of global variables also in the contemporaneous period. Lastly, in the uncertainty model, we identify the economic policy risk shock. This is characterized by GDP growth and the EMBI+ together with EPU moving in opposite directions, as well as the monetary authority not reacting to the current events immediately.

For Brazil, Figures B.1 and B.2 show the decomposition of GDP growth over the estimation period 2001–2019. The Global Financial Crisis (GFC) impacts Brazilian GDP growth via a fall in foreign demand, coupled with sinking commodity prices, and an increase in economic policy uncertainty.[20] The subsequent expansionary policy contributed

[18] In the half-yearly report Banco de España (2021) we decompose the revisions of the projections to disentangle the effect from changes in the technical assumptions, high-frequency indicators/nowcasting, and revisions of historical data.

[19] Note that a commodity shock would also have appreciation effects on the domestic currencies of these economies, potentially posing deflationary pressures. However, in our application sign restrictions hold for one period (i.e., static sign restrictions) and in the short run the exchange rate pass-through effect is weaker than the inflationary effect. Pedersen (2015) provides evidence of this dominant inflationary effect for the case of Chile as a copper exporter using a similar model setup. Hence, for our set of countries it is more likely that the inflationary effect prevails in the short term.

[20] Although Brazil is a relatively closed economy (exports represent only 11.3% of GDP), and soybeans

more substantially to the exit from the crisis as of 2009, with favorable foreign demand also playing a relevant role. The impact of the collapse of oil prices since October 2014 and the global financial turbulences linked to the Chinese stock turmoil in the summer of 2015 is also recorded by the respective satellite models. This is also reflected by negative foreign demand shocks around 2015–2016 driven mainly by Chinese imports. Political noise surrounding the impeachment of former President Dilma Rousseff, which covered the first semester of 2016, is reflected in the uncertainty satellite model, as well. Low growth from 2016 to 2019 is driven, according to these results, by negative external shocks, low commodity prices and increasing uncertainty, which were especially visible around the last presidential elections, at the end of 2018. In the last plot of Figure B.2, we see the initial estimate of potential output and the corresponding alternative estimate that includes the long-lasting effects on potential output. The difference between both lines is what makes up the effect that we include in the steady-state for the scenario.

Figures B.3 and B.4 display the GDP growth decomposition over the period 2001-2019 for Mexico. As for Brazil, the model results go largely in line with the historical narrative of the Mexican economic developments in the 21st century, and its salient events. For example, in the case of the GFC, the model shows the relevance of the external sector in explaining the 2009 GDP fall, a natural element for a very open economy, strongly intertwined with the US, the epicentre of the crisis. The model also shows that, during the GFC, upsurges in economic policy uncertainty and plummeting commodity prices also played a role. Despite Mexico being a net oil importer of refined petroleum products (yet overall a net crude oil exporter), the latter finding is easily rationalized by the importance of the public oil company, PEMEX, particularly for the country's fiscal position. The model indicates that economic policy risk and commodity shocks negatively contribute to growth also at the end of the sample. This time span coincides with a period of higher perceived risk, related to government (structural) policy reforms and reversals, and to the increasingly delicate financial situation of PEMEX, whose high debt and persistent budget deficits have sparked investors' worries. Overall, external shocks play a larger role than in Brazil, both in contractions and recoveries, reflecting Mexico's progressively higher openness. Conversely, in Mexico commodity shocks seem short-lived with respect to Brazil. As before, the last plot shows the estimated trend component of GDP and how the scenario kicks in to simulate long-term effects on growth.

and iron ore (its main export raw materials) only represent 20% of the export basket, the effect of oil prices is much higher as they impact directly on the public oil firm PETROBRAS, which accounts for 2% of Brazilian GDP and 10% of Brazilian investment. The company slashed investment by 33% both in 2014 and 2015 to adjust to lower oil prices and also in response to a widespread corruption case. The direct and indirect effects of PETROBRAS declining investment have been estimated to subtract around 2 percentage points from GDP growth in 2015. For a detailed analysis see this press article.

3.2 Applications

Next, we proceed to show the empirical applications that illustrate the sensitivity of the models. Table C.1 shows the values assumed in the conditional forecast for the ten variables that enter the benchmark model. Using these assumptions, we generate the conditional forecasts that deliver the baseline projections. The purpose of these projections is to set the baseline which we use as a reference for the macrofinancial scenarios. For the explicit growth projections for Brazil and Mexico using the methodology of this paper refer to Banco de España (2021).

In Table 1 we show the deviations of the variables assumed in each satellite model to construct the macrofinancial risk scenarios. These deviations are constructed in a similar way for both countries and are intended just as stylized examples.[21]

Table 1: Deviations from the technical assumptions and steady-state of the GDP growth baseline projections used in the risk scenarios of Brazil and Mexico

Deviations	**External**	**Commodity**	**Uncertainty**	**Potential**
Foreign demand	+1 pp			
Oil prices		+3 STD		
EMBI+			+3 STD	
EPU			+3 STD	
Steady-state				-0.2 pp

Notes: The deviations from the technical assumptions and steady-state of the baseline projections correspond to the different satellite models. These deviations for the risk scenarios are in terms of standard deviations (STD) and percentage points (pp), and they last for one year in the technical assumptions whereas the change is permanent for the steady-state of the quarterly growth rate of output.

All three sign-restricted satellite models assume an initial impact in the first quarter of a year which persists for the rest of that year. After this year, the conditioning paths revert to the baseline technical assumptions. As such we consider temporary scenarios that exhibit the main impact in the first year and then the effect fades away in the next periods. The external scenario simulates a more buoyant foreign demand by assuming an increase of 1 percentage point. The commodity scenario simulates a rise in oil prices. It assumes that oil prices increase by 3 standard deviations. The uncertainty scenario simulates increased financial and economic policy tensions. It assumes that the EMBI+ and the EPU increase by 3 standard deviations.[22] The last scenario simulates a slowdown

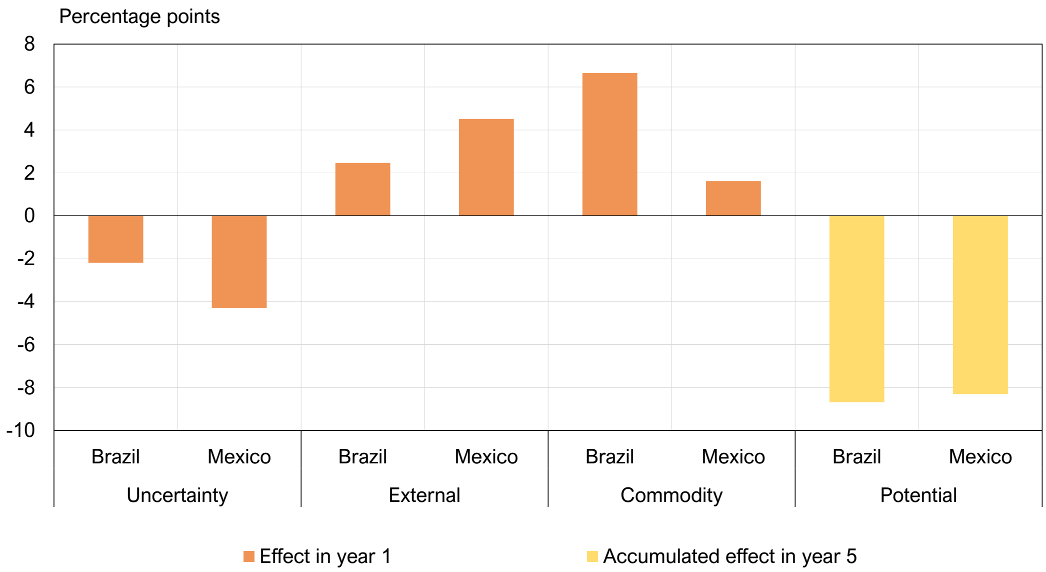
[21] For an example of how this methodology has been applied to more realistic risk scenarios, see Banco de España (2020) or Banco de España (2021).

[22] We take 3 standard deviations as an example to have a sizeable magnitude that illustrates the effects

of potential output. To capture the long-run effect we extend the effect until year 5. For this scenario, we use the auxiliary model explained before and assume that labor, capital, and TFP grow at a rate that is 3 standard deviations below their average rate during the forecasting horizon (i.e., the effect is evenly distributed along the periods). This results in a slowdown of potential output that implies a deviation of -0.2 percentage points for the quarterly growth rate steady-state. Using these deviations from the baseline conditioning paths, we generate conditional forecasts that result in the macrofinancial scenarios.

The impact of the risk scenarios on the baseline projections is summarized in Figure 2. Brazil appears to be more resilient than Mexico in the uncertainty scenario; the negative effect on GDP growth in the first year in Mexico doubles that in Brazil. Because historical episodes of financial distress have been larger in Brazil (as exemplified by the resilience of growth to the tightening of financial conditions during the electoral crisis in the summer of 2002), without a comparable decline in GDP, the model interprets that Brazilian growth projections are less affected by changes in these variables.

Figure 2: Impact of the risk scenarios on the GDP growth baseline projections of Brazil and Mexico



Notes: The baseline projections are conducted using the benchmark model and the risk scenarios using the satellite models. The impact of the risk scenarios is expressed in terms of deviations with respect to the baseline projections.

In the external scenario, the positive impact on growth is larger in Mexico than in Brazil (i.e., about twice as large). This suggests that Mexico is more sensitive to changes in foreign demand. The Brazilian economy is relatively more closed in comparison to Mexico.[23] Hence, this is in line with the greater elasticity of Mexico's GDP growth to

on GDP growth given the historical shocks of both countries.

[23]Since the 2000s, Mexico has increased its trade openness (measured as the sum of exports and imports as a share of GDP) from 50% to 70% whereas Brazil's trade openness has remained much lower at 20%–30% during recent times.

foreign demand.

Oil prices have a larger positive effect on growth in Brazil than in Mexico. In this case, the magnitude of the deviations from the baseline assumptions is the same in both countries by design. Both countries are oil producers (mainly because of PETROBRAS in Brazil and PEMEX in Mexico), but the sensitivity of GDP growth to oil prices in this model is unambiguously larger in Brazil. The last scenario simulates a slowdown of potential output in line with the current discussion on the scarring effects from the COVID-19 pandemic on developing economies, see International Monetary Fund (2021b). Although the production function is calibrated for each country, the mix of inputs in the production function does not differ that much. Therefore, the accumulated effect after five years is roughly similar in both countries.

4 Concluding Remarks

In this paper, we introduce a toolkit to assess macrofinancial risks to GDP growth in Brazil and Mexico, the two largest economies of Latin America and two of the countries which are considered of material importance for the Spanish banking sector. We use BVARs to construct a benchmark model for the baseline projections and various satellite models to simulate risk scenarios through conditional forecasts. The model seems to perform well in comparison with the projections obtained from the consensus of private analysts, and also seems to be coherent with the standard economic narrative of GDP growth and the origin of contractions and expansions in both countries. One recurrent application of this toolkit is in the Banco de España publication of the half-yearly report on Latin American economies.

We showcase the sensitivity of the models by evaluating the impact of a series of illustrative scenarios: an increase in foreign demand, a rise in oil prices, tighter financial conditions together with higher economic policy uncertainty, as well as a slowdown of potential output growth. In the model, Mexico's GDP growth is more sensitive to changes in domestic financial stress and economic policy uncertainty, and foreign demand. Conversely, Brazil is relatively more sensitive to fluctuations in oil prices. Finally, were a slowdown of the potential output to materialize, the long-run effect on output would be about the same for both countries.

This flexible toolkit allows for interesting additional extensions. For example, it would be worth including variables of capital flows to capture the effect of a potential capital flight during crises. Another possibility is to define a fiscal satellite model to simulate scenarios on fiscal policy, both on the revenue and on the expenditure side, which would be very relevant in the context of soaring fiscal deficits derived from policies implemented to deal with the pandemic. Also, these models could be easily adapted for other relevant Latin American countries. Given the importance of Brazil and Mexico for the Spanish economy, we expect that the use of this toolkit for scenario analysis will be useful for taking informed policy decisions at the Banco de España and other institutions.

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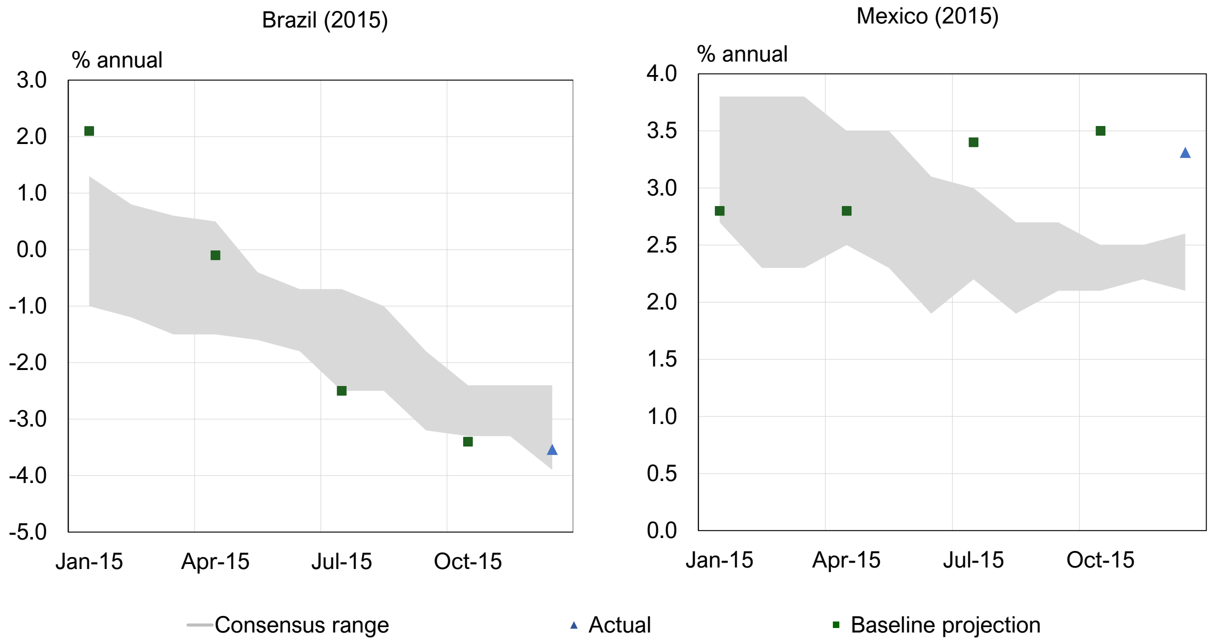
Appendix

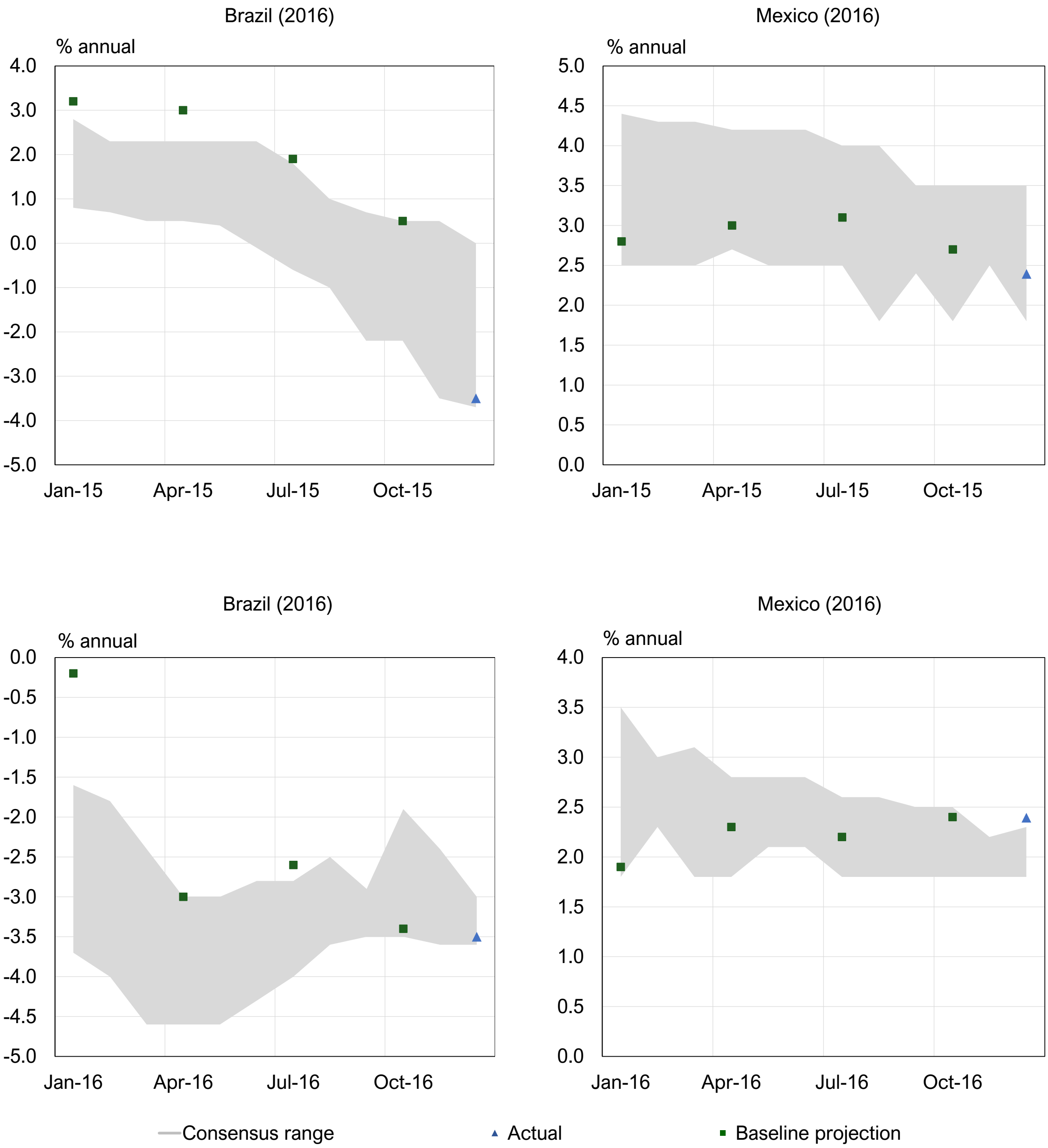
A Forecasting Exercise

Figure A.1: Forecasting exercise for the GDP growth baseline projections of Brazil and Mexico between 2015-2019



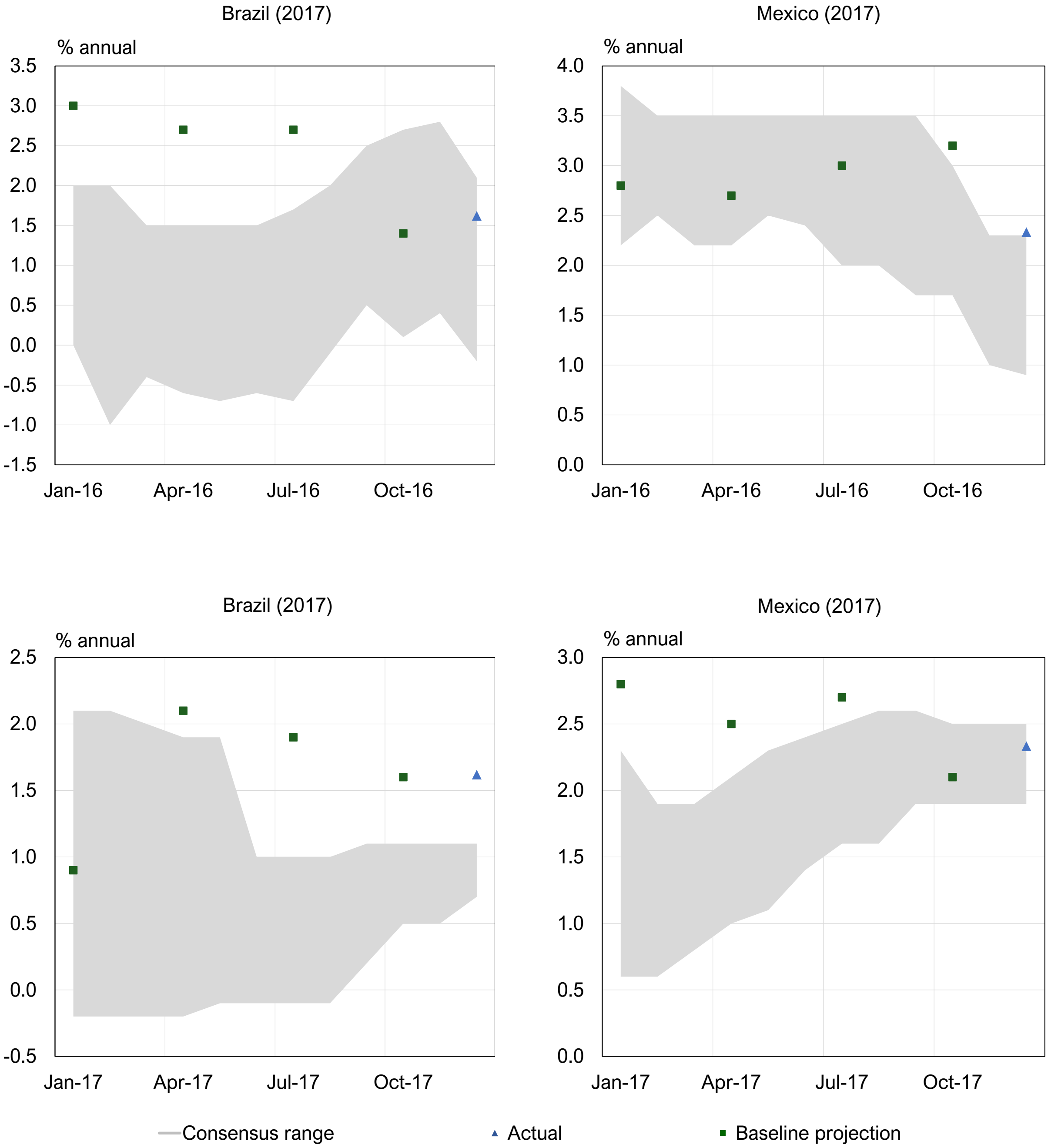
Notes: Comparison between the range of forecasts from private analysts (Consensus Forecasts), the actual growth of that year, and the baseline projections using the benchmark model.

Figure A.2: Forecasting exercise for the GDP growth baseline projections of Brazil and Mexico between 2015-2019 (continued)



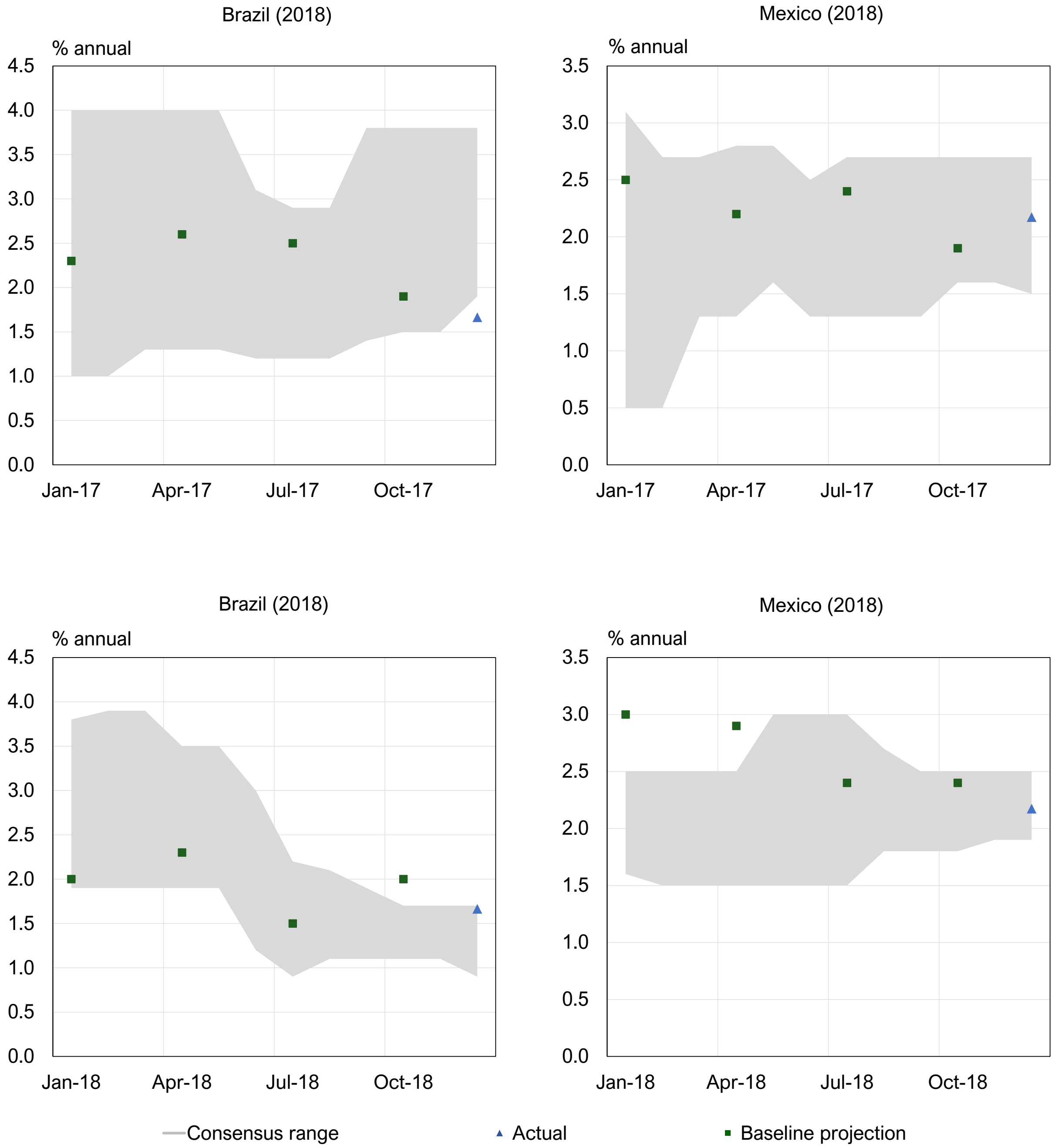
Notes: Comparison between the range of forecasts from private analysts (Consensus Forecasts), the actual growth of that year, and the baseline projections using the benchmark model.

Figure A.3: Forecasting exercise for the GDP growth baseline projections of Brazil and Mexico between 2015-2019 (continued)



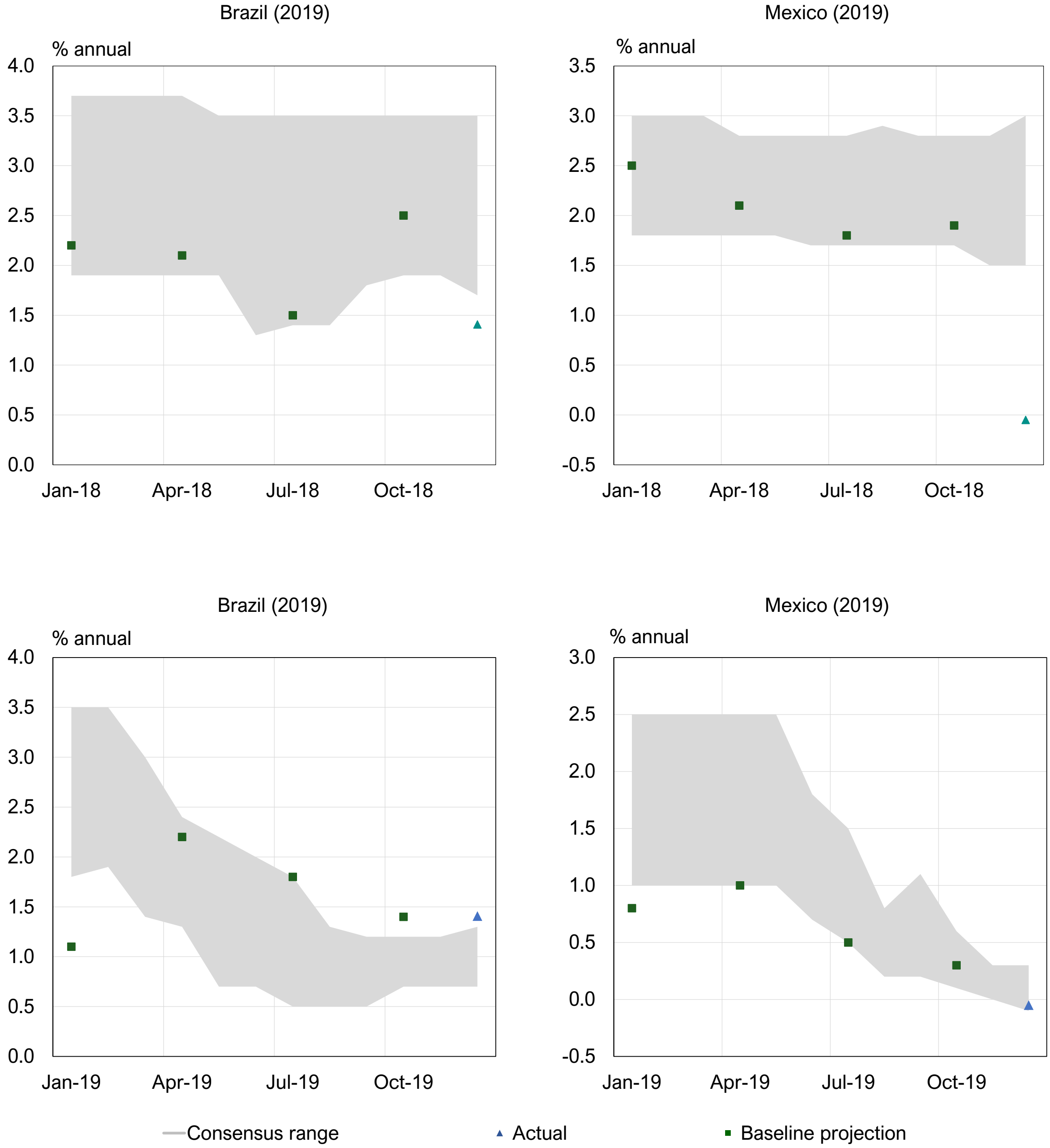
Notes: Comparison between the range of forecasts from private analysts (Consensus Forecasts), the actual growth of that year, and the baseline projections using the benchmark model.

Figure A.4: Forecasting exercise for the GDP growth baseline projections of Brazil and Mexico between 2015-2019 (continued)



Notes: Comparison between the range of forecasts from private analysts (Consensus Forecasts), the actual growth of that year, and the baseline projections using the benchmark model.

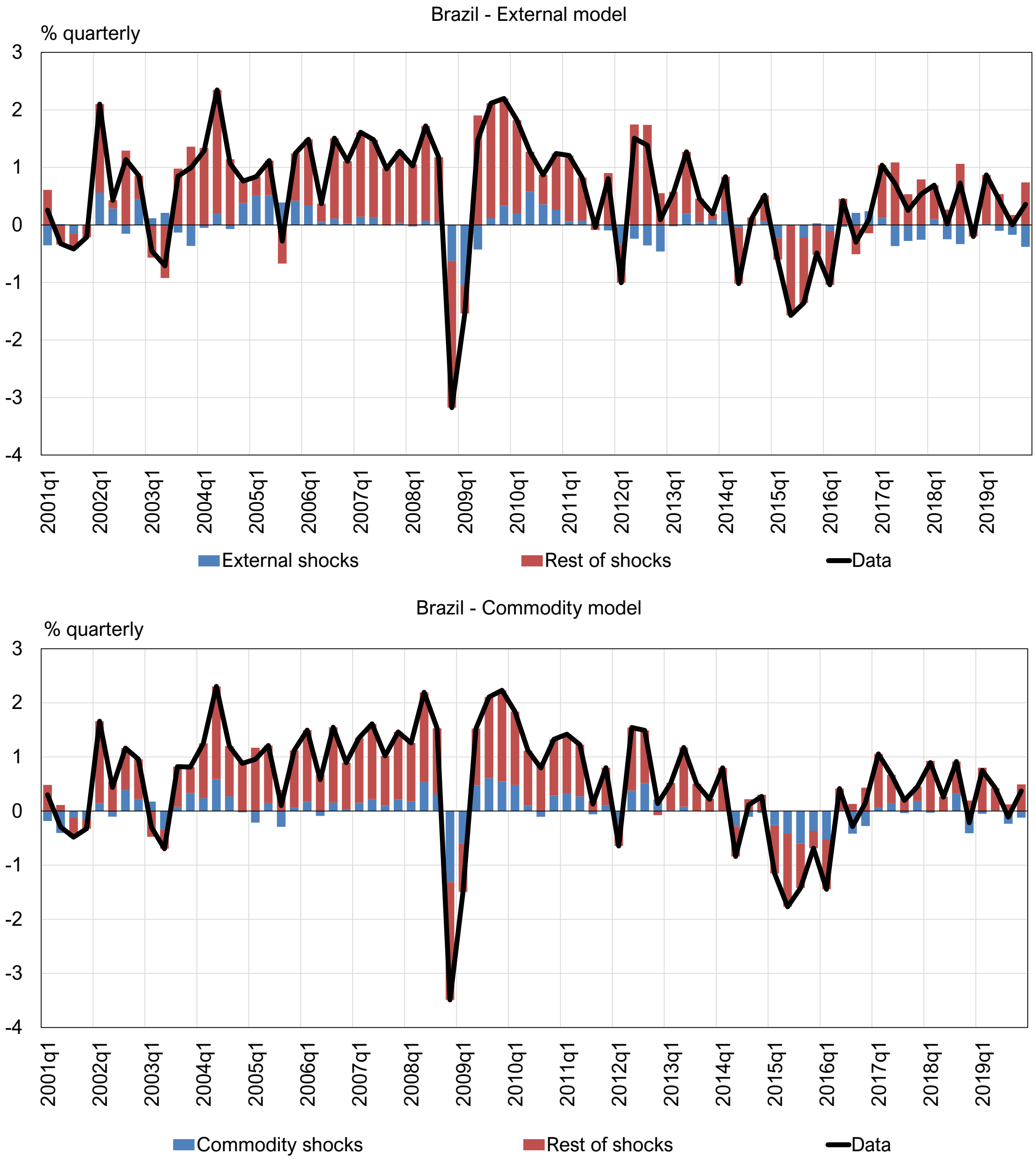
Figure A.5: Forecasting exercise for the GDP growth baseline projections of Brazil and Mexico between 2015-2019 (continued)



Notes: Comparison between the range of forecasts from private analysts (Consensus Forecasts), the actual growth of that year, and the baseline projections using the benchmark model.

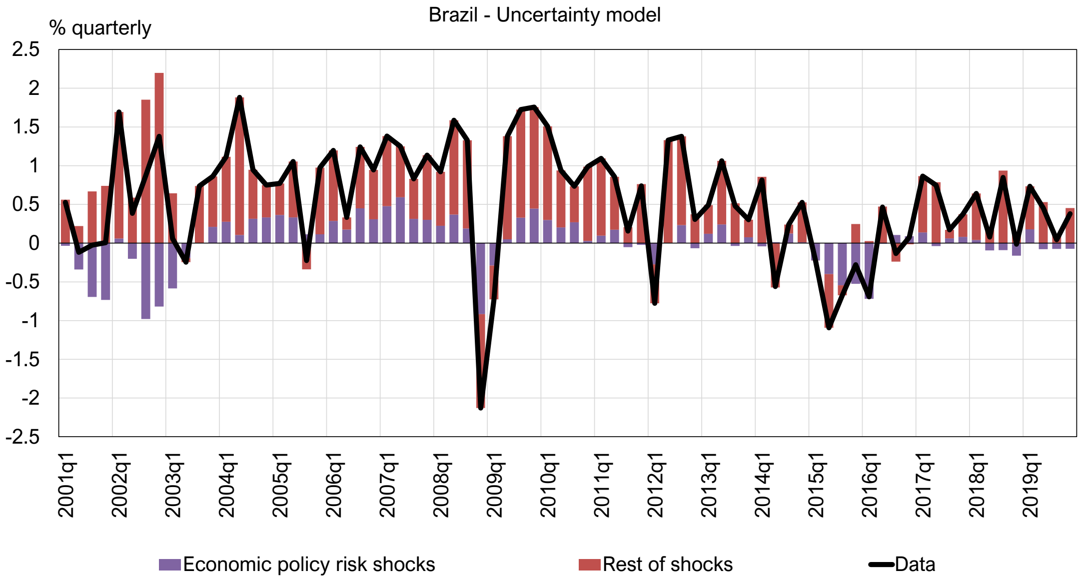
B Historical Decompositions and Potential Output

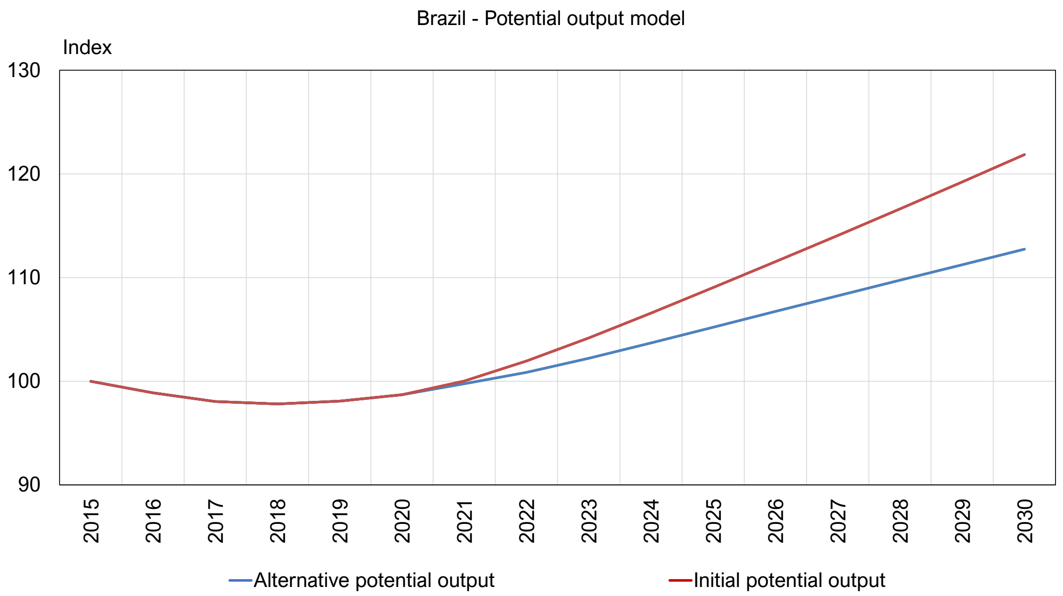
Figure B.1: Historical decomposition of GDP growth and potential output from the satellite models of Brazil



Notes: The historical series are decomposed by the structural shocks of the respective satellite model. The series of potential output are constructed using the auxiliary model.

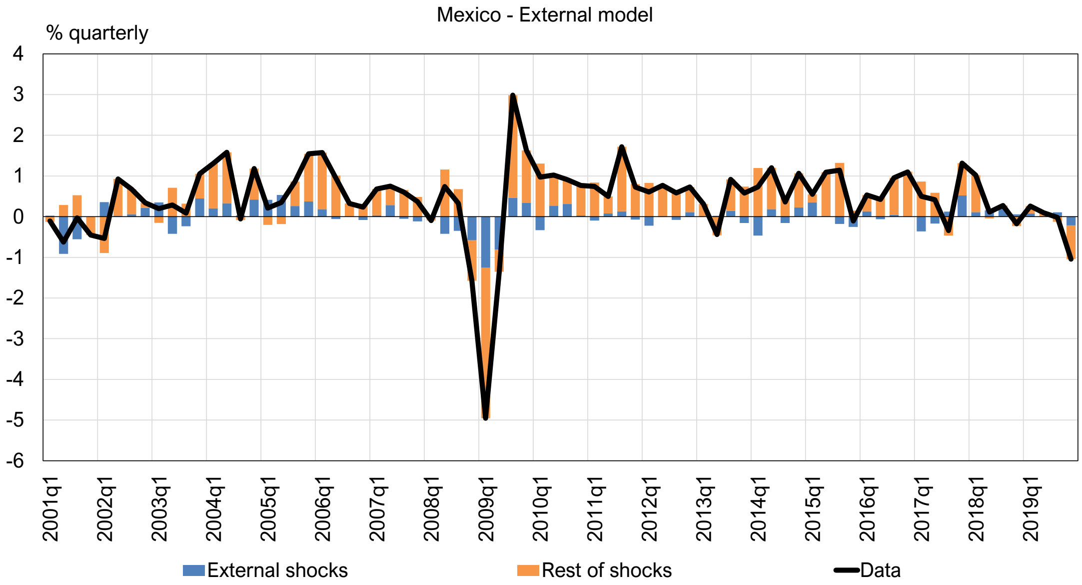
Figure B.2: Historical decomposition of GDP growth and potential output from the satellite models of Brazil (continued)

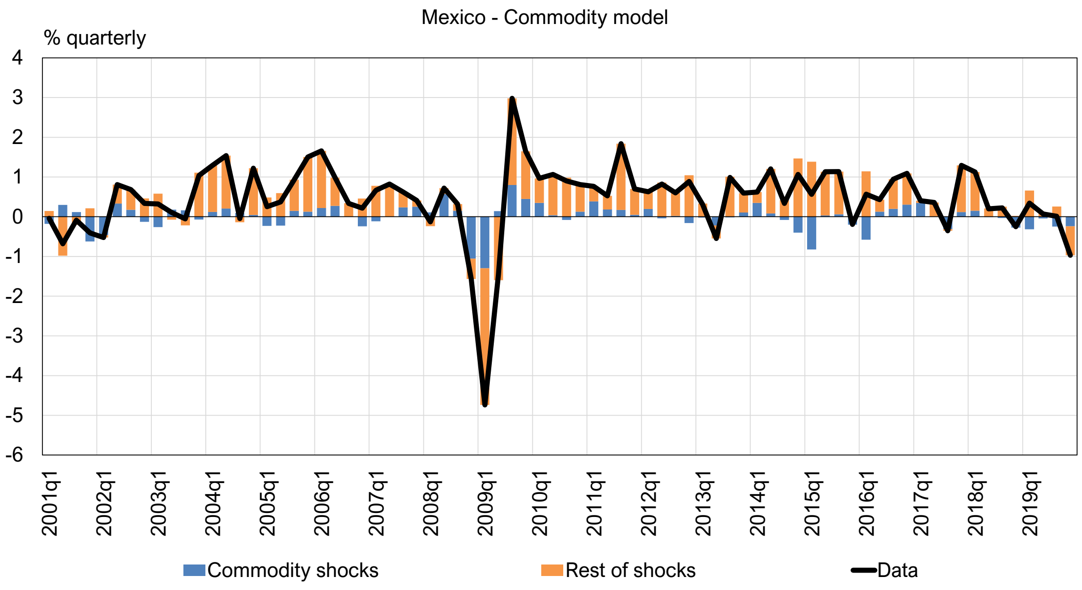




Notes: The historical series are decomposed by the structural shocks of the respective satellite model. The series of potential output are constructed using the auxiliary model.

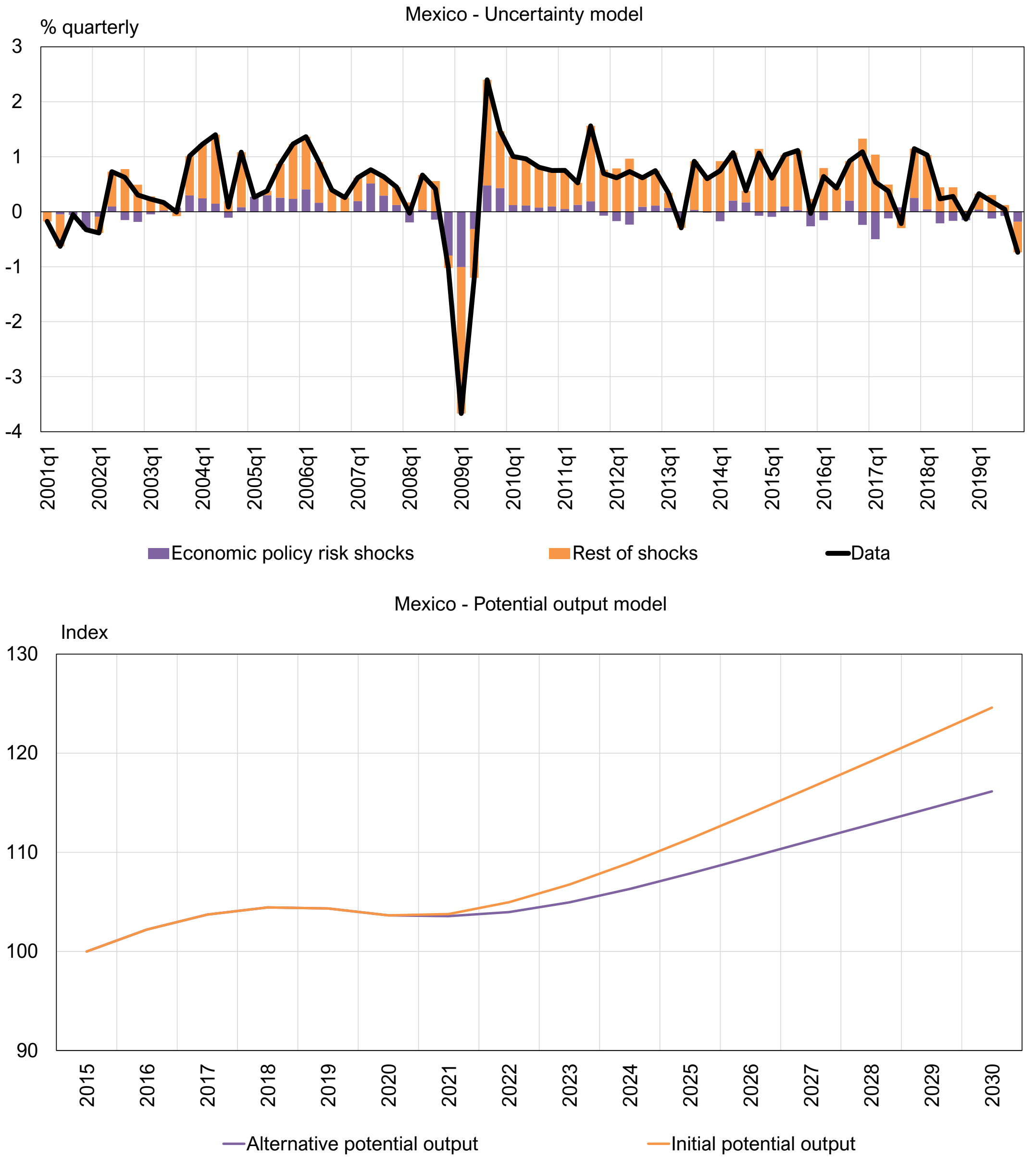
Figure B.3: Historical decomposition of GDP growth and potential output from the satellite models of Mexico





Notes: The historical series are decomposed by the structural shocks of the respective satellite model. The series of potential output are constructed using the auxiliary model.

Figure B.4: Historical decomposition of GDP growth and potential output from the satellite models of Mexico (continued)



Notes: The historical series are decomposed by the structural shocks of the respective satellite model. The series of potential output are constructed using the auxiliary model.

C Technical Assumptions

Most of the variables are directly taken from the Eurosystem's technical assumptions or, whenever this is not possible, they are constructed using a similar methodology. Oil prices and interest rates are based on prices traded in futures markets and the VIX, the exchange rate, EMBI+, and EPU are held fixed for the forecasting horizon based on the ten-day average prior to the cut-off date. The benchmark model estimates a steady-state of quarterly GDP growth of around 0.5% for Brazil and Mexico which is in line with the long-run annual growth rate of about 2% estimated in International Monetary Fund (2021a).

Table C.1: Technical assumptions and steady-state used in the GDP growth baseline projections of Brazil and Mexico

Baseline projection	**2021**	**2022**
Global variables		
Foreign demand of Brazil (growth rates)	10.2	4.6
Foreign demand of Mexico (growth rates)	14.8	3.4
Oil prices (log)	4.1	4.0
Short-term interest rate of the US (%)	0.1	0.3
VIX (log)	3.1	3.1
Local variables		
Interest rate of Brazil (%)	2.4	4.2
Interest rate of Mexico (%)	3.8	4.0
Exchange rate of Brazil (growth rates)	4.5	0.0
Exchange rate of Mexico (growth rates)	-6.5	0.1
EMBI+ of Brazil (basis points)	270.1	270.1
EMBI+ of Mexico (basis points)	200.8	200.8
EPU of Brazil (log)	4.5	4.5
EPU of Mexico (log)	4.7	4.7
GDP steady-state of Brazil (growth rates)	0.5	
GDP steady-state of Mexico (growth rates)	0.5	

Notes: The technical assumptions and steady-state correspond to the benchmark model. The annual average and growth rate values are based on the methodology and technical assumptions of the Eurosystem's March 2021 MPE, with cut-off date 16th of February 2021.
Source: Eurosystem and own calculations.

D Data Details

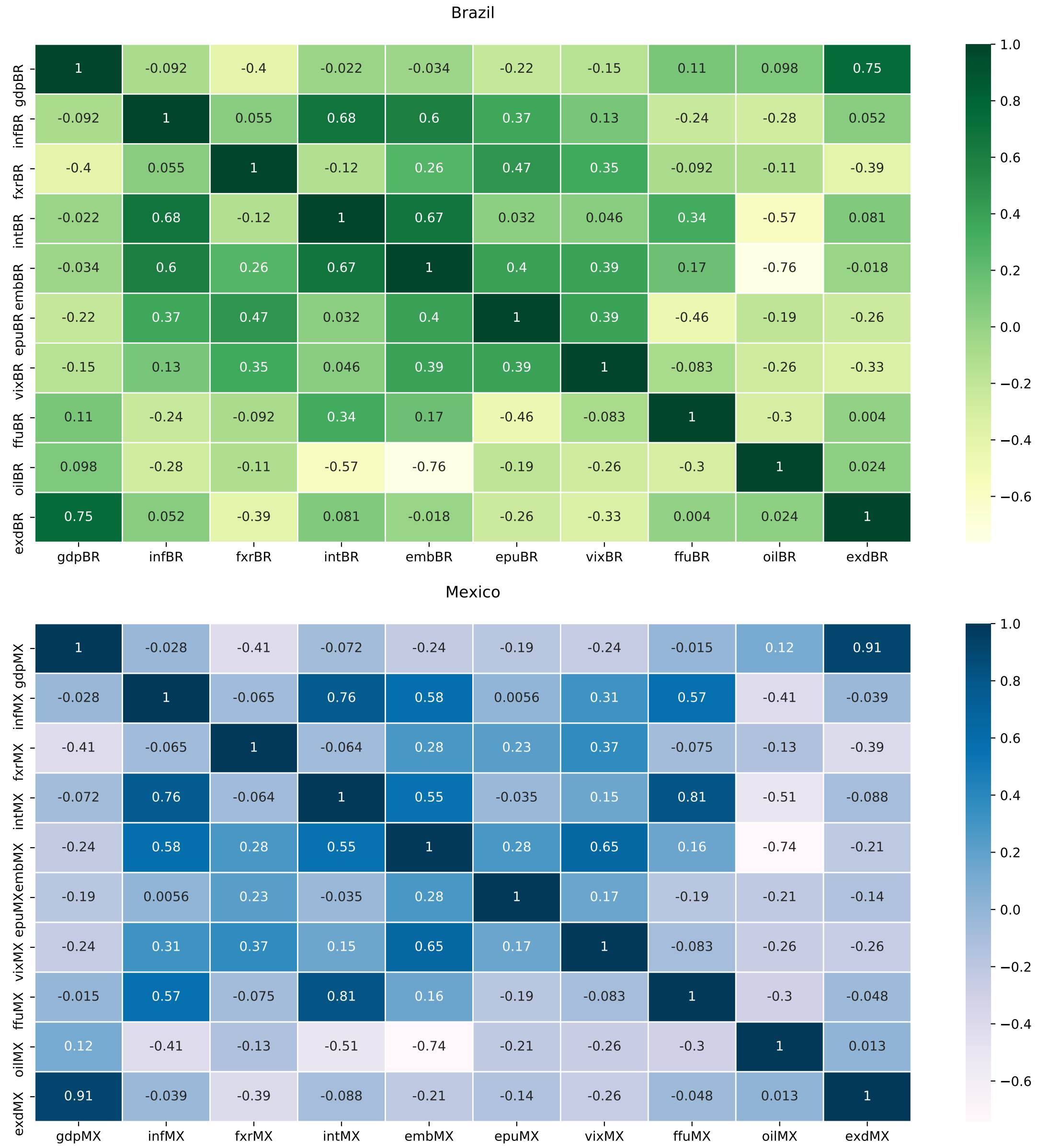
Table D.1: Descriptive statistics of model variables of Brazil and Mexico

	gdpBR	**infBR**	**fxrBR**	**intBR**	**embBR**	**epuBR**	**vixBR**	**ffuBR**	**oilBR**	**exdBR**
Mean	0.55	1.44	1.55	12.64	413.05	4.59	2.93	1.99	4.04	1.09
Std. dev.	1.79	0.67	8.18	5.11	325.25	0.33	0.34	1.89	0.50	2.40
Median	0.89	1.39	0.01	12.29	272.39	4.58	2.89	1.31	4.10	1.25
Maximum	7.66	4.37	37.58	26.33	1855.08	5.40	3.99	6.70	4.81	10.41
Minimum	-9.21	0.17	-14.56	2.00	152.73	3.68	2.34	0.23	2.96	-9.24

	gdpMX	**infMX**	**fxrMX**	**intMX**	**embMX**	**epuMX**	**vixMX**	**ffuMX**	**oilMX**	**exdMX**
Mean	0.44	0.98	1.04	6.74	213.60	4.63	2.93	1.99	4.04	0.83
Std. dev.	2.53	0.32	5.00	3.13	80.43	0.26	0.34	1.89	0.50	3.55
Median	0.60	0.93	0.10	6.96	195.07	4.60	2.89	1.31	4.10	0.87
Maximum	12.40	2.29	26.44	17.10	402.67	5.25	3.99	6.70	4.81	17.87
Minimum	-16.82	0.29	-8.63	3.00	85.23	4.06	2.34	0.23	2.96	-17.68

Notes: The mnemonic of the model variables is composed of the abbreviation of the variable in lower case (see Section 2.1 for details) and the country code in upper case, which follows the ISO classification (i.e., Brazil (BR) and Mexico (MX)). The values represent the descriptive statistics of variables for the sample periods 2000Q1–2020Q4.
Source: Own calculations.

Figure D.1: Correlation matrices for model variables of Brazil and Mexico



Notes: The mnemonic of the model variables is composed of the abbreviation of the variable in lower case (see Section 2.1 for details) and the country code in upper case, which follows the ISO classification (i.e., Brazil (BR) and Mexico (MX)). The values represent the correlation among variables for the sample periods 2000Q1–2020Q4.

Table D.2: Global and auxiliary variables data codebook

Variable	Unit	Description	Source
Foreign demand	Quarterly growth rates	Weighted average of real imports.	National sources, DOTS, and own calculations.
Oil prices	Log	Brent oil prices.	Bloomberg and own calculations.
US short-term interest rate	%	US 3-month short term interest rate.	National sources.
VIX	Log	Market-implied volatility.	CBOE and own calculations.
Production factors	Levels	Labor, capital, and TFP series for the production function.	PWT 10.0, national sources, and own calculations.

Table D.3: Local variables data codebook

Variable	Unit	Description	Source
Real GDP	Quarterly growth rates	Seasonally adjusted GDP at constant prices.	National sources and own calculations.
Core CPI Inflation	Quarterly growth rates	Seasonally adjusted core consumer price index.	National sources and own calculations.
Interest rate	%	Monetary policy interest rate proxy. SELIC in Brazil and TIIE in Mexico.	National sources.
Exchange rate	Quarterly growth rates	Bilateral exchange rate vis-à-vis the USD.	National sources and own calculations.
EMBI+	Basis points	Public debt sovereign spread between Brazil or Mexico and the US.	JPM and own calculations.
EPU	Log	News-based economic policy uncertainty index.	Ghirelli et al. (2020) and own calculations.