Weather Shocks

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Abstract

How much do weather shocks matter? The literature addresses this question in two isolated ways: either by looking at long-term effects through the prism of calibrated theoretical models, or by focusing on both short and long terms through the lens of empirical models. We propose a framework that reconciles these two approaches by taking the theory to the data in two complementary ways. We first document the propagation mechanism of a weather shock using a Vector Auto-Regressive model on New Zealand Data. To explain the mechanism, we build and estimate a general equilibrium model with a weather-dependent agricultural sector to investigate the weather's business cycle implications. We find that weather shocks: (*i*) explain about 35% of GDP and agricultural output fluctuations in New Zealand; (*ii*) entail a welfare cost of 0.30% of permanent consumption; (*iii*) critically increases the macroeconomic volatility under climate change, resulting in a higher welfare cost peaking to 0.46% in the worst case scenario of climate change.

Keywords : Agriculture, Business Cycles, Climate Change, Weather Shocks

JEL classification: C13, E32, Q54

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1 Introduction

Among the many shocks and disturbances driving business cycles, weather shocks have received little attention as a serious source of economic fluctuations in modern macroeconomic models. Yet over the last 40 years, heat waves and droughts have been causing significant damages at global level peaking to a total value of US$25 billion in 2012.[1] Both the frequency and the intensity of these adverse events tend to follow an upward trend, suggesting that weather shocks are likely to become a more frequent source of business cycles in the coming years. This growing source of macroeconomic fluctuations is emerging as one of the most important facets of global warming, in particular for agricultural-based countries. In such economies, weather shocks generate detrimental fluctuations in the agricultural sector that can spread to the rest of the economy.

The economic literature has devoted considerable efforts to quantify the effects of the weather on economic activity in two isolated ways: either by looking at long-term effects through the prism of theoretical models, or by focusing on both short and long-term effects using empirical analysis.[2] Theoretical models exemplified by Nordhaus (1991) have been strongly criticized in particular regarding their lack of empirical foundations (see Pindyck, 2017). If these models are useful to rationalize long term implications of climate, they become irrelevant for short run analysis at a business cycle frequency. In contrast, empirical models provide important quantitative insights on the short term transmission channels. However, these channels have never been yet interpreted from a general equilibrium perspective. The lack of an economic framework that tackles the short-term dimension of the weather is a major issue in a climate change context, as policymakers are expected to more frequently cope with short-term adverse weather events with important implications (e.g., food insecurity, recessions, currency depreciation, etc.).

Therefore, the main objective of the paper is to fill the gap by providing a quantitative framework that directly addresses the short term dimension of the weather. This paper contributes to the current literature by reconciling theoretical models of the weather with the data, using the weather as an observable variable. The resulting framework is able to disentangle the contribution of weather shocks from alternative sources of business cycles and originally price

[1] The cumulative sum of estimated damage caused by droughts or extreme temperatures worldwide is calculated from EM-DAT data, and set in real 2012 terms using the US GDP deflator.

[2] See Acevedo et al. (2017) for a survey on weather shocks, Nordhaus (2018) for a summary of the evolution of the canonical model of climate change over the three decades, and Deschenes and Greenstone (2007) for an empirical assessment of long term effects of climate change on agricultural output.

this contribution into consumption-equivalent welfare losses. Most of the literature considers climate change solely as a trend phenomenon, leaving the cost of weather fluctuations as a second order issue. Hence, this paper also contributes to the literature by quantifying climate change through a rise in the variability of weather events.

In this paper, our methodology follows a two-step strategy. In a first step, we document the transmission mechanisms of weather shocks using an a-theoretical model. Since the time-varying productivity of agricultural land is directly measurable from soil moisture observations, we build a weather index at a macro level that captures unsatisfactory levels of soil moisture for New Zealand.[3] This aggregate measure of the weather is included in a Structural Vector Auto-Regressive (SVAR) model, alongside seven macroeconomic series from New Zealand. The impulse response functions analysis documents the transmission mechanism of weather shocks in a small-open economy environment and provides a benchmark for the development of a general equilibrium model. In a second step, we enrich a Dynamic Stochastic General Equilibrium (DSGE) model with a weather-dependent agricultural sector facing exogenous weather.[4] Entrepreneurs involved in the agricultural sector (i.e., farmers) are endowed with land with a time-varying productivity determined by both economic and weather conditions. The model is estimated through Bayesian techniques on the same sample as the SVAR model to provide a complementary representation of the data. In addition to its empirical relevance, the estimated model provides a detailed understanding of how weather shocks propagate in the economy and yields several predictions on climate change from a general equilibrium perspective.

We get three main results from the aforementioned strategy. First, both the SVAR and the DSGE models provide a similar picture about the transmission of an adverse weather shock through a large and persistent contraction of agricultural production, accompanied by a decline in consumption, investment and a rise in hours worked. At an international level, a weather shock causes current account deficits and a depreciation of the domestic currency. Second, we find that weather shocks play a non-trivial role in driving the business cycles in New Zealand.

[3] We use New Zealand data for two reasons. First, New Zealand has faced many weather shocks, in particular droughts, which have caused severe damages to its agricultural sector. Second, the size of the country is relatively small compared to other countries such as the United States. So when a drought strikes New Zealand, most of the regions are affected at the same time. The choice to rely on such data leads to a specific modeling strategy for the SVAR and DSGE models.

[4] Treating the weather as an exogenous process is a main departure from Nordhaus (1991)-type models, but this departure is necessary to avoid most of the critiques raised by Pindyck (2017). The empirical and theoretical grounds motivating the feedback loop effect between human activity and CO_2 emissions are considered as very fragile in these models, because we yet know little about climate sensitivity to temperatures changes. Treating weather as exogenous is thus a conservative approach with respect to the current practice in the literature.

On the one hand, the inclusion of weather-driven business cycles strikingly improves the statistical performance of the model. On the other, weather shocks drive an important fraction of the unconditional variance, in particular for GDP, consumption and agricultural output. The resulting consequence is a high welfare cost of business cycles induced by weather shocks. In particular, we find that households would be willing to give up 0.30% of their unconditional consumption to rule out weather shocks, which is remarkably high with respect to other sources of disturbances in our model. A third result concerns an original counterfactual analysis on climate change. We increase the volatility of weather shocks in accordance with IPCC (2014)'s climate change projections for 2100, and evaluate how these structural changes in the distribution of weather shocks affect macroeconomic volatility. We find that climate change critically increases the variability of key macroeconomic variables, such as GDP, agricultural output or the real exchange rate. The corollary of this structural change is an increase in the welfare cost of weather driven business cycles peaking up to 0.46% in the worst-case climate change scenario.

Our work contributes to the literature that connects the macroeconomy with the weather through the lens of theoretical models. This literature is mainly dominated by integrated assessment models (IAMs) pioneered by Nordhaus (1991). In a nutshell, economic activity generates a negative externality through greenhouse gas emissions that adversely change temperatures. Higher temperatures deteriorate aggregate production through a damage function in the production technology of firms. The externality resulting from greenhouse gas emissions is not properly taken into account by firms. This market failure motivates a kind of Pigouvian tax that internalizes the social cost of the externality by setting a price on an additional ton of emissions. This price is estimated so that it is equal to the social marginal damages resulting from that additional ton of emissions. Nordhaus' pioneer models can be classified into two categories: those with a single region (DICE models – Dynamic Integrated model of Climate and the Economy) and those with several regions (RICE models – Regional Integrated model of Climate and the Economy). The literature is obviously not limited to Nordhaus' models. As noted by Hassler and Krusell (2012), the increased interest in climate change in the 1990s led to the development of many models, 21 of which are listed by Kelly and Kolstad (1999b). A classification into five broad categories is suggested by Santon et al. (2009): welfare optimization, general equilibrium, partial equilibrium, simulation, and cost minimization. In this literature, the conception of climate faces two main critiques initiated by IPCC (2014) and Pindyck (2017).

The first critique is conceptual and concerns the deterministic nature of these models. Under this assumption, agents have perfect knowledge about future states of climate and economic fundamentals. This leaves no role for uncertainty, economic fluctuations and their possible costs in terms of welfare. In addition, the IAMs' assessment of climate change only accounts for shifts in the mean of climate variables but not in their variability, resulting in a possibly large underestimation of the cost of climate change. The second critique is empirical. The usual practice in this literature is to calibrate the model without estimating structural parameters. In absence of explicit empirical foundations, Pindyck (2017) argues that these models can be used to provide any result one desires. Stern (2016) points out shortcomings in the consideration of certain risks in many IAM models, leading these models to underestimate the impacts of climate change. Some recent IAM models, however, incorporate uncertainties (see for example Kelly and Kolstad, 1999a; Leach, 2007; Gerlagh and Liski, 2017). Some alternative models including DSGEs, as mentioned by Stern (2016), also have the ability to take uncertainty into account. In particular, Golosov et al. (2014) develop such a model to derive an analytical formula for the social cost of carbon. We complement this literature by tackling the short-term dimension of the weather, and evaluate their social costs in a context of climate change. Most of this literature consider climate change as an increase in the mean of climate variables, in this paper we analyze climate change from a different perspective by considering an increase in the variance of climate variables. We find that the implications from a rise in the variability of climate is non-trivial and should be more considered in the literature of climate change. Unlike IAMs models that limit the analysis to a calibration exercise, we also take the model to the data by estimating the structural parameters of the model to avoid Pindyck's critique.

Another strand of the literature employs empirical models to examine the short run effects of the weather on economic activity. In particular, some authors focus on the relationship between temperatures and productivity. Dell et al. (2012) show that high temperatures have a detrimental effect on economic growth, but only in poor countries. These results are contrasted by the empirical study of Burke et al. (2015) who show that the relationship between high temperatures and productivity is non-linear, for both poor and rich countries. The studies of Acevedo et al. (2017) and Mejia et al. (2018), conducted on larger samples, confirm these results. In addition, Fomby et al. (2013) show that in the case of developed countries, droughts have a negative effect on growth, in particular for the agricultural sector. Our analytical framework builds on these studies to model how climate can affect economic activity, but from a general equilibrium perspective. We also rely on the results of empirical studies that focus more on the weather and the economy at business cycle frequency. For example, Buckle et al. (2007) and Kamber et al. (2013) underline the importance of weather variations as a source of aggregate fluctuations, along with international trade price shocks, using a structural VAR model for New Zealand. Bloor and Matheson (2010) find evidence of the importance of the weather, more particularly the occurrence of El Niño events, on agricultural production and total output in New Zealand. Cashin et al. (2017) also investigate the effects of El Niño on the world economy, using a country-by-country analysis. More specifically, they find evidence of negative effects of an El Niño shock on real output growth in New Zealand. Lastly, in a recent study, Donadelli et al. (2017) propose a framework related to ours. In a real business cycle model, they introduce temperature levels as an explanatory factor of productivity for the US economy. In their model, productivity is affected by the unpredictable component of temperatures. Their results show that a one-standard deviation temperature shock causes a 1.4 percentage point decrease in productivity growth. The authors emphasize the importance of temperature shocks regarding welfare costs. Our article complements this study by taking a theoretical model to the data, instead of limiting the analysis to a calibration exercise. In addition, our measure of the weather is not limited to temperatures, as our weather index also includes the role of rainfalls as a determinant of agricultural productivity.

The remainder of this article is organized as follows: Section 2 provides empirical evidence regarding the impact of weather shocks on macroeconomic variables. Section 3 and Section 4 sketch the DSGE model and present its estimation, respectively. Section 5 provides evidence on the importance of introducing weather shocks in the model. Section 6 analyzes the short-term effects of weather shocks. Section 7 illustrates how the parameters of the weather-dependent agricultural sector affect our results. Section 8 assesses the fluctuations and welfare costs induced by weather shocks under different climate scenarios. Section 9 concludes.

2 Business Cycle Evidence on Weather Shocks

How do we measure the weather? In most of the models in environmental economics, weather and climate measurements are solely based on temperature records. In agricultural economics these measures are often supplemented by rainfall observations in order to characterize agricultural returns patterns. In this paper, the weather is measured through soil moisture deficits.

Soil moisture deficits depict the balance ratio between rainfalls and temperatures. Rainfalls typically boost the productivity of the land by favoring crop growth, and conversely the evapotranspiration process induced by higher temperatures reduces land productivity.[5] Based on observations of soil moisture deficits, we build a macroeconomic index[6] that aims at providing an accurate measure of land productivity in New Zealand. A graphical representation of this index is provided in Figure 1. By construction, the index values range from -4 to +4, where positive values indicate a soil moisture deficit, while negative ones indicate an excess of moisture.

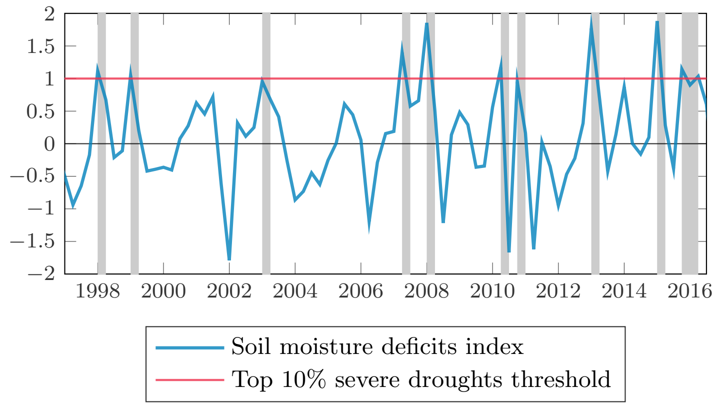


Figure 1: Weather index measuring soil moisture deficits in New Zealand.

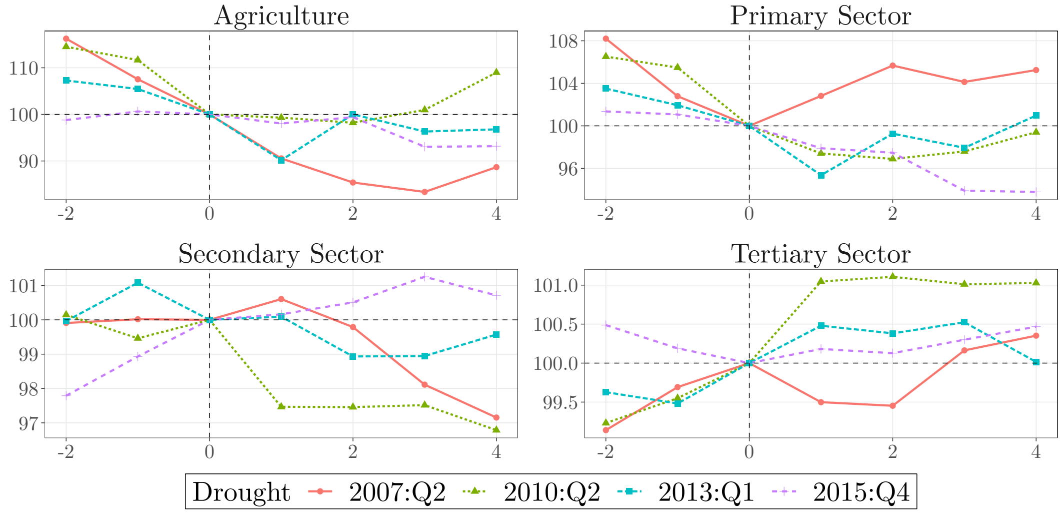
As shown in Figure 1, New Zealand has experienced cyclical changes in its soil water deficits index over the last two decades, oscillating between periods of high volumetric water content in soils and periods of droughts. Assuming a normal distribution of the weather, the 10th percent of the most severe episodes can be inferred directly from the time series when the soil moisture deficits index peaks above 1. In the same way as for NBER recessions, the index allows to easily date and monitor severe weather events which are very likely to be costly for the agricultural sector as shown by Kamber et al. (2013) and Mejia et al. (2018). In recent years, New Zealand has undergone numerous episodes of severe droughts of various intensities that have disrupted its economy to a greater or lesser extent, most notably in 2007, 2010, 2013 and 2015.

What is the supply-side adjustment of New Zealand following a severe drought? A preliminary assessment of these extreme events on the sectoral reallocation is performed through the examinations of changes in the relative share of each sector in the total production of New Zealand. Figure 2 reports these changes in the shares of agriculture, primary, secondary, and tertiary sectors in total activity, two quarters before and four quarters after the four most severe

[5]See Doorenbos and Kassam (1979) and Narasimhan and Srinivasan (2005) for a analysis of soil moisture on crop yields.

[6]More details on the construction of the index can be found in the online appendix.

Figure 2: Sectoral re-allocations following severe weather shocks.



Notes: The lines show the evolution before and after a drought for each sector's share in total production, after normalizing the sector's share to 100 at the time of the drought.

droughts. For convenience, each sector's share of the total activity is normalized to 100 at the time of the drought. Each line corresponds to a drought episode reported by the index at hand. After a drought shock, the share of the agricultural sector in total output declines substantially although temporarily. A similar pattern is observed for the primary sector, although the magnitude of the reaction is naturally not as important as for agriculture because the primary sector includes mining and fishing which are less sensitive to the weather. Regarding the secondary sector, the result is unclear suggesting that there is no salient effects. As for the tertiary sector, it tends to experience a relative expansion, in accordance with Mejia et al. (2018), suggesting that weather shocks possibly generate positive spillover effects.

	correlation	t-stat	p-value	95% Confidence interval
Agriculture Only	-0.31	-2.99	0.00	$[-0.48, -0.10]$
Primary Sector	-0.25	-2.41	0.02	$[-0.44, -0.04]$
Secondary Sector	-0.10	-0.91	0.37	$[-0.30, 0.11]$
Tertiary Sector	0.39	3.90	0.00	$[0.19, 0.55]$

Notes: The significance of correlations is tested using the Pearson test.

Table 1: Correlations of Sectoral GDP with the weather index.

To complete the assessment, we compute correlations between the time series of the weather and the relative share of different sectors used in the previous figure. Table 1 also corroborates the presence of possible sectoral adjustments. In particular, the share of the agricultural sector is negatively correlated with the weather index, as is, to a lesser extent, the GDP of the primary and secondary sectors. On the other hand, the activity of the tertiary sector is positively correlated with the drought measure.

To investigate further the interactions between the weather and other standard macroeconomic time series, a structural vector autoregressive model is employed. A few constraints on the VAR's equations are necessary to portray New Zealand's specific situation: (i) we impose an exogenous weather (i.e., the weather is not Granger caused by any other variable),[7] (ii) we force domestic variables to have no effect on foreign variables as Cushman and Zha (1997).[8] The VAR includes 8 observable variables. Six of them represent the domestic block: GDP, agricultural production, hours worked, consumption, investments, and variations of the real effective exchange rate. The foreign block contains a measure of GDP for the rest of the world.[9] All these variables are taken in real terms and expressed in percentage deviations from a log-linear trend. In addition, the restricted VAR model is estimated with one lag, as suggested by both Hannan-Quinn and Schwarz criteria. Once the restricted VAR is estimated, some further restrictions on the contemporaneous effects of the covariates are imposed to estimate the Structural VAR.[10]

To investigate the effects of an adverse weather shock, we examine the impulse responses to a one-standard-deviation of the drought variable. A lower triangular Choleski decomposition of the error variance-covariance matrix is used to derive the orthogonal impulse responses. The results are depicted in Figure 3, where each panel represents the response of one of the variables to a weather shock. Overall, a shock to the weather equation generates a contraction of New Zealand's economy in the similar magnitude as Buckle et al. (2007): a rise in soil moisture deficits implies a contemporaneous 0.12% contraction of agricultural production, as already suggested by the two previous assessments. The depression in agricultural production reaches a peak decline of 1.27% after three periods. It is simultaneously followed by a 0.05%

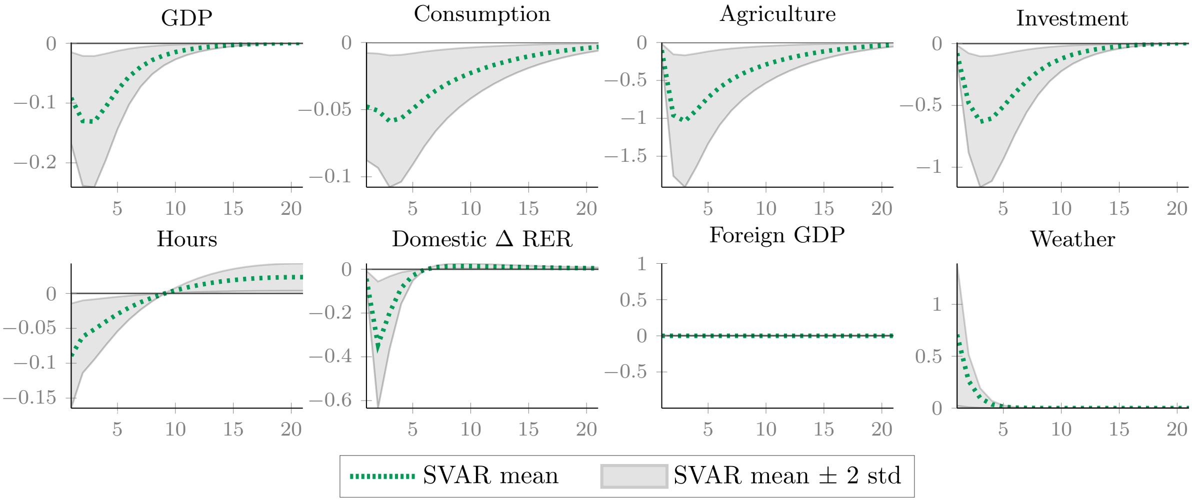
[7] As the historical data only cover a restricted period of time, we assume that human activities do not significantly affect the occurrence of droughts.

[8] In particular, a first constraint concerns the small open economy nature of New Zealand with respect to its trading partners. Letting New Zealand be the domestic country and NZ trading partners be the foreign country, we prevent both domestic shocks and variables to cause fluctuations on foreign variables. We follow Cushman and Zha (1997) and create an exogenous block for the variables from the rest of the world. We impose a second constraint on the VAR's equations concerning the weather itself. In particular, exogeneity is also imposed for the weather variable, so that it can affect the domestic macroeconomic variables, and so that neither domestic nor foreign macroeconomic variables can affect the weather variable. More details are given in the paper's online appendix.

[9] We use a weighted average of GDP for New Zealand's top trading partners, namely Australia, Germany, Japan, the United Kingdom and the United States, where the weights are set according to the relative share of each partner's GDP in the total value.

[10] Specifically, we disable the correlation link between the shock on the weather and foreign variables to be consistent with the small open economy situation. More details on the estimation strategy can be found in the online Appendix.

Figure 3: SVAR impulse response to a 1% weather shock (drought) in New Zealand.



Notes: The green dashed line is the Impulse Response Function. The gray band represents 95% error band obtained from 10,000 Monte-Carlo simulations. The response horizon is in quarters. Time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis.

decline in consumption and a 0.1% decline in investment. The adjustment of the labor market is naturally slower and materialize first through a contraction in hours worked, followed by a late rise occurring 10 quarters after the realization of the weather shock, thus suggesting that the weather mimics the dynamic patterns of a TFP shock. The weather shock vanishes five periods after its realization, although its effects on the economy are strikingly very persistent, in particular for the labor market. This underlines the presence of an unusual propagation mechanism inherent to the weather which is to be taken into account in the modeling of the DSGE presented in the remainder of the article. More specifically, the presence of a slow adjustment effect will require a specific friction for the farmer problem.

3 The Model

Our model is a two-sector, two-good economy in a small open economy setup with a flexible exchange rate regime.[11] The home economy, i.e., New Zealand, is populated by households and firms. The latter operate in the agricultural and the non-agricultural sectors. Workers from the agricultural sector face unexpected weather conditions that affect the productivity of their land. Households consume both home and foreign varieties of goods, thus creating a trading

[11]Our small open economy setup includes two countries. The home country (here, New Zealand) participates in international trade but is too small compared to its trading partners to cause aggregate fluctuations in world output, price and interest rates. The foreign country, representing most of the trading partners of the home country, is thus not affected by macroeconomic shocks from the home country, but its own macroeconomic developments affect the home country through the trade balance and the exchange rate.

channel adjusted by the real exchange rate. The general structure of the model is summarized in Figure 4. The remainder of this section presents the main components of the model.

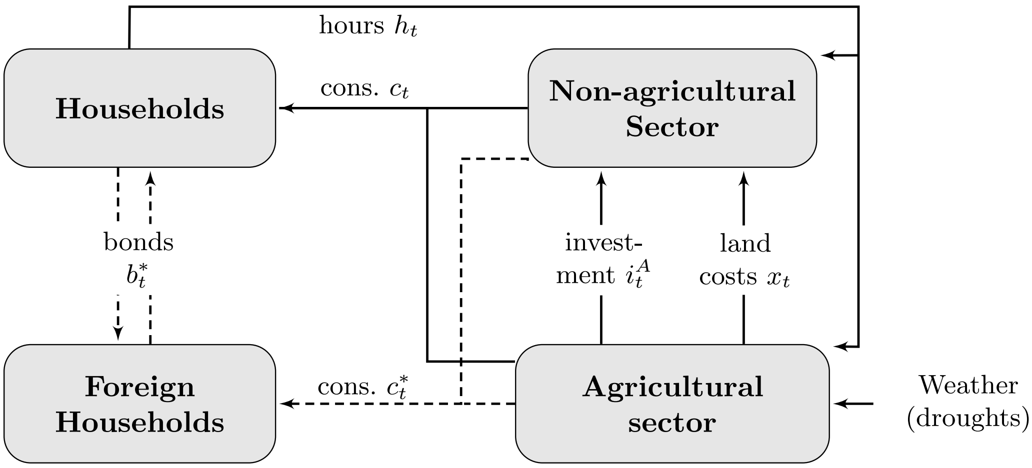


Figure 4: The theoretical model.

3.1 Agricultural Sector

The economy is populated by a unit mass $i \in [0, 1]$ of infinite living and atomistic entrepreneurs. A fraction n_t of these entrepreneurs are operating in the agricultural sector while the remaining fraction $1 - n_t$ operates in the non-agricultural sector. We allow any of the entrepreneurs to switch from one sector to another assuming that the fixed portion of agricultural firms is subject to an exogenous shock: $n_t = n \times \varepsilon_t^N$ where ε_t^N is a stochastic $AR(1)$ process.[12] The fraction $i \in [0, n_t]$ of entrepreneurs operating in the agricultural sector is referred to as farmers.

To investigate the implications of variations of the weather as a source of aggregate fluctuations, a weather variable denoted ε_t^W is introduced in the model. More specifically, this variable captures variations in soil moisture that affect the production process of agricultural goods. To be consistent with the SVAR model, we assume that the aggregate drought index follows an autoregressive process with only one lag:

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

where $\rho_W \in [0, 1)$ is the persistence of the weather shock and $\sigma_W \geq 0$ its standard deviation. In the model, shock processes are all normalized to one in the steady state so that a positive

[12]More specifically, the $AR(1)$ shock is given by: $\log(\varepsilon_t^N) = \rho_N \log(\varepsilon_{t-1}^N) + \sigma_N \eta_t^N$, with $\eta_t^N \sim \mathcal{N}(0, 1)$ and $0 \leq \rho_N \leq 1$.

realization of η_t^W – thus setting ε_t^W above one – depicts a possibly prolonged episode of dryness that damages agricultural output. The stochastic nature of the model imposes that farmers are surprised by contemporaneous and future weather shocks. We do not consider the perspective of news shocks about the weather, as the usual forecast horizon for farmers about weather shocks lies between 1 and 15 days.[13]

Treating the weather as an exogenous process is rather conservative with respect to the canonical setup of Nordhaus (1991). As argued by Pindyck (2017), empirical and theoretical grounds motivating the feedback loop effect between human activity and CO_2 emissions are considered as very fragile in these models. Under the weather exogeneity assumption, there is no CO_2 feedback loop, instead we just let the data be informative about the distribution of weather shocks.

The outcome of farmers' activity in the agricultural sector encompasses a large variety of goods such as livestock, vegetables, plants, or trees. All of these agricultural goods typically require land, labor and physical capital as input to be produced. The general practice in agricultural economics is to explicitly feature the input-output relationship by imposing a functional form on the technology of the agricultural sector.[14] Among many possible functional forms, the Cobb-Douglas production function has become popular in this economic field following the contribution of Mundlak (1961).[15] We accordingly assume that agricultural output is Cobb-Douglas in land, physical capital inputs, and labor inputs:

$$y_{it}^A = \left[\Omega\left(\varepsilon_t^W\right)\ell_{it-1}\right]^{\omega}\left[\varepsilon_t^Z\left(k_{it-1}^A\right)^{\alpha}\left(\kappa_A h_{it}^A\right)^{1-\alpha}\right]^{1-\omega}, \tag{2}$$

where y_{it}^A is the production function of the intermediate agricultural good that combines an amount of land ℓ_{it-1} (subject to the weather $\Omega\left(\varepsilon_t^W\right)$ through a function described later on), physical capital k_{it-1}^A, and labor demand h_{it}^A. Production is subject to an economy-wide technology shock ε_t^Z following an $AR(1)$ shock process affecting the two sectors. The parameter $\omega \in [0,1]$ is the elasticity of output to land, $\alpha \in [0,1]$ denotes the share of physical capital in the

[13]For example, in New Zealand the NIWA provides forecast services to farmers about weather shocks at a high frequency level (1 or 2 days ahead), medium frequency level (6 days ahead) and probabilistic forecast out of fifteen days.

[14]See Chavas et al. (2010) for a survey about the building of theoretical models in agricultural economics over the last century.

[15]We refer to Mundlak (2001) for discussions of related conceptual issues and empirical applications regarding the functional forms of agricultural production. In an alternative version of our model based on a CES agricultural production function, the fit of the DSGE model is not improved, and the identification of the CES parameter is weak.

production process of agricultural goods, and $\kappa_A > 0$ is a technology parameter endogenously determined in the steady state.[16] We include physical capital in the production technology, as, in developed countries the agricultural sector heavily relies on mechanization. Because of the delays in the settlement of physical capital and land, these two variables naturally embody "time to build" features *à la* Kydland and Prescott (1982).

Each farmer owns a land ℓ_{it} that is subject to changes depending both on economic and meteorological conditions. During the production process of agricultural goods between $t-1$ and t, land ℓ_{it-1} is subject to the unexpected realization of the weather ε_t^W. Agricultural production is tied up with exogenous weather conditions through a damage function $\Omega(\cdot)$ in the same spirit as the Integrated Assessment Models literature pioneered by Nordhaus (1991). We opt for a simple functional form for this damage function:[17]

$$\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}, \tag{3}$$

where θ determines elasticity of land productivity with respect to the weather. Imposing $\theta = 0$ shuts down the propagation of weather-driven business cycles. The effective units of land in the production function are denoted $\Omega\left(\varepsilon_t^W\right)\ell_{it-1}$.

In addition to being contemporaneously impacted by weather fluctuations, agricultural production is also subject to effects that spread over time, which we call *weather hysteresis effects*. These hysteresis effects that imply atypical supply dynamics have been well established in the economic literature. For the case of cattle breeding for example, Rosen et al. (1994) document the persistence of livestock induced by the biological process of gestation and maturation of dairy cattle. In the presence of weather shocks, prolonged severe droughts entail early liquidation of stocks combined with a drop in the fertility rate. These changes in the population size and characteristics have permanent effects in the future production of agricultural goods. Kamber et al. (2013) have shown that beyond the immediate rise in slaughter, there tends to be

[16]This parameter has the same interpretation as Restuccia et al. (2008): as long as $\kappa_A > 1$, 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_A allows marginal products of physical capital and labor to be equal across sectors.

[17]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 IAM-based outcome as modelers have so much freedom in choosing a functional form as well as the values of the parameters so that the model can be used to provide any result one desires. 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.

slightly less slaughter for several following years, as stock levels are rebuilt. Hysteresis effects are not limited to the production of animal stocks. Crops are also subject to specific cycles. For example, Narasimhan and Srinivasan (2005) have shown that soil moisture deficits exhibit persistence that is directly connected to the interaction between rainfalls and evapotranspiration, as lands require several months to recover their average productivity levels. In addition, the crop growth process spans over multiple periods. A drought occurring at a specific stage of the process (e.g., during pollination[18]) may entail a critical loss on the final crop yield at harvest time. This temporal gap between the drought and the harvest period needs a specific device that captures this well documented persistence mechanism. To do so, we relax the standard assumption in agricultural economics of fixed land and assume that the productivity of land is possibly time-varying. In particular, each farmer owns land with a productivity (or efficiency) following an endogenous law of motion given by:

$$\ell_{it} = \left[(1-\delta_\ell) + v\left(x_{it}\right)\right] \ell_{it-1} \Omega\left(\varepsilon_t^W\right), \tag{4}$$

where $\delta_\ell \in (0,1)$ is the rate of decay of land productivity that features the desired persistence effect. We assume that the marginal product of land is increasing in the accumulation of land productivity. This is captured by assuming that land expenditures x_{it} yield a gross output of new productive land $v\left(x_{it}\right)\ell_{it-1}$ with $v'\left(\cdot\right) > 0$, $v''\left(\cdot\right) \geq 0$. More specifically, x_{it} can be viewed as agricultural spending on pesticides, herbicides, seeds, fertilizers and water used to maintain the farmland productivity.[19] In a presence of a drought 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 pastures. There is yet no micro-evidence about the functional form of land costs $v\left(x_{it}\right)$, so we adopt here a conservative approach by imposing the functional form: $v\left(x_{it}\right) = \frac{\tau}{\phi} x_{it}^{\phi}$ where $\tau \geq 0$ and $\phi \geq 0$. For $\phi \to 0$, land productivity exhibits constant return, while for $\phi > 0$ land costs exhibits increasing returns. The parameter τ allows here to pin down the amount of *per capita* land in the deterministic steady state.

[18]See Hane et al. (1984) for an evaluation of the relationship between water used by crops at various growth stages.

[19]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.

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

$$i_{it}^{A} = k_{it}^{A} - (1 - \delta_K)\, k_{it-1}^{A}, \tag{5}$$

where $\delta_K \in [0, 1]$ is the depreciation rate of physical capital and i_{it}^{A} is investment of the representative farmer.

Real profits d_{it}^{A} of the farmer are given by:

$$d_{it}^{A} = p_t^A y_{it}^{A} - p_t^N \left(i_{it}^{A} + S\left(\varepsilon_t^i \frac{i_{it}^{A}}{i_{it-1}^{A}} \right) i_{it-1}^{A} \right) - w_t^A h_{it}^{A} - p_t^N x_{it}, \tag{6}$$

where $p_t^A = P_t^A / P_t$ is the relative production price of agricultural goods, 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 is an investment cost shock making investment growth more expensive. It follows an $AR(1)$ shock process:

$$\log(\varepsilon_t^I) = \rho_I \log(\varepsilon_{t-1}^I) + \sigma_I \eta_t^I, \tag{7}$$

where $\rho_I \in [0, 1)$ denotes the root of the $AR(1)$, and $\sigma_I \geq 0$ the standard deviation of the innovation.

We assume that a representative farmer is a price taker. The profit maximization he or she faces can be cast as choosing the input levels under land efficiency and capital law of motions as well as technology constraint:

$$\max_{\left\{h_{it}^A, i_{it}^A, k_{it}^A, \ell_{it}, x_{it}\right\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} d_{it+\tau}^{A} \right\}, \tag{8}$$

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

The original equation that is worth commenting is the optimal demand for intermediate expenditures:

$$\frac{p_t^N}{v'(x_{it})\, \ell_{it-1} \Omega\left(\varepsilon_t^W\right)} = E_t \left\{ \Lambda_{t,t+1} \left(\omega \frac{y_{it+1}^{A}}{\ell_{it}} + \frac{p_{t+1}^N}{v'(x_{it+1})\, \ell_{it}} \left[(1 - \delta_\ell) + v(x_{it+1}) \right] \right) \right\}. \tag{9}$$

The left-hand side of the equation 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. A weather shock deteriorates the expected marginal benefit of lands and rise the current cost of land maintenance. The shape of the cost function $v\left(x_{it}\right)$ critically determines the response of agricultural production following a drought shock. A concave cost function, i.e., $v''\left(x_{it}\right) < 0$, 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 $\phi \geq 0$ is preferred to feature an increase in spending x_{it} 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 $j \in [0, 1]$ of identical households that consume, save and work in the two production sectors. The representative household maximizes the welfare index expressed as the expected sum of utilities discounted by $\beta \in [0, 1)$:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\sigma} \left(C_{jt+\tau} - bC_{t-1+\tau}\right)^{1-\sigma} - \frac{\chi \varepsilon^H_{t+\tau}}{1+\sigma_H} h^{1+\sigma_H}_{jt+\tau} \right], \tag{10}$$

where the variable C_{jt} is the consumption index, $b \in [0, 1)$ is a parameter that accounts for external consumption habits, h_{jt} is a labor effort index for the agricultural and non-agricultural sectors, and $\sigma > 0$ and $\sigma_H > 0$ represent consumption aversion and labor disutility coefficients, respectively. Labor supply is affected by a shift parameter $\chi > 0$ pinning down the steady state of hours worked and a labor supply $AR(1)$ shock ε^H_t that makes hours worked more costly in terms of welfare.

Following Horvath (2000), we introduce imperfect substitutability of labor supply between the agricultural and non-agricultural sectors to explain co-movements at the sector level by defining a CES labor disutility index:

$$h_{jt} = \left[\left(h^N_{jt}\right)^{1+\iota} + \left(h^A_{jt}\right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{11}$$

The labor disutility index consists of hours worked in the non-agricultural sector h^N_{jt} and agriculture sector h^A_{jt}. Reallocating labor across sectors is costly and is governed by the substitutability parameter $\iota \geq 0$. If ι equals zero, hours worked across the two sectors are perfect substitutes, leading to a negative correlation between the sectors that is not consistent with the data. 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:

$$\sum_{s=N,A} w^s_t h^s_{jt} + r_{t-1} b_{jt-1} + rer^*_t r^*_{t-1} b^*_{jt-1} - T_t \geq C_{jt} + b_{jt} + rer^*_t b^*_{jt} + p^N_t rer_t \Phi(b^*_{jt}). \tag{12}$$

The income of the representative household is made up of labor income with a real wage w^s_t in each sector s ($s = N$ for the non-agricultural sector, and $s = A$ for the agricultural one), real risk-free domestic bonds b_{jt}, and foreign bonds b^*_{jt}. 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 purchases are affected by the foreign real exchange rate rer^*_t (an increase in rer^*_t can be interpreted as an appreciation of the foreign currency). The real exchange rate is computed from the nominal exchange rate e^*_t adjusted by the ratio between foreign and home price, $rer^*_t = e^*_t P^*_t / P_t$. In addition, the government charges lump sum taxes, denoted T_t. The household's expenditure side includes its consumption basket C_{jt}, bonds and risk-premium cost $\Phi(b^*_{jt})$=$0.5\chi_B (b^*_{jt})^2$ paid in terms of domestic non-agricultural goods at a relative market price $p^N_t = P^N_t / P_t$.[20] The parameter $\chi_B > 0$ denotes the magnitude of the cost paid by domestic households when purchasing foreign bonds.

We now discuss the allocation of consumption between non-agricultural/agricultural goods and home/foreign goods. First, the representative household allocates total consumption C_{jt} between two types of consumption goods produced by the non-agricultural and agricultural sectors denoted C^N_{jt} and C^A_{jt}, respectively. The CES consumption bundle is determined by:

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}} (C^N_{jt})^{\frac{\mu-1}{\mu}} + (\varphi)^{\frac{1}{\mu}} (C^A_{jt})^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \tag{13}$$

where $\mu \geq 0$ denotes the substitution elasticity between the two types of consumption goods,

[20] 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 open economy models.

and $\varphi \in [0,1]$ is the fraction of agricultural goods in the household's total consumption basket. The corresponding consumption price index P_t reads as follows: $P_t = [(1-\varphi)\,(P^N_{C,t})^{1-\mu} + \varphi(P^A_{C,t})^{1-\mu}]^{\frac{1}{1-\mu}}$, where $P^N_{C,t}$ and $P^A_{C,t}$ are consumption price indexes of non-agricultural and agricultural goods, respectively.

Second, each index C^N_{jt} and C^A_{jt} is also a composite consumption subindex composed of domestically and foreign produced goods:

$$C^s_{jt} = \left[(1-\alpha_s)^{\frac{1}{\mu_S}}\,(c^s_{jt})^{\frac{(\mu_s-1)}{\mu_s}} + (\alpha_s)^{\frac{1}{\mu_s}}\,(c^{s*}_{jt})^{\frac{(\mu_s-1)}{\mu_s}}\right]^{\frac{\mu_s}{(\mu_s-1)}} \quad \text{for } s = N, A \tag{14}$$

where $1-\alpha_s \geq 0.5$ denotes the home bias, i.e., the fraction of home-produced goods, while $\mu_S > 0$ is the elasticity of substitution between home and foreign goods. In this context, the consumption price indexes $P^s_{C,t}$ in each sector s are given by: $P^s_{C,t} = \left[(1-\alpha_s)\,(P^s_t)^{1-\mu_s} + \alpha_s(e^*_t P^{s*}_t)^{1-\mu_s}\right]^{\frac{1}{(1-\mu_s)}}$, for $s = N, A$. In this expression, P^s_t is the production price index of domestically produced goods in sector s, while P^{s*}_t is the price of foreign goods in sector s.

Finally, demand for each type of good is a fraction of the total consumption index adjusted by its relative price:

$$C^N_{jt} = (1-\varphi)\left(\frac{P^N_{C,t}}{P_t}\right)^{-\mu} C_{jt} \text{ and } C^A_{jt} = \varphi\left(\frac{P^A_{C,t}}{P_t}\right)^{-\mu} C_{jt}, \tag{15}$$

$$c^s_{jt} = (1-\alpha_s)\left(\frac{P^s_t}{P^s_{C,t}}\right)^{-\mu_s} C^s_{jt} \text{ and } c^{s*}_{jt} = \alpha_s\left(e^*_t\frac{P^{s*}_t}{P^s_{C,t}}\right)^{-\mu_s} C^s_{jt} \text{ for } s = N, A. \tag{16}$$

3.3 Non-agricultural Sector

There exists a continuum of perfectly competitive non-agricultural firms indexed by $i \in [1, n_t]$, with 1-n_t denoting the relative size of the non-agricultural sector in the total production of the economy. These firms are similar to agricultural firms except in their technology as they do not require land inputs to produce goods and are not directly affected by weather. Each representative non-agricultural firm has the following Cobb-Douglas technology:

$$y^N_{it} = \varepsilon^Z_t\left(k^N_{it-1}\right)^{\alpha}\left(h^N_{it}\right)^{1-\alpha}, \tag{17}$$

where y^N_{it} is the production of the i^{th} intermediate goods firms that combines physical capital k^N_{it-1}, labor demand h^N_{it} and technology ε^Z_t. The parameters α and $\alpha-1$ represent the output elasticity of capital and labor, respectively. Technology is characterized as an $AR(1)$ shock process:

$$\log(\varepsilon_t^Z) = \rho_Z \log(\varepsilon_{t-1}^Z) + \sigma_Z \eta_t^Z, \tag{18}$$

where $\rho_Z \in [0, 1)$ denotes the $AR(1)$ term in the technological shock process and $\sigma_Z \geq 0$ the standard deviation of the 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.[21]

The law of motion of physical capital in the non-agricultural sector 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 and i_{it}^N is investment from non-agricultural firms.

Real profits are given by:

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

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.

3.4 Authority

The public authority consumes some non-agricultural output 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 affected by a standard $AR(1)$ stochastic shock:

$$\log(\varepsilon_t^G) = \rho_G \log(\varepsilon_{t-1}^G) + \sigma_G \eta_t^G, \qquad \eta_t^G \sim \mathcal{N}(0, 1), \tag{22}$$

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

where $1 > \rho_G \geq 0$ and $\sigma_G \geq 0$. This shock captures variations in absorption which are not taken into account in our setup such as political cycles and international demand in intermediate markets.

The government budget constraint equates spending plus interest payment on existing debt to new debt issuance and taxes:

$$G_t + r_{t-1} b_{t-1} = b_t + T_t. \tag{23}$$

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 (2010b), our foreign economy bowls down to a small set of key equations that determine New Zealand exports and real exchange rate dynamics. The foreign country is determined by an endowment economy characterized by an exogenous foreign consumption:[22]

$$\log\left(c_{jt}^*\right) = (1-\rho_C)\log\left(\bar{c}_j^*\right) + \rho_C \log\left(c_{jt-1}^*\right) + \sigma_C \eta_t^C, \qquad \eta_t^C \sim \mathcal{N}(0,1), \tag{24}$$

where the $0 \leq \rho_C < 1$ is the root of the process, $\bar{c}_j^* > 0$ is the steady state foreign consumption and $\sigma_C \geq 0$ is the standard deviation of the shock. The parameters σ_C and ρ_C are estimated in the fit exercise to capture variations of the foreign demand. A rise in the demand triggers a boost in the exportation of New Zealand goods, followed by an appreciation of the foreign exchange rate.

Each period, foreign households solve the following optimization scheme:

$$\max_{\{c_{jt}^*, b_{jt}^*\}} E_t \left\{ \sum_{\tau=0}^{\infty} \beta^\tau \varepsilon_{t+\tau}^E \log\left(c_{jt+\tau}^*\right) \right\}, \tag{25}$$

$$s.t. \qquad r_{t-1}^* b_{jt-1}^* = c_{jt}^* + b_{jt}^*. \tag{26}$$

[22]For simplicity, our foreign economy boils down to an endowment economy *à la* Lucas (1978) in an open economy setup where consumption is exogenous. Most of the parameters and the steady states are symmetric between domestic and the foreign economy. Consistently 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.

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

$$\log(\varepsilon_t^E) = \rho_E \log(\varepsilon_{t-1}^E) + \sigma_E \eta_t^E, \tag{27}$$

with $\eta_t^E \sim \mathcal{N}(0,1)$. This shock temporary raises the household's discount factor and drives down the foreign real interest rate and naturally leads capital to flow to New Zealand. Regarding the budget constraint, it comprises consumption and domestic bonds purchase, the latter are remunerated at a predetermined real rate r_{t-1}^*. In absence of specific sectoral shocks, all sectoral prices of the foreign economy are perfectly synchronized, i.e., $P_t^* = P_t^{A*} = P_t^{N*}$. 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 $P_t^* = P_{C,t}^{A*} = P_{C,t}^{N*}$.

3.6 Aggregation and Equilibrium Conditions

After aggregating all agents and varieties in the economy and imposing market clearing on all markets, the standard general equilibrium conditions of the model can be deducted.

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

$$(1-n_t)\,Y_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{P_t^N}{P_{C,t}^N}\right)^{-\mu_N}\left(\frac{P_{C,t}^N}{P_t}\right)^{-\mu} C_t + \alpha_N \left(\frac{1}{e_t^*}\frac{P_t^N}{P_{C,t}^{N*}}\right)^{-\mu_N}\left(\frac{P_{C,t}^{N*}}{P_t^*}\right)^{-\mu} C_t^*\right] + G_t + I_t + n_t x_t + \Phi(b_t^*), \tag{28}$$

where the total supply of home non-agricultural goods is given by $\int_{n_t}^1 y_{it}^N \,\mathrm{d}i = (1-n_t)\,Y_t^N$, and total demands from both the home and the foreign economy read as $\int_0^1 c_{jt}\,\mathrm{d}j = C_t$ and $\int_0^1 c_{jt}^*\,\mathrm{d}j = C_t^*$, respectively, with $1-\alpha_N$ and α_N the fraction of home and foreign home-produced non-agricultural goods, respectively. Aggregate investment, with $\int_{n_t}^1 i_{it}^N\,\mathrm{d}i = (1-n_t)\,I_t^N$ and $\int_0^{n_t} i_{it}^A\,\mathrm{d}i = n_t I_t^A$, is given by: $I_t = (1-n_t)\,I_t^N + n_t I_t^A$. Turning to the labor market, the market clearing condition between household labor supply and demand from firms in each sector is $\int_0^1 h_{jt}^N \mathrm{d}j = \int_{n_t}^1 h_{it}^N \mathrm{d}i$ and $\int_0^1 h_{jt}^A \mathrm{d}j = \int_0^{n_t} h_{it}^A \mathrm{d}i$. This allows us to write the total number of hours worked: $H_t = (1-n_t)\,H_t^N + n_t H_t^A$. Aggregate real production is given by:

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

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

$$n_t Y_t^A = \varphi \left[(1-\alpha_A) \left(\frac{P_t^A}{P_{C,t}^A} \right)^{-\mu_A} \left(\frac{P_{C,t}^A}{P_t} \right)^{-\mu} C_t + \alpha_A \left(\frac{1}{e_t^*} \frac{P_t^A}{P_{C,t}^{A*}} \right)^{-\mu_A} \left(\frac{P_{C,t}^{A*}}{P_t^*} \right)^{-\mu} C_t^* \right], \tag{29}$$

where $\int_0^{n_t} y_{it}^A \, \mathrm{d}i = n_t Y_t^A$. In this equation, the left side denotes the aggregate production, while the right side denotes respectively demands from home and foreign (i.e., imports) households.

Given the presence of intermediate inputs, the GDP is given by:

$$gdp_t = Y_t - p_t^N n_t X_t. \tag{30}$$

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

$$b_t^* = r_{t-1}^* \frac{rer_t^*}{rer_{t-1}^*} b_{t-1}^* + tb_t, \tag{31}$$

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

$$tb_t = p_t^N \left[(1-n_t) Y_t^N - G_t - I_t - n_t X_t - \Phi(b_t^*) \right] + p_t^A n_t Y_t^A - C_t. \tag{32}$$

The general equilibrium condition is defined as a sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and prices $\{\mathcal{P}_t\}_{t=0}^{\infty}$ such that for a given sequence of quantities $\{\mathcal{Q}_t\}_{t=0}^{\infty}$ and the realization of shocks $\{\mathcal{S}_t\}_{t=0}^{\infty}$, the sequence $\{\mathcal{P}_t\}_{t=0}^{\infty}$ guarantees simultaneous equilibrium in all markets previously defined.

4 Estimation

The model is estimated using Bayesian methods and quarterly data for New Zealand. We estimate the structural parameters and the sequence of shocks following the seminal contributions of Smets and Wouters (2007) and An and Schorfheide (2007). In a nutshell, a Bayesian approach can be followed by combining the likelihood function with prior distributions for the parameters of the model to form the posterior density function. The posterior distributions are drawn through the Metropolis-Hastings sampling method. We solve the model using a linear approximation to the model's policy function, and employ the Kalman filter to form the likelihood function and compute the sequence of errors. For a detailed description, we refer the reader to the original papers.

4.1 Data

The Bayesian estimation relies on the same sample as the one used by the VAR model over the sample period 1994Q2 to 2016Q4.[23] Therefore, each observable variable is composed of 91 observations. The dataset includes 8 times series: output, consumption, investment, hours worked, agricultural production, foreign production, variations of the real effective exchange rate and the drought index.

Concerning the transformation of the series, the point is to map non-stationary data to a stationary model. Observable variables that are known to have a trend (namely here, output, investment and foreign output) are made stationary in three steps. First, they are divided by the working age population. Second, they are taken in logs. And third, they are detrended using a quadratic trend. We thus choose to neglect the low frequency component (i.e., the trend) in all empirical variables for two main reasons: (i) the sample employed here is too short to observe any trend effects on the weather making the use of trend on the weather irrelevant;[24] (ii) dealing with trends in open economy models is challenging when economies are not growing at the same rate, the solution adopted in estimated open economy models is simply to neglect trends as in Justiniano and Preston (2010b). For hours worked, the correction method of Smets and Wouters (2007) is applied: it consists of multiplying the number of paid hours by the employment rate. Finally, turning to the weather index, daily data from weather stations are collected and then spatially and temporally aggregated to compute an index of soil moisture for each local state composing New Zealand.[25] The local values of the index are then aggregated at the national level by means of a weighted mean, where the weights are chosen according to the relative size of the agricultural output in each state. The resulting index is, by construction, zero mean.

The vector of observable is given by:

$$\mathcal{Y}_t^{obs} = 100 \times \left[\hat{y}_t, \quad \hat{c}_t \quad \hat{\imath}_t, \quad \hat{h}_t, \quad \hat{y}_t^A, \quad \hat{y}_t^*, \quad \Delta\widehat{rer}_t \quad \hat{\omega}_t\right]', \tag{33}$$

[23]Series for world output and hours worked for the period 1989-Q2 and 1993-Q4 are not available. This incomplete sub-sample is, however, used to initialise the Kalman filter. Only time periods after the presample enter the actual likelihood computations.

[24]In the IAM literature, the time horizon considered is usually higher than 100 years, which allows to measure long-terms effects from trends.

[25]The index is computed following Kamber et al. (2013). More details are provided in the online appendix.

where $\hat{y}_t$ is the output gap, $\hat{c}_t$ is the consumption gap, $\hat{\imath}_t$ is the investment gap, $\hat{h}_t$ is an index of hours worked, $\hat{y}_t^A$ is the agricultural production gap, $\hat{y}_t^*$ is the foreign production gap, $\widehat{rer}_t$ is New Zealand real exchange rate and finally $\hat{\omega}_t$ is the drought index.

The corresponding measurement equations are given by:

$$\mathcal{Y}_t = 100 \times \left[\widetilde{gdp}_t, \quad \tilde{C}_t, \quad \tilde{p}_t^N + \tilde{I}_t, \quad \tilde{H}_t, \quad \tilde{n}_t + \tilde{p}_t^A + \tilde{Y}_t^A, \quad \tilde{C}_t^*, \quad -\Delta \widetilde{rer}_{t+1}^*, \quad \tilde{\varepsilon}_t^W \right]', \tag{34}$$

where all these variables are expressed in percentage deviations from their steady state: $\tilde{x}_t = \log(x_t/\bar{x})$. Note that in the model, the real exchange rate corresponds to the price of the foreign currency, we thus take the minus of the growth rate of the real exchange rate to get the real exchange rate of New Zealand.

4.2 Calibration and Prior Distributions

Table 4 summarizes the calibration of the model. We fix a small number of parameters that are commonly used in the literature of real business cycle models , including β=0.9883, the discount factor; $\bar{H}^N$=$\bar{H}^A$=1/3, the steady state share of hours worked per day; δ_K=0.025, the depreciation rate of physical capital; α=0.33, the capital share in the technology of firms; and g=0.22, the share of spending in GDP.

The portfolio adjustment cost of foreign debt is taken from Schmitt-Grohé and Uribe (2003), with $\chi_B = 0.0007$.[26] The current account is balanced in steady state assuming $\bar{b}^* = \overline{ca} = 0$. Regarding the openness of the goods market, our calibration is strongly inspired by Lubik (2006), with a share α_N of exported non-agricultural goods set to 25% and to 45% for agricultural goods α_A in order to match the observed trade-to-GDP ratio of New Zealand. Turning to agricultural sector, the share of agricultural goods in the consumption basket of households is set to $\varphi = 15\%$, as observed over the sample period. In addition, the land-to-employment ratio $\bar{\ell}$=0.4 is based on the hectares of arable land (hectares per person) in New Zealand (FAO data provided by the World Bank).

The rest of the parameters are estimated using Bayesian methods. Table 6 and Figure 5 report the prior (and posterior) distributions of the parameters for New Zealand. Overall, our prior distributions are either relatively diffuse or consistent with earlier contributions to Bayesian

[26]The value of this parameter marginally affects dynamics of endogenous variables, but it allows to remove an unit root component induced by the open economy setup.

estimations such as Smets and Wouters (2007). In particular, priors for the persistence of the $AR(1)$ processes, the labor disutility curvature σ_H, the consumption habits b and the investment adjustment cost κ are directly taken from Smets and Wouters (2007).[27] The standard errors of the innovations are assumed to follow a Weibull distribution with a mean of 1 and a standard deviation of 2. The Weibull distribution is more diffuse than the Inverse Gamma distribution (both type 1 and 2), has a positive support and provides a better fit in terms of data density. Substitution parameters μ, μ_N, and μ_A are each assumed to follow a Gamma distribution with a mean of 2 and a standard deviation of 1 in order to have a support that lies between 0 and 5. The risk aversion parameter σ_C is assumed to follow a Normal distribution with a mean of 2 and a standard deviation of 0.35 in the same vein as Smets and Wouters (2007). The labor sectoral cost ι follows a diffuse Gaussian distribution with a mean of 1 and a standard deviation of 0.75, as the literature of two-sector models suggests that this parameter is above zero to get a positive correlation link across sectors.

Regarding priors for the agricultural sector, the land efficiency decay rate parameter δ_ℓ is assumed to follow a Beta distribution with prior mean and standard deviation of 0.2 and 0.07, respectively. This prior is rather uninformative as it allows this decay rate to be either close to 0 or 0.40, the latter would imply an annual decay rate of 180%. Regarding the land share in the production function ω, first, under decreasing return this parameter must be below 1, second, the economic literature suggests that this parameter is close to 20%,[28] we thus impose accordingly a Beta distribution on ω with a mean of 0.2 and standard deviation 0.12 to allow this parameter to be either close to 0 or 0.50. The land cost parameter ϕ is also assumed to follow a diffuse Gaussian distribution with prior mean and standard deviation both set to 1, so that the response of output is consistent with that of the VAR model. One of the key parameters in the paper is the damage function parameter θ that is possibly subject to controversy. 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 IAM-based outcome as modelers have so much freedom in choosing a functional form as well as the values of the parameters so that the model can be used to provide any result one desires. To avoid the legitimate criticisms

[27] Note that for any shock process, we divide by 100 the standard deviation of the stochastic disturbance in order to use the same prior distribution as Smets and Wouters (2007) for the estimated standard deviation: $\log(\varepsilon_t^m) = \rho_m \log(\varepsilon_{t-1}^m) + \frac{\sigma_m}{100}\eta_t^m$ with $m = \{Z, G, I, H, W, N, C, E\}$.

[28] The share of land ω in the production function is estimated at 15% for the Canadian economy by Echevarría (1998), while Restuccia et al. (2008) calibrates this parameter 18% for the US economy.

inherent to IAMs, we adopt here a conservative approach on the value of this key parameter of the damage function and set a very diffuse prior with a uniform distribution with zero mean and standard deviation 500. This very flat prior only allows the data be informative about the posterior distribution of this parameter.

4.3 Posterior Distributions

In addition to the prior distributions, Table 6 reports the estimation results that summarize the means and the 5th and 95th percentiles of the posterior distributions, while the latter are illustrated in Figure 5.[29] According to Figure 5, the data were fairly informative, as their posterior distributions did not stay very close to their priors. However, we assess the identification of our parameters using methods developed by Iskrev (2010), these identification methods show that sufficient and necessary conditions for local identification are fulfilled by our estimated model.

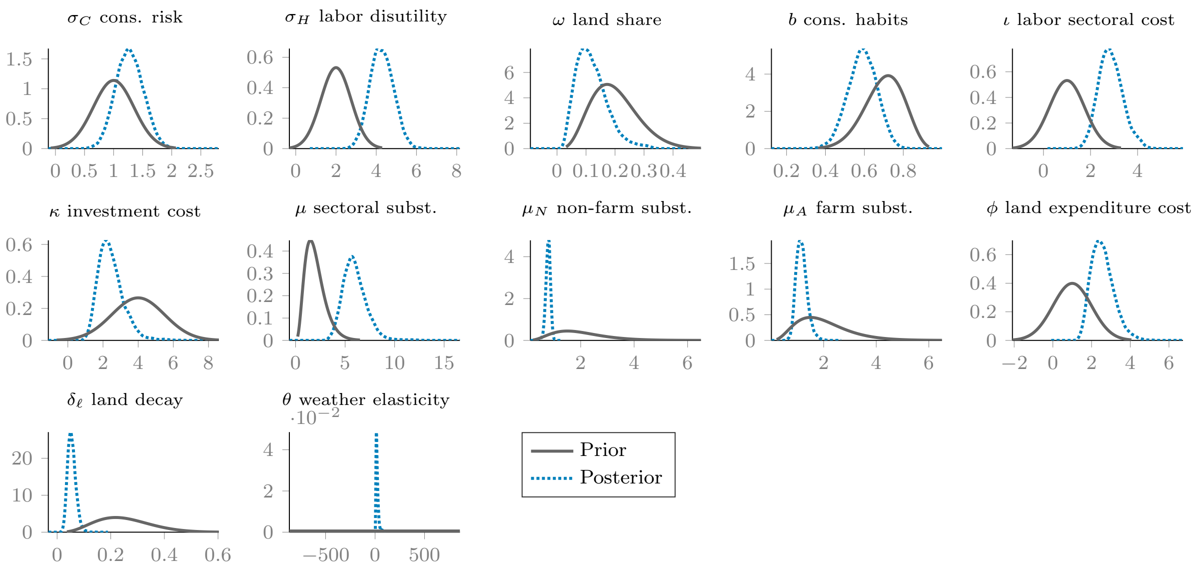


Figure 5: Prior and posterior distributions of structural parameters for New Zealand (excluding shocks).

While our estimates of the standard parameters are in line with the business cycle literature (see, for instance, Smets and Wouters (2007) for the US economy or Lubik (2006) for New Zealand), several observations are worth making regarding the means of the posterior distributions of structural parameters. Strikingly, the land-weather elasticity parameter θ has a

[29]The posterior distribution combines the likelihood function with prior information. To calculate the posterior distribution to evaluate the marginal likelihood of the model, the Metropolis-Hastings algorithm is employed. We compute the posterior moments of the parameters using a total generated sample of 800, 000, discarding the first 80, 000, and based on eight parallel chains. The scale factor was set in order to deliver acceptance rates close to 24%. Convergence was assessed by means of the multivariate convergence statistics taken from Brooks and Gelman (1998). We estimate the model using the dynare package Adjemian et al. (2011).

high posterior value that is clearly different from 0. This implies that even with loose priors, the model suggests that variable weather conditions matter for generating business cycles consistently with empirical evidence of Kamber et al. (2013) and Mejia et al. (2018). The land expenditure cost ϕ suggests that the returns to scale for land expenditures lies between quadratic and cubic functional form. Substitution seems to be an important pattern of consumption decisions of households, especially at a sectoral level. However, the substitution between home and foreign goods appears to be rather low for both sectors. Regarding the labor reallocation parameter ι in the utility function of households, the data favor a costly labor reallocation across sectors, which is in line with the findings of Iacoviello and Neri (2010) for the housing market.

Notice that the value of θ may appear critically high, and thus could question the relevance of the damage function and its resulting interpretation of the weather cycles on economic activity. To gauge the relative magnitude of the damage function on land productivity, we first examine the unconditional mean of the damage function. Recall that the weather volatility from Table 6 is $\sigma_W = 0.81/100$. Therefore since all random shocks are Gaussian, the unconditional mean of weather shocks is given by: $E\left(\varepsilon_t^W\right) = e^{0+0.5\sigma_W^2/(1-\rho_W^2)} = 1.000038$. The resulting average damage, $\Omega\left(E\left(\varepsilon_t^W\right)\right) = 0.99921$, is actually reasonable: weather shocks through the damage function actually generate a permanent loss to land productivity that is below 0.0008%. Second, we also examine the contemporaneous effects of a weather shock on land productivity. The realization of an average weather shock (*i.e.*, $\sigma_W \eta_t^W = 0.81$) slashes land productivity by 15% *ceteris paribus*, while the realization of an extreme drought (*i.e.*, $\sigma_W \eta_t^W = 1.5$) cuts land productivity by 26% through the damage function. These results are rather reasonable as an extreme drought would directly reduce agricultural production by 3.6%.[30] We thus conclude that a high value for θ is necessary to map the changes in the weather index and agricultural production cycles.

To assess how well the estimated model captures the main features of the data, we report in Table 7 and Table 8 both the moments simulated by the model and their empirical counterpart. First, the model does a reasonably job through its steady state ratios in replicating the observed mean. The model performs quite well in terms of volatility for most of observable variables, except for total output and consumption as both are clearly overstated by the model while the

[30] An extreme drought materializes in the model as: $\varepsilon_t^W = 1+1.5/100$, the damage on land productivity is given by $\Omega\left(\varepsilon_t^W\right) = .7343$, the direct effect on agricultural production is given by $\Omega\left(\varepsilon_t^W\right)^\omega = 0.9636$. These calculations neglect previous realizations of weather shocks (and any other disturbances), and neglect any reactions from farmers in terms of labor demand and land expenditures.

theoretical volatility of foreign output is understated. The model performs very well at replicating the persistence of all observable variables. Finally regarding the correlation with GDP, the model replicates the sign of all the correlations, but not their full magnitude. In particular, the correlation with the foreign GDP is not captured by the model, this is a well known puzzle in international economic that can be easily solved by imposing a positive correlation across shocks in the model's covariance matrix.

5 Do Weather Shocks Matter?

A natural question to ask is whether weather shocks significantly explain part of the business cycle. To provide an answer to this question, two versions of the model are estimated – using the same data and priors. In an alternative version of the model, which we consider as a benchmark, the damage function given in Equation 3 is neutralized by imposing $\theta = 0$. Under this assumption, any fluctuation in the weather has no implication for agriculture and thus does not generate any business cycles. In contrast, we compare the benchmark model with the version presented previously in the model section, characterized by the presence of weather-driven business cycles with $\theta \neq 0$.

Table 2 reports for the two models the corresponding data density (Laplace approximation), posterior odds ratio and posteriors model probabilities, which allow us to determine the model that best fits the data from a statistical standpoint. Using a uninformative prior distribution over models (i.e., 50% prior probability for each model), we compute both posterior odds ratios and model probabilities taking the model $\mathcal{M}\left(\theta=0\right)$, i.e., the one with no weather damage as the benchmark.[31] We conduct a formal comparison between models and refer to Geweke (1999) for a presentation of the method to perform the standard Bayesian model comparison employed in Table 2 for our two models. Briefly, one should favor a model whose data density, posterior odds ratio and model probability are the highest compared to other models.

We examine the hypothesis H_0: $\theta = 0$ against the hypothesis H_1: $\theta \neq 0$. To do this, we evaluate the posterior odds ratio of $M\left(\theta \neq 0\right)$ on $M\left(\theta = 0\right)$ using Laplace-approximated marginal data densities. The posterior odds of the null hypothesis of no significance of weather-

[31] As underlined by Rabanal (2007), it is important to stress that the marginal likelihood already takes into account that the size of the parameter space for different models can be different. Hence, more complicated models will not necessarily rank better than simpler models, and $\mathcal{M}\left(\theta \neq 0\right)$ will not inevitably be favored to the benchmark model.

Model type	$\mathcal{M}(\theta = 0)$	$\mathcal{M}(\theta \neq 0)$
Model description	No Weather Damage Model	Weather-Driven Business Cycles
Damage function $\Omega\left(\varepsilon_t^W\right)$	1	$\left(\varepsilon_t^W\right)^{-\theta}$
Prior probability	1/2	1/2
Laplace approximation	-1449.597	-1443.841
Posterior odds ratio	1.000000	118.9675
Posterior model probability	0.003151	0.996849

Table 2: Prior and posterior model probabilities

driven fluctuations is 118.97:1 which leads us to strongly reject the null, *i.e.*, weather shocks do matter in explaining the business cycles of New Zealand. This result is confirmed in terms of log marginal likelihood and posterior odds ratio. This is an important result from the model that highlights the non-trivial role of the weather in driving the business cycles of New Zealand.

6 Weather Shocks as Drivers of Aggregate Fluctuations

This section discusses the propagation of a weather shock and its implications in terms of business cycle statistics.

6.1 Propagation of a Weather Shock

We first report the simulated Bayesian system's responses of the main macroeconomic variables following a standard weather shock in Figure 6.[32] We also report the responses from the SVAR estimation for observable variables which are common between the SVAR and the DSGE model. Unlike the SVAR model, the DSGE model provides the underlying micro-founded mechanisms that drives the propagation of a weather shock.

From a business cycle perspective, this shock acts as a standard (sectoral) negative supply shock through a combination of rising hours worked and falling output. Consistently with the SVAR model, a drought event strongly affects business cycles through a large decline in agricultural output (1.5%), as the weather influences land input in the production process of agricultural goods. Land productivity is strongly negatively affected by the drought. This result is in line with Kamber et al. (2013), as New Zealand's farmers rely extensively on rainfall and pastures to support the agricultural sector. A drought shock decreases land productivity by 22% in the model. To compensate for this loss, farmers can use more non-agricultural

[32]The impulse response functions (IRFs) and their 90% highest posterior density intervals are obtained in a standard way when parameters are drawn from the mean posterior distribution, as reported in Figure 5.

goods as inputs to reestablish their land productivity. For instance, dairy or crop producers may require more water to irrigate their grasslands or cultures to offset the dryness. Farmers may also use more pesticides, as droughts are often followed by pest outbreaks (Gerard et al., 2013). The demand effect for these non-agriculture goods is captured in the model by a rise in inputs x_{it} in Equation 4, which results in a dramatic increase in land costs. The surge in non-agriculture goods has a positive side effect on non-agriculture output. Both the drop in the agricultural production and the rise in non-agriculture output alter the sectoral price structure. As the drought causes a reduction in the agricultural production and a rise in land costs, the relative price in the agricultural sector rises through a market clearing effect. Since relative prices are negatively correlated accross sectors, the price of non-agricultural goods declines in response, thus fueling the demand for non-agricultural goods. With respect to the SVAR model, the DSGE model predicts a higher contraction of economic activity combined with a weaker response of the real exchange rate. In addition, the SVAR model predicts a weaker response of consumption following a weather shock while for labor supplies, a drought induces a reduction in hours worked followed by a persistent increase.

From an international standpoint, the decline in domestic agricultural production generates trade balance deficits. Two factors might explain this. First, around fifty percent of New Zealand's merchandise exports are accounted for by agricultural commodities over the sample period. As both output and price competitiveness of the agricultural sector are deteriorated, New Zealand exports decline. However, the decline price in relative price of non-agricultural fuels the external demand for non-agricultural, thus explaining why this sector experiences a boom. Taken together, the effect of the agricultural sector outweighs the other sector, through a fall in the trade balance and the current account. In the meantime, the domestic real exchange rate depreciates driven by the depressed competitiveness of farmers, which helps in restoring their competitiveness. This reaction of the exchange rate is consistent with the prediction of the SVAR model in Figure 3.

6.2 The Contribution of Weather Shocks on Aggregate Fluctuations

Figure 7 reports the forecast error variance decomposition for four observable variables, i.e., aggregate real production (gdp_t), real agricultural production (Y_t^A), real consumption (C_t) and hours worked (H_t). Five different time horizons are considered, ranging from two quarters

($Q2$), to ten ($Q10$) and fifty quarters ($Q50$) along with the unconditional forecast error variance decomposition ($Q\infty$). In each case, the variance is decomposed into four main components related to supply shocks (technology, labor supply and sectoral reallocation shock), demand shocks (government spending, household preferences and investment shocks), foreign shocks (consumption and foreign preferences), and obviously the weather shocks.

For GDP (gdp_t), supply shocks are the main drivers of the variance in both the short and the long term, followed by demand and foreign shocks. Interestingly, we find that foreign shocks are a sizable driving force of output in the short run by contributing up to 18% of the volatility of GDP. Unlike Justiniano and Preston (2010a) who find a trivial contribution of foreign shock in small open economy models, our model is able to capture the key role of foreign shock as a driver of economic fluctuations. Foreign shocks play a non-negligible role: they account for 18.4% of New Zealand's production in the short run, and 8.1% in the long run. By increasing the time horizon, the contribution of demand and foreign shocks tends to reduce and are gradually replaced by weather shocks, starting from 3.7% at two-quarter horizon to 35% for the unconditional variance.

Turning to agricultural production, supply shocks account for most fluctuations in the short run. They are responsible for 89% of the variance of agricultural production at two-quarter horizon. Domestic and foreign demand shocks play a trivial role in the volatility of agricultural production. The importance of supply shocks declines in the long run, although remaining non-negligible, explaining 57% of agricultural production for the unconditional variance. Weather shocks remarkably drive the variance of agricultural production after a time lag of two quarters. In addition, increasing the time horizon magnifies this result. Thus the weather is a key determining factor of agricultural fluctuations according to the theoretical representation of the data by our model. Concerning the variance of consumption, it is mainly affected, in the short term, by foreign shocks. Weather shocks play a significant role in the same way as for agricultural production, starting from a more distant time horizon. Finally for working hours, they are only slightly affected by weather shocks. Supply shocks are the main drivers of the variance of hours worked as they drive most of the variance of hours.

Overall, we find that weather shocks cause important macroeconomic fluctuations. The increasing contribution of the weather in the time horizon highlights an interesting persistence mechanism which can be associated to the weather hysteresis effects discussed in the business cycle evidence section.

6.3 Historical Decomposition of Business Cycles

An important question one can ask of the estimated model is how important were weather shocks in shaping the recent New Zealand macroeconomic experience. Figure 8 displays the year-over-year growth rate in per capital of real agricultural production, GDP, consumption and hours worked. The blue dotted line is the result of simulating our model's response to all of the estimated shocks and to the initial conditions. The dotted line shows the result of this same simulation when we feed our model only the weather shock.

A notable feature of agricultural production is the important contribution of the weather to its fluctuations. More specifically, this weather contribution oscillates between +4% and -6% over the sample period. During periods of good soil moisture, land productivity is enhanced, which fuels the higher supply of agricultural goods. In contrast, drought periods are associated with lower levels of agricultural output. Severe droughts coincide with a sharp drop in agricultural production driven by the weather shock. In particular, one fourth of agricultural slowdown following the most severe drought in 2008 is strikingly accounted by the weather shock. In 2016, a prolonged episode of drought also contributed by 5% to the contraction of the agricultural supply.

The weather contribution is not limited to the supply of agricultural goods, the remaining panels in Figure 8 show that real output, consumption and hours growth rates are also affected by the weather, but the absolute contribution is on average lower than for agricultural production. For GDP and consumption, the weather's contribution to the growth rate of these variables oscillates between +2% to -2%. Regarding the labor market, the model suggests that weather-driven changes in aggregate labor demand oscillates between -0.5 to 0.9% on the sample period. There is an overall clear spillover mechanism from the agricultural sector to the rest of the economy, which allows the weather to propagate and generate business cycles. Weather-driven fluctuations in agriculture are translated to other selected variables and contribute to their fluctuations. Severe droughts also have important implications for these variables, as the 2008 and 2016 droughts entailed a joint 1% contraction in GDP and consumption while labor supplied increased by 1%.

7 Inspecting the Propagation Mechanism

The originality of the model lies in the introduction of a weather-dependent agricultural sector that relies on a set of structural parameters driving the response of the economy following a weather shock. In this section, we investigate how critical these parameters are by contrasting the responses of the model under different calibrations for three key parameters: the land expenditure cost ϕ, the labor sectoral cost ι, and the land efficiency decay rate δ_ℓ. Each parameter is likely to affect both the propagation and the steady state of the model. To disentangle the short run from the long run, we draw the steady state of the model prior to the realization of the shock in $t = 1$. All the IRFs are expressed in percentage deviations from the steady state of the estimated model.

We first consider the parameter ϕ shaping the land cost function (see Equation 6). This cost function critically determines the marginal cost of rising the land productivity. Recall that a stability condition for land productivity dynamics imposes that $\phi > 1/(1 - \delta_\ell)$, as a result this condition does not allow to examine dynamics under decreasing and constant returns to scale. In Figure 9, we thus contrast the IRFs from the model using the estimated cost curvature ($\phi = 2.57$) with lower ($\phi = 1.57$) and higher ($\phi = 3.57$) increasing returns. The value of this parameter clearly affects the propagation mechanism of a weather shock. Under highly increasing returns, the marginal cost of land costs (e.g., fertilizers and water) rises after a drought, while it tends to be less responsive with a lower ϕ. The main implication of lower returns lies in the response of the agricultural sector, through a positive spike of its relative price generating a strong recession in this sector, before quickly adjusting back to steady state. This relative price distortion across sectors clearly reshapes the response of the non-agricultural sector and total production by creating a quick recession that is not consistent with empirical evidence of the SVAR model. The steady state of the model is also affected. A rise in ϕ increases land expenditures, since the latter are accounted as intermediate consumption, a increase in land expenditures mechanically reduces the GDP (through Equation 30).

We next turn to the labor substitutability parameter ι from the labor disutility index (Equation 11). This parameter determines the household labor supply substitution across sector, we thus contrast a situation with a perfect labor mobility across sectors at a business cycle frequency versus a very costly substitution. Figure 10 reports the IRFs under a linear substitution index ($\iota = 0$) versus the estimated value ($\iota = 2.9$) and a high substitution cost ($\iota = 5$). When

$\iota = 0$, households face no cost of adjusting their labor supply to sectoral wages differentials so that during a weather event, the households increase their labor supply in the non-agricultural sector as the equilibrium wage is higher in this sector. Labor supply is thus flowing to the sector with the highest wage, thus boosting the non-agricultural one. At a macro level, the perfect reallocation generates a strong negative correlation link between sector, and translates into an expansion of the economy. This propagation mechanism is clearly at odd with the SVAR model. In contrast, the increase in the cost of labor reallocation reduces this substitution mechanism and amplifies the recession. The steady state, however, is not affected by this parameter.

Finally, we investigate how the rate of decay of land productivity, denoted δ_ℓ (see Equation 4), shapes the responses of the model by contrasting 3 different calibration from low to high decay rates. Figure 11 reports the corresponding IRFs. This parameter determines the hysteresis effect of the weather by ruling how quickly the land (and thus the economy) returns to its steady state following a drought shock. For a low value of the decay rate, macroeconomic fluctuations are amplified and more persistent, as land productivity requires more time to recover from a drought. Conversely, a higher value reduces the persistence, but mechanically increases the steady state intermediate expenditures in land productivity.

8 Climate Change Implications

We now turn to the implications of climate change for aggregate fluctuations and welfare. The IPCC defines climate change as "*a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*" (IPCC, 2014). In our framework, climate is supposed to be stationary, which makes our setup irrelevant for analyzing changes in mean weather values. However unlike standard models, our framework is able to tackle the implications of a change in the variance of weather shocks. As a first step, we assess the change in the variance of the weather shock by estimating it under different climate scenarios. Then, in a second step, we use the estimates of these variances for each scenario and investigate the effects on aggregate fluctuations.

8.1 Climate Change and Macroeconomic Volatility

We use the estimated DSGE model to assess the effects of a shift in the variability of the weather shock process. We do so in a two-step procedure. First, the simulations are estimated with the value of the variance of the weather shock that is estimated during the fit exercise, which corresponds to historical variability. Second, new simulations are made after altering the variability of the weather shock so it corresponds to the one associated with climate change (we refer to Appendix A for a description of the method determining the change in weather variability). Hence, we proceed to four different alterations of the variance of the weather process.

To measure the implications of climate change on aggregate fluctuations of a representative open economy, we compare the volatility of some macroeconomic variables under historical weather conditions (for the 1989–2014 period) to their counterpart under future climate scenarios (for the 2015–2100 period), normalizing the values of the historical period of each variable to 100. Table 3 report these variations for some key variables.

The first scenario, with regard to the volatility of the weather shock for New Zealand is clearly optimistic, as the variance of drought events is declining by 8.03%. As a result, macroeconomic fluctuations in the country naturally decrease. Agriculture output is particularly affected by this structural change, with a 3.39% decrease of its variance. In contrast, the other scenario for which the rise in variance of the weather shock ranges between 14.11% for the less pessimistic scenario to 51.91% for the most pessimistic one, exhibit a strong increase in the volatility of macroeconomic variables. As a matter of facts, the variance of total output rises by 5.22% under the RCP 4.5 scenario, and by 19.19% under the RCP 8.5 scenario. Agricultural production volatility experiences an important shift of 21.88% under the worst-case scenario. We also observe a dramatic increase in the variance of consumption of 27.09%, relative price of agricultural goods of 16.8%, net foreign asset of 31.86%. The variance of the current account rises by 11.45% while the variance of the real exchange rate rises by 7.54%. For the remaining macroeconomic variables, the changes are relatively smaller.

We therefore find some important changes in the volatility of key macroeconomic variables induced by climate change, which could be very critical, especially for developing economies. Wheeler and Von Braun (2013) find similar effects of climate change on crop productivity which could have strong consequences for food availability for low-income countries. Adapting

		1994-2016 Historical	2100 (projections) RCP 2.5	RCP 4.5	RCP 6.0	RCP 8.5
Var(η_t^W)	Weather shock	100	91.97	114.11	119.44	151.91
Var(gdp_t)	GDP	100	97.03	105.22	107.19	119.19
Var(C_t)	Consumption	100	95.81	107.36	110.15	127.09
Var($p_t^N I_t$)	Investment	100	99.24	101.34	101.85	104.94
Var($p_t^A Y_t^A$)	Agriculture	100	96.61	105.95	108.20	121.88
Var(p_t^A)	Agricultural price	100	97.40	104.56	106.29	116.80
Var(H_t)	Hours	100	99.26	101.29	101.78	104.77
Var(R_t)	Real interest rate	100	99.99	100.01	100.02	100.05
Var(rer_t)	Exchange rate	100	98.83	102.05	102.82	107.54
Var(tb_t)	Trade balance	100	98.23	103.11	104.29	111.45
Var(b_t^*)	Net Foreign Asset	100	95.31	108.24	111.36	130.32
E($\mathcal{W}_t$)	Welfare	-624.4944	-624.4629	-624.5497	-624.5707	-624.6980
λ (%)	Welfare cost	0.3035	0.2791	0.3464	0.3626	0.4613

Table 3: Changes in variances of simulated observables under climate change scenarios.

Notes: The model is first simulated as described in Section 4. Theoretical variances of each variable are then estimated and normalized to 100. Then, variances of weather (η_t^W) shocks are modified to reflect different climate scenarios (compared to the reference 1994–2016 period, changes in the volatilities are as follows: RCP 2.5, −8.03%; RCP 4.5, +14.11%; RCP 6.0, +19.44%; RCP 8.5, +51.91%). New simulations are estimated using the modified variances of these shocks, and the theoretical variances of the variables of interest are then compared to those of the reference period.

our setup to a developing economy by increasing the relative share of the agricultural sector, and reducing the intensity of the capital, would critically exacerbate the results reported in Table 3.

8.2 The welfare cost of weather-driven business cycles under climate change

To get a welfare perspective on climate change, we compute how much consumption households are willing to abandon to live in an economy free of weather shocks. We compute the path of the economy contrasting two regimes using a second order approximation to the welfare index to obtain an accurate of the welfare cost.[33] The regime a is free of weather shocks (i.e., $\sigma_W = 0$ in Equation 1) while regime b includes weather shocks as estimated in the fit exercise. We introduce λ as the fraction of consumption that the household would be willing to give up to live in the regime a rather than the b. Put differently λ denotes the welfare cost of weather shocks and is computed as:

$$E_t \sum_{\tau=0}^{\infty} \beta^\tau \mathcal{U}\left((1-\lambda)\left[C_{t+\tau}^a - bC_{t-1+\tau}^a\right], h_{t+\tau}^a\right) = E_t \sum_{\tau=0}^{\infty} \beta^\tau \mathcal{U}\left(C_{t+\tau}^b - bC_{t-1+\tau}^b, h_{t+\tau}^b\right). \qquad (35)$$

The last two rows of Table 3 report the corresponding welfare mean and cost computed

[33]See the online appendix for the closed-form expression of the welfare index up to second order.

under alternative scenarios. First of all, the simulations show that today, New Zealanders would be willing to give up to 0.3% of their unconditional consumption in order to live in an economy free of droughts. The magnitude of this cost is not negligible, as our model evaluates the welfare costs of business cycles induced by productivity shocks to 0.08%, 0.05% for spending shocks, 0.06% for investment shocks, 0.75% for labor supply shocks, 0.12% for sector reallocation shock, 0.003% for foreign consumption shock and 0.06% for foreign discount factor.[34] In the literature of uncertainty in macroeconomics, the welfare cost of business cycles is typically low under a CRRA utility specification (e.g., Lucas (1987, chap. 3) and Lucas (2003, section II)). This literature usually concludes that business cycles induce trivial welfare costs. However in presence of weather shocks, we find that the welfare cost of the weather is non-trivial, even with a variant of a CRRA utility function.[35] This conflicting result with the standard macroeconomic literature is directly connected to the weather hysteresis effect: when an adverse weather shock deteriorates land productivity, agricultural output is low for an extended period of time as livestock and crops need time to recover. The resulting consequence is an higher uncertainty for households on their agricultural consumption which naturally drives the welfare cost of business cycles. By disabling the persistence mechanism of land productivity in Equation 4, the welfare cost of business cycles becomes trivial by representing 0.009% of permanent consumption. The magnitude of these results can be contrasted with those of Donadelli et al. (2017) who consider temperature shocks and who find an even larger welfare cost peaking to 18.1%.

We approximate climate change by increasing the variance of weather shocks. The results from this exercise are illustrative as we do not account for crop and livestock adaptation. Therefore, these costs can be interpreted as a maximum bound of the feasible welfare costs. In all our scenarios except for the optimistic RCP 2.5, households would be worse off under the new weather conditions in which the volatility of droughts has increased. Under the optimistic scenario, they would only abandon only 0.30% of their permanent consumption. In the worst-case scenario, this fraction would reach 0.46%. With respect to the benchmark situation over the 1994-2016 period, the welfare cost increased by 0.09, from 0.19 for the historical period to 0.28% for the worst-case scenario. This suggests that there is a strong non-linear relationship

[34]On average, these costs lie in the ballpark of estimates obtained in the RBC literature, see for example Otrok (2001) except for the labor supply shock. The latter generates important welfare costs as it directly affects utility function.

[35]In this paper, the utility function is not exactly the same as Lucas (1987, chap. 3) as it also features consumption habits. However by disabling consumption habits b, the welfare cost of the weather remains high up to 0.08% in the baseline scenario.

between the variance of the shock and the welfare cost as exemplified by Donadelli et al. (2017) for temperature shocks.

9 Conclusion

In this paper, we have investigated how the weather can play an autonomous role in generating business cycles. We have developed and estimated a DSGE model for a small open economy, New Zealand. Our model includes an agricultural sector that faces exogenous weather variations affecting land productivity, and in turn the production of agricultural goods. We find from a statistical standpoint that weather shocks do matter in explaining the business cycles of New Zealand. Both the SVAR and the DSGE models find that a weather shock generates a recession through a contraction of agricultural production and investment combined with a rise in hours worked. Our business cycle decomposition exercises also show that weather shocks are an important driver of agricultural production and, in a smaller proportion, of the GDP. Finally, we use our model to the analysis of climate change by increasing the variance of weather shocks consistently with projections in 2100. The rise in the variability of weather events leads to an increase in the variability of key macroeconomic variables, such as output, agricultural production or the real exchange rate. In addition, we find important welfare costs incurred by weather-driven business cycles, as today households are willing to pay 0.30% of their unconditional consumption to live in a world with no weather shocks, and this cost is increasing in the variability of weather events.

The analysis of weather-driven business cycles is a burgeoning research area given the important context of climate change. In this paper, we have analyzed the importance of weather shocks on the macroeconomic fluctuations of a developed economy. However, the application of our framework to developing countries could highlight the high vulnerability of their primary sectors to weather shocks. In addition, from a policymaker's perspective, our framework could be fruitfully employed to evaluate the optimal conduct of monetary policy to mitigate the destabilizing effects of weather shocks for different scenarios of climate change. Fiscal policy could also play a role in a low-income country, for instance by providing disaster payments, which may be seen as insurance schemes paid by the tax payers. These disaster payments may make sense in the absence of well-functioning insurance markets. Another possibility could be the introduction of trends in the model, which could be affected by weather events both in the short and in the long run. This would provide a scope for crop adaptation and environmental policies aiming at offsetting the welfare costs of weather. Finally, weather shocks could also have implications for financial markets, through a possible rise in the equity premium as predicted by the risk disaster theory in asset pricing.

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A Building Projections up to 2100

To investigate the potential impact of climate change on aggregate fluctuations, we assume that the volatility the weather (η_t^W) (Equation 1) will be affected by climate change. Instead of arbitrarily setting a value for this shift, we provide an approximation using a proxy for the drought index. To do so, we rely on monthly climatic data simulated from a circulation climate model, the Community Climate System Model (CCSM). The resolution of the dataset is a $0.9° \times 1.25°$ grid. Simulated data are divided into two sets: one of historical data up to 2005 and one of projected data from 2006 to 2100. The projected data are given for four scenarios of greenhouse gas concentration trajectories, the so-called Representative Concentration Pathways (RCPs). The first three, i.e., the RCPs of 2.6, 4.5 and 6.0, are characterized by increasing greenhouse gas concentrations, which peak and then decline. The date of this peak varies among scenarios: around 2020 for the RCP 2.6 scenario, around 2040 for the RCP 4.5 and around 2080 for the RCP 6.0. The last scenario, the doom and gloom 8.5 pathway, is based on a quickly increasing concentration over the whole century. The first panel of Figure 12 shows emissions and projections of the emissions of one of the major greenhouse gases, i.e., CO_2, up to 2100.[36]

For these four scenarios, soil moisture deficit data are not available. We therefore use total rainfall as proxy, as rainfalls are strongly correlated with droughts, although the effects of temperatures on the evapotranspiration of lands is not taken into account. Simulated data for each scenario are provided on a grid on a monthly basis. We aggregate them at the national level on a quarterly basis. More details on the aggregation can be found in the online appendix.

These data are then used to estimate the evolution of the volatility of the weather shock. We do so using a rolling window approach. In the DSGE model, we assume that the weather shock is autoregressive of order one. We therefore fit an $AR(1)$ model on each window. The size of the latter is set to 25.5 years, i.e., the length of the sample data used in the DSGE model, so each regression is estimated using 102 observations. The standard error of the residuals are then extracted to give a measure of the evolution of the volatility of the weather shock. The middle panel in Figure 12 illustrates the evolution of the standard error for each scenario. It is then possible to compute the average growth rate of the standard error over the century depending on the climate scenario.[37] The results are displayed in the right panel of Figure 12. In the best-case scenario, RCP 2.5, the variance of the climate measure is reduced by 4.1%; under the RCP 4.5 and RCP 6.0 scenarios, it increases by 6.82% and 9.29%, respectively; under the pessimistic RCP 8.5 scenario, it drastically increases by 23.25%.

[36] The data used to graph the CO_2 emission projections are freely available at `http://www.pik-potsdam.de/~mmalte/rcps/`.

[37] More details on the procedure can be found in the appendix.

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	0.22
φ	Share of agricultural goods in consumption basket	0.15
$\bar{H}^N = \bar{H}^A$	Hours worked	1/3
$\bar{\ell}$	Land per capita	0.40
α_N	Openness of non-agricultural market	0.25
α_A	Openness of agricultural market	0.45
χ_B	International portfolio cost	0.0007

Table 4: Calibrated parameters on a quarterly basis.

		Prior distributions			Posterior distribution	
		Shape	Mean	Std.	Mean	[5%:95%]
SHOCK PROCESS $AR(1)$						
Economy-wide TFP (SD)	$\sigma_Z \times 100$	$\mathcal{W}$	1	2	2.09	*[1.77:2.39]*
Hours supply (SD)	$\sigma_H \times 100$	$\mathcal{W}$	1	2	6.13	*[4.78:7.45]*
Spending (SD)	$\sigma_G \times 100$	$\mathcal{W}$	1	2	4.00	*[3.49:4.49]*
Investment (SD)	$\sigma_I \times 100$	$\mathcal{W}$	1	2	6.19	*[4.85:7.48]*
Sector reallocation (SD)	$\sigma_N \times 100$	$\mathcal{W}$	1	2	8.85	*[6.88:10.69]*
Weather (SD)	$\sigma_W \times 100$	$\mathcal{W}$	1	2	0.81	*[0.71:0.91]*
Foreign time-preference (SD)	$\sigma_E \times 100$	$\mathcal{W}$	1	2	5.33	*[4.47:6.10]*
Foreign consumption (SD)	$\sigma_C \times 100$	$\mathcal{W}$	1	2	0.69	*[0.6:0.77]*
Economy-wide TFP (AR term)	ρ_Z	$\mathcal{B}$	0.5	0.2	0.33	*[0.18:0.47]*
Labour supply (AR term)	ρ_H	$\mathcal{B}$	0.5	0.2	0.88	*[0.82:0.94]*
Spending (AR term)	ρ_G	$\mathcal{B}$	0.5	0.2	0.85	*[0.79:0.91]*
Investment (AR term)	ρ_I	$\mathcal{B}$	0.5	0.2	0.40	*[0.23:0.56]*
Sector reallocation (AR term)	ρ_N	$\mathcal{B}$	0.5	0.2	0.85	*[0.79:0.92]*
Weather (AR term)	ρ_W	$\mathcal{B}$	0.5	0.2	0.38	*[0.24:0.52]*
Foreign time-preference (AR term)	ρ_E	$\mathcal{B}$	0.5	0.2	0.23	*[0.08:0.37]*
Foreign consumption (AR term)	ρ_C	$\mathcal{B}$	0.5	0.2	0.95	*[0.91:0.98]*
STRUCTURAL PARAMETERS						
Risk consumption	σ_C	$\mathcal{N}$	2	0.35	1.27	*[0.89:1.65]*
Labor disutility	σ_H	$\mathcal{N}$	2	0.75	4.27	*[3.33:5.20]*
Land expenditure cost	ϕ	$\mathcal{N}$	1	1	2.57	*[1.64:3.46]*
Share of land in agricultural output	ω	$\mathcal{B}$	0.2	0.1	0.12	*[0.03:0.19]*
Consumption habits	b	$\mathcal{B}$	0.7	0.1	0.59	*[0.47:0.71]*
Labor sectoral cost	ι	$\mathcal{N}$	1	0.75	2.85	*[2.00:3.66]*
Substitutability by type of goods	μ	$\mathcal{G}$	2	1	5.96	*[4.05:7.74]*
Substitutability home/foreign	μ_A	$\mathcal{G}$	2	1	1.16	*[0.83:1.49]*
Substitutability home/foreign	μ_N	$\mathcal{G}$	2	1	0.78	*[0.65:0.92]*
Land efficiency decay rate	δ_ℓ	$\mathcal{B}$	0.2	0.07	0.05	*[0.03:0.08]*
Investment cost	κ	$\mathcal{N}$	4	1.5	2.44	*[1.41:3.57]*
Land-weather elasticity	θ	$\mathcal{U}$	0	500	20.59	*[5.34:36.19]*
Marginal log-likelihood						-1443.84

Table 5: Prior and posterior distributions of structural parameters and shock processes.

Notes: The column entitled "Shape" indicates the prior distributions using the following acronyms: $\mathcal{N}$ describes a normal distribution, $\mathcal{G}$ a Gamma, $\mathcal{U}$ an Uniform, $\mathcal{B}$ a Beta, and $\mathcal{W}$ a Weibull.

Table 6: Prior and posterior distributions of structural parameters and shock processes.

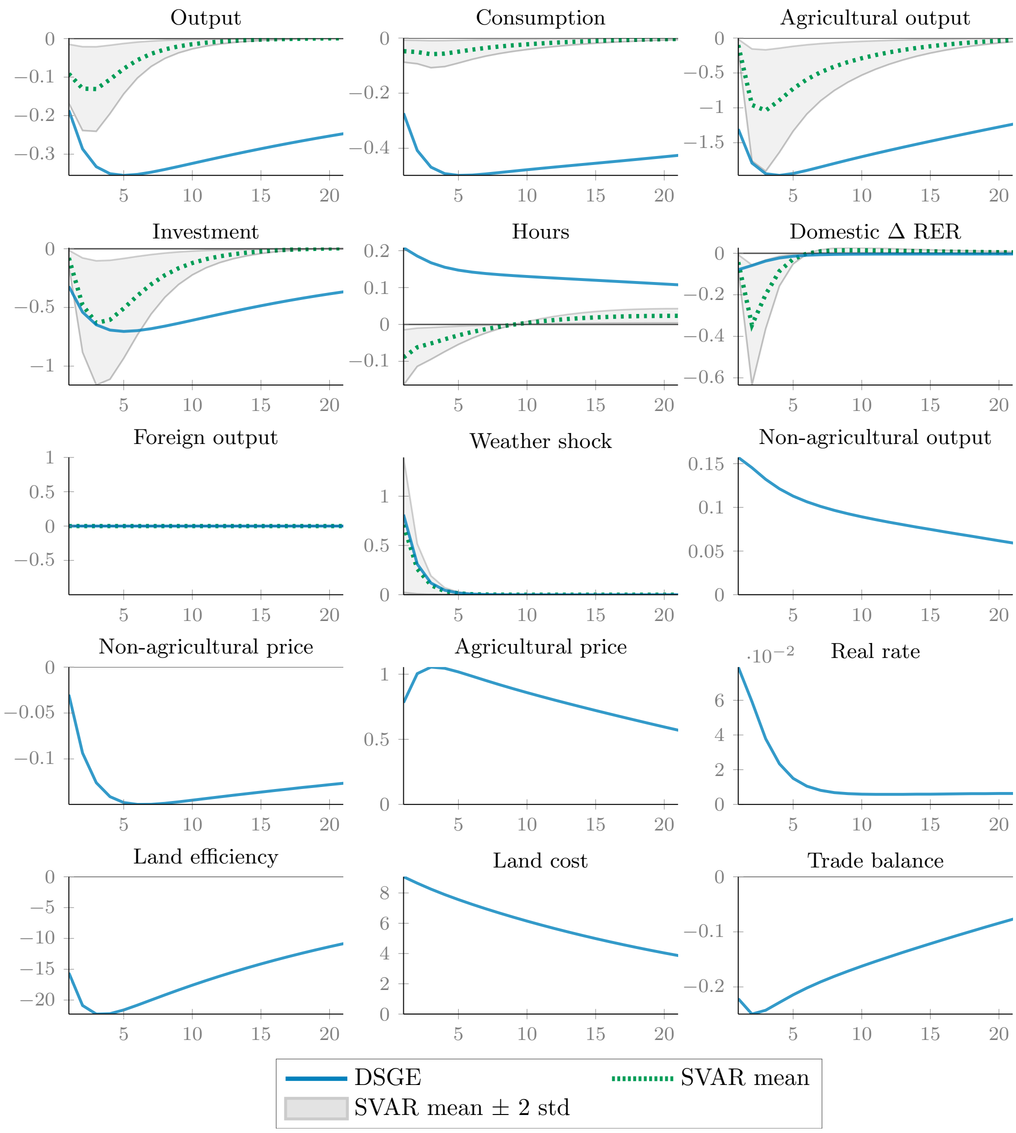


Figure 6: System response to an estimated weather shock η_t^W for the estimated DSGE and SVAR model (when available).

Notes: Blue lines are the Impulse Response Functions (IRFs) generated when parameters are drawn from the mean posterior distribution, as reported in Figure 5. IRFs are reported in percentage deviations from the deterministic steady state. Dotted green lines are the means of the distributions of the Impulse Response Functions (IRFs) of the SVAR model and gray areas are their 90 confidence intervals.

Variable	Interpretation	Model	Data
$\bar{C}/\bar{Y}$	Ratio of consumption to output	0.55	0.57
$\bar{I}/\bar{Y}$	Ratio of investment to output	0.23	0.22
$400 \times (\bar{r}-1)$	Real interest rate	4.72	4.75
$(1-\varphi)\,\alpha_N + \varphi\alpha_A$	Goods market openness	0.28	0.29
$n\bar{Y}^A/\bar{Y}$	Ratio of agricultural production to GDP	0.08	0.07

Table 7: Steady state ratios (empirical ratios are computed using data between 1990 to 2017).

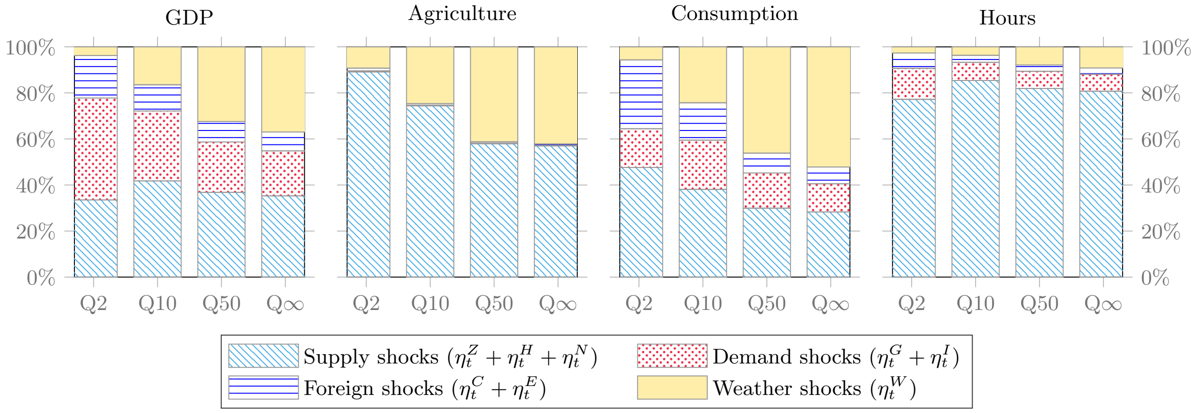


Figure 7: Forecast error variance decomposition at the posterior mean for different time horizons (one, ten, forty and unconditional) for four observable variables.

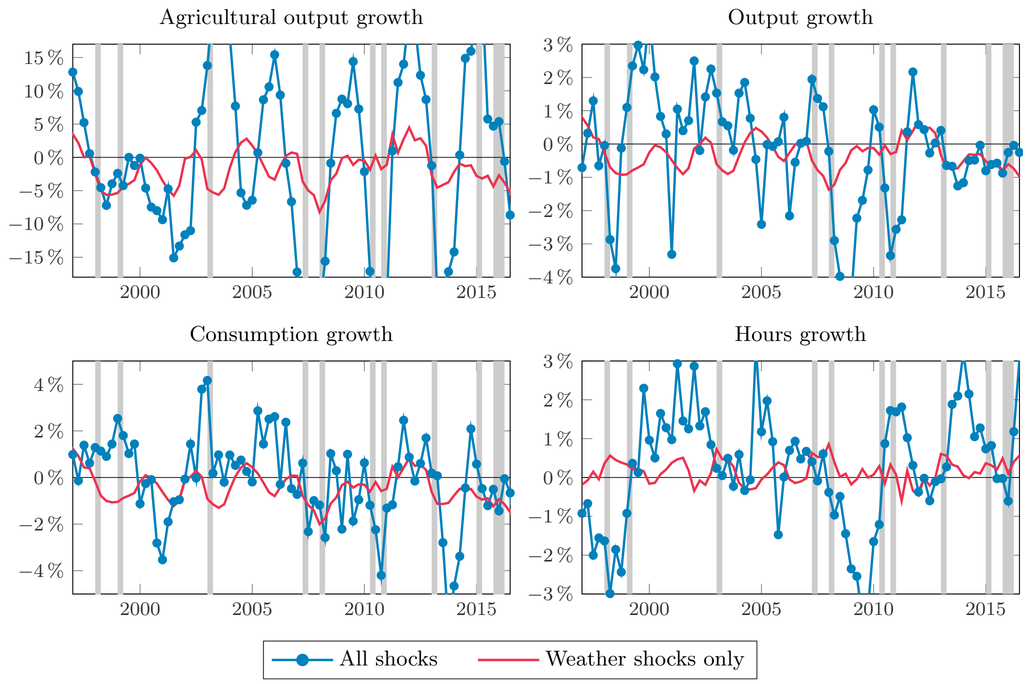


Figure 8: The role of weather shocks on selected variables.

Notes: All data are demeaned. Blue line and red 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 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. Shaded area indicates the 10th percent of the most severe drought episodes, as inferred from the time series of the weather index.

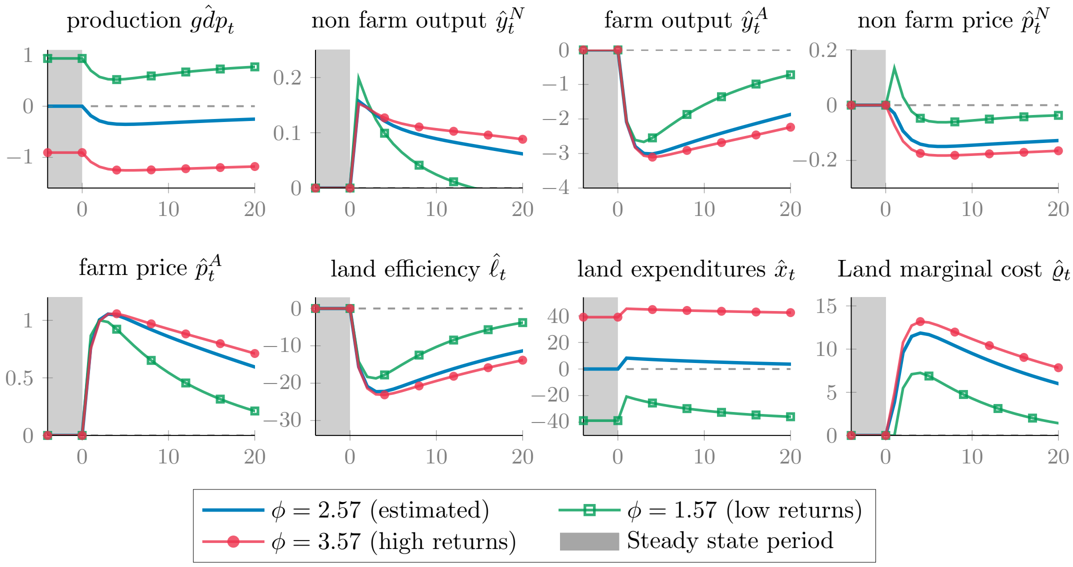


Figure 9: Impulse response functions (in percentage deviations from steady state of the estimated model) for different values of the land expenditure cost ϕ following a weather shock in t=1.

Notes: IRFs are expressed in percentage deviations of the estimated model's steady state. Prior to period 1 (shaded area), the model is at at its deterministic steady state. The weather shock occurs at $t = 1$.

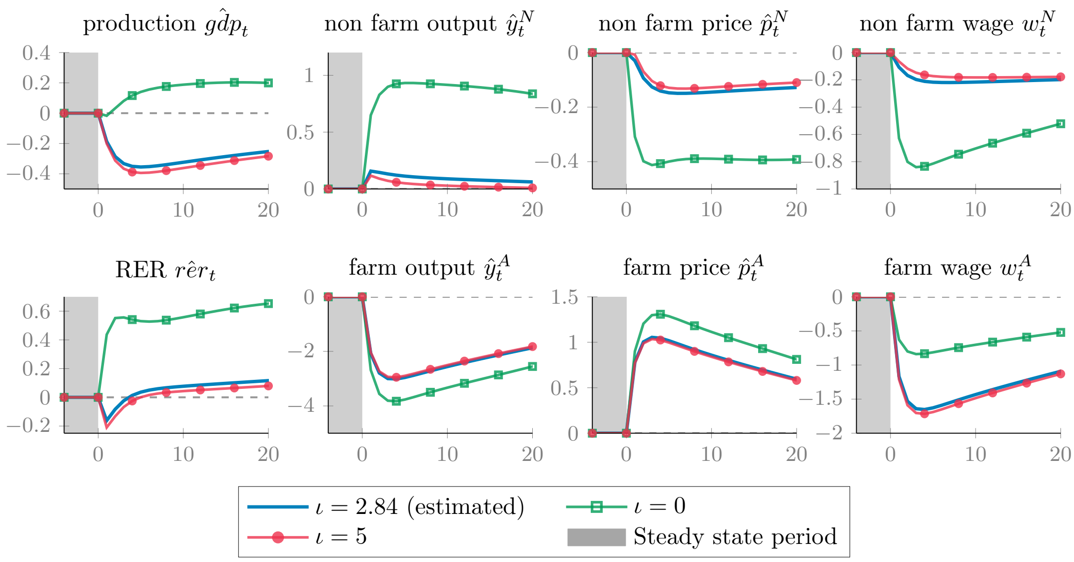


Figure 10: Impulse response functions (in percentage deviations from steady state) following a weather shock for various degrees of labor substitution across sectors $\iota = 0$, 2.84 and 5.

Notes: IRFs are expressed in percentage deviations of the estimated model's steady state. Prior to period 1 (shaded area), the model is at at its deterministic steady state. The weather shock occurs at $t = 1$.

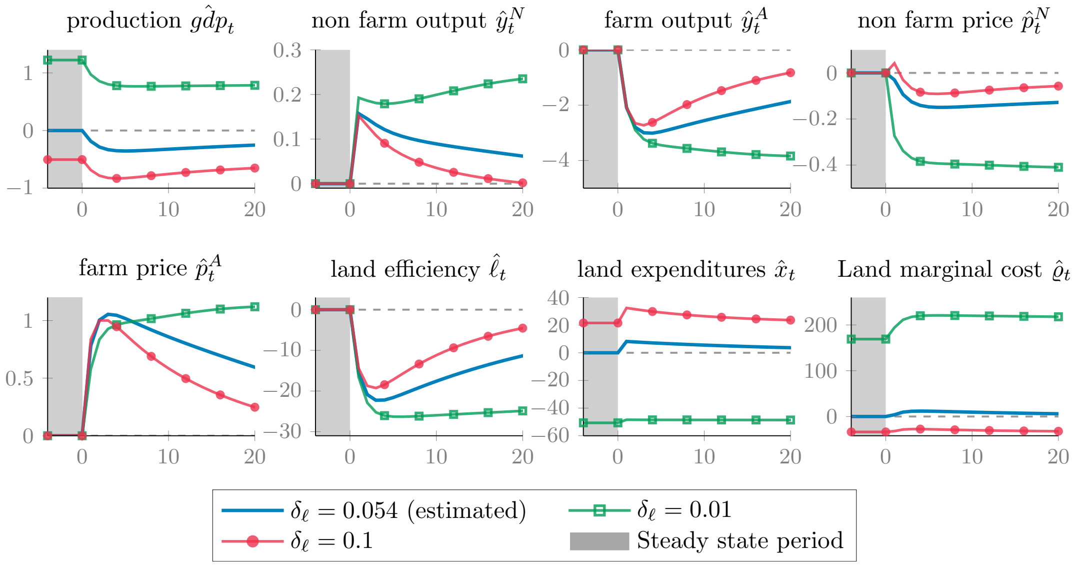
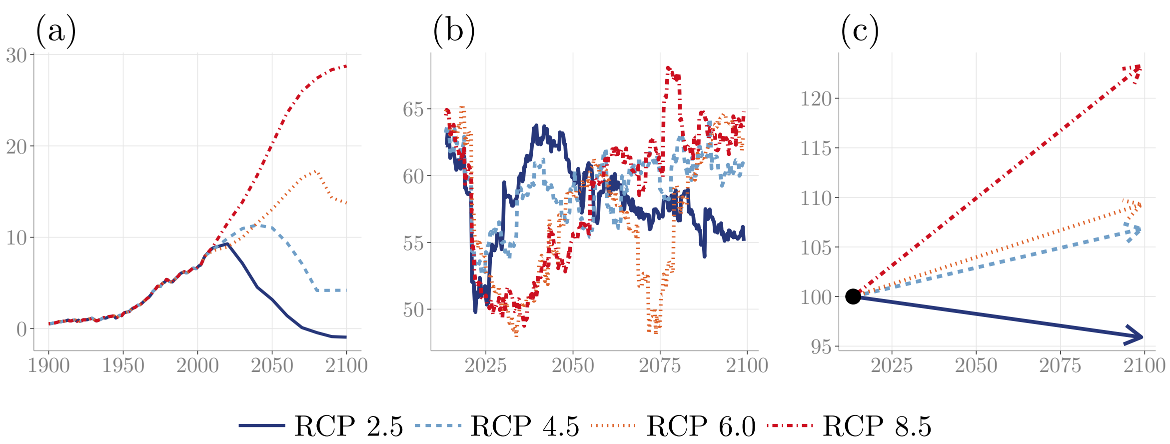


Figure 11: Impulse response functions (in percentage deviations from steady state) following a weather shock for various decay rates of land efficiency $\delta_\ell = 0.01$, 0.054 and 0.10.

Notes: IRFs are expressed in percentage deviations of the estimated model's steady state. Prior to period 1 (shaded area), the model is at at its deterministic steady state. The weather shock occurs at $t = 1$.

Figure 12: Estimations of the increase of the standard error of the weather shock under four different climate scenarios.



Notes: The curves of panel (a) represents historical CO_2 emissions as well as their projections up to 2100 under each scenario. The estimation of the standard errors of projected precipitations σ_t^W for each representative concentration pathway is represented in panel (b). Their linear trend from 2013 to 2100 is depicted in panel (c).

	Standard Deviation		Autocorrelation		Correlation w/ output	
	Model	*Data*	Model	*Data*	Model	*Data*
Total output	3.18	*[2.38;3.19]*	0.89	*[0.92;0.96]*	1.00	*[1.00;1.00]*
Consumption	4.75	*[2.18;2.92]*	0.93	*[0.85;0.93]*	0.69	*[0.60;0.80]*
Hours	2.75	*[2.45;3.28]*	0.84	*[0.95;0.98]*	0.24	*[-0.15;0.26]*
Investment	9.63	*[10.4;14.0]*	0.88	*[0.91;0.96]*	0.71	*[0.55;0.78]*
Agricultural output	13.50	*[11.6;15.6]*	0.91	*[0.88;0.95]*	0.53	*[0.22;0.56]*
Foreign output	2.11	*[3.01;4.03]*	0.95	*[0.97;0.99]*	0.15	*[0.51;0.75]*
RER variations	3.36	*[3.14;4.22]*	0.27	*[0.06;0.45]*	0.03	*[-0.14;0.27]*
Weather	0.88	*[0.75;1.01]*	0.38	*[0.18;0.54]*	-0.11	*[-0.22;0.19]*

Table 8: Comparison of theoretical business cycles moments with their empirical counterpart at a 95% confidence interval.