Asymmetric sectoral responses to weather shocks: An Application to Uruguay *

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Abstract

Climate change has increased the frequency and intensity of droughts in several countries, with significant macroeconomic consequences—particularly in the agricultural sector. Uruguay is one such country that has recently faced adverse weather conditions affecting its productive capacity. This work aims to complement previous studies on the topic in three main areas. First, we document asymmetries in the empirical responses of agricultural sub-sectors to weather shocks. Second, we extend a structural model to account for differences in the transmission of weather shocks across sectors. Third, instead of estimating the model using Bayesian methods, we select key parameters to replicate the impulse response functions obtained from our empirical estimations. Our results highlight important asymmetries and non-monotonic responses in the productive capacity of crops and livestock-dairy sectors following weather shocks in Uruguay.

*The views expressed herein are those of the authors and should not be attributed to the Central Bank of Uruguay, its Executive Board, or its Management.

1 Introduction

Extreme climate events are becoming increasingly frequent, particularly affecting countries like Uruguay, where agricultural production forms the backbone of exports. In this paper, we analyze the short-run macroeconomic effects of drought shocks on the Uruguayan economy. Whereas most of the existing literature focuses on the response of the aggregate agricultural sector, we separate agricultural activities into crop production and livestock and dairy and find notable differences in their responses.

Our results show that the impact on crop production is sharply concentrated within the first two years following a drought shock, while the effects on livestock and dairy production are more persistent, extending up to four years after the initial shock. This persistence is mainly driven by hysteresis effects: droughts can cause cattle deaths, leading to a direct destruction of productive capital and slower recovery in subsequent periods.

To interpret these findings, we build a small open economy model following Gallic and Vermandel (2020), extending it to explicitly separate the two agricultural sub-sectors. We calibrate the model to Uruguayan data and show that incorporating these asymmetric sectoral responses helps match the observed overall behavior of GDP after drought shocks.

In a small open economy like Uruguay, where agricultural production forms a sizable portion of exports, these sectoral dynamics are critical for maintaining macroeconomic stability. Fluctuations in sectoral output directly translate into shifts in the trade balance and the real exchange rate. Specifically, while a collapse in crop exports may trigger an immediate external shock, the more persistent decline in livestock and dairy exports—which reflects the destruction of productive capital—can lead to prolonged periods of currency pressure and reduced national income. Therefore, treating the agricultural sector as a single homogeneous block may lead to an underestimation of the long-term risks to the external balance and the overall timing of economic recovery.

We employ a two-step procedure to analyze these effects. First, we utilize local projections to estimate the response of macroeconomic variables to drought shocks, a method chosen for its ability to handle potential non-linearities in climate impacts. We identify these shocks using the Soil Moisture Deficit Index (SMDI), which we construct by accumulating high-frequency soil water availability data (PAD) provided by the National Institute of Agricultural Research (INIA). This index effectively captures the persistent dry conditions in Uruguay's primary agricultural regions.

Our empirical findings highlight a sharp contrast between aggregate and sectoral dynamics. While aggregate variables like GDP, consumption, and investment show no statistically significant response to average drought conditions, the impact on agricultural sub-sectors is profound. Crop production experiences a sharp, immediate decline of approximately 4% but recovers within a year. In contrast, the livestock and dairy sector faces more moderate initial drops (1.5%) but suffers from persistent losses that accumulate over two years.

To interpret these asymmetries, we develop a small open economy DSGE model featuring sector-specific damage functions and hysteresis effects in land and livestock. This framework allows us to model how the destruction of productive capital, such as cattle deaths, leads to the slower recovery observed in the dairy sector. Distinct from traditional Bayesian approaches, we calibrate our model by matching the impulse response functions generated in our empirical analysis, ensuring the theoretical results align closely with observed Uruguayan data.

The paper is organized as follows. Section 2 presents the estimated impulse response functions of domestic macroeconomic variables to drought shocks. Next, in section 3 we present the structural model and in section 4 we explain the calibration of the parameters. Finally, section 5 concludes.

2 Empirical Evidence

This section presents the main empirical result in this paper that the primary sectors of the economy experience heterogeneous responses after drought shocks. We divide the output of the primary sectors between the production of crops and the production of livestock and diary. The effect on crops is concentrated within the year after the shock, whereas the effect on livestock and dairy is more persistent and lasts beyond the year. We begin by presenting the measure of drought shocks, the Soil Moisture Deficit Index (SMDI). The SMDI is based on measurements of the temperature and humidity at the ground level in geographical areas in Uruguay where primary sector activities are carried out. Next, we include the SMDI in a VAR model to study the disaggregated response of the primary sectors to shocks in this variable.

2.1 Soil Moisture Deficit Index

Following Clevy and Evans (2025), we construct the Soil Moisture Deficit Index based on soil level water availability (PAD[1]) from the Instituto Nacional de Investigación Agrícola (INIA). The PAD is an intra-monthly indicator of the hydrological resources in Uruguay estimated at local levels, covering a national grid. It is the result of a model that factors in precipitations, evaporation, surface runoff, water intake by plants, and other soil properties.

The impact of weather conditions on the crops and livestock and diary sectors is greater when these persist over time. To address this issue, Narasimhan and Srinivasan (2005) propose the methodology to construct the SMDI by accumulating successive observations of the PAD. As Clevy and Evans (2025) show, the SMDI captures well known drought events in Uruguay, correlating with anomalies of crop yields.

To construct the index, we aggregate data over the time dimension to produce a quarterly measure of weather that matches the frequency of macroeconomic indicators. Additionally, we aggregate spatially to generate a single index representative of the key rain-fed regions critical to the agricultural sector. [2] The process begins with calculating the monthly soil water deficit, derived from the daily data averages provided by INIA. For each month t and year i, the soil moisture deficit ($SD_{i,t}$) is computed as outlined in Equation (1). This involves comparing the soil water in each grid for a given month and year to its historical mean for that month (MSW), effectively removing seasonality and providing a standardized measure of soil moisture deficit, as detailed below:

[1] Porcentaje de Agua Disponible in spanish.

[2] Notably, we do not distinguish between the areas where crops or livestock are mainly grown and construct the same index for both sectors. Constructing separate indexes does not significantly affect the results.

$$SD_{i,t} = \begin{cases} \frac{SW_{i,t}-MSW_t}{MSW_t-minSW_t} \times 100 & \text{, if } SW_{i,t} \leq MSW_t \\ \frac{SW_{i,t}-MSW_t}{maxSW_t-MSW_t} \times 100 & \text{, if } SW_{i,t} \geq MSW_t \end{cases} \tag{1}$$

The soil water deficit is then accumulated to capture the drought severity into a singular index, the soil moisture deficit index following equation 2. In any given time period the SMDI will range from -4 to +4 representing wet to dry conditions. 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).[3]

$$SMDI_t = \frac{\sum_{i=1}^{t} SD_i}{25t + 25} \tag{2}$$

Figure 1 shows the evolution over time of the constructed SMDI. The shaded areas in the graph denote periods of large agricultural output losses due to droughts.[4] The SMDI is able to identify almost all of the episodes as they coincide with relatively large values of the index.

[3] We refer the reader to Clevy and Evans (2025) for further details on the construction of the index and other properties such us the correlation with known drought events and crop yield anomalies.

[4] These episodes are identified by the ministry of agriculture, livestock and fishing (MGAP)

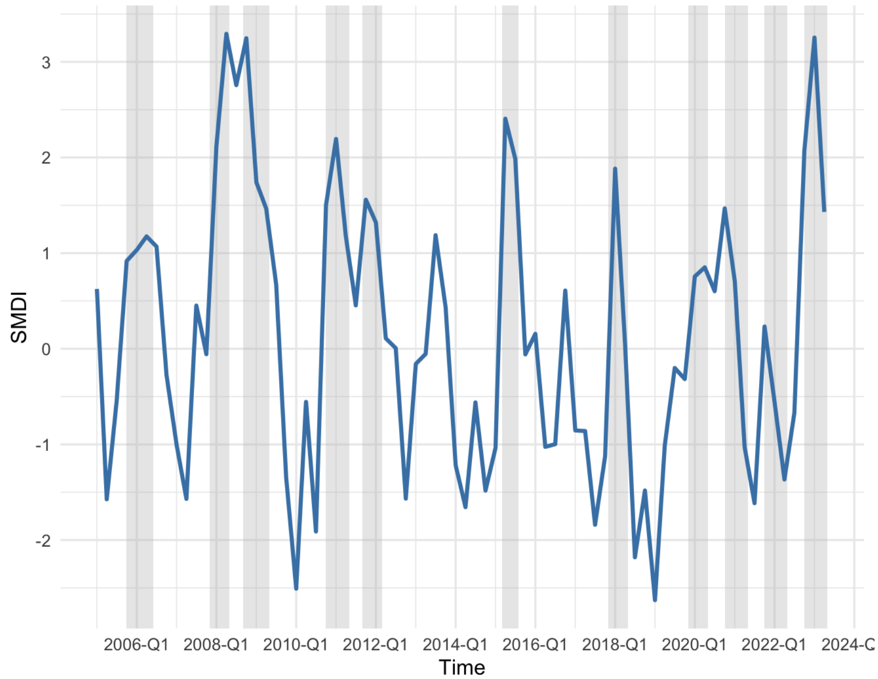

Figure 1: Soil Moisture Deficit Index over time

2.2 Data Preparation

Our baseline dataset consists of quarterly macroeconomic and financial series for Uruguay over the period 2005Q1–2024Q4, drawn from standard official sources (national accounts, price indices, labor market statistics and external sector indicators), complemented with a measure of global activity (trade–partner GDP) and domestic financial variables (policy rate, nominal exchange rate, sovereign spread, among others). With the exception of interest rates, spreads and index variables that are already in rates or deviations, all real and nominal macroeconomic aggregates are expressed in natural logarithms prior to the empirical analysis.

To remove systematic seasonal patterns, we apply standard seasonal adjustment to all logged macroeconomic series used in the local projections. In particular, each quarterly series is seasonally adjusted using the X–13–ARIMA–SEATS filter, yielding seasonally adjusted log series for total GDP, crop GDP, livestock and dairy GDP, private consumption, investment, employment, the real effective exchange rate, trade–partner GDP and the relevant price indices.

2.3 Local Projections Methodology

To quantify the dynamic effects of drought shocks on Uruguayan macroeconomic variables we estimate impulse response functions using the local projection (LP) approach of Jordà (2005). For each variable of interest we run a sequence of horizon–by–horizon regressions, specifying the dependent variable as a cumulative change so that the resulting coefficients can be directly interpreted as cumulative impulse responses.

2.3.1 Construction of the drought shock

Let S_t denote the quarterly Soil Moisture Deficit Index (SMDI), aggregated over the main agricultural regions. We first filter out the predictable component of S_t by fitting a univariate AR(1) model,

$$S_t = \rho S_{t-1} + u_t, \tag{3}$$

and define the innovation

$$\tilde{u}_t = S_t - \hat{\rho} S_{t-1}, \tag{4}$$

as the raw drought shock. For ease of interpretation we rescale this innovation so that a shock of size one corresponds to a one–standard–deviation event,

$$\varepsilon_t = \frac{\tilde{u}_t - \bar{\tilde{u}}}{\hat{\sigma}_{\tilde{u}}}, \tag{5}$$

where $\bar{\tilde{u}}$ and $\hat{\sigma}_{\tilde{u}}$ denote the sample mean and standard deviation of $\tilde{u}_t$, respectively. We also flip the sign of the index so that a positive value of ε_t corresponds to *more severe drought conditions* (lower soil moisture), which makes the interpretation of the estimated responses more transparent.

2.3.2 Baseline regression specification

Let $y_{j,t}$ denote the (log) value of macroeconomic variable j at quarter t (for instance, total GDP, crop GDP, livestock and dairy GDP, consumption, investment, employment, or the real exchange rate). We are interested in the effect of a drought shock at time t on the level of y_j in future periods. To obtain a measure of cumulative effects, we follow Jordà (2005) and Li et al. (2024) and specify the dependent variable as the change in y_j between $t-1$ and $t+h$:

$$\Delta^{(h)} y_{j,t} \equiv y_{j,t+h} - y_{j,t-1}, \qquad h = 0, 1, \ldots, H. \tag{6}$$

For each horizon h and each variable j we estimate the regression

$$\Delta^{(h)} y_{j,t} = \beta_{j,h}\, \varepsilon_t + \boldsymbol{\gamma}'_{j,h} \mathbf{Z}_{t-1} + \boldsymbol{\delta}'_{j,h} \mathbf{D}_t + u^{(h)}_{j,t+h}, \tag{7}$$

where:

- ε_t is the standardized drought shock defined above.
- $\mathbf{Z}_{t-1}$ is a vector collecting P lags of first differences of (i) the variable of interest $y_{j,t}$ and (ii) a small set of macro controls, in our case aggregate domestic and foreign GDP and the drought index itself. This corresponds to including $\Delta y_{j,t-\ell}$, $\Delta \mathrm{GDP}_{t-\ell}$, $\Delta \mathrm{GDP}^*_{t-\ell}$ and $\Delta S_{t-\ell}$ for $\ell = 1, \ldots, P$ as right–hand–side controls.[5]
- $\mathbf{D}_t$ is a vector of contemporaneous dummy variables that control for extraordinary events, most notably the COVID–19 pandemic.
- $u^{(h)}_{j,t+h}$ is an error term capturing all remaining shocks at horizon h.

Equation (7) is estimated by ordinary least squares separately for each horizon $h = 0, \ldots, H$. Given that the dependent variable $\Delta^{(h)} y_{j,t}$ is defined over overlapping horizons (for $h > 0$), the regression residuals exhibit serial correlation and heteroskedasticity. To obtain valid inference we compute heteroskedasticity– and autocorrelation–robust standard errors using the Newey–West estimator, with the truncation lag chosen as a function of the horizon and the number of included lags.

2.3.3 Identification and interpretation

The coefficient $\beta_{j,h}$ in (7) is the parameter of interest. Under the identifying assumption that, conditional on the controls $\mathbf{Z}_{t-1}$ and $\mathbf{D}_t$, the standardized shock ε_t is exogenous with respect to the error term $u^{(h)}_{j,t+h}$,

$$\mathbb{E}\left[\varepsilon_t\, u^{(h)}_{j,t+h} \,\middle|\, \mathbf{Z}_{t-1}, \mathbf{D}_t \right] = 0, \tag{8}$$

[5]In the implementation we set $P = 3$.

$\beta_{j,h}$ identifies the causal effect of a one–standard–deviation drought innovation on the cumulative change in y_j between $t-1$ and $t+h$. It can be read as the *cumulative percentage change* in Y_j between $t-1$ and $t+h$ induced by a one–standard–deviation drought shock at time t.

This exogeneity assumption is justified by the physical nature of the shock: droughts are driven by weather and climate dynamics that are plausibly orthogonal to short–run fluctuations in domestic macroeconomic activity. Moreover, by extracting innovations from an AR(1) model for the drought index we remove predictable components of S_t that could be correlated with macroeconomic variables, and by including lags of $\Delta y_{j,t}$, ΔGDP_t and ΔS_t we further control for local dynamics and potential feedback effects.

Collecting the sequence $\{\hat{\beta}_{j,h}\}_{h=0}^{H}$ for each variable j yields the cumulative impulse response function of that variable to an adverse drought shock, which we report together with pointwise confidence bands constructed from the Newey–West standard errors.

2.4 Estimated Impulse Responses after a Weather Shock

Figure 9 shows the responses of output, consumption, employment, investment, real exchange rate and the SMDI. The response of SMDI shows the Niño-Niña cyclical pattern in weather conditions, moving from dryer to more humid soils, with a frequency of around 3 years. The macro variables shown in Figure 9 show mostly non-significant responses and where significant they are economically small responses. Output, investment and consumption show no statistically significant effects, employment falls after 8 quarters by 0.5% and the real exchange rate rises by 1% after 8 quarters. Note that the results show the average responses of these variables after 'regular' drought conditions and not extreme episodes such as the one of 2023-2024.[6]

[6] These results stand in constrast to what Clevy and Evans (2025) report. We find little to no significant effects on most aggregate variables, lower persistence of the effects and opposite reactions in the real exchange rate and employment. We have several differences with their analysis. To begin with, we do not use Hodrick-Prescott filter to extract the cycle component of the variables, we seasonally adjust variables and work with long differences. Second and perhaps most notably, we employ local projections instead of a structural VAR. We prefer the estimations produced by local projections because it does not impose any structure to the impulse response function whereas the VAR model does. Moreover, as Li et al. (2024) explain, this implies

Figure 2: Response of Macroeconomic Variables

Figure 3 shows the response of the Crop and Livestock and Dairy sectoral value added. The response reflects the main empirical result of the paper, Crops are affected negatively throughout the year after the shock, but this effect disappears quickly after 4 quarters. On the other hand, Livestock and Dairy show negative effects that accumulate over 2 years after the shock. The drop in crop's value added is pointly estimated at 4%, larger than the estimated peak fall of 1.5% in Livestock and Dairy.

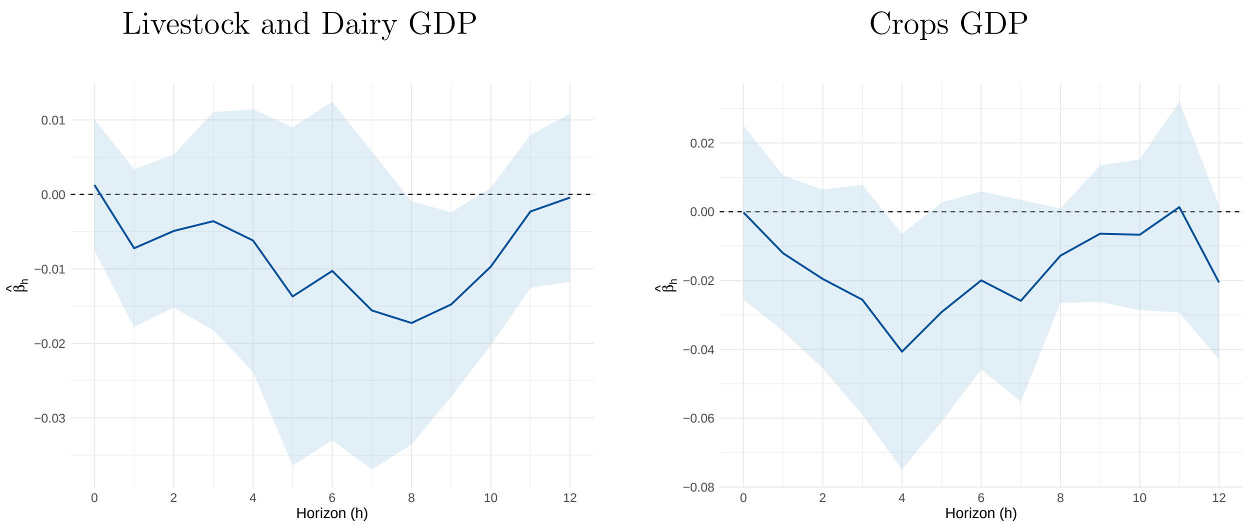

Figure 3: Response of Sectoral Value Added

The empirical evidence suggests that the impact of a drought extends well beyond primary farm activities, propagating through the domestic manufacturing chain. As illustrated by the responses of tightly linked industries (Figure 4), the contraction in livestock and crop production is mirrored by the sectors that utilize them as primary inputs, such as animal slaughter, milk derivatives, and grain mills. Notably, the response of animal slaughter follows the persistent trajectory of the livestock sector, with losses accumulating through the second year after the shock. This confirms that the drought triggers a systemic disruption in the industrial processing value chain, where the destruction of biological capital at the farm level leads to a prolonged reduction in industrial output.

that local projections are an unbiased estimator in contexts where the true model is not linear, which is a natural thing to consider with drought shocks.

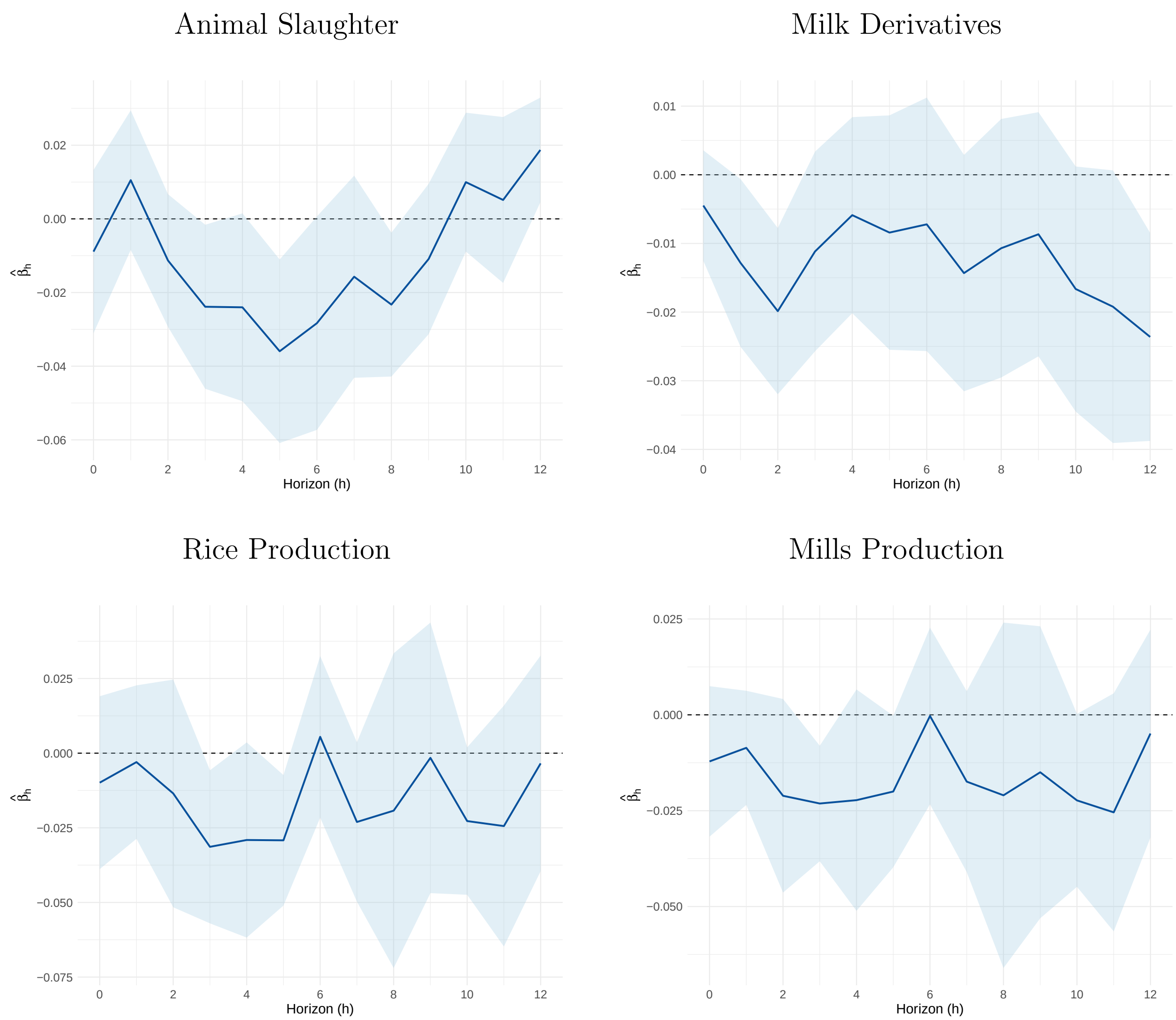

Figure 4: Output response of tightly linked manufacturing sectors

Beyond production volumes, these sectoral asymmetries are fundamentally reflected in Uruguay's trade profile and price dynamics (see Appendices A.1 and A.2). Total exports experience a significant contraction during the second year, driven by the divergent timelines of agricultural commodities. While soy exports collapse by an accumulated 50% within the first year, the drop in meat and dairy exports is more persistent, matching the multi-year decline seen in livestock production. These findings—combined with the observed increase in the prices of meat and milk derivatives during the second year—support the main thesis of this paper: that drought shocks in Uruguay are characterized by heterogeneous sectoral dynamics that mask different risks to macroeconomic stability. Specifically, for a small open economy, the 'crop shock' presents an immediate external balance challenge, whereas the 'livestock shock' represents a more enduring erosion of export capacity

3 Structural model

Our theoretical model is based on the work of Gallic and Vermandel (2020), who developed and estimated a DSGE model with weather shocks for New Zealand. Our model is also closely related to Clevy and Evans (2025), who applied the framework in Gallic and Vermandel (2020) to the case of Uruguay. In contrast to these studies, we decompose the agricultural sector into two sub-sectors to analyze the differing reactions of livestock and dairy and crop production to weather shocks.

As in Clevy and Evans (2025), we focus on Uruguay. In contrast to Clevy and Evans (2025), we extend their modelling approach to consider two different agricultural subsectors that could be affected differently by weather shocks. In fact, expert judgment and the results shown in the previous section suggest that the propagation of humidity deficits could lead to different production strategies in the distinctive agricultural sub-sectors to mitigate the adverse effects of such shocks. To account for these different responses over time, we also extend the damage functions considered by Gallic and Vermandel (2020) to capture more detailed dynamics in terms of investment and production decisions within the agricultural sector.

The model represents a three-sector, three-good economy within a small open economy framework, under a flexible exchange rate regime. The home economy consists of households and firms, with the latter operating in both the agricultural and non-agricultural sectors. Workers in the agricultural sectors are exposed to unexpected weather conditions that influence the productivity of their land used for production. Households consume both domestic and foreign goods, creating a trade channel that is influenced by the movement in the real exchange rate.

Our small open-economy framework includes two countries. The home country engages in international trade but is too small relative to its trading partners to cause aggregate fluctuations in world output, prices, or interest rates. The foreign country, which represents the majority of the home country's trading partners, is unaffected by domestic macroeconomic shocks. However, foreign macroeconomic developments influence the home country through the trade balance and exchange rate. The remainder of this section outlines the main components of the model.

3.1 Agricultural sector

The economy is populated by a unit mass of infinitely living, atomistic entrepreneurs, each denoted by $i \in [0,1]$. A fraction n_t of these entrepreneurs operate in the agricultural sector, while the remaining fraction $1-n_t$ operates in the non-agricultural sector. The fraction n_t of entrepreneurs operating in the agricultural sector is referred to as farmers. The agricultural sector is subdivided into the crops and livestock and diary sub-sectors.

Entrepreneurs switch between sectors exogenously. The fraction of agricultural entrepreneurs (*farmers*) is subject to an exogenous shock: $n_t = n \times \varepsilon_{n,t}$, where $\epsilon_{n,t}$ follows a stochastic AR (1) process given by:

$$\log(\varepsilon_{n,t}) = \rho_n \log(\varepsilon_{n,t-1}) + \sigma_n \eta_{n,t} \tag{9}$$

Within the agricultural sector, a fraction $n_{1,t}$ of the entrepreneurs operate in the crops sub-sector, while the remaining fraction $1 - n_{1,t}$ operates in the livestock and diary sub-sector. Consequently, the total mass of entrepreneurs producing crops and livestock and dairy are, respectively, $n_t n_{1,t}$ and $n_t(1-n_{1,t})$. We assume that the faction $n_{1,t}$ follows an AR(1) process:

$$\log(n_{1,t}) = (1-\rho_{n_1})\log(n_1) + \rho_{n_1}\log(n_{1,t-1}) + \sigma_{n_1}\eta_{n_1,t}, \tag{10}$$

In the last two equations, $\eta_{n,t}$ and $\eta_{n_1,t} \sim \mathcal{N}(0,1)$ and $0 \leq \rho_n,\rho_{n_1} \leq 1$. Production in each agricultural sub-sector requires land, labor, and physical capital as inputs. A common practice in agricultural economics is to explicitly model the input-output relationship by specifying a functional form for agricultural production technology.[7] Consistent with this approach, we assume that agricultural output of each farmer in sub-sector $j = A_1, A_2$ fol-

[7]See Chavas et al. (2010) for a survey on the development of theoretical models in agricultural economics over the past century.

lows a Cobb-Douglas production function, incorporating land, physical capital, and labor as inputs:[8]

$$y_{jt} = (\xi_{j,t}\ell_{j,t-1})^{\omega_j} \left(\varepsilon_t^Z (k_{jt-1})^{\gamma_j} (\kappa_j h_{jt}^d)^{1-\gamma_j}\right)^{1-\omega_j} \tag{11}$$

where y_{jt} is the production output of each farmer in the agricultural sub-sector j that combines an amount of land ℓ_{jt-1}, the productivity of the land $\xi_{j,t}$, physical capital k_{jt-1} and labor demand h_{jt}^d. In the agricultural sub-sector j, the parameter $\omega_j \in [0,\, 1]$ is the elasticity of output to land, $\gamma_j \in [0, 1]$ denotes the share of physical capital in the production, and $\kappa_j > 0$ is a technology parameter endogenously determined in the steady state.[9]

Production in each agricultural sub-sector is subject to two shocks. First, an economy-wide technology shock ε_t^Z following an AR(1) process and affecting symmetrically all sectors. Second, a weather shock ε_t^S that affects the productivity of the land, $\xi_{j,t}$. The weather shock, ε_t^S, captures variations in soil moisture that affect the production process in the agricultural sectors. To remain consistent with empirical evidence in section 2, we assume that the weather condition has the following stochastic process:

$$\log\left(\varepsilon_t^S\right) = \sum_{j=0}^{Q} \sigma_{S,j}\eta_{t-j}^S, \quad \eta_t^S \sim \mathcal{N}(0,1), \tag{12}$$

where $\sigma_{S,j}$ represents the estimated effect on the soil moisture conditions after j periods. In the model, soil moisture process has an unconditional mean normalized to one in the steady state, so that a positive realization of η_t^S has a dynamic effect on soil moisture deficit governed by $\sigma_{S,0}, \sigma_{S,1}, \ldots, \sigma_{S,Q}$. The stochastic nature of the model means that farmers are surprised by both contemporaneous and future weather shocks. We do not consider the perspective of news shocks related to the weather, but the potential lagged effects of weather shocks on

[8]Among the various possible functional forms, the Cobb-Douglas production function has gained popularity in this field. For further discussion on related conceptual issues and empirical applications of agricultural production functional forms, see Mundlak (2001) and the seminal work of Mundlak (1961).

[9]This parameter has the same interpretation as Restuccia et al. (2008): as long as $\kappa_j > 1$, the productivity of land in the agricultural sector is below the productivity of non-agricultural firms. Since capital and labor are perfectly mobile in the deterministic steady, κ_j allows marginal products of physical capital and labor to be equal across sectors.

land productivity could generate anticipated effects that influence production decisions in the agricultural sector.

Formally, the effect of weather shocks on the productivity of land is modelled through a damage function that depend on current and past weather conditions:

$$\xi_{j,t} = \left(\varepsilon_t^S\right)^{-\theta_{j0}} \left(\varepsilon_{t-1}^S\right)^{-\theta_{j1}} \left(\varepsilon_{t-2}^S\right)^{-\theta_{j2}} \left(\varepsilon_{t-3}^S\right)^{-\theta_{j3}} \tag{13}$$

where parameters θ_{j0}, θ_{j1}, θ_{j2}, and θ_{j3} determine elasticities of land productivity with respect to the realizations of the weather shock in the recent periods (ε_t^S). Imposing that these parameters are zero shuts down the propagation of weather-driven business cycles on the land productivity, $\xi_{j,t}$. This damage function in (13) is consistent with the Integrated Assessment Models literature pioneered by Nordhaus (1991), which assumes that weather conditions affect the productivity of the economy.[10]

The empirical findings in Section 2—which show a sharp, temporary contraction in crops versus a moderate but persistent decline in livestock—suggest that weather shocks propagate through different mechanisms in each sub-sector. To interpret these results within our structural framework, we introduce sector-specific land damage functions (Equation 15) and a time-varying law of motion for land (Equation 14). These modeling choices allow us to capture the atypical supply dynamics that characterize agricultural production. The specification of these functions is grounded in the following biological and environmental evidence regarding sectoral hysteresis:

Livestock and Dairy Hysteresis: Beyond the immediate impact of a drought, the livestock sector is subject to 'weather hysteresis effects' driven by biological cycles. As documented by Rosen et al. (1994), the persistence of livestock dynamics is tied to the lengthy gestation and maturation processes of dairy cattle. Severe droughts often force the

[10]The literature on IAMs traditionally connects temperatures to output through a simple quadratic damage function in order to provide an estimation of future costs of carbon emissions on output. However, Pindyck (2017) raised important concerns about the outcome based on IAM, as modelers have so much freedom to choose a functional form as well as the values of the parameters so that the model can be used to provide any result desired. To avoid the legitimate criticisms inherent to IAMs, our model is solved up to a first approximation to the policy function. This does not allow us to exploit the non-linearities of the damage function which critically drives the results of IAM literature through a quadratic term in the damage function.

early liquidation of stocks and cause a drop in fertility rates, leading to a direct destruction of productive capital that requires years to rebuild. Consequently, while slaughter rates may rise temporarily during a drought, production remains depressed for several subsequent years as farmers work to restore stock levels.[11] As documented in Section 2, the response of animal slaughter closely mimics that of Livestock and Dairy GDP indicating that the drought is not merely a localized 'farm' problem but an industrial-wide disruption that propagates through the entire processing value chain of the Uruguayan economy.

Crop and Soil Dynamics: Hysteresis in the crop sector stems from both environmental and physiological factors. Soil moisture deficits exhibit a natural persistence, lands often require several months of average rainfall to recover their standard productivity levels. Furthermore, the crop growth process is highly sensitive to the timing of the shock. A drought occurring during a critical stage, such as pollination (Hane and Pumphrey, 1984), can result in a total loss of the final harvest, even if weather conditions improve later in the season. These mechanisms create a significant temporal gap between the initial drought and the eventual recovery of output.

$$\ell_{\mathrm{jt}} = \left[(1-\delta_\ell) + v_j\left(x_{jt}\right)\right]\chi_{j,t}\ell_{jt-1} \tag{14}$$

where $\delta_\ell \in (0,1)$ is the rate of decay of land that features the desired persistence effect and $\chi_{j,t}$ corresponds to the hysteresis effects of weather condition in the evolution of land used for production. At the same time, we assume that the marginal product of land is increasing in the accumulation of land. This is captured by assuming that land expenditures x_{jt} yield a gross output of new productive land $v_j\left(x_{jt}\right)\ell_{jt-1}$ with $v_j'(\cdot) > 0, v_j''(\cdot) \geq 0$. More specifically, x_{jt} can be viewed as agricultural spending on pesticides, herbicides, seeds, fertilizers, and water used to maintain farmland productivity. [12] In presence of an adverse weather shock, the farmer can optimally offset the soil dryness by increasing field irrigation or the feeding budget, as the feed rationing of cattle is based on the use of local forage produced by country

[11] See Kamber et al. (2013).

[12] Cropping costs consist of charges for fertilizers, seeds and chemicals; for pasture, these costs concern fence and watering equipment; while for animal production costs, these include purchased feed and bedding as well as medical costs

pastures. There is yet no micro-evidence about the functional form of land costs $v_j(x_{jt})$, so we adopt here a conservative approach by imposing the functional form: $v_j(x_{it}) = \frac{\tau_j}{\phi_j} x_{jt}^{\phi_j}$ where $\tau_j \geq 0$ and $\phi_j \geq 0$. For $\phi_j \to 1$, land productivity exhibits constant returns to scale, while for $\phi_j > 1$ land costs exhibits increasing returns to scale. The parameter τ_j allows to calibrate the steady state share of per capita land in each agricultural sub-sector. The hysteresis effect of weather conditions is also capture by a damage function given by:

$$\chi_{j,t} = \left(\varepsilon_t^S\right)^{-\vartheta_{j0}} \left(\varepsilon_{t-1}^S\right)^{-\vartheta_{j1}} \left(\varepsilon_{t-2}^S\right)^{-\vartheta_{j2}} \left(\varepsilon_{t-3}^S\right)^{-\vartheta_{j3}} \tag{15}$$

where parameters ϑ_{j0}, ϑ_{j0}, ϑ_{j0}, and ϑ_{j0} control the magnitude of the hysteresis effects of recent weather conditions on the effective land used in production.

The law of motion of physical capital in the agricultural sector $j = A_1, A_2$ is given by:

$$i_{jt} = k_{jt} - (1 - \delta_K) k_{jt-1}, \tag{16}$$

where $\delta_K \in [0,1]$ is the depreciation rate of physical capital and i_{jt} is investment of the representative farmer in sub-sector j. Real profits d_{jt} of each farmer in sub-sector $j = A_1, A_2$ are given by:

$$d_{jt} = p_{jt} y_{jt} - p_t^N \left(i_{jt} + S\left(\varepsilon_t^i \frac{i_{jt}}{i_{jt-1}} \right) i_{jt-1} \right) - w_{jt} h_{jt} - p_{Nt} x_{jt}, \tag{17}$$

where $p_{jt} = P_{jt}/P_t$ is the relative price of agricultural goods in sub-sector j, $p_{Nt} = P_{Nt}/P_t$ is the relative price of non-agricultural goods, w_{jt} is the real wage rate in sub-sector j, the function $S(x) = 0.5\kappa(x-1)^2$ is the convex cost function as in Christiano et al. (2005) which features a hump-shaped response of investment consistently with VAR models, and ε_t^i represents an investment specific shock. This last shock follows an $AR(1)$ shock process:

$$\log\left(\varepsilon_t^I\right) = \rho_I \log\left(\varepsilon_{t-1}^I\right) + \sigma_I \eta_t^I, \tag{18}$$

where $\rho_I \in [0,1)$ determines the persistence of the $AR(1)$ process, and $\sigma_I \geq 0$ the standard deviation of the innovations. Farmers in each sub-sector $j = A_1, A_2$ are price takers. The profit maximization they face can be cast as choosing the input levels subject to the land and capital evolution as well as the specified production function:

$$\begin{aligned} &\max_{\left\{h_{jt}^d, i_{jt}, k_{jt}, \ell_{jt}, x_{jt}\right\}} \quad E_t \left\{ \textstyle\sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} d_{jt+\tau} \right\} \\ &\text{s.t.}(11)(14), (16) \end{aligned} \tag{19}$$

where E_t denotes the expectation operator and $\Lambda_{t,t+\tau}$ is the household stochastic discount factor between periods t and $t+\tau$. The optimal conditions for this maximization determine the demand for all inputs used in production. One interesting condition yields an optimal demand for intermediate expenditures given by equation (20):

$$\frac{p_{Nt}}{v_j'\left(x_{jt}\right)\ell_{\mathrm{jt-1}}\chi_{j,t}} = E_{\mathrm{t}}\left\{\Lambda_{t,t+1}\left(\omega_j\frac{y_{jt+1}}{\ell_{\mathrm{jt}}}+\frac{p_{Nt+1}}{v_j'\left(x_{jt+1}\right)\ell_{jt}}\left[\left(1-\delta_\ell\right)+v_j\left(x_{jt+1}\right)\right]\right)\right\} \tag{20}$$

The left-hand side of equation (20) captures the current marginal cost of land maintenance, while the right-hand side corresponds to the sum of the marginal product of land productivity with the value of land in the next period in each sub-sector j. First, a weather shock deteriorates the expected marginal benefit of lands through a reduction in the expected value of $y_{j,t+1}/\ell_{j,t+1}$). Second, a weather shock also rises the current cost of land maintenance due a fall in $\chi_{j,t}$. Importantly, the shape of the cost function $v\left(x_{jt}\right)$ critically determines the response of agricultural production following a drought shock. A concave cost function, i.e., $v''\left(x_{jt}\right)<0$, would generate a negative response of land expenditures and a decline in the relative price of agricultural goods, which would be inconsistent with the VAR model. Therefore, a linear or convex cost function with $\phi_j \geq 1$ is preferred to feature an increase in spending x_{jt} in sub-sector j following an adverse weather shock. A second reason motivating increasing returns is the stability of land productivity dynamics: if a farmer decreases her land maintenance expenditures when land productivity is already low, this further deteriorates land productivity to reach zero.

3.2 Households

There is a continuum of unit mass of identical households that consume, save and work in the production sectors. The representative household maximizes the expected sum of utilities discounted by $\beta \in [0,1)$:

$$E_t\sum_{\tau=t}^{\infty}\beta^\tau\left[\frac{1}{1-\sigma}\left(C_\tau-b\mathcal{H}_\tau\right)^{1-\sigma}-\frac{\chi\varepsilon_{t+\tau}^h}{1+\sigma_h}h_{t+\tau}^{1+\sigma_h}\right] \tag{21}$$

where the variable C_t is consumption, $b \in [0,1)$ is a parameter that accounts for external habit in consumption. The representative household takes as given the external habit, but in equilibrium it is equal to the past level of consumption, $\mathcal{H}_\tau = C_{\tau-1}$. h_t is a labor effort index for the production sectors, and $\sigma > 0$ and $\sigma_h > 0$ represent the coefficient of relative risk aversion and the inverse of the Frisch labor supply, respectively. Labor supply is affected by an AR(1) shock ε_t^h. The labor disutility parameter $\chi > 0$ determines the steady state of hours worked.

Following Horvath (2000), labor supply is imperfectly substitutable across sectors by defining a CES labor disutility index:

$$h_t = \left[(h_{Nt})^{1+\iota} + (h_{A_1t})^{1+\iota} + (h_{A_2t})^{1+\iota}\right]^{1/(1+\iota)}. \tag{22}$$

The labor disutility index consists of hours worked in the non-agricultural sector h_{Nt}^N, and in the two agriculture sub-sectors h_{A_1t} and h_{A_2t}. Reallocating labor across sectors is costly and is governed by the substitutability parameter $\iota \geq 0$. Positive values of ι capture some degree of sector specificity and imply that relative hours respond less to sectoral wage differentials.

Expressed in real terms and dividing by the consumption price index P_t, the budget constraint for the representative household can be represented as:

$$\sum_{s=N,A_1,A_2} w_{st}h_{st} + r_{t-1}b_{t-1} + rer_t r_{t-1}^* b_{t-1}^* - T_t \geq C_t + b_t + rer_t b_t^* + p_{Nt} rer_t \Phi\left(b_t^*\right) \tag{23}$$

The income of the representative household is made up of labor income with a real wage w_{st} in each sector s, real risk-free domestic bonds b_t, and foreign bonds b_t^*. Domestic and foreign bonds are remunerated at a domestic rate r_{t-1} and a foreign rate r_{t-1}^*, respectively. Household's foreign bond are denominated in foreign currency so that to express returns in domestic currency they have to be multiplied by the real exchange rate rer_t. The real exchange rate is computed from the nominal exchange rate e_t adjusted by the ratio between foreign and home price, $rer_t = e_t P_t^*/P_t$, where P_t^* is the foreign price level. In addition, the government charges lump sum taxes, denoted T_t. The household's expenditure side includes its consumption basket C_t, bonds and risk-premium cost $\Phi\left(b_t^*\right) = 0.5\varrho_B \left(b_t^*\right)^2$ paid in terms of domestic non-agricultural goods. The parameter $\varrho_B > 0$ denotes the magnitude of the cost paid by domestic households when purchasing foreign bonds, and usually is calibrated close to zero to induce stationarity in the model dynamics.[13]

We now discuss the allocation of consumption among the different types of goods produced either domestically or abroad. First, the representative household allocates total consumption C_t between two types of consumption goods produced by the non-agricultural and agricultural sectors denoted C_{Nt} and C_{At}, respectively. The CES consumption bundle is determined by:

$$C_t = \left[(1-\varphi)^{\frac{1}{\mu_{NA}}} \left(C_{Nt}\right)^{\frac{\mu_{NA}-1}{\mu_{NA}}} + (\varphi)^{\frac{1}{\mu_{NA}}} \left(C_{At}\right)^{\frac{\mu_{NA}-1}{\mu_{NA}}}\right]^{\frac{\mu_{NA}}{\mu_{NA}-1}}, \tag{24}$$

where $\mu_{NA} \geq 0$ denotes the substitution elasticity between the two types of consumption goods, and $\varphi \in [0,1]$ is the fraction of agricultural goods in the total consumption basket of the household. Second, consumption in agricultural goods is also a CES combination of the two types of products:

$$C_{At} = \left[(1-\varphi_A)^{\frac{1}{\mu_A}} \left(C_{A_1 t}\right)^{\frac{\mu_A-1}{\mu_A}} + (\varphi_A)^{\frac{1}{\mu_A}} \left(C_{A_2 t}\right)^{\frac{\mu_A-1}{\mu_A}}\right]^{\frac{\mu_A}{\mu_A-1}}. \tag{25}$$

In the last expression, μ_A is the elasticity of substitution between agricultural goods A_1 and A_2, while φ_A determines the share in consumption of goods A_2 in the total spending in agricultural goods. Third, the consumption in C_{Nt}, $C_{A_1 t}$, and $C_{A_2 t}$ are composite of goods produced domestically and abroad:

$$C_{st} = \left[(1-\alpha_s)^{\frac{1}{\mu_s}} \left(c_{st}\right)^{\frac{\mu_s-1}{\mu_s}} + (\alpha_s)^{\frac{1}{\mu_s}} \left(c^*_{st}\right)^{\frac{\mu_s-1}{\mu_s}}\right]^{\frac{\mu_s}{\mu_s-1}} \text{ for } s = N, A_1, A_2, \tag{26}$$

where c_{st} is the consumption of good type s produced domestically, c^*_{st} is the consumption of god type s imported, $1-\alpha_s \geq 0.5$ defines the home bias for each type of goods, and $\mu_s > 0$ is the elasticity of substitution between home and foreign produced goods of each type. Taking as given prices, the static maximization of the consumption basket for household provide a demand for each type of goods produced domestically and abroad as:

$$C_{Nt} = (1-\varphi)\left(\frac{P^C_{Nt}}{P_t}\right)^{-\mu_{NA}} C_t \text{ and } C_{At} = \varphi\left(\frac{P^C_{At}}{P_t}\right)^{-\mu_{NA}} C_t \tag{27}$$

[13] This cost function aims at removing a unit root component that emerges in open economy models without affecting the steady state of the model. We refer to Schmitt-Grohé and Uribe (2003) for a discussion of closing small open economy models.

$$C_{A_1t} = (1-\varphi_A)\left(\frac{P^C_{A_1t}}{P^C_{At}}\right)^{-\mu_A} C_{At} \text{ and } C_{A_2t} = \varphi_A\left(\frac{P^C_{A_2t}}{P^C_{At}}\right)^{-\mu_A} C_t \tag{28}$$

$$c_{st} = (1-\alpha_s)\left(\frac{P_{st}}{P^C_{st}}\right)^{-\mu_s} C_{st} \text{ and } c^*_{st} = \alpha_s\left(\frac{e_t P^*_{st}}{P^C_{st}}\right)^{-\mu_s} C_{st} \text{ for } s = N, A_1, A_2 \tag{29}$$

where P^*_{st} is the foreign price (in foreign currency) of goods $s = N, A_1, A_2$. The different price levels for the overall consumption basket (P_t) and its components (P^C_{At}, P^C_{Nt}, $P^C_{A_1t}$, $P^C_{A_2t}$) are given by

$$P_t = \left[(1-\varphi)\left(P^C_{Nt}\right)^{1-\mu} + \varphi\left(P^C_{At}\right)^{1-\mu}\right]^{\frac{1}{1-\mu}} \tag{30}$$

$$P^C_{At} = \left[(1-\varphi_A)\left(P^C_{A_1t}\right)^{1-\varphi_A} + \omega_A\left(P^C_{A_2t}\right)^{1-\mu_A}\right]^{\frac{1}{1-\mu_A}} \tag{31}$$

$$P^C_{st} = \left[(1-\alpha_s)\left(P_{st}\right)^{1-\mu_s} + \alpha_s\left(e_t P^*_{st}\right)^{1-\mu_s}\right]^{\frac{1}{1-\mu_s}} \text{ for } s = N, A_1, A_2 \tag{32}$$

3.3 Non-agricultural sector

There exists a continuum of perfectly competitive non-agricultural firms of mass $1-n_t$. This mass denotes the relative size of the non-agricultural sector in the total production of the economy. These firms are similar to agricultural firms except in that they do not require land input to produce goods and are not directly affected by weather. Each representative non-agricultural firm has the following Cobb-Douglas technology:

$$y_{Nt} = \varepsilon^Z_t\left(k_{Nt-1}\right)^{\gamma_N}\left(h^d_{Nt}\right)^{1-\gamma_N}, \tag{33}$$

where y^N_{Nt} is the production of non-agricultural of each firm that combines physical capital k_{Nt-1}, labor demand h^d_{Nt} and subject to the technology shock ε^Z_t. The parameter γ_N governs the output elasticity of capital and labor. Technology is characterized as an AR(1) shock process:

$$\log\left(\varepsilon^Z_t\right) = \rho_Z \log\left(\varepsilon^Z_{t-1}\right) + \sigma_Z \eta^Z_t, \tag{34}$$

where $\rho_Z \in [0,1)$ determines the persistence of technological shock and $\sigma_Z \geq 0$ is the standard deviation of the innovation in this shock. Technology is assumed to be economy-wide (i.e., the same across sectors) by affecting both agricultural and non-agricultural sectors. This shock captures fluctuations associated with declining hours worked coupled with increasing output.[14]

The law of motion of physical capital in the non-agricultural sector is given by:

$$i_{Nt}^{N} = k_{Nt} - (1 - \delta_K)\, k_{Nt-1}, \tag{35}$$

where $\delta_K \in [0, 1]$ is the depreciation rate of physical capital and i_{Nt} is investment from non-agricultural firms. Real profits are given by:

$$d_{Nt} = p_{Nt} y_{Nt} - p_{Nt} \left(i_{Nt} + S\left(\varepsilon_t^i \frac{i_{Nt}}{i_{Nt-1}} \right) i_{Nt-1} \right) - w_{Nt} h_{Nt}, \tag{36}$$

Firms maximize the discounted sum of profits:

$$\max_{\left\{h_{Nt}^d, i_{Nt}, k_{Nt}\right\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} d_{Nt+\tau} \right\} \tag{37}$$

subject to the constraints given by the production technology (33) and the capital evolution (35).

3.4 Authority

The public authority consumes some non-agricultural goods produced domestically G_t, issues debt b_t at a real interest rate r_t and charges lump sum taxes T_t. Public spending is assumed to be exogenous, $G_t = Y_t^N g \varepsilon_t^G$, where $g \in [0, 1)$ is a fixed fraction of non-agricultural goods g consumed by the government in the steady state and ε_t^G is an AR(1) shock process:

$$\log\left(\varepsilon_t^G\right) = \rho_G \log\left(\varepsilon_{t-1}^G\right) + \sigma_G \eta_t^G, \quad \eta_t^G \sim \mathcal{N}(0, 1), \tag{38}$$

where $1 > \rho_G \geq 0$ and $\sigma_G \geq 0$. This shock captures variations in absorption which are not taken into account by the other source of fluctuations in the model. The government budget constraint equates spending plus interest payment on existing debt to new debt issuance and taxes:

$$p_{Nt} G_t + r_{t-1} b_{t-1} = b_t + T_t \tag{39}$$

[14] The lack of sectoral data for hours worked does not allow to directly measure sector-specific TFP shocks.

3.5 Foreign economy

Following the literature on estimated small open economy models exemplified by Adolfson et al. (2007), Adolfson et al. (2008) and Justiniano and Preston (2010), the foreign economy is characterized by a set of key equations that determine Uruguay exports and real exchange rate dynamics. For simplicity, the foreign economy is modeled as an endowment economy à la Lucas Jr (1978), where its total consumption is exogenous. Most of the parameters and the steady states are symmetric between domestic and the foreign economy, but considering that the relative size of Uruguay is nil. Consistently with this and with the restricted VAR model featuring a small open economy, the foreign economy is only affected by its own consumption shocks but not by shocks of the home economy. Hence, the foreign country is determined by an endowment economy characterized by an exogenous foreign consumption:

$$\log\left(C_t^*\right) = (1-\rho_C)\log\left(\bar{C}^*\right) + \rho_C \log\left(C_{t-1}^*\right) + \sigma_C \eta_t^C, \quad \eta_t^C \sim \mathcal{N}(0,1), \tag{40}$$

where the $0 \leq \rho_C < 1$ controls the persistence of this shock, $\bar{C}^*$ is the steady state foreign consumption and $\sigma_C \geq 0$ is the standard deviation of the innovation for this shock. The parameters σ_C and ρ_C are estimated in the fit exercise to capture variations of the foreign demand. The export of the different type of goods produced in Uruguay are given by

$$c_{Nt}^x = \alpha_N^* \left(\frac{P_{Nt}}{e_t P_{Nt}^*}\right)^{-\mu_N^*} C_{Nt}^* \tag{41}$$

$$c_{A_1 t}^x = \alpha_{A_1}^* \left(\frac{P_{A_1 t}}{e_t P_{A_1 t}^*}\right)^{-\mu_{A_1}^*} C_{A_1 t}^* \tag{42}$$

$$c_{A_2 t}^x = \alpha_{A_2}^* \left(\frac{P_{A_2 t}}{e_t P_{A_2 t}^*}\right)^{-\mu_{A_2}^*} C_{A_2 t}^* \tag{43}$$

where the foreign consumption in non-agricultural goods (C_{Nt}^*) and the two type of agricultural goods ($C_{A_1 t}^*$ and $C_{A_2 t}^*$) are:

$$C_{Nt}^* = (1-\varphi^*)\left(\frac{P_{Nt}^*}{P_t^*}\right)^{-\mu_{NA}^*} C_t^* \tag{44}$$

$$C_{A_1 t}^* = (1-\varphi_A^*)\left(\frac{P_{A_1 t}^*}{P_{At}^*}\right)^{-\mu_A^*} C_{At}^* \text{ and } C_{A_2 t}^* = \varphi_A^* \left(\frac{P_{A_2 t}^*}{P_{At}^*}\right)^{-\mu_A^*} C_{At}^* \tag{45}$$

with

$$C_{At}^{*} = \varphi^{*}\left(\frac{P_{At}^{*}}{P_{t}^{*}}\right)^{-\mu_{NA}^{*}} C_{t}^{*} \text{ and } P_{At}^{*} = \left[(1-\varphi_{A}^{*})(P_{A_1 t}^{*})^{1-\mu_{A}^{*}} + \varphi_{A}^{*}(P_{A_2 t}^{*})^{1-\mu_{A}^{*}}\right]^{\frac{1}{1-\mu_{A}^{*}}} \tag{46}$$

In the expression above, we have assumed that the home exports to the foreign economy are negligible, implying that $P_{Nt}^{C*} = P_{Nt}^{*}$, $P_{A_1 t}^{C*} = P_{A_1 t}^{*}$, and $P_{A_2 t}^{C*} = P_{A_2 t}^{*}$. Note that with this specification, a rise in the foreign consumption C_t^* triggers a boost in the exports of domestic goods, followed by an appreciation of the foreign exchange rate. To determine the foreign interest rate r_t^*, we assume that the representative foreign household has the following optimal condition for holding foreign bonds:

$$1 = \beta r_t^* E_t\left[\frac{\varepsilon_{t+1}^* C_t^*}{\varepsilon_t^* C_{t+1}^*}\right] \tag{47}$$

where variable ε_t^* is a time-preference shock for the foreign economy modeled as an AR(1) process:

$$\log\left(\varepsilon_t^*\right) = \rho_{\varepsilon*}\log\left(\varepsilon_{t-1}^*\right) + \sigma_{\varepsilon*}\eta_t^*, \tag{48}$$

with $\eta_t^* \sim \mathcal{N}(0,1)$. This shock temporary raises the foreign household's discount factor and drives down the foreign real interest rate and naturally leads capital inflows to the domestic economy. For simplicity, we assume the absence of specific sectoral shocks in the foreign economy, all sectoral prices of the foreign economy are perfectly synchronized, i.e., $P_t^* = P_{Nt}^* = P_{At}^* = P_{A_1 t}^* = P_{A_2 t}^*$. In addition, the small size of the domestic economy implies that the import/exports flows from the home to the foreign country are negligible, thus implying that $P_t^* = P_{Nt}^* = P_{A_1 t}^* = P_{A_2 t}^*$.

3.6 Aggregation and equilibrium conditions

The market clearing involves the optimal decisions of all agents and sectors in the economy already described, and the standard the market clearing conditions. First, labor market equilibrium for the three type of labor inputs imply:

$$h_{Nt} = (1-n_t)h_{Nt}^d \quad, h_{A_1 t} = n_t n_{1,t} h_{A_1 t}^d, \text{ and } h_{A_2 t} = n_t(1-n_{1,t})h_{A_2 t}^d \tag{49}$$

We can also define the aggregate labor input as $h_t = h_{Nt} + h_{A_1 t} + h_{A_2 t}$.

Second, the market clearing condition for non-agricultural goods is determined when the aggregate supply is equal to aggregate demand:

$$(1-n_t)y_{Nt} = c_{Nt} + c^x_{Nt} + G_t + I_t + n_t n_{1,t} x_{A_1 t} + n_t(1-n_{1,t})x_{A_2 t} + rer_t \Phi(b^*_t) \tag{50}$$

where the aggregate investment is given by $I_t = n_t n_{1,t} i_{A_1 t} + n_t(1-n_{1,t}) i_{A_2 t} + (1-n_t) i_{Nt}$.

Third, the equilibrium conditions for the agricultural sub-sectors A_1 and A_2 are:

$$n_t n_{1,t} y_{A_1 t} = c_{A_1 t} + c^x_{A_1 t} \text{ and } n_t(1-n_{1,t}) y_{A_2 t} = c_{A_2 t} + c^x_{A_2 t} \tag{51}$$

Using the previous conditions for the production in each sector, we can define the aggregate real production as:

$$Y_t = (1-n_t)\, p_{Nt} y_{Nt} + n_t n_{1,t} p_{A_1 t} y_{A_1 t} + n_t(1-n_{1,t}) p_{A_2 t} y_{A_2 t} \tag{52}$$

However, the total GDP requires to subtract the value of intermediate inputs:

$$gdp_t = Y_t - p_{Nt} \left(n_t n_{1,t} x_{A_1 t} + n_t(1-n_{1,t}) x_{A_2 t} \right) \tag{53}$$

The balance of payment identity determines the law of motion for the total amount of real foreign debt:

$$rer_t b^*_t = r^*_{t-1} \frac{rer_t}{rer_{t-1}} b^*_{t-1} + tb_t \tag{54}$$

where tb_t is the real trade balance that can be expressed as follows:

$$tb_t = p_{Nt} c^x_{Nt} + p_{A1t} c^x_{A_1 t} + p_{A_2 t} c_{A_2 t} - \frac{e_t P^*_{Nt}}{P_t} c^*_{Nt} - \frac{e_t P^*_{A_1 t}}{P_t} c^*_{A_1 t} - \frac{e_t P^*_{A_2 t}}{P_t} c^*_{A_2 t} \tag{55}$$

4 Parametrization of the structural model and simulations

To implement the quantitative simulations of the structural model, we divide the set of parameters into three groups. The first group is calibrated to match key steady-state ratios observed in Uruguay. For the second group, we adopt the Bayesian estimation strategy used in Gallic and Vermandel (2020) and Clevy and Evans (2025). Finally, for the third group of parameters, we set their values to match the estimated impulse responses for the agricultural subsectors obtained in Section 2.

Table 1 reports the values of the parameters calibrated to match the main macroeconomic ratios of Uruguay in the structural model. For the discount factor (β), the capital depreciation rate (δ_K), and the capital share in production across sectors (γ, γ_{A_1}, γ_{A_2}), we follow Gallic and Vermandel (2020) and Clevy and Evans (2025). The steady-state labor supply in each sector ($h_{j,SS}$, for $j = N, A_1, A_2$) is set such that hours worked correspond to one third of available time.

Public spending as a share of GDP is set to $g = 0.216$, corresponding to the average observed between 2016 and 2022. According to Clevy and Evans (2025), Uruguay has approximately five times more arable land per capita than New Zealand. Since the New Zealand calibration assumes $\bar{\ell} = 0.4$, we set $\ell_{j,SS} = 2.0$ for $j = A_1, A_2$ in the case of Uruguay.

The share of agricultural goods in total consumption is taken from the Uruguayan Consumer Price Index, yielding $\varphi = 0.17$. Based on national accounts data, the share of imported non-agricultural goods in non-agricultural consumption is set to 25 percent ($\alpha_N = 0.25$). For agricultural goods, the import share of crop products is approximately 23 percent ($\alpha_{A_1} = 0.225$), while for livestock and dairy products it is 10 percent ($\alpha_{A_2} = 0.10$). Within total agricultural consumption, livestock and dairy products account for about 70 percent, implying $\varphi_A = 0.7$. Finally, the portfolio adjustment cost parameter is set to the standard small value used in Schmitt-Grohe and Uribe (2003).

Table 2 reports the parameters that govern elasticities in preferences as well as inertia in consumption and investment. For this group of parameters, we use the point estimates obtained with Bayesian methods in Clevy and Evans (2025), based on macroeconomic time series for Uruguay. Note that our model features two agricultural subsectors, in contrast to the single agricultural sector in Clevy and Evans (2025). For this reason, we assign the same parameter values to both agricultural subsectors, using the estimates reported in Clevy and Evans (2025). Finally, since this parameter is not considered in Clevy and Evans (2025), we include a conservative calibration for the elasticity of substitution between the two types of agricultural goods in consumption, setting $\mu_A = 1.0$.

The last group of parameters is more directly related to the effects of weather conditions

Table 1: Calibrated parameters based on macroeconomic ratios in Uruguay

Parameter	Definition	Value
β	Discount factor	0.9883
γ	Share of capital in the non-agricultural output	0.33
γ_{A_1}	Share of capital in the crop agricultural output	0.33
γ_{A_2}	Share of capital in the livestock and diary agricultural output	0.33
δ_K	Depreciation rate of capital	0.025
g	Share of public spendings in non-agricultural output	0.216
φ	Share of agricultural goods in total consumption	0.17
φ_A	Share of livestocks-diary agricultural goods in total agricultural consumption	0.7
α_N	Share of imported goods in the non-agricultural consumption	0.25
α_{A_1}	Share of imported goods in the consumption of crop products	0.225
α_{A_2}	Share of imported goods in the consumption of livestock and diary products	0.1
ϱ_B	portfolio adjustment cost	0.0007
$h_{j,SS}$	Hour worked at the steady state in each sector and sub-sector	1/3
$\ell_{j,SS}$	Land per capita at the steady state in each agricultural sub-sector	2

on agricultural production in both subsectors. We further decompose this group into two subsets. The first subset governs the dynamics of weather shocks affecting the soil moisture index estimated in Section 2. Table 3 reports the values of the parameters $\sigma_{S,j}$ for $j = 0, \ldots, Q$.

The other subset of parameters in this group governs the effects of weather shocks on the damage functions and the dynamics of land productivity in both agricultural subsectors. Accordingly, Table 4 reports the parameters that primarily determine the impact of weather shocks on crop and livestock–dairy production. Some of these parameters also affect the responses of other variables, reflecting the general equilibrium structure of the model. For this set of parameters, we initially adopt the Bayesian point estimates reported in Clevy and Evans (2025) as calibrated values, as shown in column 3 of Table 4. To assess how well this calibration replicates the empirical responses of crop and livestock–dairy production to

Table 2: Calibrated parameters mainly based on Clevy and Evans (2025)

Parameter	Definition	Value
σ	Risk aversion consumption	0.28
σ_h	Inverse of the Frisch elasticity of the labor supply	1.9
b	Habits in consumption	0.66
κ	Coefficient for adjustment cost on investment	2.43
ι	Inverse of the substitution elasticity across labor types	2.48
μ_{NA}	Elasticity of substitution in consumption non-agriculture vs agriculture	3.35
μ_A	Elasticity of substitution in consumption crops vs livestock-diary	1.00
μ_N	Elasticity of substitution non-agricultural domestic vs imported	1.46
μ_{A_1}	Elasticity of substitution crops domestic vs imported	1.97
μ_{A_2}	Elasticity of substitution livestock-diary domestic vs imported	1.97
ω_{A_1}	Share of land in the livestock-diary agricultural output	0.11
ω_{A_2}	Share of land in the crop agricultural output	0.11

weather shocks, Figure 5 compares the model-implied impulse responses with the estimated responses from Section 2.

Table 3: Calibrated based on section 2

Parameter	Value
$\sigma_{S,0}$	1.15
$\sigma_{S,1}$	0.48
$\sigma_{S,2}$	-0.21
$\sigma_{S,3}$	-0.43
$\sigma_{S,4}$	-0.66
$\sigma_{S,5}$	-0.69
$\sigma_{S,6}$	-0.49
$\sigma_{S,7}$	-0.41
$\sigma_{S,8}$	-0.26
$\sigma_{S,9}$	-0.16
$\sigma_{S,10}$	-0.18
$\sigma_{S,11}$	0.29

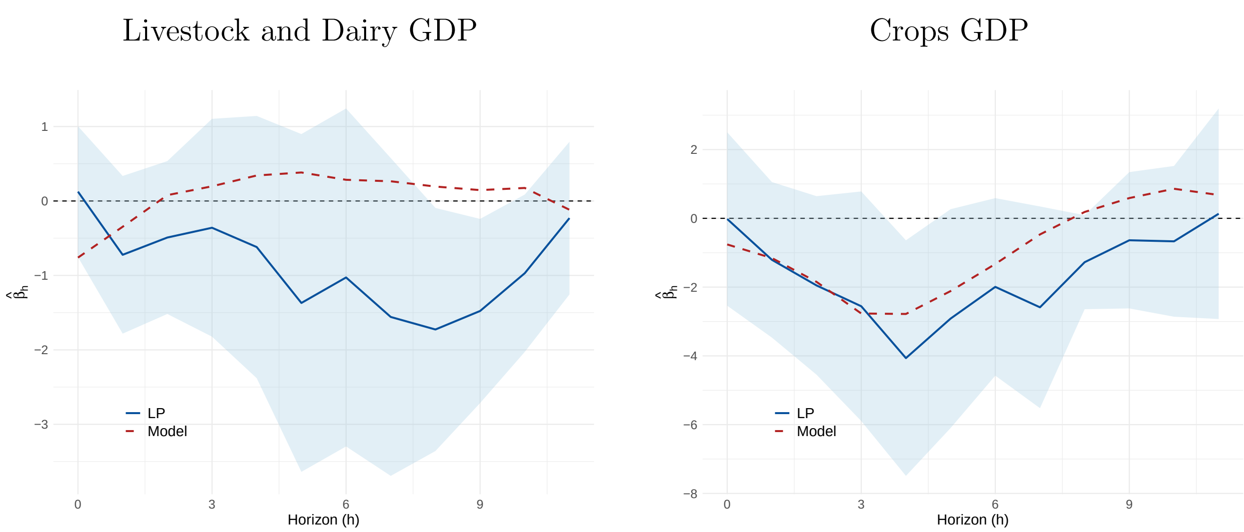

Figure 5: Response of Sectoral Value Added.

Model (symmetric damage functions) vs LP estimates

As shown in Figure 5, the calibration of the parameters reported in Table 4 is unable

Table 4: Calibrated parameters on matching estimated responses

Parameter	Definition	Bayesian	Value	S. E.
$\theta_{A_1 0}$	Param. 1 damage crop production	5.25	0.00	0.12
$\theta_{A_2 0}$	Param. 1 damage livestock-diary production	5.25	0.20	0.10
$\vartheta_{A_1 0}$	Param. 1 damage on land for crop	5.25	11.97	0.42
$\vartheta_{A_1 1}$	Param. 2 damage on land for crop	–	2.52	0.08
$\vartheta_{A_1 2}$	Param. 3 damage on land for crop	–	6.48	0.17
$\vartheta_{A_1 3}$	Param. 4 damage on land for crop	–	0.00	0.14
$\vartheta_{A_2 0}$	Param. 1 damage on land for livestock-diary	5.25	4.94	0.28
$\vartheta_{A_2 1}$	Param. 2 damage on land for livestock-diary	–	0.00	0.03
$\vartheta_{A_2 2}$	Param. 3 damage on land for livestock-diary	–	0.25	0.12
$\vartheta_{A_2 3}$	Param. 4 damage on land for livestock-diary	–	8.29	0.08
δ_ℓ	Land decay rate	0.07	0.11	0.00
ϕ_{A_1}	Shape of the land cost crop	1.72	1.24	0.00
ϕ_{A_2}	Shape of the land cost livestock-diary	1.72	1.20	0.00

to reproduce the estimated responses within the structural model. We therefore explore an alternative approach to selecting the values of the parameters in Table 4.

Formally, we choose these parameters to match the estimated responses of crop output and livestock–dairy output to a weather shock. Specifically, the parameter values are selected to minimize the quadratic distance between the model-implied and empirically estimated impulse responses for these two variables. The estimated standard deviations of the responses are used to construct the weighting matrix in this quadratic distance.

Let Θ_1 denote the set of parameters listed in Tables 1, 2, and 3, and let $\tilde{\Theta}_1$ denote their calibrated values. Similarly, let Θ_2 denote the set of parameters listed in Table 4. The matching approach consists of finding the values of Θ_2 that solve:

$$\min_{\hat{\Theta}_2} \left(\hat{\Psi} - \Psi(\hat{\Theta}_2 \mid \tilde{\Theta}_1)\right)' \hat{V}^{-1} \left(\hat{\Psi} - \Psi(\hat{\Theta}_2 \mid \tilde{\Theta}_1)\right), \tag{56}$$

where $\hat{\Psi}$ is the vector of stacked impulse responses for crop output and livestock–dairy output, estimated in Section 2 over a horizon of twelve quarters, and $\Psi(\hat{\Theta}_2 \mid \tilde{\Theta}_1)$ is the corresponding vector of stacked impulse responses obtained from model simulations. These model-implied responses are computed using $\Theta_2 = \hat{\Theta}_2$, conditional on the calibrated parameters $\Theta_1 = \tilde{\Theta}_1$. The weighting matrix $\hat{V}$ is diagonal and contains the sample variances of the estimated responses included in $\hat{\Psi}$.

The values of the parameters in Θ_2 are reported in column 4 of Table 4, together with the corresponding inferred standard errors shown in column 5.[15] We highlight several key differences between the calibration based on Clevy and Evans (2025) and the calibration obtained through the matching of the estimated responses. First, the damage functions differ in their impact on production and on land productivity. Second, consistent with the estimated responses, there are economically meaningful asymmetries across agricultural subsectors in their responses to weather shocks. Capturing these asymmetries requires damage functions that differ across subsectors and feature distinct dynamic effects. Third, the matching procedure implies a lower degree of curvature in the cost functions for investment in land productivity in each agricultural subsector, along with a slightly lower land decay rate. To highlight the quantitative implications of using these alternative parameter values, Figure 6 displays the model-implied responses alongside the estimated responses presented in Section 2.

[15] Standard errors are computed using the Delta method applied to the first-order conditions associated with (56).

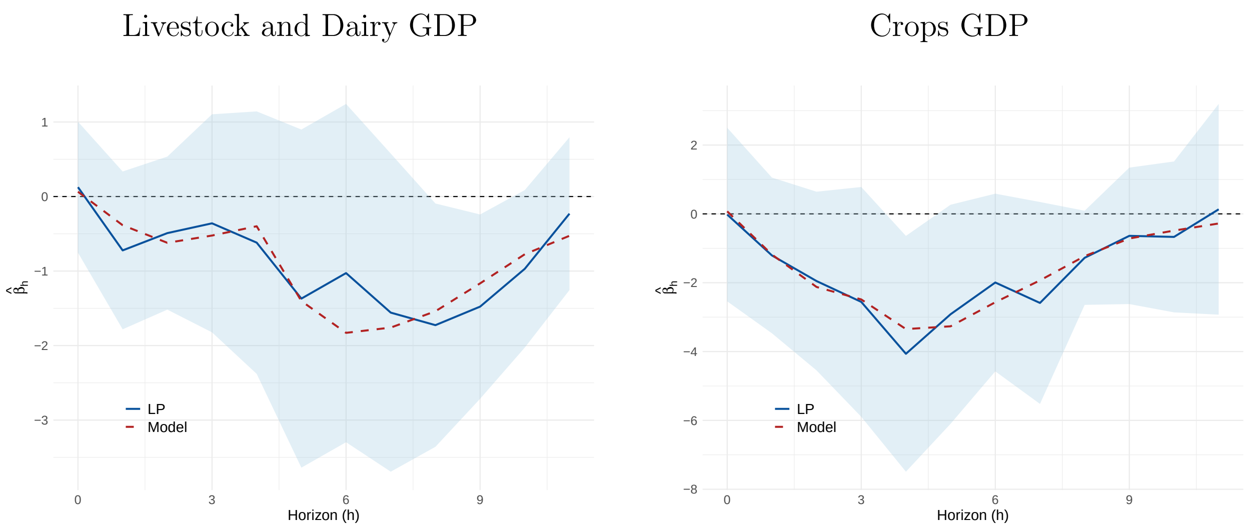

Figure 6: Response of Sectoral Value Added.

Model (asymmetric damage functions) vs LP estimates

5 Final comments

This paper studies the macroeconomic effects of drought shocks in Uruguay, with a particular focus on the heterogeneous responses across agricultural sub-sectors. First, while aggregate macroeconomic indicators may appear relatively stable following 'regular' drought conditions, this stability is a result of offsetting sectoral dynamics. Using both local projection techniques, we document that drought shocks have markedly asymmetric impacts across primary sectors in the Uruguayan economy. Crop production reacts sharply but recovers quickly, while livestock and dairy sector exhibits more delayed yet persistent declines in output. These patterns suggest distinct propagation mechanisms and underline the importance of sector-specific modeling approaches.

Our results demonstrate that the shock propagates far beyond the farm gate, affecting the downstream industrial processing value chain. The persistent decline in the livestock and dairy sectors is mirrored by contractions in animal slaughter and milk derivatives, confirming that biological hysteresis at the primary level creates a multi-year drag on industrial output.

To account for these findings, we develop a small open economy DSGE model calibrated to Uruguayan data that explicitly distinguishes between crop and livestock-dairy activities. The model incorporates key features such as sector-specific damage functions, endogenous land dynamics, and hysteresis effects, allowing us to replicate the main stylized facts uncovered in the empirical analysis.

Our results highlight two central conclusions. First, regular adverse weather shocks have mild aggregate effects, that mask important sectoral dynamics. Crops respond more immediately, while livestock and dairy production face longer-lasting disruptions. Second, modeling the agricultural sector as a single homogeneous block may misrepresent the transmission of climate shocks to the broader economy.

These insights suggest that sector-specific stabilization policies—such as those targeting the multi-year recovery of livestock populations—may be more effective than broad aggregate stimulus in mitigating the long-term costs of climate events.

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A Empirical Appendix

A.1 Drought effects on prices

We studied the effect on overall prices and specific subsets of the consumption basket. These were grouped into non-tradables, tradables and meat and dairy. Figure 7 shows the IRF estimation results. There are no significant effects on overall CPI nor in non-tradable prices. Tradable prices increase mildly (less than 1%) during the second year after the drought, following the evolution of the exchange rate. The price of meat and milk derivatives shows temporal increases of around 1% from the third quarter after the shock up until the eighth quarter, coinciding with when the output effects are more prevalent in this sector. Finally, fruits and vegetables prices show a small temporal increase 7 quarters after the shock. To interpret this result one has to take into account several facts. First, the construction of the droughts index is focused on the production of other sectors, and puts little to no weight to the areas where fruits and vegetables are grown. Second, we are considering "regular" droughts. Finally, prices are seasonally adjusted, which could capture part of the effect on these prices, that have strong seasonal pattern.

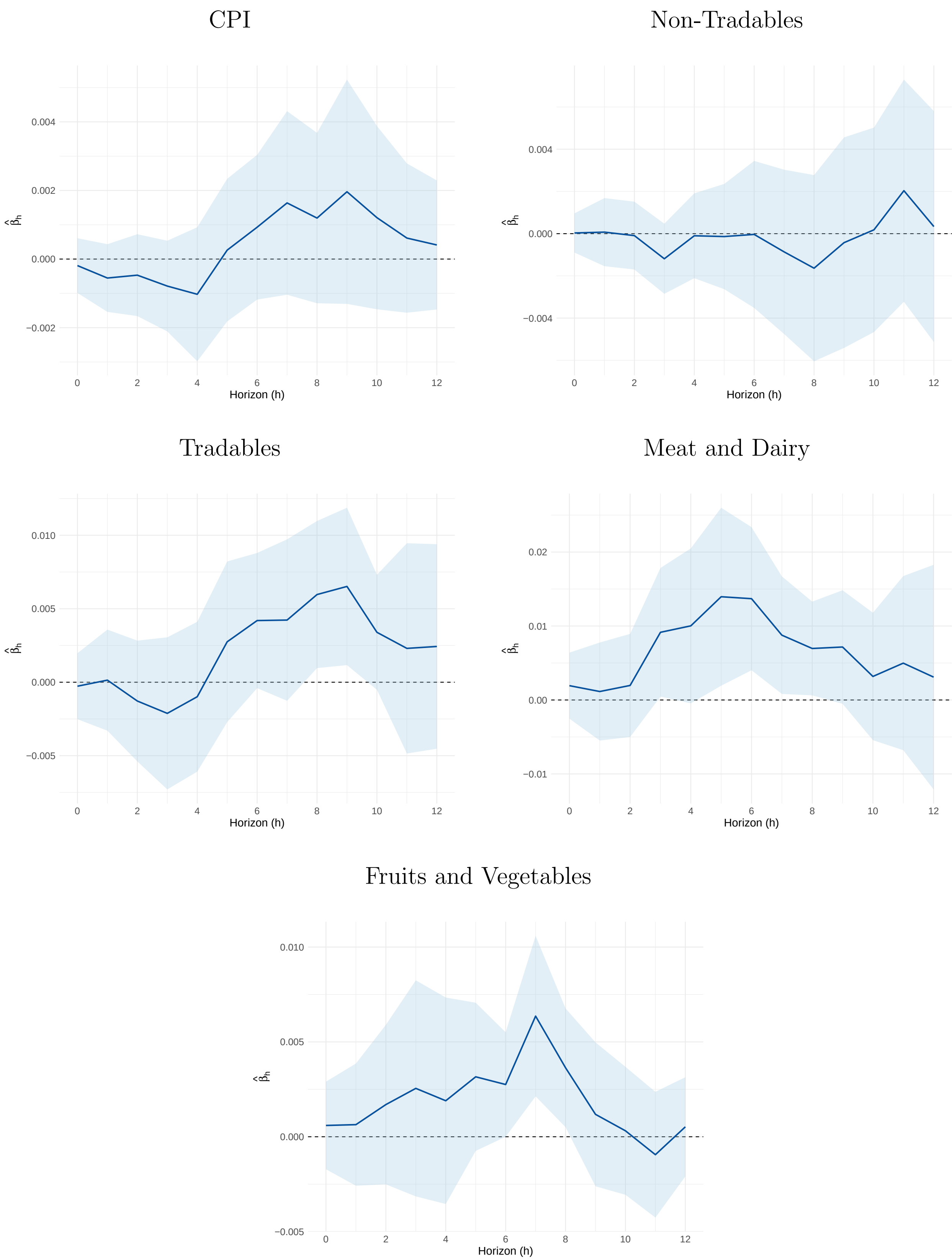

Figure 7: Price effects

A.2 Drought effects on sectoral exports

Figure 8 shows the results of estimating the response of sectoral exports to a drought shock. Total exports experience a temporal up to the second quarter and decrease during the second year after the shock. Soy export fall within the first year after the shock by an accumulated amount of 50%. There are no significant effects on livestock exports (that is exports of the living animals) whereas products derivated from meat and milk show the same pattern as Livestock and Dairy production with significant effects in the second year after the shock. Finally Forestry shows an increase in exports during the first year after the shock.

Figure 8: Effects on sectoral exports

A.3 IRF matching: symmetric vs asymmetric dammage functions

The model matches fairly well the response of employment and the exchange rate. But misses the second year drop in GDP, Consumption and Investment. One reason why this is posible is that World Output (trading partners) has a curious response to our weather shocks. It expands during the year after the shock, and it contracts in the second year. In the model there is no response coming from world GDP as the shocks are unrelated.

COMENTARIOS

- Que el world output reacciones a condiciones locales de weather no tiene por qué ser tan sorprendente, es sabido que estas condiciones de sequías responden al fenómeno del niño la niña que se origina en el pacífico y que tiene efectos muy diversos a nivel mundial (con patrones de abundancia de agua y sequías que pueden ser importantes.
- Se podría hacer un ejercicio simple en que en el modelo hay una reaction function del wgdp al shock de weather que replique exactamente lo que pasa en los datos.

PODRÍAMOS PROBAR DE INCLUIR UNA RESPUESTA DEL WORLD OUTPUT AL SHOCK DE WEATHER.

Figure 9: Response of Macroeconomic Variables

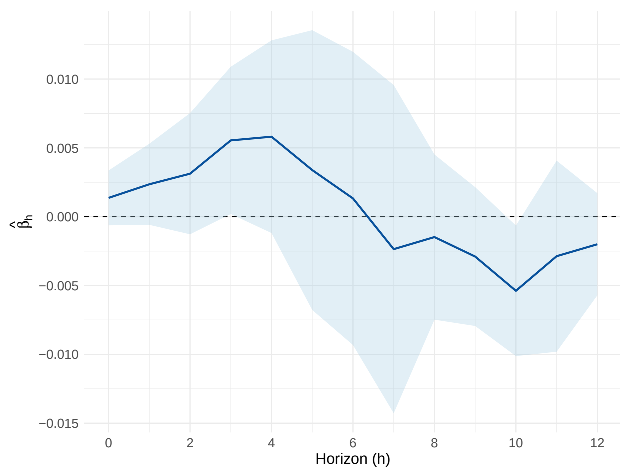

Figure 10: Response of World Output