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The Macroeconomic Impact of Droughts in Uruguay

A General Equilibrium Analysis Using the Soil Moisture Deficit Index

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The Macroeconomic Impact of Droughts in Uruguay: A General Equilibrium Analysis Using the Soil Moisture Deficit Index

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ABSTRACT: Uruguay recently confronted the impact of a once-in-a-century severe drought, which affected key agricultural areas, and caused significant direct losses to the agricultural sector, especially for soybean production and cattle farming - important exports in Uruguay's trade matrix. From October 2022 to April 2023, rainfall was about 47 percent below historical averages, contributing to a decline in agricultural output and impacting overall GDP growth. The frequency of recent climate shocks witnessed in Uruguay combined with its rich climate data make it the ideal candidate to understand if weather shocks matter and through which transmission mechanisms. Using the empirical and theoretical framework outlined in Gallic and Vermandel (2020) we document that weather shocks play an important role in business cycle dynamics in Uruguay.

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WORKING PAPERS

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1 Introduction

Uruguay's exposure to extreme climate events has been increasing, causing substantial economic losses. Uruguay confronted the impact of a once-in-a-century severe drought, which mostly affected the agricultural sector lowering agricultural output between the last quarter of 2022 and the second quarter of 2023 by 25 percent on a year-on-year basis. Rain and floods are also becoming more frequent, forcing vulnerable groups to relocate (3 percent of the population in 2015-19) and impacting livelihoods. Uruguayan agricultural sectors are increasingly exposed to weather events impacting negatively crop yields and food production more broadly (Figure 1). As La Niña conditions prevailed for four consecutive years since 2020,[1] Uruguay confronted the impacts of one of the worst dry spells in the last century (Figure 2). While the overall rainfall deficit was the largest in 2020, the primary sector direct losses were only significant in 2023, as soil moisture anomalies were more prominent during the October – April period (Figure 3), which is critical for soybean production.

Figure 1: Climate Events: Agriculture Losses (1978-2019)

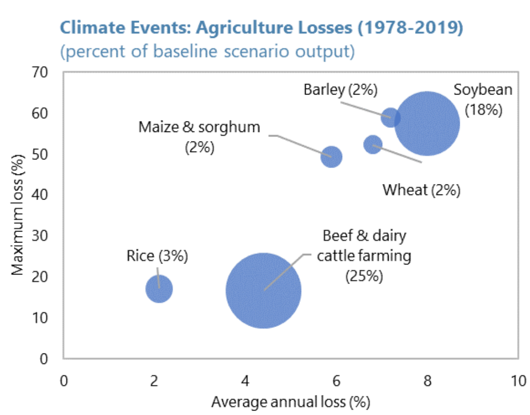
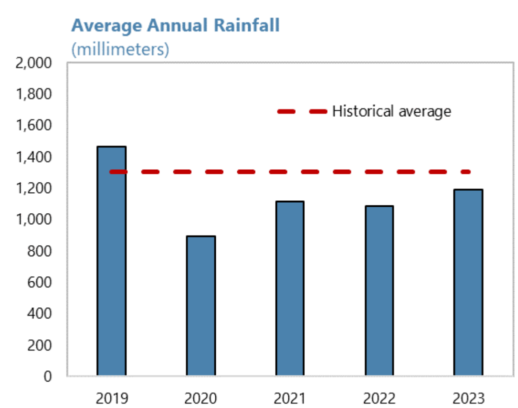


Figure 2: Average Annual Rainfall



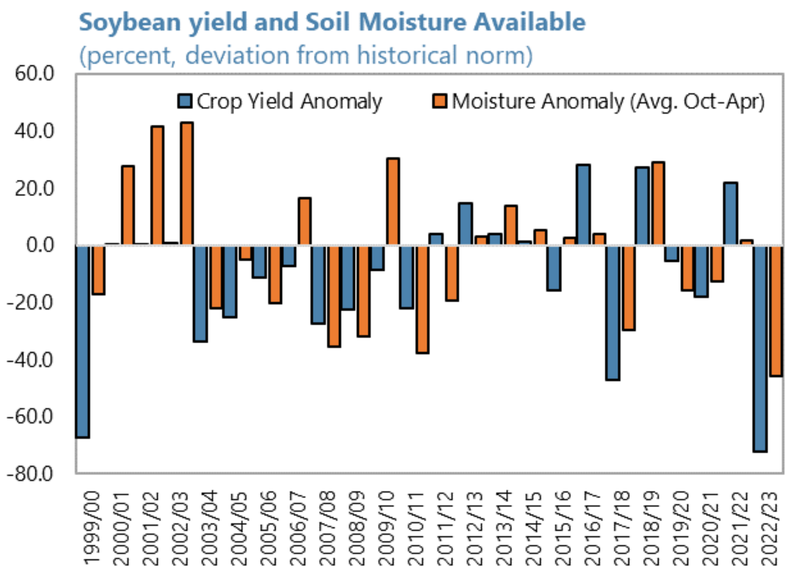
Sources: BCU, FAO, MGAP; and IMF staff calculations.
Notes: Figure 1, shows average annual losses (in percent) compared to maximum losses (in percent) in the agricultural sector due to climate events. Baseline refers to the initial forecast of crop production by MGAP. Calculations from Hernández et al. (2018).
Figure 2, displays the average annual rainfall in Uruguay compared to the historical average. Historical average calculated from 1981-2010 using INUMET (Uruguayan Institute of Meteorology) methodology.

[1] Four calendar years or three consecutive seasons, giving it the name 'triple-dip' La Niña.

As weather events have become more frequent, the modeling of climate change impacts has become a priority. As recurrent responses to climate shocks have put pressure on fiscal space, the authorities have focused on enhancing the modeling of fiscal impacts from climate change (i.e. coastal floods, excessive rainfall, droughts) and integrating them into the national budget. This study's approach contributes to widening the authorities' toolkit for impact assessments. Due to similarities between New Zealand and Uruguay - two small open economies that feature a prominent agricultural sector and are susceptible to droughts - the empirical and theoretical framework of Gallic and Vermandel (2020) is employed. To tailor the analysis to the Uruguayan economy we calculate a Uruguay-specific soil moisture deficit index (a climate measure derived from granular weather station data) and re-estimate and calibrate the Dynamic Stochastic General Equilibrium (DSGE) model to the Uruguayan economy.

Considering the importance of the agricultural sector for Uruguay's economy, especially for goods exports, it is paramount to accurately measure weather shock events, which in this work is captured through soil moisture conditions. As explained in Gallic and Vermandel (2020), the soil moisture deficit index (SMDI) depicts the balance between rainfall and temperatures - rainfall typically boosts the productivity of the land by promoting crop growth, and higher temperatures accelerate the evapotranspiraton process reducing land productivity. A key input for this endeavor is the soil water available (*porcentaje de agua disponible*, PAD is the acronym in Spanish) indicator produced by the National Institute of Agriculture Research (INIA). This high frequency indicator relies on INIA's spatially distributed hydrologic modeling and daily inputs captured through a nation-wide grid coverage. The PAD allows for a comprehensive assessment of soil moisture conditions as it factors in precipitations, surface runoff, infiltration, evaporation, water plant uptake and soil properties. For the modeling of macroeconomic impacts of weather shocks, the PAD is used to develop a soil moisture deficit indicator (SMDI) following the methodology of Narasimhan and Srinivasan (2005). Long-term PAD reference values for each month are obtained for period 2000-2023. As drought impacts are larger when dry conditions are sustained over time, the SMDI is calculated on an incremental basis. The SMDI succeeds in capturing periods of drought-related losses and crop yield anomalies (see Figure 3 and 4).

Figure 3: Soil Moisture Anomaly and Crop Yields



Sources: INIA, MGAP; and IMF staff calculations.
Notes: Crop yield anomaly is the effective yield compared to the average yield of the crop, as measured by OPYPA. Soil moisture anomaly between October to April (important planting and harvesting season) is taken from INIA and is part of the first stage of the calculation of the soil moisture deficit index.

We find that a rise in the soil moisture deficit index (drought) causes a prolonged fall in overall GDP, agricultural output and investment. According to the Structural VAR model that includes key macroeconomic variables, an adverse weather shock, a one-standard deviation rise in the drought variable, generates a contraction in Uruguay's economy, implying a contemporaneous 0.1 percent decrease in the primary activity sector (which includes agricultural, fishing and mining output) and a peak decline in GDP of 0.3 percent after 3 quarters.[2] The weather variable vanishes after one year, however its impact on the economy is persistent – impacting primary activity output for 2 years in the SVAR and up to 5 years in the DSGE model. In the empirical model the weather shock

[2]Detailed agricultural output is not available, therefore we use output in the primary activity sector.

manifests itself through the labor market by a fall on impact of employment followed by a rebound, which mimics the behavior of a Total Factor Productivity (TFP) shock.[3] In both the SVAR and DSGE models, the real exchange rate, which acts as a shock absorber, depreciates driven by the depressed competitiveness of farmers, which helps to restore part of their competitiveness. Analysis of a recent severe drought episode shows that rare, but intense, droughts have an estimated impact of around one percent of GDP loss.

Work analyzing the impact of droughts in Uruguay through an empirical or theoretical lens is scarce. A prominent example of recent theoretical work is Giuliano et al. (2024), who analyze the impact of climate shocks more broadly than our focus - with the ability to assess the impact of both floods and droughts - and for a longer time horizon - analyzing the potential impact of climate change, which may bring more frequent weather shocks. More broadly, our estimates are in line with the impact of droughts found by Akyapi et al. (2022), who utilize billions of geospatial weather observations from their global dataset of daily measurements of temperature and precipitation to estimate the macro-fiscal effect of climate shocks. Our focus and contribution to the literature is derived from reconciling the empirical impacts of droughts in Uruguay with a theoretical model that explains the short-term dimension of weather shocks, focusing on the business cycle frequency. We take an agnostic approach to the impact of weather shocks on the Uruguayan economy and allow our empirical strategy to inform our understanding. The creation of the SMDI for Uruguay is novel and is crucial for our exercise.

The paper is structured as follows: Section 2 explains the construction of the soil moisture deficit index, Section 3 outlines the empirical strategy and results while Section 4 details the model used the calibration and estimation.

[3] Increase in employment following a positive technology shock is discussed further in Gali (1999).

2 Soil Moisture Deficit Index

The construction of the soil moisture deficit index lies at the heart of our paper. To produce our weather variable we use spatial data on the soil water available (PAD - *Porcentaje de Agua Disponible*) from INIA-GRAS, who publish detailed soil moisture data every 10 days for nation-wide grids (30km x 30km approximately). The PAD allows for a comprehensive assessment of soil moisture conditions as it factors in precipitations, surface runoff, infiltration, evaporation, water plant uptake and soil properties. We construct our index following the principals of Narasimhan and Srinivasan (2005), such that the drought index must be able to reflect short-term dry conditions, the index should not feature seasonality and the drought index should be spatially comparable.

Figure 3 highlights the correlation between soil moisture anomaly during the important planting and harvesting season for economically important crops for Uruguay (soybean and rice are planted between October and December and harvested in late March-April) and the resulting fall in crop yields.

To create the index we need to aggregate along the time dimension, to produce a quarterly index that can be used as a weather variable alongside quarterly macroeconomic variables, and spatially so that we capture one index that is representative of the most important rain-fed areas for the agricultural sector.[4] For the latter, maps for Uruguay's crop production from the U.S. Department of Agriculture are used to aggregate relevant grids, covering around 80 percent of the national soybean production. Therefore, we start by computing the monthly soil water deficit, which is derived from the average of the daily data provided by INIA and for each month m and each year y the soil moisture deficit $SD_{y,m}$ is calculated following Equation 1. The soil water in each grid for a particular month and year is compared against its historical median soil water for that month (MSW) - removing seasonality and providing a measure of soil moisture deficit. This calculation is outlined below:

[4] Section A.1 contains an alternative SMDI, which has countrywide coverage. Our results are robust to this alternative index.

$$
\begin{aligned}
SD_{y,m} &= \frac{SW_{y,m} - MSW_m}{MSW_m - \min SW_m} \times 100, \quad \text{if} \quad SW_{y,m} \leq MSW_m, \\
SD_{y,m} &= \frac{SW_{y,m} - MSW_m}{\max SW_m - MSW_m} \times 100, \quad \text{if} \quad SW_{y,m} > MSW_m.
\end{aligned} \tag{1}
$$

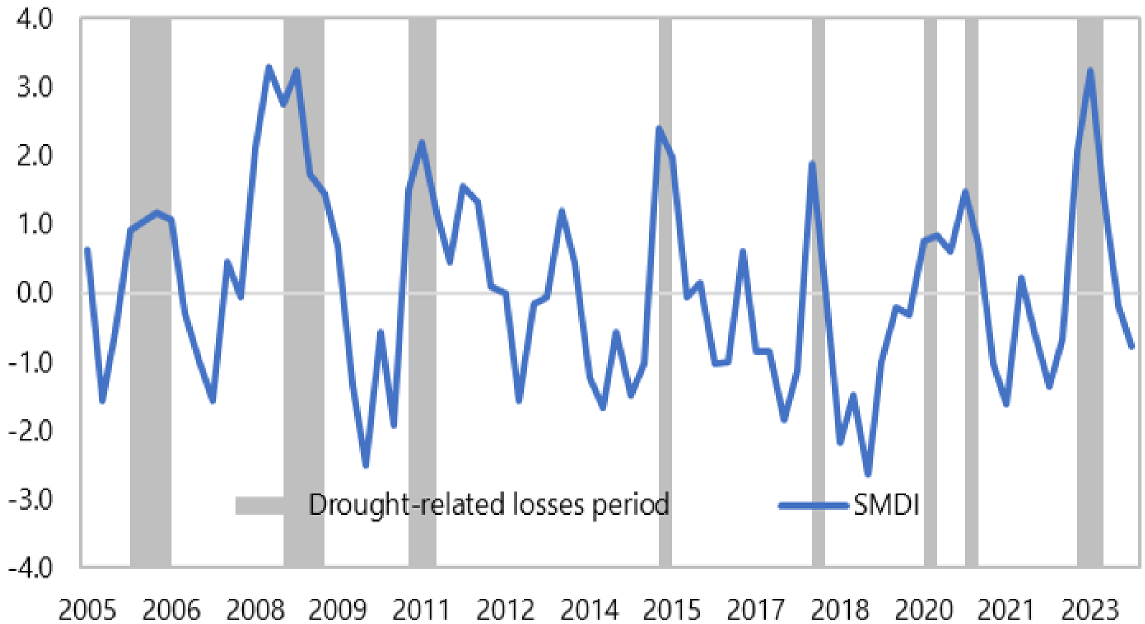
The soil water deficit is then accumulated to capture the drought severity into a singular index, the soil moisture deficit index. In any given time period the SMDI will range from -4 to +4 representing wet to dry conditions.[5] The normalization procedure of the SMDI allows it to be comparable to similar indices created for other countries such as in Narasimhan and Srinivasan (2005) and Gallic and Vermandel (2020).

$$
SMDI_{y,m} = 0.5 \times SMDI_{y,m-1} + \frac{SD_{y,m}}{50} \tag{2}
$$

The SMDI succeeds in capturing periods of drought-related losses (see Figure 4). Drought-related loss period defined by Oficina de Programación y Política Agropecuaria (OPYPA) are shown by the gray bars. The SMDI peaks during these periods and most notably, and recently, for the severe drought of 2022-2023 where it reaches above 3.

[5]This is achieved by dividing the soil moisture deficit $SD_{y,m}$ by 50 as shown in Equation 2 and is outlined in Narasimhan and Srinivasan (2005).

Figure 4: Soil Moisture Deficit Index



Sources: INIA-GRAS, OPYPA, and IMF staff calculations.
Notes: Quarterly Soil Moisture Deficit Index is derived from INIA-GRAS data and compared against drought-related loss periods from OPYPA. Positive values signify dry conditions, whereas negative values show periods of wet conditions.

3 Empirical Analysis

To estimate the response of the Uruguayan economy to weather shocks we follow the empirical strategy outlined in Gallic and Vermandel (2020), and analyze the impulse response functions from a drought shock. Our analysis is conducted at the macroeconomic level, using data available at the quarterly frequency starting in 2005Q2 until 2023Q2.[6] We transform the data used to a per-capita nature and seasonally adjust series that are not already seasonally adjusted using the X-13 seasonal adjuster in R.[7] The weather variable used for our analysis is the SMDI that we have derived for Uruguay, which is outlined in

[6]Due to the nature of the statistical accounting of contributions to growth from the agricultural sector we do not include 2023Q3 and 2023Q4 data in our analysis as agricultural output in these quarters are estimations of the future yields from the crops planted. Therefore primary activity in these quarters are estimates. The same sample period is used for the VAR and DSGE analysis.

[7]Annual population data are converted into quarterly using spline interpolation.

Section 2. The Rest of the World GDP uses the weighted average GDP of Uruguay's main trading partners and updates their weights each quarter according to Uruguay's exports and imports.[8]

- **Gross Domestic Product:** Real per capita output, expenditure approach, seasonally adjusted. *Source:* Banco Central del Uruguay.

- **Rest of the World Gross Domestic Product:** Weighted average of GDP of main trading partners. Seasonally Adjusted. *Source:* Haver and IMF staff calculations.

- **Agricultural Output (Primary Activity):** Primary sector per capita output (agriculture, fishing and mining). Seasonally Adjusted. *Source:* Banco Central del Uruguay.

- **Consumption:** Household final consumption expenditure, seasonally adjusted. *Source:* Banco Central del Uruguay.

- **Investment:** Gross fixed capital formation, seasonally adjusted. *Source:* Banco Central del Uruguay.

- **Employment:** Labor force status for people aged 15 to 64 years. Employment Rate. *Source:* Instituto Nacional de Estadística de Uruguay.

- **Real Effective Exchange Rate:** Global real effective exchange rate for Uruguay *Source:* Banco Central del Uruguay.

- **Weather:** Soil moisture deficit index for Uruguay. *Source:* INIA-GRAS and IMF staff calculations.

[8]Results are robust to assuming fixed weights for Uruguay's main trading partners, by using the average weight over the sample period.

3.1 Identification Strategy

The identification strategy is a two stage procedure. In the first stage, a restricted VAR model is estimated to reflect the small open economy assumption that we use for Uruguay. This small open economy assumption reflects the idea that Uruguay's macroeconomic variables may react to foreign shocks, but domestic shocks do not significantly impact the rest of the world. Therefore, the foreign variables (rest of the world GDP) is assumed to be exogenous. A similar assumption is made for our weather variable, such that changes in the weather may impact the Uruguayan economy but movements in domestic variables do not impact the weather.[9] Following the Hannan-Quinn and Schwarz criteria a lag of one is chosen for the restricted VAR and SVAR estimation.

In the second stage, once the restricted VAR is estimated, similar restrictions are imposed in the SVAR model outlined in Equation 3, where the restrictions placed on the A_0 matrix can be seen in Equation 4. The SVAR of order p, is written below such that X_t is the $n \times 1$ vector of variables at time t, where n is 8, and is formed of a domestic weather block, a foreign economy block and a domestic economy block. The vector of variables, X_t, is assumed to be a linear function of its past values X_{t-l} with l being the number of lags $l = 1, ..., p$. A_l is the $n \times n$ matrix of lagged parameters and C is the n vector of constants. The $n \times 1$ disturbances η_t are assumed to be normally distributed as $\eta_t \sim N(0, \sum_\eta)$.

$$A_0 X_t = C + \sum_{l=1}^{p} A_l X_{t-l} + \eta_t, \tag{3}$$

The restrictions placed on A_0 outlined in Equation 4 help us identify the orthogonal structural disturbances contained in vector η_t. Variables are written with a hat to denote that the data is logged and detrended - except the real effective exchange rate, which is in log differences and the SMDI which is not transformed. The weather variable $\hat{\omega}_t$ is ordered first, followed by foreign real output $\hat{y}_t^\star$ such that these variables are contemporaneously

[9] Since our analysis period in on the shorter term basis and spans the business cycle we feel that this assumption is justified.

affected by themselves only, following the exogeneity assumptions previously outlined. Domestic real GDP $\hat{y}_t$ is assumed to be the most exogenous domestic variable and is therefore ordered third. The domestic variables $(\hat{y}_t, \hat{y}_t^A, \hat{h}_t, \hat{c}_t, \hat{i}_t, r\hat{e}r_t)$ are able to respond contemporaneously to changes in the weather and foreign output. Agricultural output (primary activity) $\hat{y}_t^A$ is assumed to contemporaneously respond to the weather, foreign output and domestic GDP. The employment rate $\hat{h}_t$ is assumed to respond to the weather, foreign output, domestic GDP and agricultural output (primary activity). Consumption $\hat{c}_t$ and investment $\hat{i}_t$ respond to weather, foreign output, GDP, agricultural output (primary activity), employment and for investment it is also able to respond to consumption. The most endogenous variable in our model is the real exchange rate $r\hat{e}r_t$, which is ordered last.

$$A_0 X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & 1 & 0 & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 & 0 & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & 1 & 0 & 0 \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & 1 & 0 \\ b_{81} & b_{82} & b_{83} & b_{84} & b_{85} & b_{86} & b_{87} & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{\omega}_t \\ \hat{y}_t^{\star} \\ \hat{y}_t \\ \hat{y}_t^A \\ \hat{h}_t \\ \hat{c}_t \\ \hat{i}_t \\ r\hat{e}r_t \end{bmatrix} \tag{4}$$

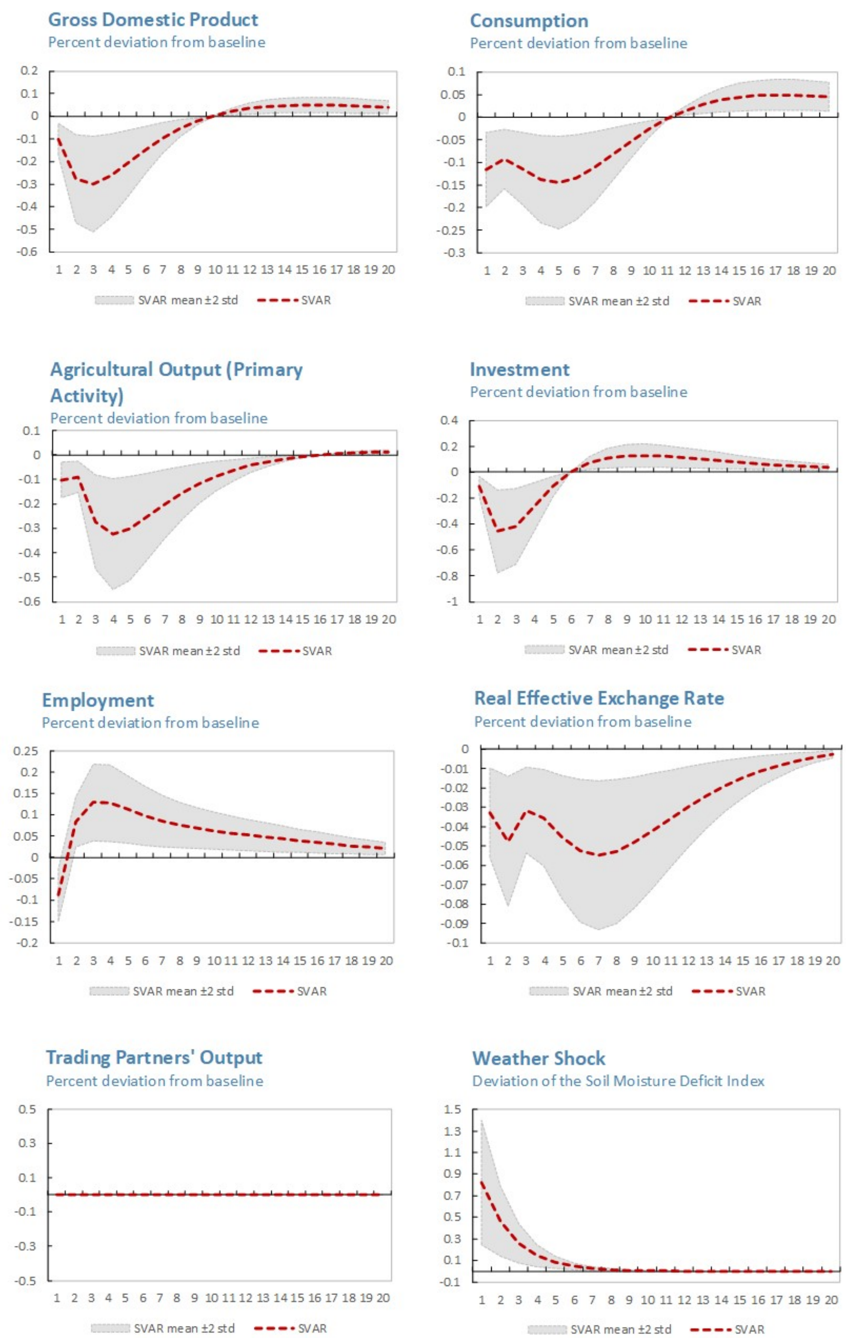
The coefficients of the restricted VAR in Equation 4 are depicted in Section A.1.

3.2 Empirical Results

Following the estimation of the SVAR we now present the empirical results obtained from an adverse weather shock of one standard deviation of the SMDI variable. This simulates the impact of a drought on the Uruguayan economy.

According to the Structural VAR model, an adverse weather shock, a one-standard deviation rise in the drought variable (Figure 5), generates a contraction in Uruguay's economy. The dashed red lines are responses to the shock, while the gray areas show the 95% error bands obtained from 10,000 Monte-Carlo simulations. Impulse responses are shown at the quarterly frequency for 20 periods (5 years). A rise in soil moisture deficits implies a contemporaneous 0.1 percent decrease in the agricultural sector (primary activities: agricultural, fishing and mining) and a peak decline in GDP of 0.3 percent after 3 quarters. The weather variable vanishes after one year, however its impact on the economy is persistent – impacting primary activity for 2 years in the SVAR. The weather shock manifests itself through the labor market by a fall on impact of employment followed by a rebound, which mimics the behavior of a TFP shock, where a fall in productivity of the worker leads the firm to hire more workers to sustain output.

Figure 5: SVAR Impulse Response from a drought shock in Uruguay



Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a one standard deviation shock to the Soil Moisture Deficit Index (weather shock). Time series is quarterly. The red dashed line is the Impulse Response Function, the gray band represents the 95% confidence intervals obtained from 10,000 Monte-Carlo simulations. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

4 The Model

The model follows the setup from Gallic and Vermandel (2020) and is replicated here for exposition and to highlight the differences in calibration and estimation of the Uruguayan economy compared to New Zealand. The model is a two-sector, two-good economy in a small open economy setup with a flexible exchange rate regime. The home economy, Uruguay, is populated by households and firms that work in the agricultural and non-agricultural sectors of the economy. The agricultural sector is the model counterpart to the primary sector (agriculture, fishing and mining) in the data - quarterly primary sector activity data will be used in the estimation of the model. The agricultural sector faces weather shocks, modelled through a cost function that impacts the productivity of land in a land-capital-labor Cobb-Douglas production function. The non-agricultural sector, which does not require land to produce, is not directly impacted by weather shocks but is impacted indirectly through the changes in the relative price of consumption goods and supply of labor. Households work and consume a bundle of domestic and foreign goods, giving importance to the real exchange rate and a foreign economy.

4.1 Agricultural Sector (Primary Activity)

The economy is populated by a unit mass of $i \in [0, 1]$ firms where a fraction of the firms $i \in [0, n_t]$ belong to the agricultural sector and the remaining fraction $1 - n_t$ belong to the non-agricultural sector.[10]

Production from the agricultural sector follows a Cobb-Douglas production function with land, which is further augmented to include a cost function for weather that impacts land productivity. Agricultural output by firm i is given by y^A_{it}, which is a combination of the land used that firm $l_{i,t-1}$, the physical capital $k^A_{i,t-1}$ and labor demanded h^A_{it}. The parameter $\omega \in [0, 1]$ is the elasticity of output to land and $\alpha \in [0, 1]$ governs the share of

[10]Firms can switch from one sector to another with the assumption that the number of agricultural firms follows a stochastic AR(1) process on the fixed portion of agricultural firms ($n_t = n \times \varepsilon^N_t$) with standard deviation parameter σ_N.

physical capital in the production process. Technology parameter $\kappa_A > 0$ is also included to help endogenously determine the steady state of the model. Motivated by the SVAR we assume that agricultural production is impacted by the weather shock, such that an increase in the weather shock (drought) causes a fall in agricultural output through a temporary drop in land productivity. The impact of weather enters the model through a cost function defined by $\Omega\left(\varepsilon_t^W\right)$ and described in more detail below. Capital and labor are subject to an economy-wide technology shock ε_t^Z, which follows a standard AR(1) process impacting both the agricultural and non-agricultural sectors.

$$y_{it}^A = \left[\Omega\left(\varepsilon_t^W\right)\ell_{it-1}\right]^\omega \left[\varepsilon_t^Z \left(k_{it-1}^A\right)^\alpha \left(\kappa_A h_{it}^A\right)^{1-\alpha}\right]^{1-\omega}, \tag{5}$$

Damage of the weather shock to land productivity depends on the estimated parameter θ that forms part of the weather cost function: $\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}$. When $\theta = 0$ the impact of weather on the business cycle is shut down. The weather shock is assumed to follow an AR(1) process:

$$\log\left(\varepsilon_t^W\right) = \rho_W \log\left(\varepsilon_{t-1}^W\right) + \sigma_W \eta_t^W, \quad \eta_t^W \sim \mathcal{N}(0,1), \tag{6}$$

with persistence $\rho_W \in [0,1)$ and standard deviation $\sigma_W \geq 0$. Although the weather shock may not be persistent it can have persistent impact on agricultural output and throughout the economy.

We assume that land is not fixed and can vary over time. This is an important assumption in the model to better capture the impact of the drought on critical cultivation periods that appear throughout the year. Therefore, land follows a law of motion defined by:

$$\ell_{it} = \left[(1-\delta_\ell) + v\left(x_{it}\right)\right]\ell_{it-1}\Omega\left(\varepsilon_t^W\right), \tag{7}$$

where $\delta_\ell \in (0,1)$ is the rate of decay of land productivity. As in Gallic and Vermandel (2020) it is assumed that the marginal product of land is increasing in the accumulation of land productivity, which is captured by assuming that land expenditures x_{it} yield a gross output of new productive land $\nu(x_{it}\ell_{it-1}$ with $\nu'(\cdot) > 0, v''(\cdot) \geq 0$. Land expenditure x_{it} can be thought of as spending on fertilizers and water used to maintain farmland that can be increased to offset the soil dryness caused by a drought.

The law of motion of physical capital in both the agricultural and non-agricultural sectors are standard. For the agricultural sector, capital accumulation through investment in capital:

$$i_{it}^A = k_{it}^A - (1-\delta_K)k_{i,t-1}^A, \tag{8}$$

where $\delta_K \in [0,1]$ is the depreciation rate of physical capital. The firms in the agricultural sector maximize their profits, which are determined by the value of their production (price of agricultural good multiplied by the volume of agricultural goods produced) taking into account the cost of labor, the cost of land expenditure and the convex cost of investment as defined in Christiano et al. (2005) to provide the hump shaped response of investment seen in the SVAR. The real profits are summarized by:

$$d_{it}^A = p_t^A y_{it}^A - p_t^N \left(i_{it}^A + S\left(\varepsilon_t^i \frac{i_{it}^A}{i_{it-1}^A}\right) i_{it-1}^A \right) - w_t^A h_{it}^A - p_t^N x_{it} \tag{9}$$

The investment cost includes a shock process, governed by ε_t^i, which follows an AR(1) process and makes investment more expensive. The representative firm in the agricultural sector is assumed to be a price taker and their maximization problem can be summarized as follows:

$$\max_{\left\{h_{it}^A, i_{it}^A, k_{it}^A, \ell_{it}, x_{it}\right\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} d_{it+\tau}^A \right\} \tag{10}$$

where E_t is the expectation operator and $\Lambda_{t,t+\tau}$ is the household stochastic discount factor between t and $t+\tau$.

4.2 Households

There is a continuum $j \in [0,1]$ of identical households that consume, save and work in the two production sectors. Households aim to maximize their welfare expressed as the sum of their utility discounted by β. Household consumption is expressed as C_{jt}. Households are assumed to have habit persistence, governed by the estimated parameter $b \in [0,1)$, such that they enjoy a similar level of consumption to their past. Households also work, with their labor effort defined as the aggregate of their work in the agricultural and non-agricultural sectors by h_{jt}. Degree of relative risk aversion and labor disutility is governed by $\sigma > 0$ and $\sigma_H > 0$, respectively. Steady state labor supply is calibrated through a shift parameter χ and ε_t^H represents a labor supply shock term that follows an AR(1) process that makes working have a greater negative impact on welfare. The utility function is given by:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\sigma} \left(C_{jt+\tau} - bC_{t-1+\tau} \right)^{1-\sigma} - \frac{\chi \varepsilon_{t+\tau}^H}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right], \tag{11}$$

where as in Horvath (2000) there is imperfect substitutability of labor supply between the agricultural and non-agricultural sectors to explain the co-movements in labor at the sector level. The CES labor disutility index consists of employment in the non-agricultural sector h_{jt}^N and agricultural sector h_{jt}^A. Labor reallocation between sectors is assumed to be costly and is governed by the substitutability parameter $\iota \geq 0$. If the estimated parameter ι is zero then work between the non-agricultural and agricultural sectors are perfect substitutes. A positive value for ι mean that there is a preference by households of work between the sectors such that employment in each sector responds less to the sector wage differential between the sectors. The CES labor disutility index is outlined below:

$$h_{jt} = \left[\left(h_{jt}^N \right)^{1+\iota} + \left(h_{jt}^A \right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{12}$$

Households maximize their utility (Equation 11) subject to a budget constraint (Equation 13). Expressed in real terms the household budget constraint is:

$$\sum_{s=N,A} w_t^s h_{jt}^s + r_{t-1} b_{jt-1} + \mathrm{rer}_t^* \, r_{t-1}^* b_{jt-1}^* - T_t \geq C_{jt} + b_{jt} + \mathrm{rer}_t^* \, b_{jt}^* + p_t^N \, \mathrm{rer}_t^* \, r_t \Phi \left(b_{jt}^* \right). \quad (13)$$

Households gain a wage for their work, defined as the real wage w_t^s multiplied by the hours worked h_{jt}^s where $s = N$ for the non-agricultural sector and $s = A$ for the agricultural sector. Households gain a return from the risk-free domestic bonds that they hold b_{jt} and $b_{j,t-1}^*$ defined by the domestic and foreign real interest rate (r_{t-1} and r_{t-1}^*, respectively), where the latter is affected by the real exchange rate rer_t^*. The real exchange rate is defined by the nominal exchange rate adjusted for the relative price differences in the foreign and home economies ($rer_t^* = e_t^* P_t^* / P_t$). Taxes are assumed to be lump sum (T_t) so that they do not distort the household's optimization problem. The last term in the budget constraint is the risk premium cost $\Phi \left(b_{jt}^* \right)$ of foreign bonds which are paid for in terms of domestic non-agricultural goods at the relative market price $p_t^N = P_t^N / P_t$.[11]

Household consumption is a CES bundle of agricultural and non agricultural goods where $\mu \geq 0$ denotes the elasticity of substitution between the two types of consumption goods and $\varphi \in [0, 1]$ is the fraction of agricultural goods in the household's consumption basket, which is calibrated using the weights in the consumer price index. The consumer price index, P_t, in the economy can be similarly written out as a CES bundle with φ governing the weight of non-agricultural priced goods $P_{C,t}^N$ and agricultural goods $P_{C,t}^A$. The CES consumption bundle is summarized below:

$$C_{jt} = \left[(1 - \varphi)^{\frac{1}{\mu}} \left(C_{jt}^N \right)^{\frac{\mu - 1}{\mu}} + (\varphi)^{\frac{1}{\mu}} \left(C_{jt}^A \right)^{\frac{\mu - 1}{\mu}} \right]^{\frac{\mu}{\mu - 1}}, \quad (14)$$

with each index C_{jt}^N and C_{jt}^A being a composite consumption subindex that is composed of domestic and foreign produced goods:

[11] The addition of the risk premium is used to avoid the unit root problem that emerges in open economy models without impacting the steady state of the model. See Schmitt-Grohé and Uribe (2003) for further discussion of this issue.

$$C_{jt}^{s}=\left[(1-\alpha_s)^{\frac{1}{\mu_s}}\left(c_{jt}^{s}\right)^{\frac{(\mu_s-1)}{\mu_s}}+(\alpha_s)^{\frac{1}{\mu_s}}\left(c_{jt}^{s*}\right)^{\frac{(\mu_s-1)}{\mu_s}}\right]^{\frac{\mu_s}{(\mu_s-1)}} \text{ for } s=N,A. \tag{15}$$

We allow for home bias in origin of consumption goods that the households consume, given by $1-\alpha_s \geq 0.5$ and $\mu_s > 0$ denotes the elasticity of substitution between home and foreign goods. In a similar way as the consumer price index of the CES consumption bundle, the production price index exists for each sector is given by a CES of the price of home and foreign goods in sector s, weighted by the home bias $1-\alpha_s$ and with an elasticity of substitution μ_s.

Demand schedules for each type of good can be defined as a function of their relative prices, weight in the consumption basket and home basket:

$$C_{jt}^{N}=(1-\varphi)\left(\frac{P_{C,t}^{N}}{P_t}\right)^{-\mu}C_{jt} \text{ and } C_{jt}^{A}=\varphi\left(\frac{P_{C,t}^{A}}{P_t}\right)^{-\mu}C_{jt}, \tag{16}$$

$$c_{jt}^{s}=(1-\alpha_s)\left(\frac{P_t^{s}}{P_{C,t}^{s}}\right)^{-\mu_s}C_{jt}^{s} \text{ and } c_{jt}^{s*}=\alpha_s\left(e_t^{*}\frac{P_t^{s*}}{P_{C,t}^{s}}\right)^{-\mu_s}C_{jt}^{s} \text{ for } s=N,A. \tag{17}$$

4.3 Non-Agricultural Sector

Production in the non-agricultural sector is similar to the agricultural sector, except firms do not face weather shocks and the Cobb-Douglas production function does not include land. Within the non-agricultural sector there exists a continuum of firms indexed by $i \in [n_t, 1]$, with $1-n_t$ denoting the relative size of the non-agricultural sector. Their Cobb-Douglas production function is given by:

$$y_{it}^{N}=\varepsilon_t^{Z}\left(k_{it-1}^{N}\right)^{\alpha}\left(h_{it}^{N}\right)^{1-\alpha}, \tag{18}$$

where y_{it}^{N} is the production of the intermediate goods firms, $k_{i,t-1}^{N}$ is the stock of physical capital of firm i, h_{it}^{N} is the labor employed in the non-agricultural sector for firm i and

ε_t^Z is the AR(1) technology shock. The parameter α governs the elasticity of capital and labor in the production on non agricultural goods.

Similarly to the agricultural firms, the non-agricultural firms also need to invest i_{it}^N to accumulate physical capital. This is given by:

$$i_{it}^N = k_{it}^N - (1 - \delta_K)\, k_{it-1}^N, \tag{19}$$

where $\delta_K \in [0, 1]$ is the depreciation rate of physical capital. Real profits are given by:

$$d_{it}^N = p_t^N y_{it}^N - p_t^N \left(i_{it}^N + S\left(\varepsilon_t^i \frac{i_{it}^N}{i_{it-1}^N} \right) i_{it-1}^N \right) - w_t^N h_{it}^N, \tag{20}$$

and firms maximize the discounted sum of profits:

$$\max_{\{h_{it}^N, i_{it}^N, k_{it}^N\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+s} d_{it+\tau}^N \right\}. \tag{21}$$

under technology and capital accumulation constraints.

4.4 Government

The government is kept purposely simple. The government consumes non-agricultural output G_{it}, issues debt b_t at a real interest rate r_t and charges lump sum taxes T_t to households. Government consumption is assumed to be exogenous, $G_t = Y_t^N g \varepsilon_t^G$ where $g \in [0, 1)$, and is impacted by a standard AR(1) stochastic shock process for ε_t^G.

$$G_t + r_{t-1} b_{t-1} = b_t + T_t \tag{22}$$

4.5 Foreign Economy

The Foreign economy is stylized as Uruguay is a small open economy, which by assumption cannot impact the foreign block. The foreign country is needed in the model to determine Uruguay's exports and real exchange rate dynamics. The foreign country is modeled as an endowment economy with exogenous foreign consumption:

$$\log\left(c_{jt}^{*}\right) = (1-\rho_C)\log\left(\bar{c}_j^{*}\right) + \rho_C \log\left(c_{jt-1}^{*}\right) + \sigma_C \eta_t^C, \quad \eta_t^C \sim \mathcal{N}(0,1), \tag{23}$$

where $0 \leq \rho_C < 1$ determines the return to steady state of foreign consumption. The parameters σ_C and ρ_C are estimated to match foreign demand.

Each period, foreign households solve the following optimization scheme:

$$\begin{aligned} &\max_{\left\{c_{jt}^{*}, b_{jt}^{*}\right\}} E_t \left\{\sum_{\tau=0}^{\infty} \beta^{\tau} \varepsilon_{t+\tau}^{E} \log\left(c_{jt+\tau}^{*}\right)\right\}, \\ &\text{s.t.} \quad r_{t-1}^{*} b_{jt-1}^{*} = c_{jt}^{*} + b_{jt}^{*}. \end{aligned} \tag{24}$$

where variable ε_t^E is a time-preference shock defined as follows:

$$\log\left(\varepsilon_t^E\right) = \rho_E \log\left(\varepsilon_{t-1}^E\right) + \sigma_E \eta_t^E \tag{25}$$

4.6 Equilibrium and Aggregation Equations

The market clearing condition for non-agricultural goods is determined by equating aggregate demand and aggregate supply:

$$\begin{aligned} (1-n_t)\,Y_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{P_t^N}{P_{C,t}^N}\right)^{-\mu_N}\left(\frac{P_{C,t}^N}{P_t}\right)^{-\mu} C_t + \alpha_N\left(\frac{1}{e_t^{*}}\frac{P_t^N}{P_{C,t}^{N_*}}\right)^{-\mu_N}\left(\frac{P_{C,t}^{N*}}{P_t^{P^*}}\right)^{-\mu} C_t^{*}\right] \\ + G_t + I_t + n_t x_t + \Phi\left(b_t^{*}\right), \end{aligned} \tag{26}$$

where aggregate real production is given by:

$$Y_t = (1-n_t)\,p_t^N Y_t^N + n_t p_t^A Y_t^A. \tag{27}$$

In addition, the equilibrium of the agricultural goods market is given by:

$$n_t Y_t^A = \varphi \left[(1-\alpha_A) \left(\frac{P_t^A}{P_{C,t}^A} \right)^{-\mu_A} \left(\frac{P_{C,t}^A}{P_t} \right)^{-\mu} C_t + \alpha_A \left(\frac{1}{e_t^*} \frac{P_t^A}{P_{C,t}^{A*}} \right)^{-\mu_A} \left(\frac{P_{C,t}^{A*}}{P_t^*} \right)^{-\mu} C_t^* \right] \tag{28}$$

GDP is given by :

$$gdp_t = Y_t - p_t^N n_t X_t \tag{29}$$

The law of motion for the total amount of real foreign debt is:

$$b_t^* = r_{t-1}^* \frac{rer_t^*}{rer_{t-1}^*} b_{t-1}^* + tb_t, \tag{30}$$

where the trade balance is:

$$tb_t = p_t^N \left[(1-n_t) Y_t^N - G_t - I_t - n_t X_t - \Phi(b_t^*) \right] + p_t^A n_t Y_t^A - C_t. \tag{31}$$

4.7 Calibration and Estimation

The model is calibrated using standard parameters from the literature and Uruguay-specific parameters calculated using historical averages. Table 1 summarizes the calibration of the model. The discount factor β, capital depreciation rate δ_K, the share of capital in output α, hours worked $\bar{H}^N = \bar{H}^A$ and international portfolio cost are all standard.[12]. The share of public spending in GDP $g = 0.216$ is derived by taking the average of the share of public consumption and public investment of GDP between 2016-2022. The share of agricultural goods in the consumption basket $\varphi = 0.17$ is calculated by aggregating the weights of the agricultural related products in Uruguay's consumer price index. Uruguay's land-to-employment $\bar{\ell} = 1.30$ parameter is derived from the World Bank's World Development Indicators (WDI) and estimates of the population and persons employed - the final

[12]The portfolio adjustment cost of foreign debt is taken from Schmitt-Grohé and Uribe (2003) and is chosen to be extremely small.

result is the average of land-to-employment between 2005 to 2021. Land-to-employment is where the largest discrepancy with respect to Gallic and Vermandel (2020) arises regarding the calibration of parameters, who calibrate their model with $\bar{\ell}^{NZ} = 0.4$ for New Zealand. This discrepancy arises as Uruguay has around a five times larger rate of arable land per capita than New Zealand.[13]. The openness of non-agricultural market α_N and agricultural market α_A are determined by the average value of non-agricultural exports as a share of non-agricultural GDP and share of agricultural exports as the share of agricultural GDP (primary sector GDP) between 2016 to 2022.

Table 1: Model Calibration

Variable	Interpretation	Value
β	Discount factor	0.9883
δ_K	Capital depreciation rate	0.025
α	Share of capital in output	0.33
g	Share of spending in GDP	0.216
φ	Share of agricultural goods in consumption basket	0.17
$\bar{H}^N = \bar{H}^A$	Hours worked	1/3
$\bar{\ell}$	Land per capita	1.30
α_N	Openness of non-agricultural market	0.10
α_A	Openness of agricultural market	0.50
χ_B	International portfolio cost	0.0007

Sources: Banco Central del Uruguay, National Statistics Agency (INE), World Bank; and IMF staff calculations.

The remaining parameters of the model are estimated using Bayesian methods utilizing the same dataset that was used in the VAR model - spanning 2005Q2 to 2023Q2. Section 3 outlines the 8 variables that are used. In order to map non-stationary data to a stationary model we follow the same procedure as in Gallic and Vermandel (2020). Observable variables that typically have a trend are divided by working age population to calculate the per-capita terms, logged and then detrended using a quadratic trend. This allows us to detract from modeling a trend in the home and foreign economies - similar to Justiniano

[13]See WDI for further information regarding arable land per capita.

and Preston (2010).

The vector of observable is given by:

$$\mathcal{Y}_t^{obs} = 100 \times \left[\hat{y}_t, \quad \hat{c}_t, \quad \hat{i}_t, \quad \hat{h}_t, \quad \hat{y}_t^A, \quad \hat{y}_t^*, \quad \Delta\widehat{rer}_t, \quad \hat{\omega}_t\right]', \tag{32}$$

where $\hat{y}_t$ is the output gap, $\hat{c}_t$ is the consumption gap, $\hat{i}_t$ is the investment gap, $\hat{h}_t$ is an index of employment, $\hat{y}_t^A$ is the agricultural production gap, $\hat{y}_t^*$ is the foreign production gap, $\widehat{rer}_t$ is the real exchange rate and $\hat{\omega}_t$ the soil moisture deficit index.

The corresponding measurement equations are given by:

$$\mathcal{Y}_t = 100 \times \left[\widetilde{gdp}_t, \quad \tilde{C}_t, \quad \tilde{p}_t^N + \tilde{I}_t, \quad \tilde{H}_t, \quad \tilde{n}_t + \tilde{p}_t^A + \tilde{Y}_t^A, \quad \tilde{C}_t^*, \quad -\Delta\widetilde{rer}_{t+1}^*, \quad \tilde{\varepsilon}_t^W\right]', \tag{33}$$

Table 2 reports the prior and posterior distributions, estimated mean parameters and posterior density intervals around the estimated parameters. To evaluate the marginal likelihood of the model the Metropolis-Hastings algorithm is used.[14] Priors are taken from Gallic and Vermandel (2020), which use Smets and Wouters (2007) as a starting point. The standard deviations of the innovations are assumed to follow a Weibull distribution with mean 1 and standard devation 2 as the Weibull distribution is more diffuse than the Inverse Gamma distribution. Substitutability parameters follow a Gamma distribution with mean 2 and a standard deviation of 1 to have a support that lies between 0 and 5. The posterior mean of the risk aversion parameter we assume follows a Normal distribution with mean of 1 and standard deviation of 0.35 (σ_C), which notably produces a lower parameter estimate than Gallic and Vermandel (2020).

For the agricultural sector parameters the land decay rate δ_ℓ is assumed to follow an uninformative prior using a Beta distribution of mean 0.2 and standard deviation 0.1. We find a slightly higher land decay rate than Gallic and Vermandel (2020). For the damage function parameter θ, which drives the impact of weather shocks on the agricultural sector,

[14] We compute the posterior moments of the parameters using a total generated 1,000,000 draws (two parallel chains of 500,000) discarding the first 25 percent of the draws. The model is estimated and simulated in Dynare (Adjemian et al. (2011)).

we take as the prior mean the posterior mean in Gallic and Vermandel (2020) and assume it follows a Normal distribution with a large standard deviation to allow the data to be informative about the value of this parameter. Our posterior mean of $\theta = 5.25$, which is below the prior mean and contains negative values for θ within the 90% posterior density interval. One reason behind this finding is the occurrence of floods and flood damage to the agricultural sector and economy of Uruguay. The excess of water may also lead to economic damage, which could be behind the possibility of the land-weather elasticity entering negative territory. The model does not allow for weather damages to the capital stock nor direct costs to the non-agricultural sectors such as manufacturing and retail, both of which can be related to flood damage as found by Ashizawa et al. (2022). Despite the lower weather cost parameter value we find similar impacts on overall output to Gallic and Vermandel (2020), albeit with lesser impact on the agricultural sector, suggesting a more indirect transmission mechanism of droughts for Uruguay.

Table 2: Model Estimation

		Prior distributions			Posterior distributions	
		Shape	Mean	Std.	Mean	[5% : 95%]
Shock Process AR(1)						
Economy-wide TFP (SD)	$\sigma_Z \times 100$	$\mathcal{W}$	1	2	2.41	[2.00 : 2.81]
Hours supply (SD)	$\sigma_H \times 100$	$\mathcal{W}$	1	2	3.86	[2.50 : 5.16]
Spending (SD)	$\sigma_G \times 100$	$\mathcal{W}$	1	2	6.38	[5.21 : 7.58]
Investment (SD)	$\sigma_I \times 100$	$\mathcal{W}$	1	2	8.17	[6.07 : 10.18]
Sector reallocation (SD)	$\sigma_N \times 100$	$\mathcal{W}$	1	2	18.77	[13.16 : 24.21]
Weather (SD)	$\sigma_W \times 100$	$\mathcal{W}$	1	2	1.21	[1.02 : 1.41]
Foreign time-preference (SD)	$\sigma_E \times 100$	$\mathcal{W}$	1	2	4.14	[3.20 : 5.05]
Foreign consumption (SD)	$\sigma_C \times 100$	$\mathcal{W}$	1	2	1.20	[1.00 : 1.40]
Economy-wide TFP (AR term)	ρ_Z	$\mathcal{B}$	0.5	0.2	0.84	[0.75 : 0.94]
Labour supply (AR term)	ρ_H	$\mathcal{B}$	0.5	0.2	0.78	[0.65 : 0.92]
Spending (AR term)	ρ_G	$\mathcal{B}$	0.5	0.2	0.67	[0.49 : 0.86]
Investment (AR term)	ρ_I	$\mathcal{B}$	0.5	0.2	0.26	[0.07 : 0.43]
Sector reallocation (AR term)	ρ_N	$\mathcal{B}$	0.5	0.2	0.28	[0.10 : 0.45]
Weather (AR term)	ρ_W	$\mathcal{B}$	0.5	0.2	0.44	[0.26 : 0.63]
Foreign time-preference (AR term)	ρ_E	$\mathcal{B}$	0.5	0.2	0.21	[0.07 : 0.35]
Foreign consumption (AR term)	ρ_C	$\mathcal{B}$	0.5	0.2	0.69	[0.56 : 0.83]
Structural Parameters						
Risk consumption	σ_C	$\mathcal{N}$	1	0.35	0.28	[0.10 : 0.45]
Labor disutility	σ_H	$\mathcal{N}$	2	0.75	1.90	[1.11 : 2.68]
Land expenditure cost	ϕ	$\mathcal{N}$	1	1	1.72	[1.25 : 2.20]
Share of land in agricultural output	ω	$\mathcal{B}$	0.2	0.08	0.11	[0.02 : 0.19]
Consumption habits	b	$\mathcal{B}$	0.7	0.1	0.66	[0.50 : 0.82]
Labor sectoral cost	ι	$\mathcal{N}$	1	0.75	2.48	[1.65 : 3.27]
Substitutability by type of goods	μ	$\mathcal{G}$	2	1	3.35	[2.06 : 4.57]
Substitutability home/foreign	μ_A	$\mathcal{G}$	2	1	1.97	[1.27 : 2.62]
Substitutability home/foreign	μ_N	$\mathcal{G}$	2	1	1.46	[0.75 : 2.17]
Land efficiency decay rate	δ_ℓ	$\mathcal{B}$	0.2	0.1	0.07	[0.03 : 0.11]
Investment cost	κ	$\mathcal{N}$	4	1.5	2.43	[0.44 : 4.72]
Land-weather elasticity	θ	$\mathcal{N}$	20.59	8	5.25	[−2.97 : 14.22]
Marginal log-likelihood						-1014.94

Sources: Prior distributions derived from Gallic and Vermandel (2020) with underlying data from Banco Central del Uruguay and the National Statistics Agency; and IMF staff calculations.
Note: The column entitled "Shape" indicates the prior distributions using the following acronyms: $\mathcal{N}$ describes a normal distribution, $\mathcal{G}$ a gamma, $\mathcal{B}$ a Beta, and $\mathcal{W}$ a Weibull.

4.8 Results

As with the SVAR model we simulate a one standard deviation weather shock in the DSGE model to analyze the impact of droughts on the Uruguayan economy. Figure 6 summarizes the results from both models, overlaying the SVAR (red dashed line) with the DSGE model results (shown as the solid blue line). The weather shock acts as a negative supply shock through a combination of rising employment and falling output. Land productivity is negatively affected by the drought, weighing heavily on agricultural output. This negative supply shock depreciates the real exchange rate, which acts as a shock absorber, and consequently helps to restore part of the competitiveness of farmers. In comparison to the SVAR the impact on consumption and agricultural output (primary activity) is greater, however the model captures well the magnitude and dynamics of the impact on investment.[15] Non-agricultural output (see Annex A.2 for additional DSGE results) rises as cost of production and therefore the relative price of non-agricultural goods to agricultural goods falls, which helps to dampen the drought's impact on overall output. The persistence of the DSGE model is notable - the impact of the weather shock lasts up to 5 years, which is 3 years longer than the SVAR results and longer than the one year it takes for the shock to subside. This persistence is also seen in Gallic and Vermandel (2020) and can be partly explained by the persistent reduction in land efficiency seen in the DSGE model, which is governed by the estimated parameter δ_ℓ that enters into the function that governs how land evolves. The motivation of such a function form is to capture the impact of weather shocks on land quality that is used for livestock and cultivation, with the potential impact on livestock to be long-lived (Rosen et al., 1994). The drought has a negative and persistent impact on land efficiency (see Annex A.2) which causes farmers to use more non-agricultural inputs to support their land productivity. The increase in labor on impact in the model is likely driven by the choice of utility function -there exists a negative wealth effect from the shock that an increase in labor supply tries to offset leading to a rise in employment.[16]

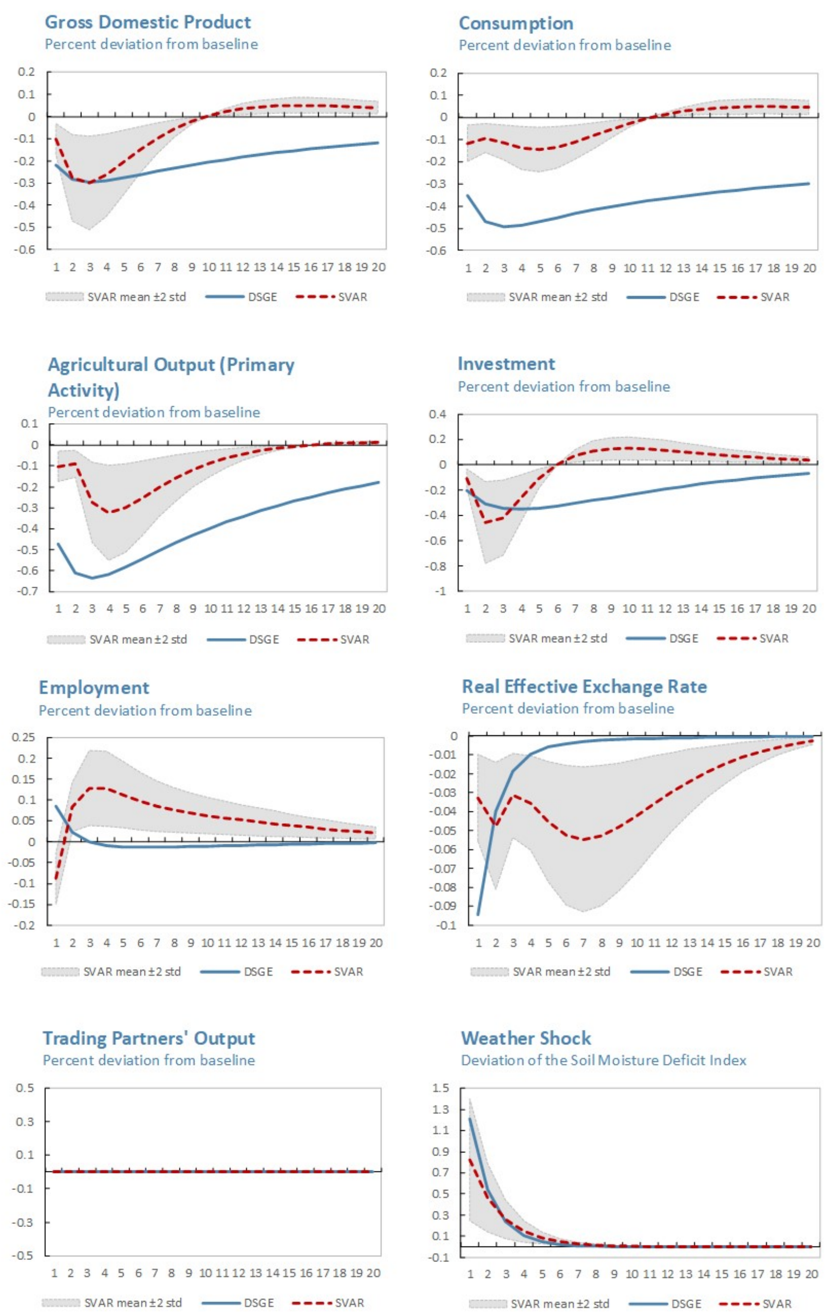
[15] During the recent severe drought of 2022-2023 real private consumption growth remained positive, as the economy continued to recover from the Covid-19 pandemic.

[16] Future research avenue could explore alternative the sensitivity of the results to alternative utility functions. such as GHH preferences Greenwood et al. (1988), which removes the wealth effect on the labor supply. Further, adding nominal rigidities to the model may help to tame the employment response to the weather shock in the same vein as explored in Gali (1999) and Galí and Rabanal (2004).

Although the results of the SVAR and DSGE models are similar, some differences do arise. In Uruguay the cultivation of crops and rearing of livestock form the major activities in the agricultural sector, with the cultivation of crops being more susceptible to droughts than the rearing of livestock. However, to keep the model tractable, and due to data restraints the agricultural sector is not split into separate sectors. Further, a severe drought has the potential for far reaching consequences on the economy, which is not only felt in the agricultural sector but also could lead to heightened water scarcity, reduced hydroelectic electricity generation (which forms an important part of Uruguay's electricity generation matrix) and an increase chance of wildfires. The financial transmission channel, where it has been shown that unusually hot days increase delinquency rates in the agricultural sector (Aguilar-Gomez et al., 2024), is also omitted from our analysis.[17]

[17]The financial channel is expected to be muted in Uruguay as credit-to-GDP is relatively low at close to 30 percent of GDP (IMF, 2024).

Figure 6: DSGE and SVAR Results



Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a one standard deviation shock to the Soil Moisture Deficit Index (weather shock) in the SVAR and DSGE models. Time series is quarterly. The red dashed line is the Impulse Response Function, the gray band represents the 95% confidence intervals obtained from the SVAR using 10,000 Monte-Carlo simulations. The blue line is the response from the DSGE model. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

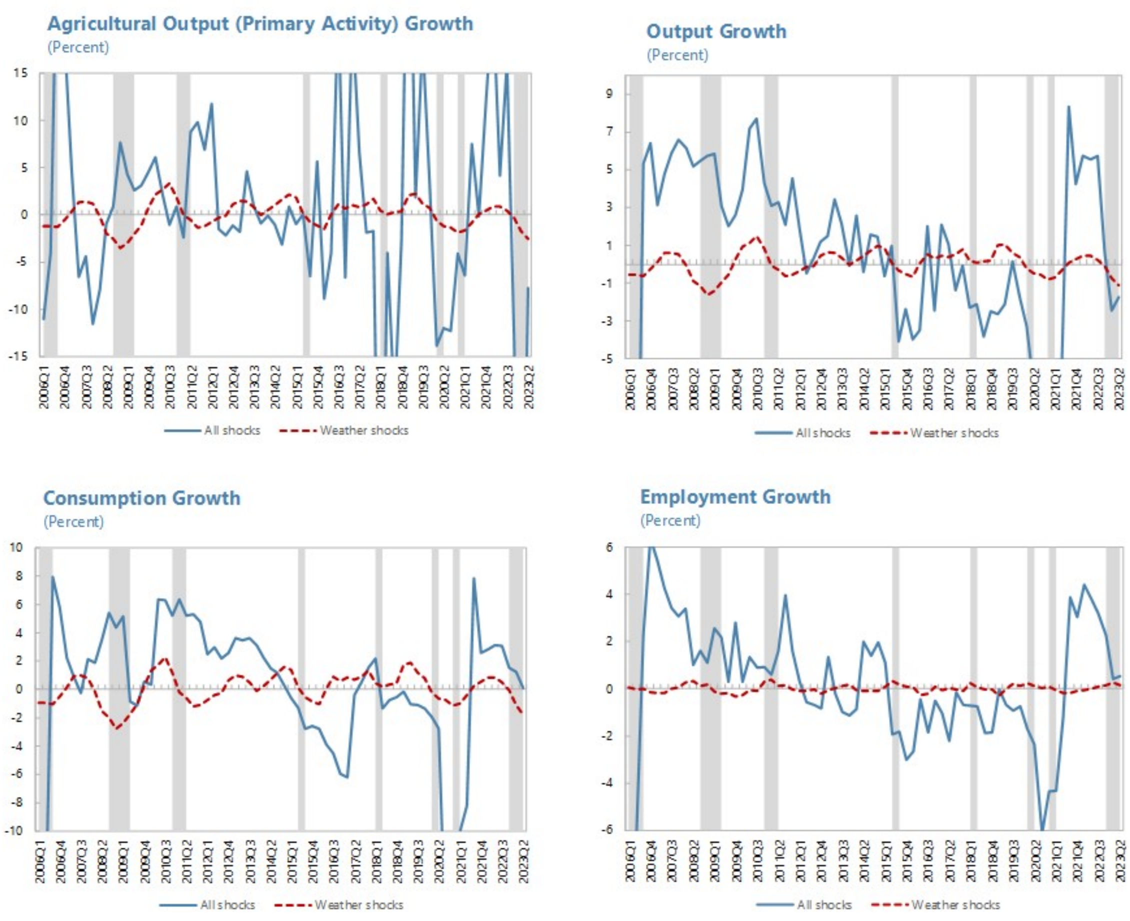
The impact of the weather shock on GDP in the DSGE model is similar between Uruguay and New Zealand, however the transmission mechanism differs. Agricultural output falls by 1.5 percent following a one standard deviation drought in New Zealand, where this decrease is more muted for Uruguay (0.6 percent). The response of investment is similar across the countries but Uruguay's consumption falls by more and employment rise is more muted. The more muted impacted on agricultural output with similar results to GDP for Uruguay signals that the impact of the drought may impact other sectors of the economy. However, part of the difference may also be explained due to the difference in agricultural data; for Uruguay we use data on the primary sector, which includes agricultural, fishing and mining activities, whereas Gallic and Vermandel (2020)'s agricultural variable includes agriculture, fishing and forestry.

5 The Importance of Weather Shocks on the Business Cycle

Figure 7 highlights the estimated impact of weather shocks on the Uruguayan economy, displaying year-on-year growth rates of main macroeconomic variables. The blue line is the result of simulating the model to all of the estimated shocks and initial conditions, whereas the red dashed line is the result of the same simulation but only using weather shocks. Notably the weather shocks have cyclical impacts on agricultural output (primary activity) growth, total output growth and consumption growth. The weather shocks cause agricultural output growth to oscillate between +3 percent and - 3 percent over the sample. In comparison with consumption growth which moves +/- 2 percent and output growth +/- one percent, the impact on employment is limited, likely due to the low share of labor force working in the primary activity sector. The fall in output growth lines up with the 2008-2009, 2011, 2015 and 2022-2023 drought-related loss periods.

The spillover of the impact of weather shocks from the agricultural sector is evident, as the shock causes weather-driven changes in consumption, co-moving with the agricultural output (primary activity) losses due to droughts. The loss in consumption growth and agricultural output (primary activity) growth helps to explain the weather-driven business cycle impacts seen on output growth.

Figure 7: The Role of Weather Shocks



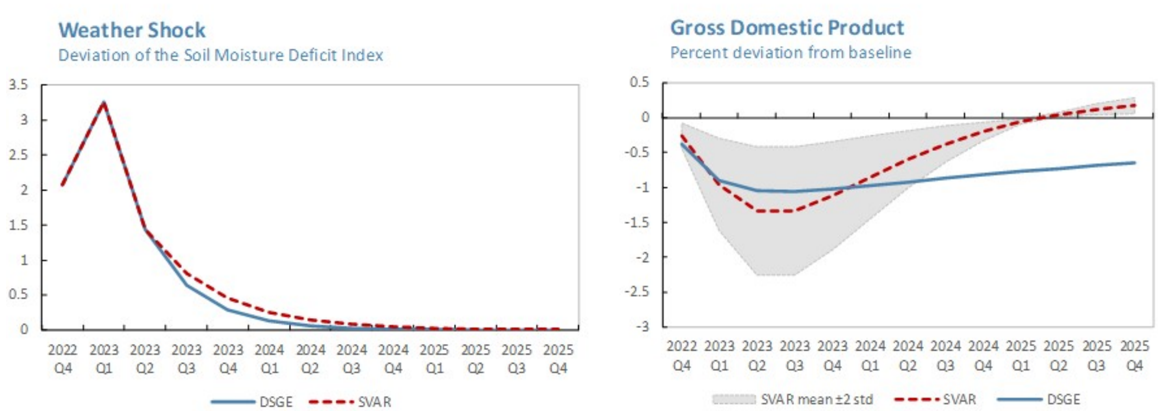
Sources: IMF staff calculations.
Notes: The role of weather shocks on selected variables. All data are demeaned. Blue line and red dashed lines are annual growth rates of selected observable variables. The blue line results of feeding the model with all shocks (i.e., the actual data), while the red dashed line results of feeding the model only with the weather shock. The red line depicts the contribution of the weather shock to the corresponding deviation.

6 The 2022-2023 Drought

To simulate the most recent drought episode faced by Uruguay we utilize the SVAR and DSGE models. We mimic the increase in the Soil Moisture Deficit Index seen between 2022Q4 and 2023Q2, where the SMDI increased to around 2 in 2022Q4 and then peaked above 3 in 2023Q1 before decreasing in 2023Q2 - after 2023Q2 we allow the SMDI to revert to the steady state following its estimated autoregressive component.

The simulated increase in the SMDI, a significant drought, is estimated to provide around a one percent fall in GDP for 2023, driven by losses in agricultural output (primary activity) and investment. According to the Structural VAR model, the impact of the drought should subside in 2024, while the DSGE model shows a longer lasting effect. However, in reality, the normalization of rainfall in the second half of 2023, shown by a fall in the SMDI (see Figure 4), is expected to bolster the primary sector recovery.

Figure 8: Estimated 2022-2023 Drought Impact



Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a weather shock calibrated to mimic the 2022-2023 drought episode in the SVAR and DSGE models. Time series is quarterly. The red dashed line is the Impulse Response Function, the gray band represents the 95% confidence intervals obtained from the SVAR using 10,000 Monte-Carlo simulations. The blue line is the response from the DSGE model. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

7 Conclusion

Uruguay has recently overcome a severe drought, with average rainfall below historical levels, losses in output in the primary sector and a spike in the soil moisture deficit index (derived in this paper). The soil moisture deficit index correlates well with periods of drought and an increase in this weather variable has important economic effects. Through the use of the SVAR and DSGE models we find that droughts impact overall production of the economy through lowering agricultural output (primary activity), consumption and investment. Movements in Uruguay's real exchange rate help to offset losses to the economy and keep agricultural exports competitive, softening the overall impact. Our findings are in the same vein as Gallic and Vermandel (2020) from which the empirical and theoretical framework is used. The novelty of our work derives from the use of their framework, which analyses climate shocks in New Zealand, to analyze the impact on Uruguay. Due to the similarities between New Zealand and Uruguay, their setup is an ideal starting point for our analysis.

Understanding further the impact and transmission mechanism of climate shocks in Uruguay, and in the case of our analysis, droughts in particular, is pertinent to enhance climate adaptation efforts. The role of weather-driven business cycles for countries susceptible to climate shocks is an important research avenue, especially in the context of climate change, which could potentially increase the frequency of climate events and therefore bring greater economic volatility.

A Annex

The Annex details additional information relating to the SVAR and DSGE models. Annex A.1 outlines the estimation of the SVAR and impulse responses when an alternative countrywide SMDI is used instead of the agricultural weighted SMDI. Annex A.2 shows additional DSGE results.

A.1 Additional SVAR Results

The coefficient of the restricted VAR is given below, the estimated A_0 matrix is outlined in Equation 34.

$$\hat{A}_0 X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.12 & 0.04 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0.14 & 0.12 & 0.09 & 1 & 0 & 0 & 0 & 0 \\ 0.13 & 0.12 & 0.11 & 0.06 & 1 & 0 & 0 & 0 \\ 0.16 & 0.10 & 0.01 & 0.08 & 0.11 & 1 & 0 & 0 \\ 0.14 & 0.14 & 0.07 & -0.19 & 0.08 & 0.11 & 1 & 0 \\ 0.13 & 0.12 & 0.09 & 0.13 & 0.21 & 0.16 & 0.10 & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{\omega}_t \\ \hat{y}_t^{\star} \\ \hat{y}_t \\ \hat{y}_t^A \\ \hat{h}_t \\ \hat{c}_t \\ \hat{i}_t \\ r\hat{e}r_t \end{bmatrix} \tag{34}$$

The estimated coefficients of the SVAR are similar to those found by Gallic and Vermandel (2020).

A.1.1 Lag selection

Table 3 outlines the lag selection test that is conducted on the SVAR. Since Hannan–Quinn information criteria and Schwarz Information Criterion show that an SVAR of lag length one is preferred we use this for our analysis. Robustness has been conducted using an SVAR with higher order lags, where the results are robust to this.

Table 3: Lag Selection

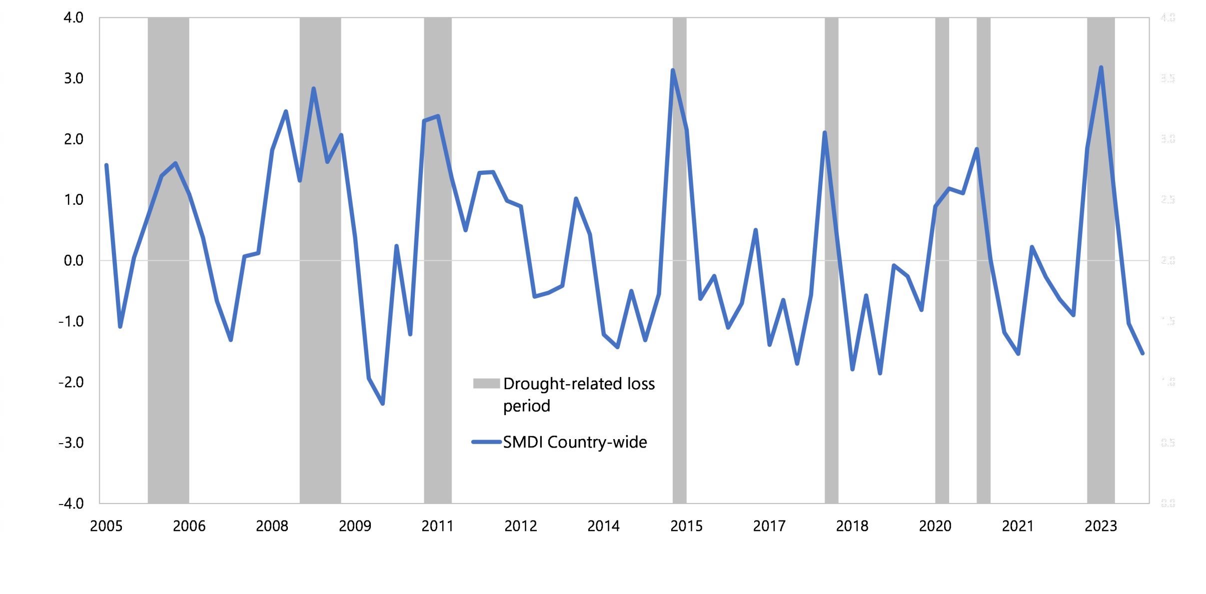
	Number of Lags			
	1	2	3	4
AIC	11.62	11.46	12.07	**11.19**
HQ	**12.55**	13.21	14.64	14.59
SC	**13.95**	15.86	18.55	19.74
FPE	112988.27	**102965.24**	230307.11	143524.80

Sources: IMF staff calculations.
Note: Lag selection of the VAR based on Akaike information criterion (AIC), Hannan–Quinn (HQ) information criteria, Schwarz Information Criterion (SC) and Final Prediction Error Criterion (FPE). Lowest result (better fit) is shown in bold.

A.1.2 SVAR Results using SMDI-Countywide

As well as producing a soil moisture deficit index that focuses on areas of agricultural importance, we construct a soil moisture deficit index for the whole country, which we label as SMDI-Countrywide and is shown in Figure 9. This index is constructed in a similar way to the original SMDI explained in Section 2, however it does not weight the soil moisture deficit of each cell in the spatial-grid by its agricultural importance but rather assigns an equal weight to each cell countrywide. Figure 9 shows that this measure is still able to track periods of drought related losses well as the index reaches its peak (an increase signifies dry conditions) during periods of drought.

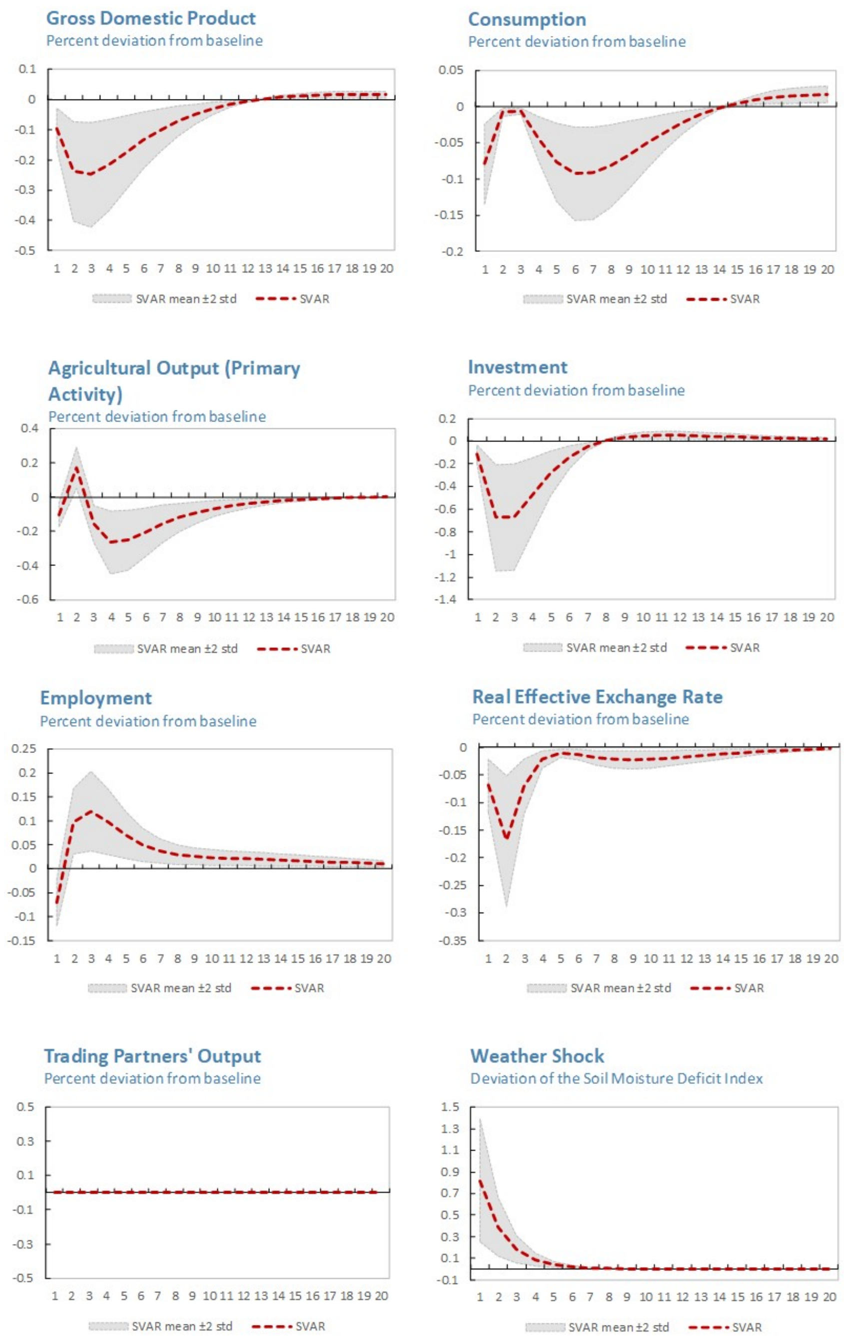
Figure 9: Soil Moisture Deficit Index Countrywide



Sources: INIA-GRAS, OPYPA, and IMF staff calculations.
Notes: Quarterly Soil Moisture Deficit Index is derived from INIA-GRAS data and compared against drought-related loss periods from OPYPA. Positive values signify dry conditions, whereas negative values show periods of wet conditions.

Figure 10 is the result of using this index as our weather variable in the SVAR. The underlying results are robust to the type of soil moisture deficit index used (SMDI or SMDI-Countrywide), as both measures show that droughts negatively impact the economy through losses in primary activity, consumption and investment. In contrast to our baseline results, which use the SMDI (weighting the cells in the grid by agricultural importance), we see a small uptick in primary output in the second quarter following the climate shock and a delayed response of consumption - where on impact consumption falls and then recovers before falling again. These results may be the outcome of how the SMDI-Countrywide is constructed, such that it picks up droughts in other parts of the country, which may not directly negatively impact the agricultural sector. Although the SMDI described in Section 2 is our preferred measure, as it more accurately captures the impact of droughts on areas of agricultural importance, the SMDI-Countrywide measure proves to be robust and requires less granular agricultural data construct.

Figure 10: SVAR Results using an alternative index: SMDI-Countrywide

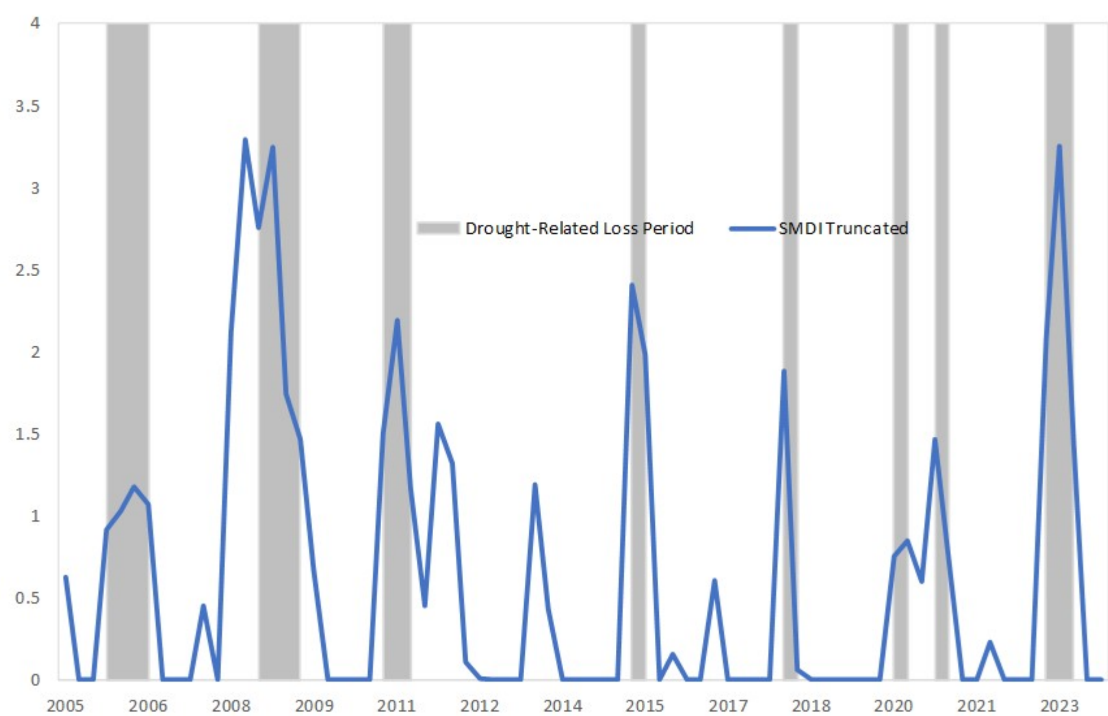


Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a one standard deviation shock to the Countrywide Soil Moisture Deficit Index (weather shock) in the SVAR model using the countrywide climate index (SMDI-Countrywide). Time series is quarterly. The red dashed line is the Impulse Response Function, the gray band represents the 95% confidence intervals obtained from the SVAR using 10,000 Monte-Carlo simulations. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

A.1.3 SVAR Results using truncated SMDI - Positive values only

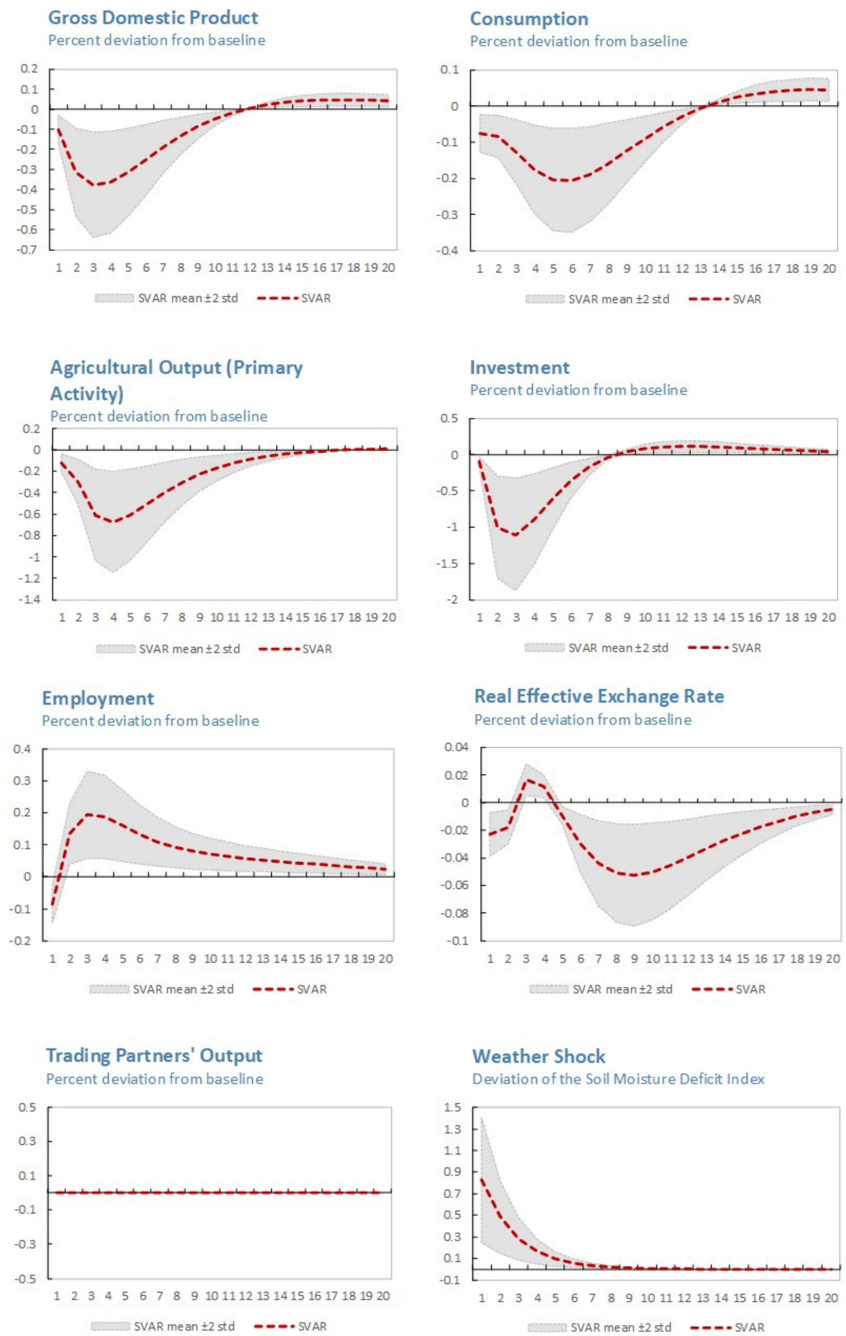
To isolate the impact of droughts on the Uruguayan economy we augment our current SMDI variable such that negative values of the SMDI, which represents periods of excess water, are set to 0. This augmented index can be seen in Figure 11. The results of this in the SVAR can be seen in Figure 12. Notably the impact of a one standard deviation drought shock has a more severe impact on agricultural output, lowering agricultural output by 0.7 percent at the peak compared to 0.3 percent when the baseline index is used.

Figure 11: Truncated Soil Moisture Deficit Index



Sources: INIA-GRAS, OPYPA, and IMF staff calculations.
Notes: Quarterly Soil Moisture Deficit Index is derived from INIA-GRAS data and compared against drought-related loss periods from OPYPA. Series has been truncated to show positive values only, which signify dry conditions.

Figure 12: SVAR Results using a Truncated Soil Moisture Deficit Index

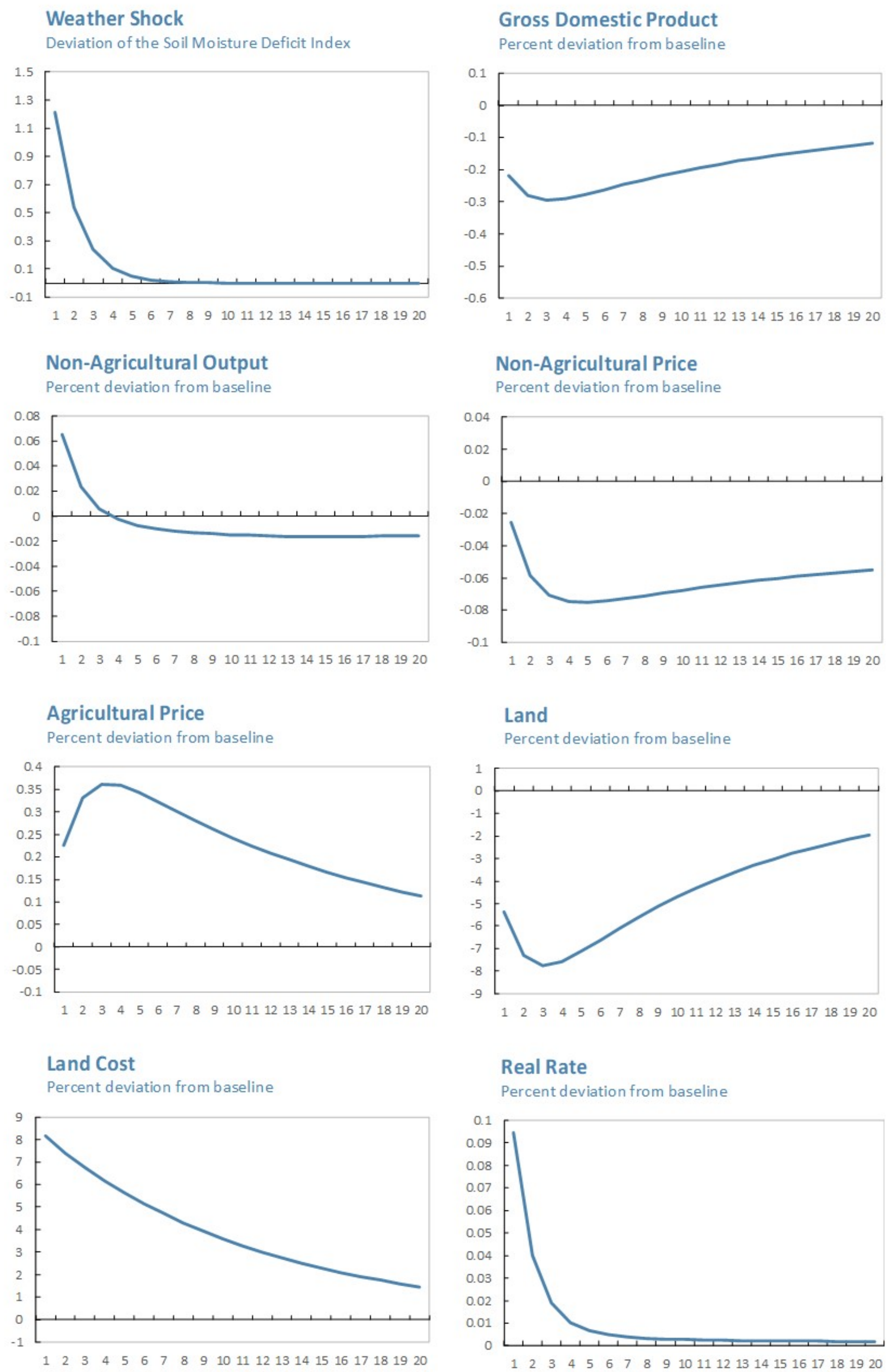


Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a one standard deviation shock to the Truncated Soil Moisture Deficit Index (weather shock) in the SVAR model using the positive SMDI. Time series is quarterly. The red dashed line is the Impulse Response Function, the gray band represents the 95% confidence intervals obtained from the SVAR using 10,000 Monte-Carlo simulations. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

A.2 Additional DSGE Results

Additional results from the DSGE model (shown in Section 4) are displayed below in Figure 13. The one standard deviation increase in the weather shock causes gross domestic product to fall, however part of this decrease is offset by the non-agricultural sector output expanding initially as the sector benefits from the relative price advantage. The non-agricultural price falls following the shock, whilst the agricultural price rises - spurred by lower land efficiency and higher land costs. Falling non-agricultural prices help to fuel foreign demand for non-agricultural goods and boost the non-agricultural domestic production. The weather shock lowers land productivity by close to 10 percent in the model. To compensate for this loss, firms in the agricultural sector use more non-agricultural goods as inputs to reestablish their land productivity (given by a higher land cost x_t). The demand effect for these non-agricultural goods is captured in the model by the rise in x_t, which represents the additional effort to combat the drought through additional use of water or alternative measures.

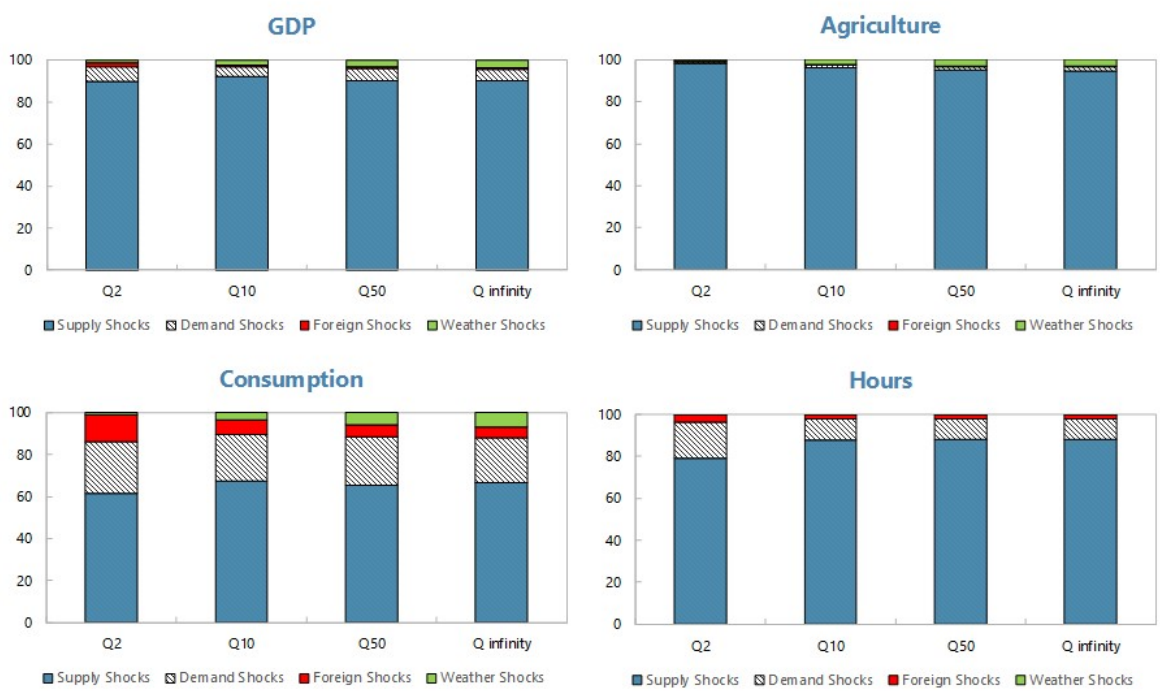
Figure 13: Additional DSGE Model results.



Sources: IMF staff calculations.
Notes: Impact on the Uruguayan economy from a one standard deviation shock to the Soil Moisture Deficit Index (weather shock) in the DSGE model. Time series is quarterly. The blue line is the response from the DSGE model. The time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

To further analyze the shocks that drive the fluctuations of the Uruguayan economy we conduct a variance decomposition exercise. Figure 14 presents the forecast error variance decomposition exercise displays at the posterior mean for different time horizons (one, ten, fifty and unconditional). Notably supply shocks, the combination of technology shock, labour supply shock and sector reallocation shock, explain the majority of movements in GDP, agricultural output, consumption and employment. Notably weather shocks play a role in the movement of GDP and agriculture but play a significantly diminished role compared to the findings of Gallic and Vermandel (2020) for New Zealand. Part of this diminished response could be explained by our sample period, which includes Covid-19, which had a particularly large impact on output, consumption and employment.[18]

Figure 14: Variance Decomposition



Sources: IMF staff calculations.
Notes: Variance decomposition of supply, demand foreign and weather socks from the DSGE estimation.

[18]Further, a small sample size (quarterly data from 2005Q2-2023Q2) may impact the accuracy of the FEVD.

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PUBLICATIONS

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