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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 theoretical models, or by focusing on short-term effects using empirical analysis. We propose a framework to bring together both the short and long-term effects through the lens of an estimated DSGE model with a weather-dependent agricultural sector. The model is estimated using Bayesian methods and quarterly data for New Zealand using the weather as an observable variable. In the short-run, our analysis underlines the key role of weather as a driver of business cycles over the sample period. An adverse weather shock generates a recession, boosts the non-agricultural sector and entails a domestic currency depreciation. Taking a long-term perspective, a welfare analysis reveals that weather shocks are not a free lunch: the welfare cost of weather is currently estimated at 0.19% of permanent consumption. Climate change critically increases the variability of key macroeconomic variables (such as GDP, agricultural output or the real exchange rate) resulting in a higher welfare cost peaking to 0.29% in the worst case scenario.

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

JEL classification: C13, E32, Q54

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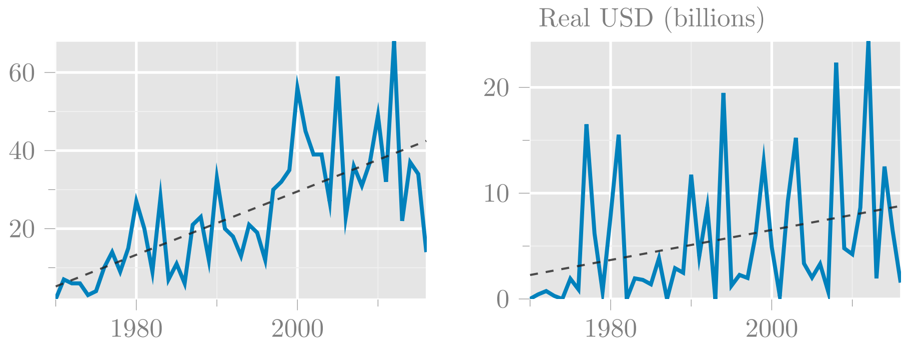
1 Introduction

Among the many shocks and disturbances driving the business cycles, the weather has received little attention as a serious source of business cycles 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 2014, as documented in Figure 1. Both the frequency and the intensity of these adverse events tend to follow an upward trend, suggesting that the weather is likely to become a more frequent source of business cycles in the coming years. This growing source of macroeconomic fluctuations, also referred to as *weather shocks*, is emerging as one of the most important facets of global warming, in particular for agricultural-based countries. In such economies, the weather generates detrimental fluctuations in the agricultural sector that can spread to the rest of the economy.



(a) Annual frequency of weather disasters

(b) Annual cost of weather disasters

Note: Data are taken from EM-DAT; IMF, World Economic Outlook database and set in real terms using the US GDP deflator.

Figure 1: Global frequency and impact of weather shocks (droughts and heat waves) between 1970 and 2016.

If long-run effects of the weather, i.e., climate effects are already well documented in the literature,[1] many uncertainties remain regarding the short-run aspects in terms of propagation, supply-side transmission channels and the potential welfare costs. More importantly, most of this literature considers the change in climate statistics as a trend phenomenon (e.g., Nordhaus and Yang, 1996; Nordhaus, 2018b, 1991), leaving the role of weather fluctuations and their underlying welfare costs as second order issues. In this article, we argue that weather driven business cycles are not a benign facet of climate change.

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

Contributions. The aim of this article is therefore to fill the gap by making three main contributions to address this question. The first contribution concerns the engineering of an aggregate measure of the weather. Unlike TFP shocks which are not observable, the time-varying productivity of agricultural lands is measurable from soil moisture observations.[2] In this paper, we build a weather index at a macro level from soil moisture deficits observations that captures unsatisfactory levels of agriculture productivity for New Zealand.[3] A second contribution lies in the documentation of the transmission mechanisms of the weather. Through the lens of a Vector Auto-Regressive (VAR) model, we gauge the quantitative interaction of the weather with seven macroeconomic time series of New Zealand. Following a shock to the weather equation in the VAR, we document the transmission mechanism of the weather in a small-open economy environment. A third contribution concerns the building of a macroeconomic model with a time-varying weather. We enrich a Dynamic Stochastic General Equilibrium (DSGE) model with a tractable weather-dependent agricultural sector. Entrepreneurs involved in the agricultural sector (i.e., farmers) are endowed with a land. The productivity of that land is endogenously determined by both economic and weather conditions. Farmers face unanticipated weather shocks affecting the efficiency of their land over the business cycles. The model is estimated through Bayesian techniques with the same sample as the VAR model to provide an alternative theoretical representation of the data. In addition to its empirical relevance, the estimated DSGE model is amenable for counterfactual experiments to assess the quantitative implications of climate change on the business cycles of an economy.

We get three main results from the aforementioned methodology. First, both the VAR and the DSGE models document the transmission of a weather shock – more specifically a drought – 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. The weather shock thus shares similar dynamic patterns with a sectoral TFP shock. Second, we find that weather shocks play a non-trivial role in driving the business cycles of New Zealand. On the one hand, the inclusion of weather-driven business cycles strikingly improves the statistical

[2] Therefore in the rest of the article, we refer to these exogenous changes in land productivity as weather shocks.

[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 VAR and DSGE models.

performance of the model. On the other hand, the weather drives 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 0.19% 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 of the welfare cost of weather driven business cycles peaking up to 0.29% in the worst-case climate change scenario. To the best of our knowledge, this article is the first to use full-information methods to estimate a theoretical model with the weather as an observable variable to gauge the current and future cost of the weather at a business cycle frequency.

Related literature. 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, this literature links climate and economic activity through a damage function that lies in the firms' production technology. Thus, an increase in temperatures due to greenhouse gas emissions causes higher damages to aggregate production. However, this literature focuses on very long run effects of climate change through deterministic simulations.[4] We build on this approach by using a damage function that connects the weather to the farmers' land productivity. We complement the IAMs literature by tackling the short-term dimension of the weather, and evaluate their social costs in a context of climate change.

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) which shows that the relationship between high

[4] A notable exception, from Cai and Lontzek (2019), expands the scope of IAMs by adding uncertainties and risks to the workhorse DICE model through ingredients of the asset price theory (e.g. recursive utility, long run risk, etc).

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 the economic activity. We focus on the agricultural sector, making productivity in this sector dependent on weather shocks. 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. Finally, 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 and its possible interaction with temperatures through evapotranspiration.

The remainder of this article is organized as follows: Section 2 provides some empirical evidences through the lens of a VAR model regarding the impact of weather shocks on macroeconomic variables. Section 3 sketches the Dynamic Stochastic General Equilibrium model. Section 4 presents the estimation of the DSGE model. Section 5 provides evidence on the importance of introducing weather shocks in the model. Section 6 discusses the propagation of a weather shock, assesses the consequences of a drought and its implication in terms of business cycles statistics, and presents the historical variance decomposition of supply of the economy. Section 7 conducts a sensitivity analysis to illustrate how the parameters of the weather-dependent agricultural sector affect our results. Section 8 provides a quantitative assessment of the implications of weather shocks under different climate projection scenarios for aggregate fluctuations, and estimates the welfare cost of weather shocks. Section 9 concludes.

2 Business Cycle Evidence

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 2. 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.

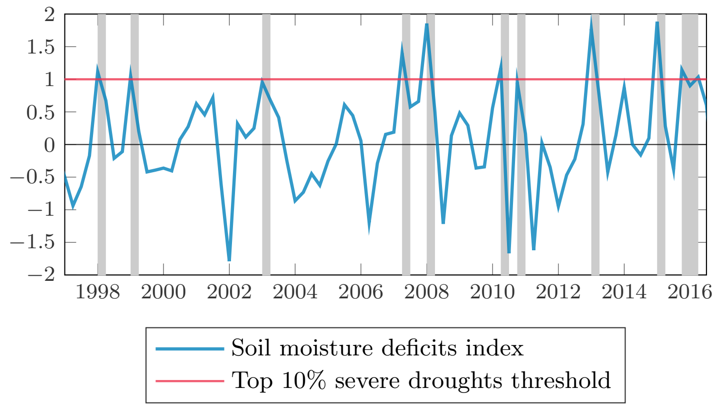


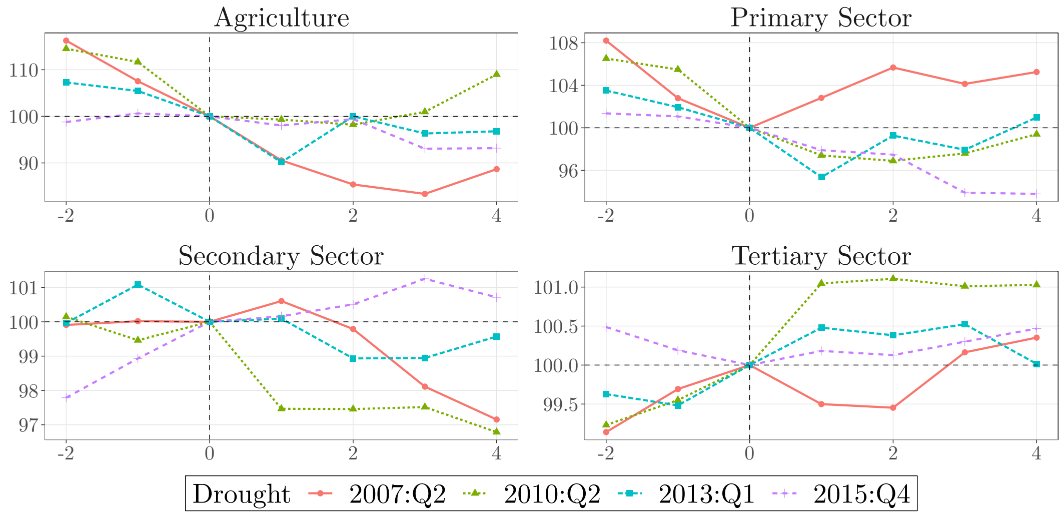
Figure 2: Weather index measuring soil moisture deficits in New Zealand.

As shown in Figure 2, 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

[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.

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.



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.

Figure 3: Sectoral re-allocations following severe weather shocks.

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 3 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 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.

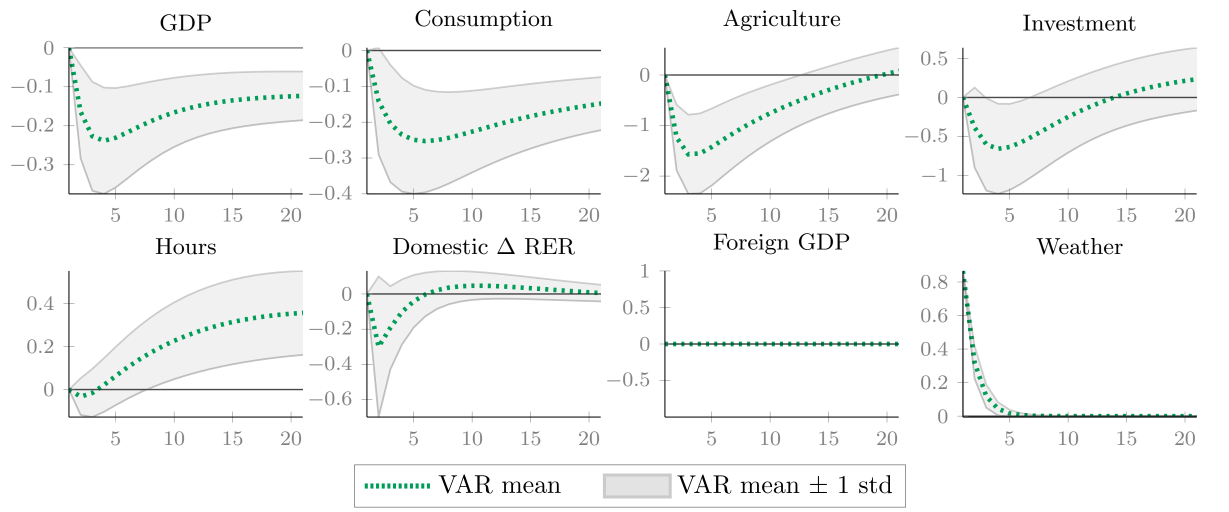
To investigate further the interactions between the weather and other standard macroeconomic time series, a vector autoregressive model is employed. A few constraints on the VAR's equations are necessary to portray New Zealand's specific situation: (i) we impose an exogenous weather (i.e., the weather 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, consumption, investments, hours worked, 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.

To investigate the effects of an adverse weather shock, we examine the impulse responses to

[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.



Notes: The green dashed line is the Impulse Response Function. The gray band represents 68% error band obtained from the 250 bootstraps runs. 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.

Figure 4: VAR impulse response to a 1% weather shock (drought) in New Zealand.

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 4, where each panel represents the response of one of the variables to a weather shock. Overall, a shock to the weather shock 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 1.5% contraction of agricultural production, as already suggested by the two previous assessments. This depression in agriculture is simultaneously followed by a 0.3% decline in consumption and a 0.6% decline in investment. The adjustment of the labor market is naturally slower and materialize through a late rise in hours worked occurring 7 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 suggests 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.[10] 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 channel adjusted by the real exchange rate. The general structure of the model is summarized in Figure 5. The remainder of this section presents the main components of the model.

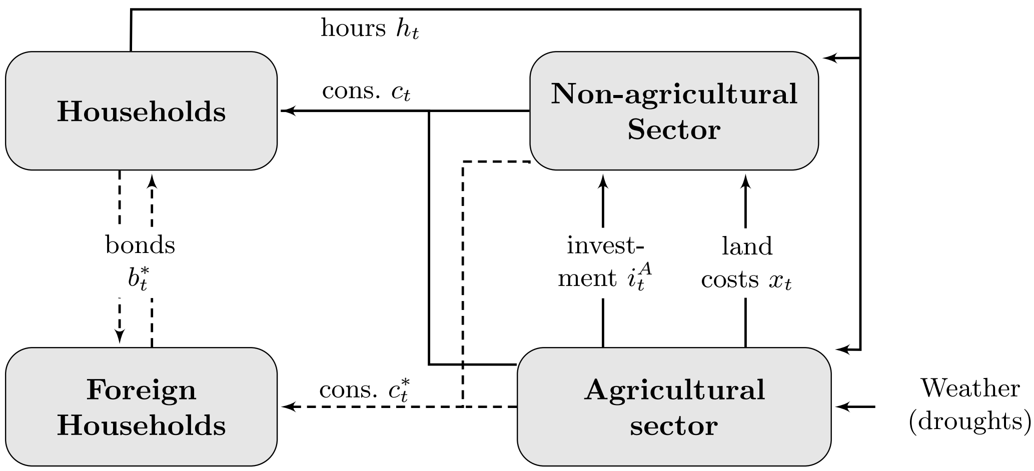


Figure 5: The theoretical model.

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.[11] The fraction $i \in [0, n_t]$ of entrepreneurs operating in the agricultural sector is referred to as farmers.

[10] 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.

[11] 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 $0 \leq \rho_N \leq 1$.

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 VAR 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 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.[12]

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 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.[13] Among many possible functional forms, the Cobb-Douglas production function has become popular in this economic field following the contribution of Mundlak (1961).[14] 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),

[12]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.

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

[14]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.

physical capital k^A_{it-1}, and labor demand h^A_{it}. Production is subject to an economy-wide technology shock ε^Z_t 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 production process of agricultural goods, and $\kappa_A > 0$ is a technology parameter endogenously determined in the steady state. 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^W_t. 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:[15]

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

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 $\Omega\left(\varepsilon^W_t\right)\ell_{it-1}$.

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.

[15]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.

Kamber et al. (2013) have shown that beyond the immediate rise in slaughter, there tends to be 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[16]) 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:

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

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.[17] 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.

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

[17]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:

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

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:

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

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 maintenace. The shape of the cost function $v(x_{it})$ critically determines the response of agricultural production following a drought shock. A concave cost function, i.e., $v'(x_{it}) < 0$, 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.

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 $\beta \in [0, 1)$:

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

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_t^H 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:

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

The labor disutility index consists of hours worked in the non-agricultural sector h_{jt}^N and agriculture sector h_{jt}^A. 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:

$$\sum_{s=N,A} w_t^s h_{jt}^s + r_{t-1} b_{jt-1} + rer_t^* r_{t-1}^* b_{jt-1}^* - T_t \geq C_{jt} + b_{jt} + rer_t^* b_{jt}^* + p_t^N rer_t \Phi(b_{jt}^*). \qquad (12)$$

The income of the representative household is made up of labor income with a real wage w_t^s 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 $p_t^N = P_t^N / P_t$.[18] 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_{jt}^N and C_{jt}^A, respectively. The CES consumption bundle is determined by:

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}} (C_{jt}^N)^{\frac{\mu-1}{\mu}} + (\varphi)^{\frac{1}{\mu}} (C_{jt}^A)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \qquad (13)$$

where $\mu \geq 0$ denotes the substitution elasticity between the two types of consumption goods, and $\varphi \in [0,1]$ is the fraction of agricultural goods in the household's total consumption basket. The corresponding consumption price index P_t reads as follows: $P_t = [(1-\varphi)(P_{C,t}^N)^{1-\mu} + \varphi(P_{C,t}^A)^{1-\mu}]^{\frac{1}{1-\mu}}$, where $P_{C,t}^N$ and $P_{C,t}^A$ are consumption price indexes of non-agricultural and

[18]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.

agricultural goods, respectively.

Second, each index C_{jt}^N and C_{jt}^A is also a composite consumption subindex composed of domestically and foreign produced goods:

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

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 $P_{C,t}^s$ in each sector s are given by: $P_{C,t}^s = \left[(1-\alpha_s) (P_t^s)^{1-\mu_s} + \alpha_s (e_t^* P_t^{s*})^{1-\mu_s} \right]^{\frac{1}{(1-\mu_s)}}$, for $s = N, A$. In this expression, P_t^s is the production price index of domestically produced goods in sector s, while P_t^{s*} 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:

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

$$c_{jt}^s = (1-\alpha_s) \left(\frac{P_t^s}{P_{C,t}^s} \right)^{-\mu_s} C_{jt}^s \text{ and } c_{jt}^{s*} = \alpha_s \left(e_t^* \frac{P_t^{s*}}{P_{C,t}^s} \right)^{-\mu_s} C_{jt}^s \text{ for } s = N, A. \tag{16}$$

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:

$$y_{it}^N = \varepsilon_t^Z \left(k_{it-1}^N \right)^\alpha \left(h_{it}^N \right)^{1-\alpha}, \tag{17}$$

where y_{it}^N is the production of the i^{th} intermediate goods firms that combines physical capital k_{it-1}^N, labor demand h_{it}^N and technology ε_t^Z. 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.[19]

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:

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

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.

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

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:[20]

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

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:

$$\max_{\left\{c^*_{jt}, b^*_{jt}\right\}} E_t \left\{ \sum_{\tau=0}^{\infty} \beta^\tau \varepsilon^E_{t+\tau} \log\left(c^*_{jt+\tau}\right) \right\}, \tag{25}$$

$$s.t. \qquad r^*_{t-1} b^*_{jt-1} = c^*_{jt} + b^*_{jt}. \tag{26}$$

where variable ε^E_t is a time-preference shock defined as follows:

$$\log(\varepsilon^E_t) = \rho_E \log(\varepsilon^E_{t-1}) + \sigma_E \eta^E_t, \tag{27}$$

with $\eta^E_t \sim \mathcal{N}\left(0,1\right)$. This shock temporary raises the household's discount factor and drives down

[20]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.

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., $P^*_t = P^{A*}_t = P^{N*}_t$. In addition, the small size of the domestic economy implies that the import/exports flows from the home to the foreign country are negligible, thus implying that $P^*_t = P^{A*}_{C,t} = P^{N*}_{C,t}$.

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:

$$(1-n_t)\,Y^N_t = (1-\varphi)\left[(1-\alpha_N)\left(\frac{P^N_t}{P^N_{C,t}}\right)^{-\mu_N}\left(\frac{P^N_{C,t}}{P_t}\right)^{-\mu} C_t + \alpha_N\left(\frac{1}{e^*_t}\frac{P^N_t}{P^{N*}_{C,t}}\right)^{-\mu_N}\left(\frac{P^{N*}_{C,t}}{P^*_t}\right)^{-\mu} C^*_t\right] + G_t + I_t + n_t x_t + \Phi(b^*_t), \quad (28)$$

where the total supply of home non-agricultural goods is given by $\int_{n_t}^1 y^N_{it}\,\mathrm{d}i = (1-n_t)\,Y^N_t$, 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 $\int_{n_t}^1 i^N_{it}\,\mathrm{d}i = (1-n_t)\,I^N_t$ and $\int_0^{n_t} i^A_{it}\,\mathrm{d}i = n_t I^A_t$, is given by: $I_t = (1-n_t)\,I^N_t + n_t I^A_t$. Turning to the labor market, the market clearing condition between household labor supply and demand from firms in each sector is $\int_0^1 h^N_{jt}\mathrm{d}j = \int_{n_t}^1 h^N_{it}\mathrm{d}i$ and $\int_0^1 h^A_{jt}\mathrm{d}j = \int_0^{n_t} h^A_{it}\mathrm{d}i$. This allows us to write the total number of hours worked: $H_t = (1-n_t)\,H^N_t + n_t H^A_t$. Aggregate real production is given by:

$$Y_t = (1-n_t)\,p^N_t Y^N_t + n_t p^A_t Y^A_t.$$

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

$$n_t Y^A_t = \varphi\left[(1-\alpha_A)\left(\frac{P^A_t}{P^A_{C,t}}\right)^{-\mu_A}\left(\frac{P^A_{C,t}}{P_t}\right)^{-\mu} C_t + \alpha_A\left(\frac{1}{e^*_t}\frac{P^A_t}{P^{A*}_{C,t}}\right)^{-\mu_A}\left(\frac{P^{A*}_{C,t}}{P^*_t}\right)^{-\mu} C^*_t\right], \quad (29)$$

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.[21] 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;[22] (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.[23] 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:

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

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

[21]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 initialize the Kalman filter. Only time periods after the presample enter the actual likelihood computations.

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

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

of hours worked, $\hat{y}_t^A$ is the agricultural production gap, $\hat{y}_t^*$ is the foreign production gap and finally $\hat{\omega}_t$ is the drought index.

The corresponding measurement equations are given by:

$$\mathcal{Y}_t = \left[\widetilde{gdp}_t, \quad \tilde{C}_t, \quad \tilde{p}_t^N + \tilde{I}_t, \quad \tilde{H}_t, \quad \tilde{n}_t + \tilde{p}_t^A + \tilde{Y}_t^A, \quad \tilde{C}_t^*, \quad -\Delta \widetilde{rer}_t^*, \quad \tilde{\varepsilon}_t^W \right]', \tag{34}$$

where all these variables are expressed in percentage deviations from their steady state: $\tilde{x}_t = \log(x_t/\bar{x})$.

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 $\chi_B = 0.0007$.[24] 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 per person in New Zealand (FAO data).

The rest of the parameters are estimated using Bayesian methods. Table 5 and Figure 6 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 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). The standard errors of the innovations are assumed to follow a Weibull distribution with a mean of 1 and a standard

[24] The value of this parameter marginally affects the dynamic of the model, but it allows us to remove a unit root component induced by the open economy setup.

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. 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.

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 0.1, respectively. This prior is rather uninformative as it allows this decay rate to be either close to 0 or close to 0.50, the latter would imply an annual decay rate of 200%. 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%.[25] We thus impose a beta distribution with mean 0.2 and standard deviation 0.1. One of the key parameter in the paper is the damage function parameter θ and 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 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.

[25]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.

4.3 Posterior Distribution

In addition to the prior distributions, Table 5 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 6.[26] According to Figure 6, 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.

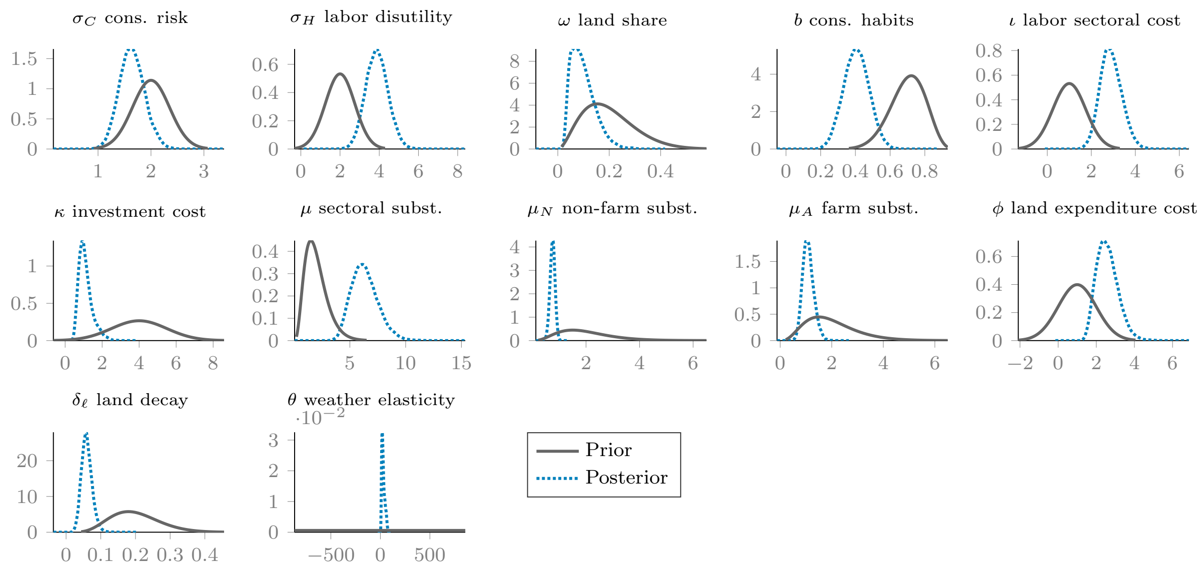


Figure 6: Prior and posterior distributions of structural parameters for New Zealand (excluding shocks).

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 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 are quadratic. Sub-

[26] 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).

stitution seems to be an important pattern of consumption decisions of households, especially at a sectoral level. However, the substitution between home and foreign non-agricultural goods appears to be rather low, contrary to the substitution degree between agricultural and non agricultural goods that is remarkably high. 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.

To assess how well the estimated model captures the main features of the data, we report in Table 6 and Table 7 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 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

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	-1473.704	-1467.206
Posterior odds ratio	1.000000	663.6605
Posterior model probability	0.001505	0.998495

Table 2: Prior and posterior model probabilities

and model probabilities taking the model $\mathcal{M}(\theta = 0)$, i.e., the one with no weather damage as the benchmark.[27] 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 ratios 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 $M(\theta \neq 0)$ on $M(\theta = 0)$ using Laplace-approximated marginal data densities. The posterior odds of the null hypothesis of no significance of weather-driven fluctuations is 663.66:1 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 7.[28] We also report the responses from the VAR estimation for observable variables which are common between the VAR and the DSGE model.

[27] 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 $\mathcal{M}(\theta \neq 0)$ will not inevitably be favored to the benchmark model.

[28] 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 6.

Unlike the VAR model, the DSGE model provides the underlying micro-founded mechanisms that drives the propagation of a weather shock.

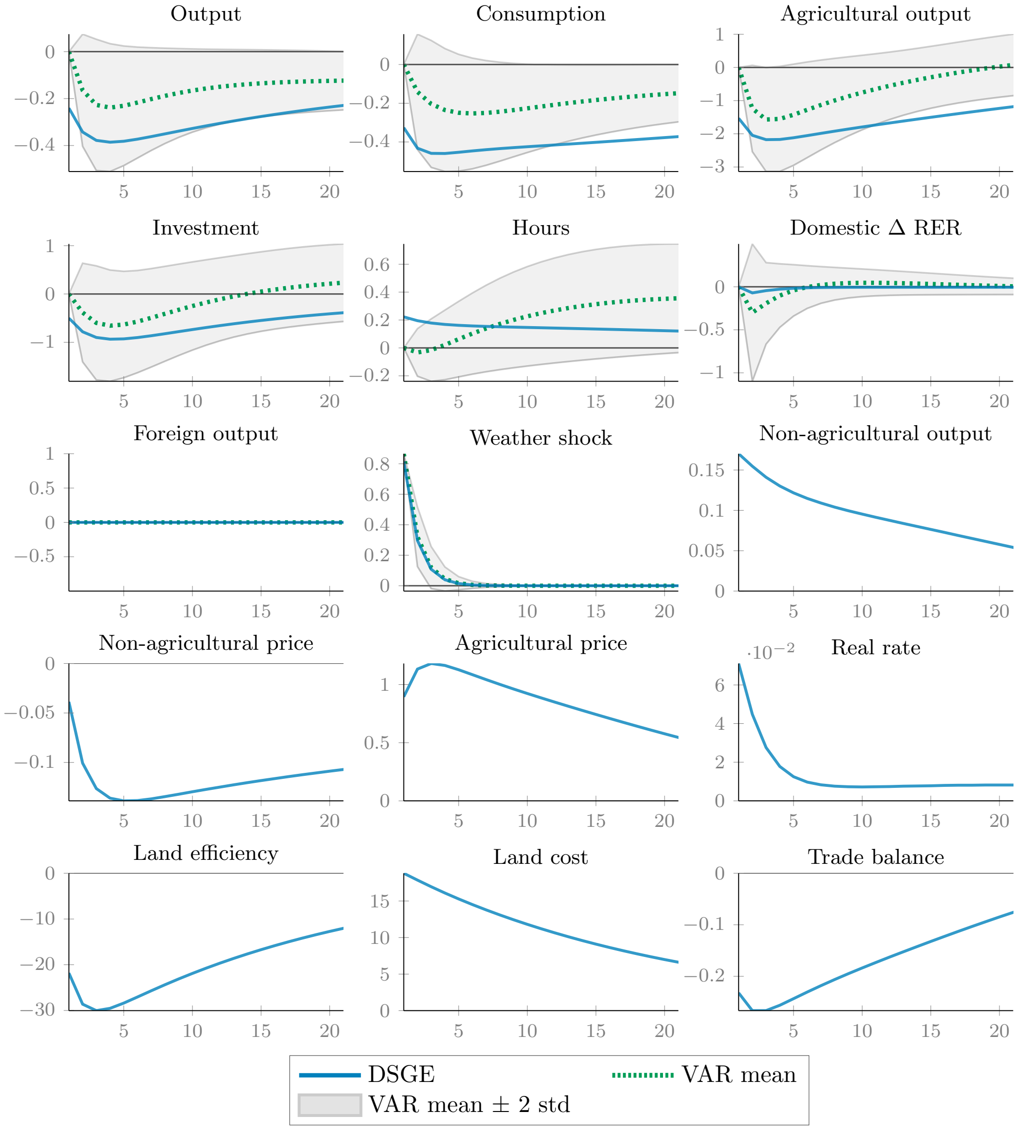


Figure 7: System response to an estimated weather shock η_t^W for the estimated DSGE and VAR model (when available).

Notes: Blue lines are the Impulse Response Functions (IRFs) generated when parameters are drawn from the mean posterior distribution, as reported in Figure 6. 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 VAR model and gray areas are their 90 confidence intervals.

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 VAR 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 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 an 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 cleaning effect. Since relative prices are negatively correlated, the price of non-agricultural goods declines in response, thus fueling the demand for non-agricultural goods. With respect to the VAR model, the DSGE model predicts a higher contraction of economic activity combined with a weaker response of the real exchange rate.

From an international standpoint, the decline in domestic agricultural production generates trade balance deficits. Two factors might explain this. First, around fifty percents 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 VAR model in Figure 4.

6.2 The Contribution of Weather Shocks on Aggregate Fluctuations

Figure 8 reports the forecast error variance decomposition for four observable variablest, 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.

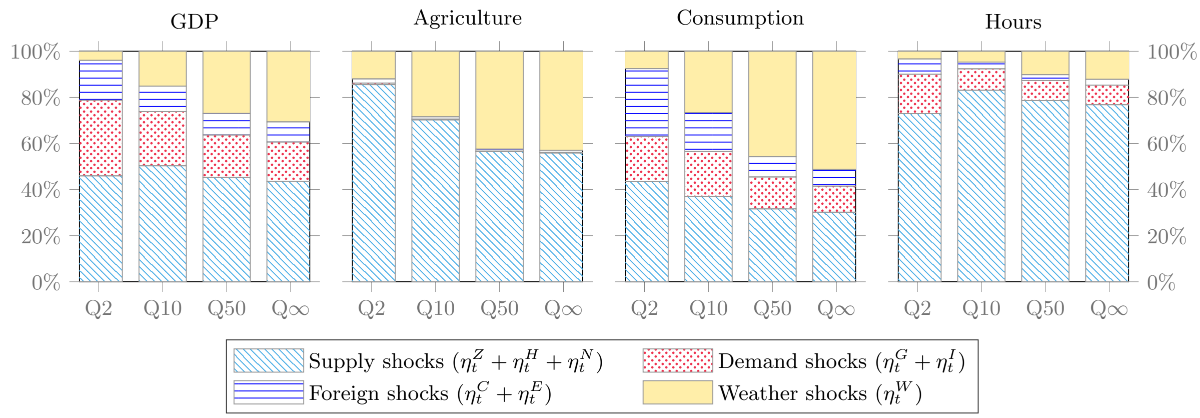


Figure 8: Forecast error variance decomposition at the posterior mean for different time horizons (one, ten, forty and unconditional) for four observable variables.

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 27.6% of New Zealand's production in the short run, and 11.8% in the long run. By increasing the time horizon, the contribution of supply, demand and foreign shocks tends to reduce and are gradually replaced by weather shocks, starting from 2% at two-quarter horizon to 30% for the unconditional variance.

Turning to agricultural production, supply shocks account for most fluctuations in the short run. They are responsible for 85% of the variance of agricultural production at one-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 58% 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 9 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. One fourth of agricultural slowdown following the most severe drought in 2008 is 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 9 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

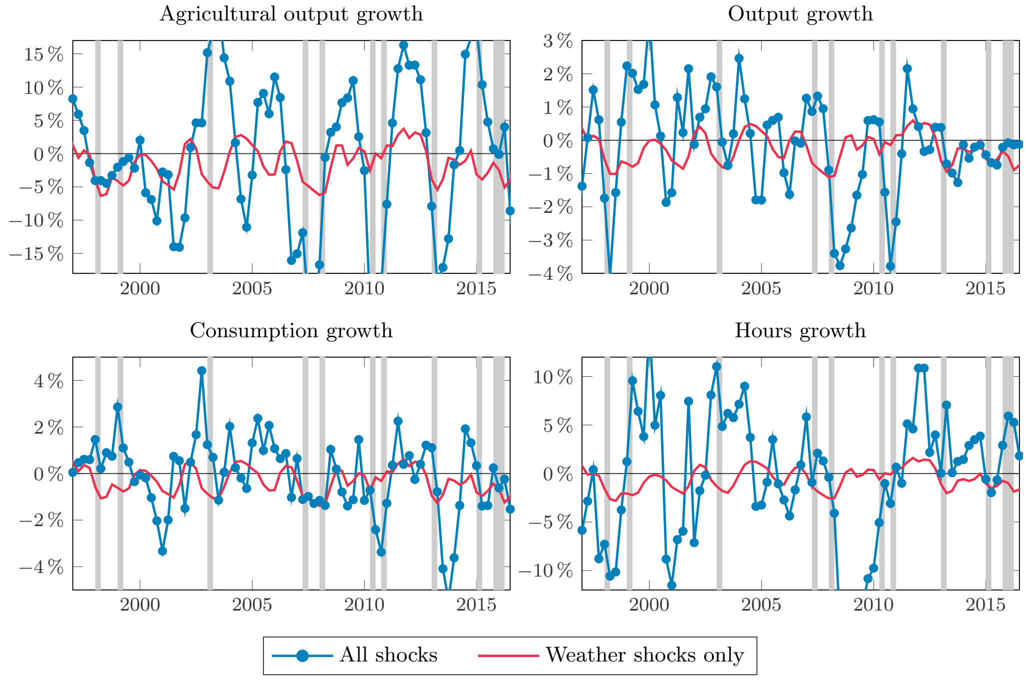


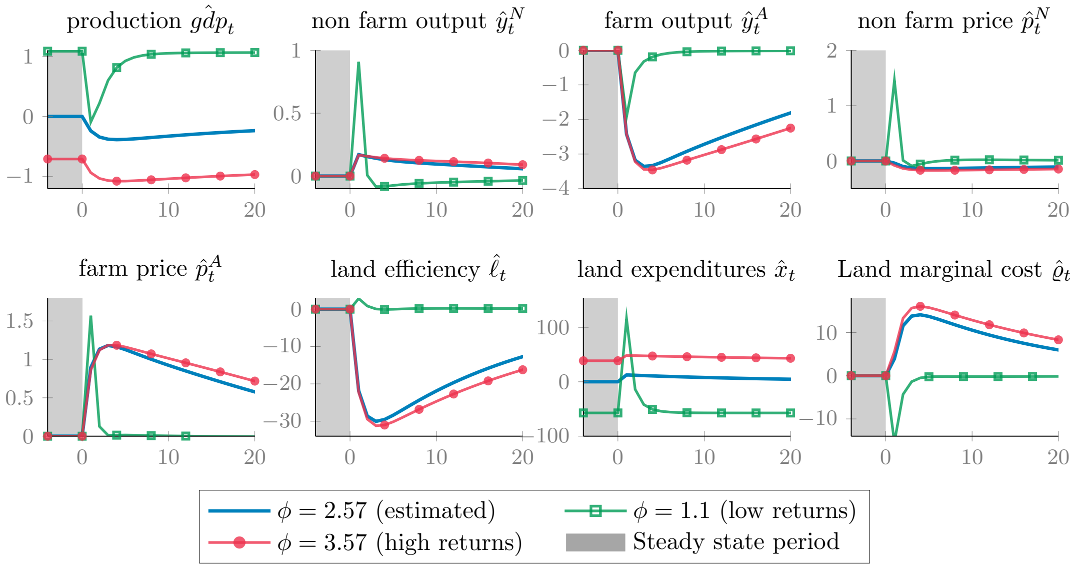
Figure 9: The role of weather shocks on selected variables.

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.

oscillates between +1% to -1%. There is a 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% drop in GDP and consumption while labor supplied declined by 2%.

7 Inspecting the Propagation Mechanism

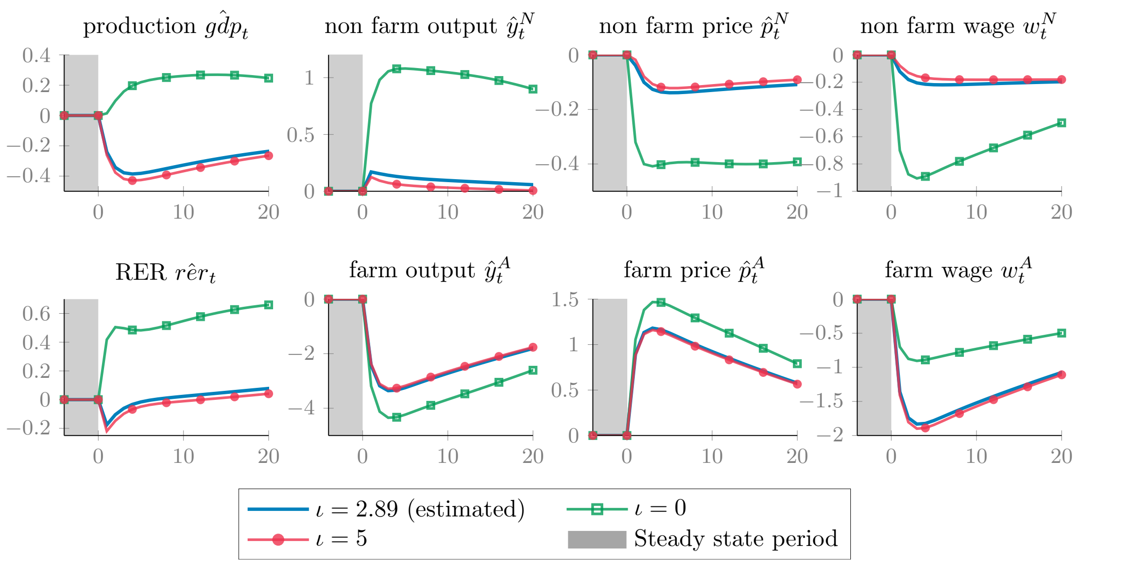
The originality of the model lies in the introduction of a weather-dependent agricultural sector that relies on a set of structural parameters driving the response of the economy following a weather shock. In this section, we investigate how critical these parameters are by contrasting the responses 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.



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 of the estimated model) for different values of the land expenditure cost ϕ following a weather shock in t=1.

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 production. IRFs under alternative calibration are reported in Figure 10, by contrasting the estimated parameter ($\phi = 2.57$) with quasi-constant returns ($\phi = 1.10$) and high-increasing returns ($\phi = 3.57$). The value of this parameter clearly affects the propagation mechanism of a weather shock. Under increasing returns, the marginal cost of land costs (e.g., fertilizers and water) rises after a drought, while it tends to decrease under quasi-constant returns. The main implication of decreasing/constant 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 VAR 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).

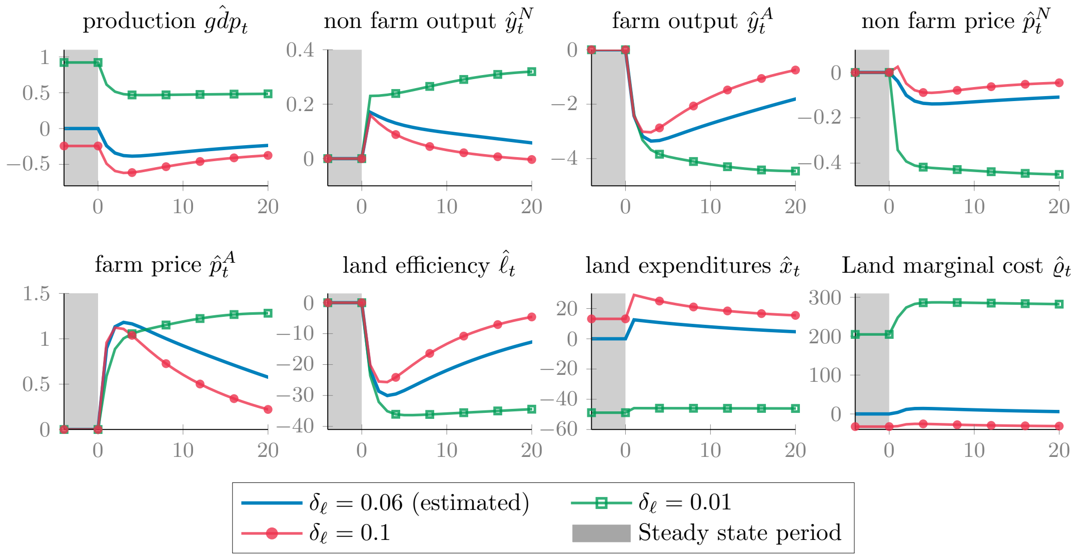


Notes: IRFs are expressed in percentage deviations of the estimated model's steady state. Prior to period 1 (shaded area), the model is at at its deterministic steady state. The weather shock occurs at $t = 1$.

Figure 11: Impulse response functions (in percentage deviations from steady state) for various degrees of labor substitution across sectors $\iota = 0$, 2.32 and 5.

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 report in Figure 11 the IRFs under a linear substitution index ($\iota = 0$) versus the estimated value ($\iota = 2.9$) and a high substitution costs ($\iota = 5$). 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 VAR 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 12 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



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: Impulse response functions (in percentage deviations from steady state) for various decay rates of land efficiency $\delta_\ell = 0.025$, 0.10 and 0.20.

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, it allows for changes 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. The results presented in this section are rather illustrative as our setup does not allow crop adaptation or any possible mechanism that would offset the structural change of weather.

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, using the values obtained from the previous section. 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 8.24%. As a result, macroeconomic fluctuations in the country naturally decrease. Agriculture output is particularly affected by this structural change, with a 3.45% 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 4.32% under the RCP 4.5 scenario, and by 15.89% under the RCP 8.5 scenario. Agricultural production volatility experiences an important shift of 22.30% under the worst-case scenario. We also observe a dramatic increase in the variance of consumption of 26.61%, relative price of agricultural goods of 18.44%, net foreign asset of 31.86%. The variance of the current account rises by 13.81% while the variance of the real exchange rate rises by 8.15%. 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 our setup to a developing economy by increasing the relative share of the agricultural sector,

		1994-2016	2100 (projections)			
		Historical	RCP 2.5	RCP 4.5	RCP 6.0	RCP 8.5
$\text{Var}(\eta_t^W)$	Weather shock	100	91.97	114.11	119.44	151.91
$\text{Var}(gdp_t)$	GDP	100	97.54	104.32	105.95	115.89
$\text{Var}(C_t)$	Consumption	100	95.88	107.23	109.97	126.61
$\text{Var}(p_t^N I_t)$	Investment	100	99.22	101.37	101.89	105.04
$\text{Var}(p_t^A Y_t^A)$	Agriculture	100	96.55	106.06	108.35	122.30
$\text{Var}(p_t^A)$	Agricultural price	100	97.15	105.01	106.91	118.44
$\text{Var}(H_t)$	Hours	100	99.02	101.72	102.37	106.31
$\text{Var}(R_t)$	Real interest rate	100	99.99	100.01	100.02	100.04
$\text{Var}(rer_t)$	Exchange rate	100	98.74	102.21	103.05	108.15
$\text{Var}(tb_t)$	Trade balance	100	97.86	103.75	105.17	113.81
$\text{Var}(b_t^*)$	Net Foreign Asset	100	95.07	108.66	111.93	131.86
$\text{E}(\mathcal{W}_t)$	Welfare	-429.3143	-429.2872	-429.3619	-429.3799	-429.4893
$\lambda\,(\%)$	Welfare cost	0.1903	0.1750	0.2171	0.2273	0.2891

Table 3: Changes in Standard-Errors 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 standard error are as follows: RCP 2.5, -8.24%; 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.

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 policy function. 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 under alternative scenarios. First of all, the simulations show that today, New Zealanders would be willing to give up to 0.1% 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 0.05%, 0.03% for spending shocks, 0.05% for investment shocks, 0.44% for labor supply shocks, 0.08% for sector reallocation shock, 0.002% for foreign consumption shock and 0.04% for foreign discount factor.[29] Using a CRRA utility function, welfare cost of business cycles are typically low as shown by Lucas (1987, chap. 3) and Lucas (2003, section II) while with the same utility function, the welfare cost of the weather is non-trivial. This conflicting result with the standard macroeconomic literature is 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 livestocks and crops needs time to recover. The resulting consequence is an higher uncertainty for households on their agricultural consumption which natural drives the welfare cost of business cycles. 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 0.18% of their permanent consumption. In the worst-case scenario, this fraction would reach 0.29%. 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 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 varia-

[29]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.

tions 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 VAR and the DSGE model 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 0.19% 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

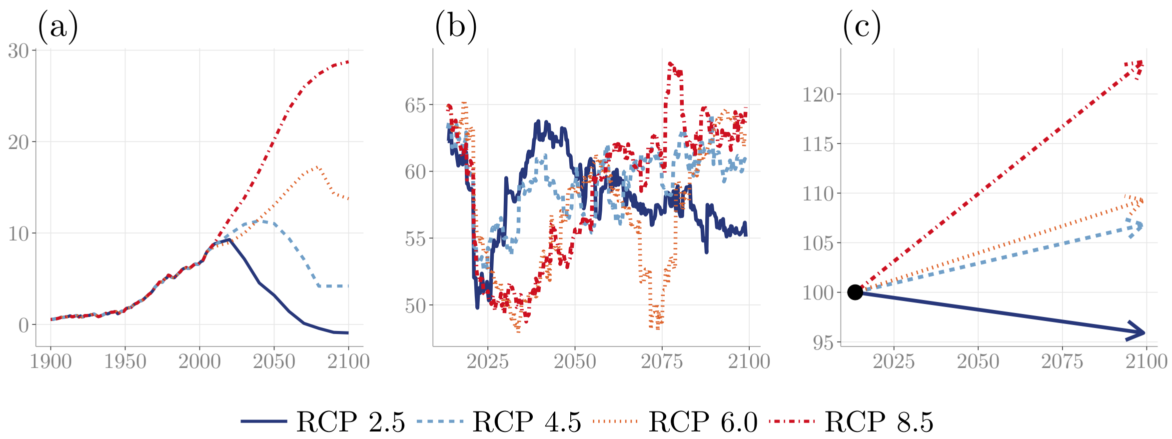
To investigate the potential impact of climate change on aggregate fluctuations, we assume that the volatility the weather (η_t^W) (Equation 1) will be affected by climate change. Instead of arbitrarily setting a value for this shift, we provide an approximation using a proxy for the drought index. To 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 13 shows emissions and projections of the emissions of one of the major greenhouse gases, i.e., CO_2, up to 2100.[30]

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 13 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

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

depending on the climate scenario.[31] The results are displayed in the right panel of Figure 13. 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%.



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).

Figure 13: Estimations of the increase of the standard error of the weather shock under four different climate scenarios.

[31] 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)	σ_Z	$\mathcal{W}$	1	2	2.1	*[1.81:2.38]*
Hours supply (SD)	σ_H	$\mathcal{W}$	1	2	5.19	*[3.95:6.33]*
Spending (SD)	σ_G	$\mathcal{W}$	1	2	3.98	*[3.48:4.46]*
Investment (SD)	σ_I	$\mathcal{W}$	1	2	9.87	*[6.76:12.81]*
Sector reallocation (SD)	σ_N	$\mathcal{W}$	1	2	8.69	*[6.78:10.56]*
Weather (SD)	σ_W	$\mathcal{W}$	1	2	0.81	*[0.71:0.91]*
Foreign time-preference (SD)	σ_E	$\mathcal{W}$	1	2	5.61	*[4.74:6.43]*
Foreign consumption (SD)	σ_C	$\mathcal{W}$	1	2	0.69	*[0.6:0.77]*
Economy-wide TFP (AR term)	ρ_Z	$\mathcal{B}$	0.5	0.2	0.5	*[0.38:0.61]*
Labour supply (AR term)	ρ_H	$\mathcal{B}$	0.5	0.2	0.89	*[0.84:0.95]*
Spending (AR term)	ρ_G	$\mathcal{B}$	0.5	0.2	0.83	*[0.77:0.89]*
Investment (AR term)	ρ_I	$\mathcal{B}$	0.5	0.2	0.42	*[0.26:0.59]*
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	0.36	*[0.23:0.51]*
Foreign time-preference (AR term)	ρ_E	$\mathcal{B}$	0.5	0.2	0.09	*[0.02:0.16]*
Foreign consumption (AR term)	ρ_C	$\mathcal{B}$	0.5	0.2	0.95	*[0.92:0.98]*
STRUCTURAL PARAMETERS						
Risk consumption	σ_C	$\mathcal{N}$	2	0.35	1.64	*[1.24:2.02]*
Labor disutility	σ_H	$\mathcal{N}$	2	0.75	3.87	*[2.98:4.84]*
Land expenditure cost	ϕ	$\mathcal{N}$	1	1	2.58	*[1.65:3.42]*
Share of land in agricultural output	ω	$\mathcal{B}$	0.2	0.1	0.1	*[0.03:0.16]*
Consumption habits	b	$\mathcal{B}$	0.7	0.1	0.4	*[0.28:0.52]*
Labor sectoral cost	ι	$\mathcal{N}$	1	0.75	2.89	*[2.11:3.7]*
Substitutability by type of goods	μ	$\mathcal{G}$	2	1	6.32	*[4.46:8.25]*
Substitutability home/foreign	μ_A	$\mathcal{G}$	2	1	1.09	*[0.74:1.43]*
Substitutability home/foreign	μ_N	$\mathcal{G}$	2	1	0.75	*[0.59:0.9]*
Land efficiency decay rate	δ_ℓ	$\mathcal{B}$	0.2	0.07	0.06	*[0.03:0.08]*
Investment cost	κ	$\mathcal{N}$	4	1.5	1.1	*[0.54:1.65]*
Land-weather elasticity - current	θ_1	$\mathcal{U}$	0	500	29.17	*[6.87:54.03]*
Marginal log-likelihood						-1467.21

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

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

	Standard Deviation		Autocorrelation		Correlation w/ output	
	Model	Data	Model	Data	Model	Data
Total output	3.37	2.72	0.85	0.95	1.00	1.00
Consumption	4.21	2.50	0.90	0.90	0.68	0.72
Hours	2.71	2.80	0.86	0.97	0.21	0.05
Investment	11.17	11.94	0.84	0.94	0.79	0.68
Agricultural output	13.48	13.32	0.91	0.92	0.50	0.40
Foreign output	2.14	3.45	0.95	0.98	0.14	0.65
RER variations	3.18	3.60	0.26	0.26	0.12	0.07
Weather	0.87	0.86	0.36	0.37	-0.12	-0.02

Table 7: Comparison of empirical business cycle moments with their theoretical counterpart

Online Appendix

Weather Shocks

2019

Contents

1 Data

1.1 Data source

The sample period begins in 1994:Q3 and extends to 2016:Q4. All data are log deviations from their trend, except share prices and the weather. Share prices are in deviation from their trend. Trends are obtained by applying an HP filter. The time reference for all indexes is 2010:Q1. More details on the data can be found in the online appendix.

Weather data are obtained from weather stations at a monthly rate. The measure we use is based on soil moisture deficit observations. We refer to the online appendix for an extensive presentation of the index.

- **Gross domestic product:** real per capita output, expenditure approach, seasonally adjusted. *Source:* Statistics New Zealand.
- **Rest of the world gross domestic product:** weighted average of GDP of top partners (Australia, Germany, Japan, the United Kingdom and the United States). US dollars, volume estimates, fixed PPPs, seasonally adjusted. *Source:* OECD.
- **Agricultural output:** real agriculture, fishing and forestry gross domestic product, seasonally adjusted. *Source:* Statistics New Zealand.
- **Consumption:** households final consumption expenditure, seasonally adjusted. *Source:* Statistics New Zealand.
- **Investment:** gross fixed capital formation, seasonally adjusted. *Source:* Statistics New Zealand.
- **Paid hours:** average weekly paid hours (FTEs) total all ind. & both sexes, seasonally adjusted. *Source:* Statistics New Zealand.
- **Employment:** labor force status for people aged 15 to 64 years, seasonally adjusted. *Source:* Statistics New Zealand.
- **Population:** actual population of working age, in thousands, seasonally adjusted. *Source:* Statistics New Zealand.
- **Real effective exchange rate:** Real Broad Effective Exchange Rate for New Zealand. *Source:* Bank for International Settlements.
- **Weather:** soil moisture deficit at the station level. *Source:* National Climate Database, National Institute of Water and Atmospheric Research.

1.2 Measuring the Weather

The measure of weather we use is an index of drought constructed following the methodology of Kamber et al. (2013). It is based on soil moisture deficit observations[1] and is collected from the National Climate Database from National Institute of Water and Atmospheric Research. Raw data is obtained from weather stations at a monthly rate. The spatial covering of these stations is depicted in 1(a), while its temporal covering is represented in 1(b). To get quarterly national representative data, both spatial and time scales need to be changed. In a first step, we average monthly values of mean soil moisture deficit at the region level. We then remove a seasonal trend by simply subtracting long term monthly statistics. Long term statistics are evaluated as the average value over the 1980 to 2016 period. Then, we follow Narasimhan and Srinivasan (2005) to create the soil moisture deficit index.

The measure of weather reads as follows:

1. We collect for each weather station the data "MTHLY: MEAN DEFICIT (WBAL)", denoted $D_{t,m}$.

[1]Named "MTHLY: MEAN DEFICIT (WBAL)" in the database.

2. For each $m = \{1, \ldots, 12\}$ month in each $t = \{1980, \ldots, 2016\}$ year, we compute monthly soil water deficit (expressed in percent) for each month as:

$$MD_{t,m} = \frac{D_{t,m} - Med(D_m)}{Med(D_m)}. \tag{1}$$

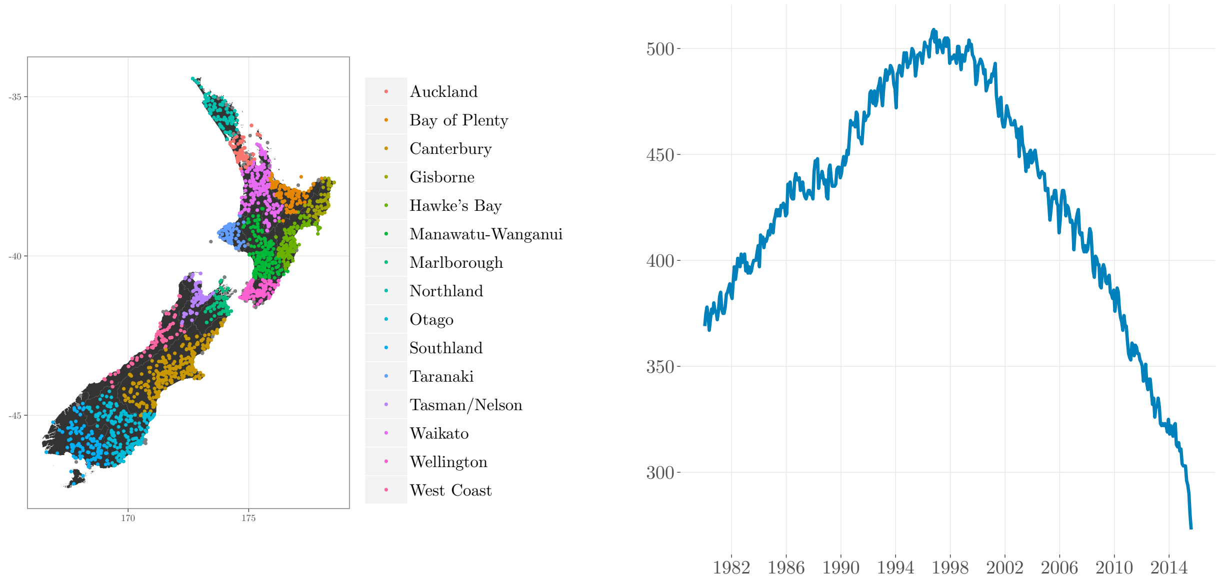
3. The index for any given month is then computed as:

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

using $SMDI_{1980,m} = \frac{SD_{1980,m}}{50}, \quad m = \{1, \ldots, 12\}$ as initial values for the series.

4. Then, we aggregate the monthly values of the index at the national level by means of a weighted mean, where the weights reflect the share of yearly agricultural GDP of each region.[2]

5. In a final step, monthly observations are quarterly aggregated.



(a) Spatial covering

(b) Temporal covering

Figure 1: Covering of weather stations used to construct the soil moisture deficit index.

2 The Restricted-VAR Model

To observe how the economy responds to a weather shock, we develop an empirical framework, and analyze the impulse response functions following a drought shock.

2.1 Modeling framework

We estimate a VAR (vector autoregressive) model on New Zealand data presented in section 6. The VAR model needs to reflect the small open economy assumption. That is, New Zealand's

[2]The regional agricultural GDP data we use ranges from 1987 to 2014. The weight after 2014 is set to the average contribution of the region to the total agricultural GDP over the whole covered period.

macroeconomic variables may react to foreign shocks, but domestic shocks should not significantly impact the rest of the world. We therefore follow Cushman and Zha (1997) and create an exogenous block for the variables from the rest of the world. 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. We therefore have three blocks: one for the domestic economy, another for the weather, and another for the rest of the world.

The model writes:

$$\begin{bmatrix} X_t^W \\ X_t^\star \\ X_t^D \end{bmatrix} = \sum_{l=1}^{p} \begin{bmatrix} A_l^{11} & 0 & 0 \\ 0 & A_l^{22} & 0 \\ A_l^{31} & A_l^{32} & A_l^{33} \end{bmatrix} \begin{bmatrix} X_{t-l}^W \\ X_{t-l}^\star \\ X_{t-l}^D \end{bmatrix} + \begin{bmatrix} \eta_t^W \\ \eta_t^\star \\ \eta_t^D \end{bmatrix}, \tag{3}$$

where $t = 1, \ldots, T$ is the time subscript, p is the lag length,[3] X_t^W, $X_t^\star$ and X_t^D are column vectors of variables for the weather block, the rest of the world, and the small open economy, respectively. The error terms η_t^W, $\eta_t^\star$ and η_t^D are exogenous and independent with zero mean and variance σ^{η^W}, $\sigma^{\eta^\star}$, and σ^{η^D}, respectively. The coefficients in A_l^{11} to A_l^{33}, are the parameters of interest that need to be estimated. The coefficients set to zero in the matrix of coefficients insure the exogeneity between blocks.

The weather block writes:

$$X_t^W = \begin{bmatrix} \hat{\omega}_t \end{bmatrix}',$$

where $\hat{\omega}_t$ is the weather measure, *i.e.*, the drought index. The international economy block writes:

$$X_t^\star = \begin{bmatrix} \hat{y}_t^\star \end{bmatrix}',$$

where $\hat{y}_t^\star$ stands for foreign real output growth. Finally, for our New Zealand economy model, the domestic block is:

$$X_t^D = \begin{bmatrix} \hat{y}_t & \hat{y}_t^A & \hat{\imath}_t & \hat{h}_t & \hat{c}_t & \widehat{rer}_t \end{bmatrix}',$$

where $\hat{y}_t$ is real GDP growth, $\hat{y}_t^A$ is agricultural real output growth, i_t denotes investment, $\hat{h}_t$ is hours worked, $\hat{c}_t$ is consumption, and $\widehat{rer}_t$ is real effective exchange rate.

For clarity purposes, Equation 3 can be rewritten in the following way:

$$X_t = \sum_{l=1}^{p} A_l X_{t-l} + \eta_t, \tag{4}$$

where $X_t = \begin{bmatrix} X_t^W & X_t^\star & X_t^D \end{bmatrix}'$ is the $n \times 1$ vector of endogenous variables at time t, $A_l = \begin{bmatrix} A_l^{11} & 0 & 0 \\ 0 & A_l^{22} & 0 \\ A_l^{31} & A_l^{32} & A_l^{33} \end{bmatrix}$, for $l = 1, \ldots, p$ are the $n \times n$ matrices of lagged parameters to be estimated, and $\eta_t = \begin{bmatrix} \eta_t^W & \eta_t^\star & \eta_t^D \end{bmatrix}'$, the $n \times 1$ vector contains white noise structural errors, normally distributed with zero mean and both serially and mutually uncorrelated.

2.1.1 The domestic weather block

The estimated VAR model contains a domestic weather block to study the impact of weather conditions on business cycle fluctuations. We rely on the same weather variable as in the DSGE model whose construction is explained in subsection 1.2. When it takes positive values, the weather variable depicts a prolonged episode of dryness. It is the only variable in the exogenous domestic weather block.

[3] We use a lag of one in the model basing our choice on the value of both Hannan-Quinn and Schwarz criteria

2.1.2 The foreign economy block

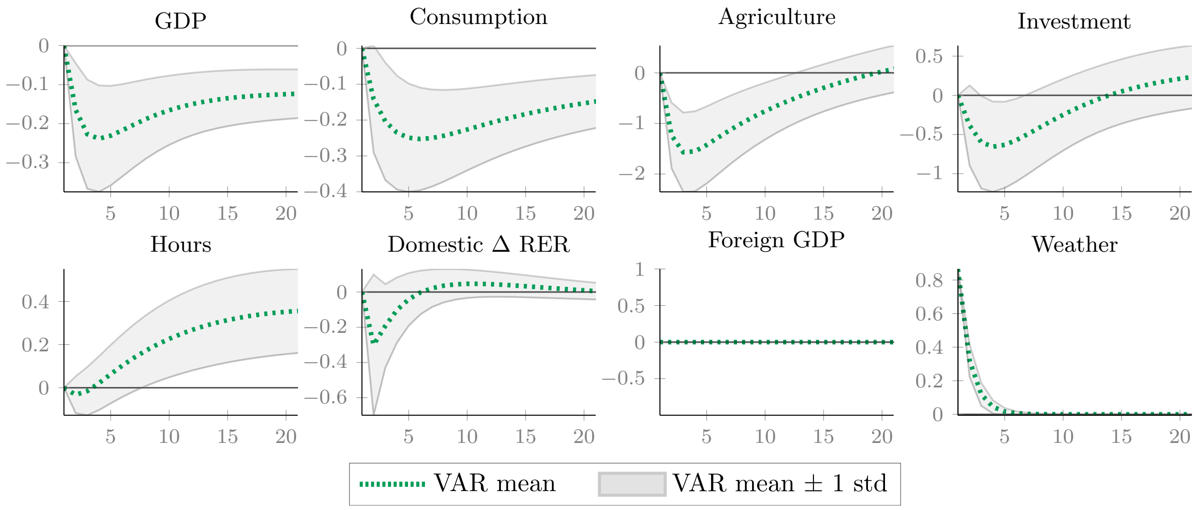
The foreign economy block comprises only one variable: real output y_t^*, computed as a weighted average of the respective value observed for New Zealand's most important historical trading partners: Australia, United States, United Kingdom and Japan. Weights are fixed according to the share of imports and exports with New Zealand at each quarter.

2.1.3 The domestic economy block

The domestic economy block comprises real output growth y_t, real agricultural output growth y_t^A, investment i_t, hours worked h_t, consumption c_t, and real effective exchange rate rer_t.

2.2 Macroeconomic response to weather shocks

We now present the empirical results of the impulse responses to a one standard deviation shock to the weather variable, *i.e.*, the drought indicator to assess the macroeconomic response following this shock. These IRFs are reported in Figure 2. The solid green lines are the responses while the gray areas are the 68% error bands obtained from 250 bootstrap runs. The responses are computed for 20 periods. We focus on the shock to the weather variable The complete set of IRFs is graphed in Figure 3 and Figure 4, where each column represents the response of the system to a specific shock.



Notes: The green dashed line is the Impulse Response Function. The gray band represents 68% error band obtained from the 250 bootstrap runs. The response horizon is in quarters.

Figure 2: VAR impulse response to a 1% weather shock (drought) in New Zealand.

Figure 2 shows multiple channels affecting the business cycles after a climate shock. Overall, the empirical evidence suggests that a drought episode acts as a negative supply shock. As in Buckle et al. (2007), it creates a significant recession through a decline of the GDP. This contractionary is triggered by the large fall in agricultural production. The drought is also accompanied by a decrease in investment and stock prices, fueled by the weaker demand for capital goods from farmers. These findings regarding the reaction of financial markets are quantitatively similar to those found by Hong et al. (2016) for the US. The results from the restricted VAR model can then be used as a guide to compare the propagation of the weather shock between the model and the VAR.

3 The non-linear model

3.1 Households

The marginal utility of consumption is given by:

$$\lambda_t^c = \left(C_t C_{t-1}^{-b}\right)^{-\sigma_C}, \tag{5}$$

The stochastic discount reads as:

$$\Lambda_{t,t+1} = \beta E_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} \right\}. \tag{6}$$

The Euler equation is given by:

$$E_t \left\{ \Lambda_{t,t+1} \right\} r_t = 1. \tag{7}$$

The real exchange rate is obtained by:

$$E_t \left\{ \frac{rer_{t+1}^*}{rer_t^*} \right\} = \frac{r_t}{r_t^*}(1 + p_t^N \Phi'(b_{jt}^*)). \tag{8}$$

The labor supply equation in each sector is:

$$\chi h_t^{\sigma_H} = C_t^{-\sigma_C} w_t^N \left(\frac{h_t^N}{h_t} \right)^{-\iota}, \tag{9}$$

$$\chi h_t^{\sigma_H} = C_t^{-\sigma_C} w_t^A \left(\frac{h_t^A}{h_t} \right)^{-\iota}. \tag{10}$$

The labor effort disutility index generating costly cross-sectoral labor reallocation:

$$h_t = \left[\left(h_t^N\right)^{1+\iota} + \left(h_t^A\right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{11}$$

The CES consumption bundle is determined by:

$$C_t = \left[(1-\varphi)^{\frac{1}{\mu}} (C_t^N)^{\frac{\mu-1}{\mu}} + \left(\varphi \varepsilon_t^A\right)^{\frac{1}{\mu}} (C_t^A)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \tag{12}$$

The consumption price index in real terms determines the relation between relative prices in the consumption basket of households:

$$1 = [(1-\varphi)\,(p_{C,t}^N)^{1-\mu} + \varphi (p_{C,t}^A)^{1-\mu}]^{\frac{1}{1-\mu}}, \tag{13}$$

where $p_{C,t}^N = P_{C,t}^N / P_t$ and $p_{C,t}^A = P_{C,t}^A / P_t$. In addition, consumption price indexes by type of good follow:

$$p_{C,t}^N = \left[(1-\alpha_N)\,(p_t^N)^{1-\mu_N} + \alpha_N {rer_t}^{1-\mu_N} \right]^{\frac{1}{(1-\mu_N)}}, \tag{14}$$

$$p_{C,t}^A = \left[(1-\alpha_A)\,(p_t^A)^{1-\mu_A} + \alpha_A {rer_t}^{1-\mu_A} \right]^{\frac{1}{(1-\mu_A)}}. \tag{15}$$

3.2 Non-agricultural Firms

Technology is given by:

$$Y_t^N = \varepsilon_t^Z \left(K_{t-1}^N\right)^{\alpha} \left(H_t^N\right)^{1-\alpha}, \tag{16}$$

Law of motion of physical capital is:

$$I_t^N = K_t^N - (1-\delta_K) K_{t-1}^N, \tag{17}$$

First order conditions, determining the real wage, the shadow value of capital goods, and the return of physical, emerge from the solution of the profit maximization problem:

$$w_t^N = (1-\alpha) p_t^N \frac{Y_t^N}{H_t^N}, \tag{18}$$

$$q_t^N = p_t^N + \kappa p_t^N \varepsilon_t^i \left(\varepsilon_t^i \frac{I_t^N}{I_{t-1}^N} - 1\right) - E_t \left\{\Lambda_{t,t+1} \frac{\kappa}{2} p_{t+1}^N \left[\left(\varepsilon_{t+1}^i \frac{I_{t+1}^N}{I_t^N}\right)^2 - 1\right]\right\}, \tag{19}$$

$$q_t^N = E_t \left\{\Lambda_{t,t+1} \left[\alpha p_{t+1}^N \frac{Y_{t+1}^N}{K_t^N} + (1-\delta_K) q_{t+1}^N\right]\right\}. \tag{20}$$

3.3 Farmers

Each farmer $i \in [n, 1]$ has a land endowment ℓ_{it}, whose time-varying productivity (or efficiency) follows a law of motion given by:

$$\ell_t = \left[(1-\delta_\ell) + \frac{\tau}{\phi} X_t^{\phi},\right] \Omega\left(\varepsilon_t^W\right) \ell_{t-1} \tag{21}$$

With a damage function:

$$\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}, \tag{22}$$

Each representative firm $i \in [n_t, 1]$ operating in the agricultural sector has the following production function:

$$Y_t^A = \ell_{t-1}^{\omega} \left[\varepsilon_t^Z \left(K_{t-1}^A\right)^{\alpha} \left(\kappa_A H_t^A\right)^{1-\alpha}\right]^{1-\omega}, \tag{23}$$

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

$$I_t^A = K_t^A - (1-\delta_K) K_{t-1}^A. \tag{24}$$

First order conditions are given by:

$$w_t^A = (1-\omega)(1-\alpha) p_t^A \frac{Y_t^A}{H_t^A}, \tag{25}$$

$$q_t^A = p_t^N + \kappa p_t^N \varepsilon_t^i \left(\varepsilon_t^i \frac{I_t^A}{I_{t-1}^A} - 1\right) - E_t \left\{\Lambda_{t,t+1} \frac{\kappa}{2} p_{t+1}^N \left[\left(\varepsilon_{t+1}^i \frac{I_{t+1}^A}{I_t^A}\right)^2 - 1\right]\right\} \tag{26}$$

$$q_t^A = E_t \left\{\Lambda_{t,t+1} \left[\alpha (1-\omega) p_{t+1}^A \frac{Y_{t+1}^A}{K_t^A} + (1-\delta_K) q_{t+1}^A\right]\right\} \tag{27}$$

$$\frac{p_t^N}{\tau X_t^{\phi-1} \ell_{t-1} \Omega\left(\varepsilon_t^W\right)} = E_t \left\{\Lambda_{t,t+1} \left(\omega \frac{Y_{t+1}^A}{\ell_t} + \frac{p_{t+1}^N}{\tau X_{t+1}^{\phi-1} \ell_t} \left[(1-\delta_\ell) + \frac{\tau}{\phi} X_{t+1}^{\phi}\right]\right)\right\} \tag{28}$$

3.4 The foreign economy

The foreign economy is determined by a set of three equations:

$$\log\left(c_t^*\right) = (1-\rho_*)\log\left(\bar{c}_j^*\right) + \rho_*\log\left(c_{t-1}^*\right) + \sigma_*\eta_t^* \tag{29}$$

$$\beta E_t\left\{\lambda_{t+1}^*/\lambda_t^*\right\} r_t^* = 1, \tag{30}$$

$$1/c_t^* = \lambda_t^*, \tag{31}$$

3.5 Closing the economy

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

$$\begin{aligned}(1-n_t)\,Y_t^N = (1-\varphi)&\left[(1-\alpha_N)\left(\frac{p_t^N}{p_{C,t}^N}\right)^{-\mu_N}\left(p_{C,t}^N\right)^{-\mu}C_t + \alpha_N\left(\frac{p_t^N}{rer_t}\right)^{-\mu_N}C_t^*\right]\\ &+ Y_t^N g\varepsilon_t^G + I_t + n_t X_t + 0.5\chi_B (B_t^*)^2.\end{aligned} \tag{32}$$

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

$$n_t Y_t^A = \varphi\left[(1-\alpha_A)\left(\frac{p_t^A}{p_{C,t}^A}\right)^{-\mu_A}\left(p_{C,t}^A\right)^{-\mu}C_t + \alpha_A\left(\frac{p_t^A}{rer_t}\right)^{-\mu_A}C_t^*\right], \tag{33}$$

The aggregation of hours, investment and output are given by:

$$H_t = (1-n_t)\,H_t^N + n_t H_t^A \tag{34}$$

$$I_t = (1-n_t)\,I_t^N + n_t I_t^A \tag{35}$$

$$Y_t = (1-n_t)\,p_t^N Y_t^N + n_t p_t^A Y_t^A \tag{36}$$

The net foreign asset position for the home country is given by:

$$B_t^* = r_{t-1}^*\frac{rer_t}{rer_{t-1}}B_{t-1}^* + tb_t,$$

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

$$tb_t = p_t^N\left[(1-n_t)\,Y_t^N - Y_t^N g\varepsilon_t^G - I_t - n_t X_t - 0.5\chi_B(B_t^*)^2\right] + p_t^A n_t Y_t^A - C_t. \tag{37}$$

And a set of structural disturbances:

$$\log(\varepsilon_t^Z) = \rho_Z\log(\varepsilon_{t-1}^Z) + \sigma_Z\eta_t^Z, \quad \text{with } \eta_t^Z \sim \mathcal{N}(0,1), \tag{38}$$

$$\log(\varepsilon_t^G) = \rho_G\log(\varepsilon_{t-1}^G) + \sigma_G\eta_t^G, \text{ with } \eta_t^G \sim \mathcal{N}(0,1), \tag{39}$$

$$\log(\varepsilon_t^I) = \rho_I\log(\varepsilon_{t-1}^I) + \sigma_I\eta_t^I, \quad \text{with } \eta_t^I \sim \mathcal{N}(0,1), \tag{40}$$

$$\log(\varepsilon_t^H) = \rho_H\log(\varepsilon_{t-1}^H) + \sigma_H\eta_t^H, \text{ with } \eta_t^A \sim \mathcal{N}(0,1), \tag{41}$$

$$\log(\varepsilon_t^W) = \rho_W\log(\varepsilon_{t-1}^W) + \sigma_W\eta_t^W, \text{ with } \eta_t^W \sim \mathcal{N}(0,1), \tag{42}$$

$$\log(\varepsilon_t^N) = \rho_N\log(\varepsilon_{t-1}^N) + \sigma_N\eta_t^N, \text{ with } \eta_t^N \sim \mathcal{N}(0,1), \tag{43}$$

$$\log(\varepsilon_t^C) = \rho_C\log(\varepsilon_{t-1}^C) + \sigma_C\eta_t^C, \text{ with } \eta_t^C \sim \mathcal{N}(0,1), \tag{44}$$

$$\log(\varepsilon_t^E) = \rho_E\log(\varepsilon_{t-1}^E) + \sigma_E\eta_t^E, \text{ with } \eta_t^E \sim \mathcal{N}(0,1). \tag{45}$$

4 Steady state

From the Euler equation, given a discount factor β, the real rate reads as:

$$\bar{r} = 1/\beta. \tag{46}$$

Given a steady state value of $\bar{h}^N$ and $\bar{h}^A$ set to 1/3, the steady state disutility of labor supply is given by:

$$\bar{h} = \left[\left(\bar{h}^N\right)^{1+\iota} + \left(\bar{h}^A\right)^{1+\iota}\right]^{1/(1+\iota)}. \tag{47}$$

Normalizing price indexes $\bar{p}^N$, $\bar{p}^A$ and $\bar{q}$ to one, the rate of return of physical capital is determined by:

$$\bar{z} = \bar{r} - (1-\delta). \tag{48}$$

The stock of capital of the non-agricultural sector is given by combining firm first order condition on physical capital and the technology constraint:

$$\bar{K}^N = \bar{H}^N \left(\frac{\bar{Z}}{\alpha}\right)^{(1/(\alpha-1))}, \tag{49}$$

and the output per firm is given by the supply curve:

$$\bar{Y}^N = \left(\bar{K}^N\right)^{\alpha} \left(\bar{H}^N\right)^{1-\alpha}. \tag{50}$$

While investment per firm is given by:

$$\bar{I}^N = \delta \bar{K}^N. \tag{51}$$

First order condition on labor demand implies that the equilibrium wage is equal to the marginal product of labor:

$$\bar{W}^N = (1-\alpha)\frac{\bar{Y}^N}{\bar{H}^N}. \tag{52}$$

Assuming perfect mobility across labor type in the deterministic steady state of the model, the underlying wage is equal across sectors:

$$\bar{W}^A = \bar{W}^N. \tag{53}$$

Reversing the marginal labor product equation, the production per farmer is given by:

$$\bar{Y}^A = \frac{\bar{H}^A \bar{W}^A}{(1-\omega)(1-\alpha)}. \tag{54}$$

Under perfect capital mobility across sectors, the invertion of the marginal product equation pins down the steady state capital per farmer:

$$\bar{K}^A = (1-\omega)\,\alpha \frac{\bar{Y}^A}{\bar{Z}}. \tag{55}$$

Given a land endowment $\bar{\ell}$, a stock of physical capital $\bar{K}^A$ and the demand for labor $\bar{H}^A$, then we compute the parameter affecting the labor productivity κ_A:

$$\kappa_A = \left[\left(\frac{\bar{Y}^A}{\bar{\ell}^{\omega}}\right)^{1/(1-\omega)} \left(\bar{K}^A\right)^{-\alpha}\right]^{1/(1-\alpha)} \frac{1}{\bar{H}^A}. \tag{56}$$

Letting $\bar{\varrho}$ denote the steady state lagrangian multiplier on the land productivity law of motion, the first order condition on land determines this lagrangian multiplier in steady state:

$$\bar{\varrho} = \left(\omega \frac{\bar{Y}^A}{\bar{\ell}} + \delta_\ell \bar{\ell} \right) / \left(r - (1 - \delta_\ell) \right).$$

From the first order condition on land expenditures, the land expenditure per farmer reads as:

$$\bar{X} = \delta_\ell \phi \bar{\varrho}. \tag{57}$$

While the shift parameter in the land augmenting productivity, τ, reads as:

$$\tau = \frac{1}{\bar{\varrho} \bar{\ell} \bar{X}^{\phi - 1}}. \tag{58}$$

The stock of physical capital per farmer is given by:

$$\bar{I}^A = \delta \bar{K}^A.$$

To compute the share of entrepreneurs operating in the agricultural sector, we must combine resources constraints in each sector by substituting consumption:

$$(1 - n) \bar{Y}^N = (1 - \varphi) \bar{C} + \bar{Y}^N g + (1 - n) \bar{I}^N + n \bar{I}^A + nX, \tag{59}$$

$$n \bar{Y}^A = \varphi \bar{C}. \tag{60}$$

We obtain the following equation:

$$(1 - n) (\bar{Y}^N - \bar{I}^N) = n \left(\frac{(1 - \varphi)}{\varphi} \bar{Y}^A + \bar{I}^A + \bar{X} \right) + \bar{Y}^N g \tag{61}$$

From the latter equation, it's straightforward to pin down the value of n:

$$n = \frac{(1 - g) \bar{Y}^N - \bar{I}^N}{(1 - \varphi) / \varphi \bar{Y}^A + \bar{I}^A + \bar{X} + \bar{Y}^N - \bar{I}^N}.$$

Finally, the consumption is given by any of the resource constraints:

$$\bar{C} = \frac{n}{\varphi} \bar{Y}^A.$$

5 The welfare cost of weather-driven business cycles

To get a welfare perspective on climate change, we compute how much consumption households are willing to abandon to stay in an equilibrium free of weather shocks.[4] Consider the following utility function:

$$U_t = \frac{1}{1 - \sigma} \left(C_{jt+\tau} - b C_{t-1+\tau} \right)^{1-\sigma} - \frac{\chi \varepsilon^H_{t+\tau}}{1 + \sigma_H} h^{1+\sigma_H}_{jt+\tau}, \tag{62}$$

The taylor expansion up to second order of the left term of the utility function is given by:

$$E\left[U_{C,t}\right] \simeq \frac{1}{1 - \sigma} \left(C - bC \right)^{1-\sigma} - \frac{1}{2} \sigma \left(C - bC \right)^{-\sigma-1} E\left[(c_t - c)^2 \right] + \frac{1}{2} \sigma b^2 \left(C - bC \right)^{-\sigma-1} E\left[(c_{t-1} - c)^2 \right]$$

[4] In standard macroeconomic models, the comparison of different scenarios is achieved through the computation of the fraction of consumption streams from alternative regime to be added (or subtracted) to achieve a benchmark reference (see for instance, Lucas (2003)). In our situation, this approach allows us to get an evaluation of the welfare cost of climate change in terms of unconditional consumption.

(63)

While for the right term of the utility function:

$$E\left[U_{H,t}\right] \simeq -\frac{\chi}{1+\sigma_H}h^{1+\sigma_H} - \frac{1}{2}\sigma_H \chi h^{\sigma_H-1} E\left[\left(h_t - h\right)^2\right] \tag{64}$$

Expressed in terms of variances, the utility function up to second order is given by:

$$E\left[U_t\right] \simeq \bar{U} - \frac{1}{2}\sigma\left(1-b^2\right)\left(C-bC\right)^{-\sigma-1} v\left(c_t\right) - \frac{1}{2}\sigma_H \chi h^{\sigma_H-1} v\left(h_t\right) \tag{65}$$

where $v\left(c_t\right)$ and $v\left(h_t\right)$ denote the variance of each endogenous variables.

Then, the welfare function up to second order is a linear function of the utility function:

$$E\left[W_t\right] = \frac{\bar{U}}{1-\beta} - \frac{1}{2}\sigma\left(1-b^2\right)\frac{\left(\bar{C}-b\bar{C}\right)^{-\sigma-1}}{1-\beta} v\left(c_t\right) - \frac{1}{2}\sigma_H \chi \frac{h^{\sigma_H-1}}{1-\beta} v\left(h_t\right) \tag{66}$$

The welfare cost between two regimes with the same steady state is given by:

$$\left(1+\lambda\right)^{1-\sigma} = \frac{\frac{1}{1-\sigma}\left(\bar{C}-b\bar{C}\right)^{1-\sigma} - \gamma_C v\left(c_t^A\right) + \gamma_H\left[v\left(h_t^B\right) - v\left(h_t^A\right)\right]}{\left[\frac{1}{1-\sigma}\left(\bar{C}-b\bar{C}\right)^{1-\sigma} - \gamma_C v\left(c_t^B\right)\right]} \tag{67}$$

Which can be expressed as:

$$\lambda = \left[\frac{\frac{1}{1-\sigma}\left(\bar{C}-b\bar{C}\right)^{1-\sigma} - \gamma_C v\left(c_t^A\right) + \gamma_H\left[v\left(h_t^B\right) - v\left(h_t^A\right)\right]}{\left[\frac{1}{1-\sigma}\left(\bar{C}-b\bar{C}\right)^{1-\sigma} - \gamma_C v\left(c_t^B\right)\right]}\right]^{1/(1-\sigma)} - 1 \tag{68}$$

6 Estimation of the DSGE Model

We apply standard Bayesian estimation techniques as in Smets and Wouters (2003, 2007). In this section, we describe the data sources and transformations. The model is estimated using 6 time series with Bayesian methods and quarterly data for New Zealand over the sample time period 1994:Q2 to 2016:Q4. Data with trends are detrended using the HP filter. The time reference for all indexes is 2010:Q1. Transformed data is shown in Figure 5.

6.1 Macroeconomic time series transformation

Concerning the transformation of the series, the point is to map non-stationary data to a stationary model. The data that are known to have a trend or unit root are made stationary in two steps. First, we divide the sample by the civilian population, denoted N_t. Second, data are taken in log and we use a first difference filtering to obtain growth rates. Real variables are deflated by GDP deflator price index denoted P_t.

As an illustration, the calculation method used to detrend real GDP per capita gap is as follows:

$$\hat{y}_t = \log\left(\frac{Y_t}{P_t N_t}\right) - \Gamma\left(\log\left(\frac{Y_t}{P_t N_t}\right)\right), \tag{69}$$

where $\Gamma\left(.\right)$ is the quadratic trend, linearized thanks to the log.

Turning to the weather index, we simply apply the logarithm function:

$$\hat{\omega}_t = \log(SMDI_t)$$

6.2 Measurement equations of the DSGE model

The final dataset includes seven times series: real GDP, real investment, hours worked, real agricultural output, consumption, foreign output and the weather index. Measurement equations read as follows:

$$\begin{bmatrix} 100 \times \hat{y}_t \\ 100 \times \hat{\imath}_t \\ 100 \times \hat{h}_t \\ 100 \times \hat{y}_t^A \\ 100 \times \hat{c}_t \\ 100 \times \hat{y}_t^* \\ 100 \times \Delta\widehat{rer}_t^* \\ 100 \times \hat{\omega}_t \end{bmatrix} = \begin{bmatrix} \log(Y_t/\bar{Y}) \\ \log(p_t^N I_t/\bar{I}) \\ \log(H_t/\bar{H}) \\ \log(n_t p_t^A Y_t^A / \left(\bar{Y}^A \bar{n}\right)) \\ \log(C_t/\bar{C}) \\ \log(Y_t^*/\bar{Y}^*) \\ \log(RER_{t-1}/RER_t) \\ \log(\varepsilon_t^W) \end{bmatrix}.$$

6.3 Comparing the VAR and the DSGE model

Since we used the VAR as a guideline for building our DSGE model, we report in Figure 6 the estimated response of the DSGE model (taken at posterior mean) following a 1% weather shock and the corresponding response of the VAR model.[5] The gray areas represent 68 and 95 percent probability intervals. Figure 6 shows that the model does very well at reproducing the estimated effects of weather shocks, including the hump-shape response of real GDP, real agricultural production and the muted response of hours. Another challenging aspect of the fit exercise is to capture the higher persistence of the response of macro-variables compared to the weather shock process. In particular, the weather requires five quarters to vanish while output, investment and hours take more than fifteen periods to go back to steady state. The introduction of an endogenous land input successfully captures this hysteresis effects. However, the model does overstate the contraction of output and its persistence while it does understate the decline in investment.

7 Building long run scenarios of weather shocks

To estimate the variability of the weather process η_t^W, we rely on simulated weather data from a circulation climate model, the Community Climate System Model (CCSM). We consider the data simulated under the four well-employed Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). They are given on a $0.9° \times 1.25°$ grid, at a monthly rate, for two distinct periods. The first one corresponds to "historical" values, and ranges from 1850 to 2005. The second one gives observations for "future" values up to 2100. Since our DSGE models is fed-up with quarterly data at the national level, we need to aggregate the raw data provided by the CCSM. To do so, we compute the average value of total rainfall at the region level by means of a weighted mean. The weight put on each cell of the grid in a given region is the proportion of the region covered by the cell. Values are then averaged for each month, at the national level. The aggregation is done using a weighted mean, where weights are set according to the share of agricultural GDP of the region.[6] Resulting data is then converted to quarterly data, by summing the monthly values of total rainfall. The final dataset of simulated data contains quarterly data of rainfall at the national level for the historical period (ranging from 1983 to 2005) and for the future period (covering 2006 to 2100) for each RCP scenario.

[5]The IRFs of the DSGE model are obtained from the measurements equations in **??** which makes them comparable with the VAR's IRFs.

[6]The regional agricultural GDP data we use ranges from 1987 to 2014. The weight after 2014 is set to the average contribution of the region to the total agricultural GDP over the whole covered period.

Scenario	Compound quarterly rate (σ_{i,η^W})	Average growth rate of the standard error ($\overline{\Delta\sigma_{i,\eta^W}}$)	Average growth rate of the variance ($\overline{\Delta\sigma^2_{i,\eta^W}}$)
RCP 2.6	-0.1218964×10^3	-4.095090	-8.022482
RCP 4.5	0.1923896×10^3	6.820885	14.10701
RCP 6.0	0.2591393×10^3	9.294213	19.45225
RCP 8.5	0.6096352×10^3	23.249574	51.90457

Notes: For each Representative Concentration Pathways, we estimate the quarterly rate of growth of the standard deviation of the weather measure (σ_{i,η^W}), the corresponding average growth rate over the whole 1989–2100 period ($\overline{\Delta\sigma_{i,\eta^W}}$) and the average growth rate of the variance ($\overline{\Delta\sigma^2_{i,\eta^W}}$) .

Table 1: Estimations of growth rates of standard errors of the weather process under different scenarios.

We then need to estimate how the variance of the weather shock changes through time in each of the $i = \{\text{RCP 2.6}, \text{RCP 4.5}, \text{RCP 6.0}, \text{RCP 8.5}\}$ scenario. We proceed by rolling window regression, the size of each window being set to 102 quarters, matching the size of the number of observations used to estimate the DSGE model. In each step of the rolling window regression, we fit an $AR(1)$ model to the data and compute the standard deviation of the residuals. We estimate the growth rate of the standard deviation $\Delta\sigma_{i,\eta^W}$ by least squares, regressing the natural logarithm of the standard deviation previously obtained on time. Then, we estimate the average growth rate $\overline{\Delta\sigma_{\eta^W}}$ of the standard deviation over the 1989–2100 period for the i^{th} scenario as:

$$\overline{\Delta\sigma_{i,\eta_W}} = (1 + \sigma_{i,\eta^W})^q - 1, \tag{70}$$

where σ_{i,η^W} is the estimated compound quarterly rate of growth for the standard error of the weather shock process under the i^{th} climate change scenario, and q is the number of quarter in the whole sample, *i.e.*, 347. **??** summarizes the estimates.

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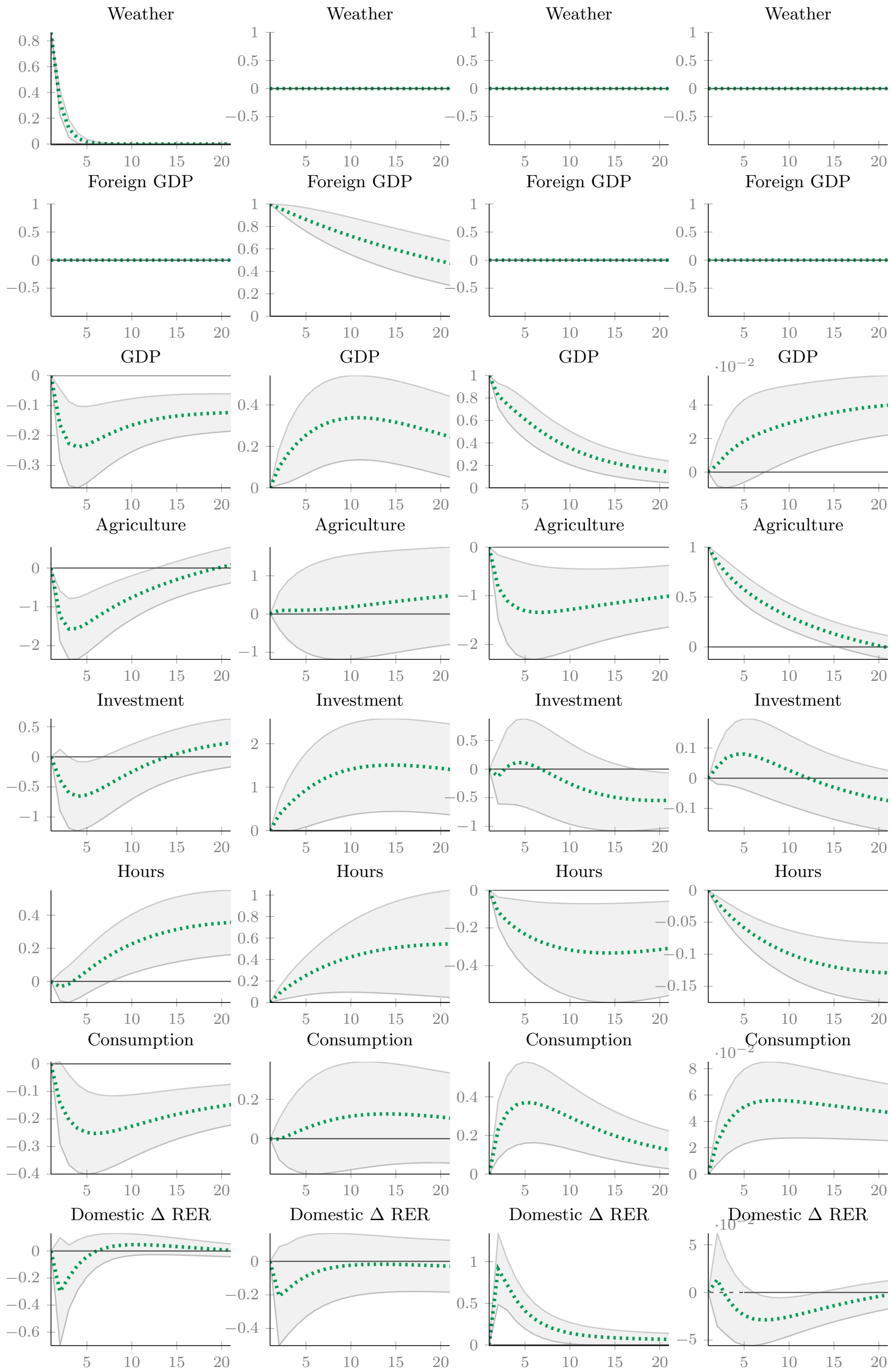
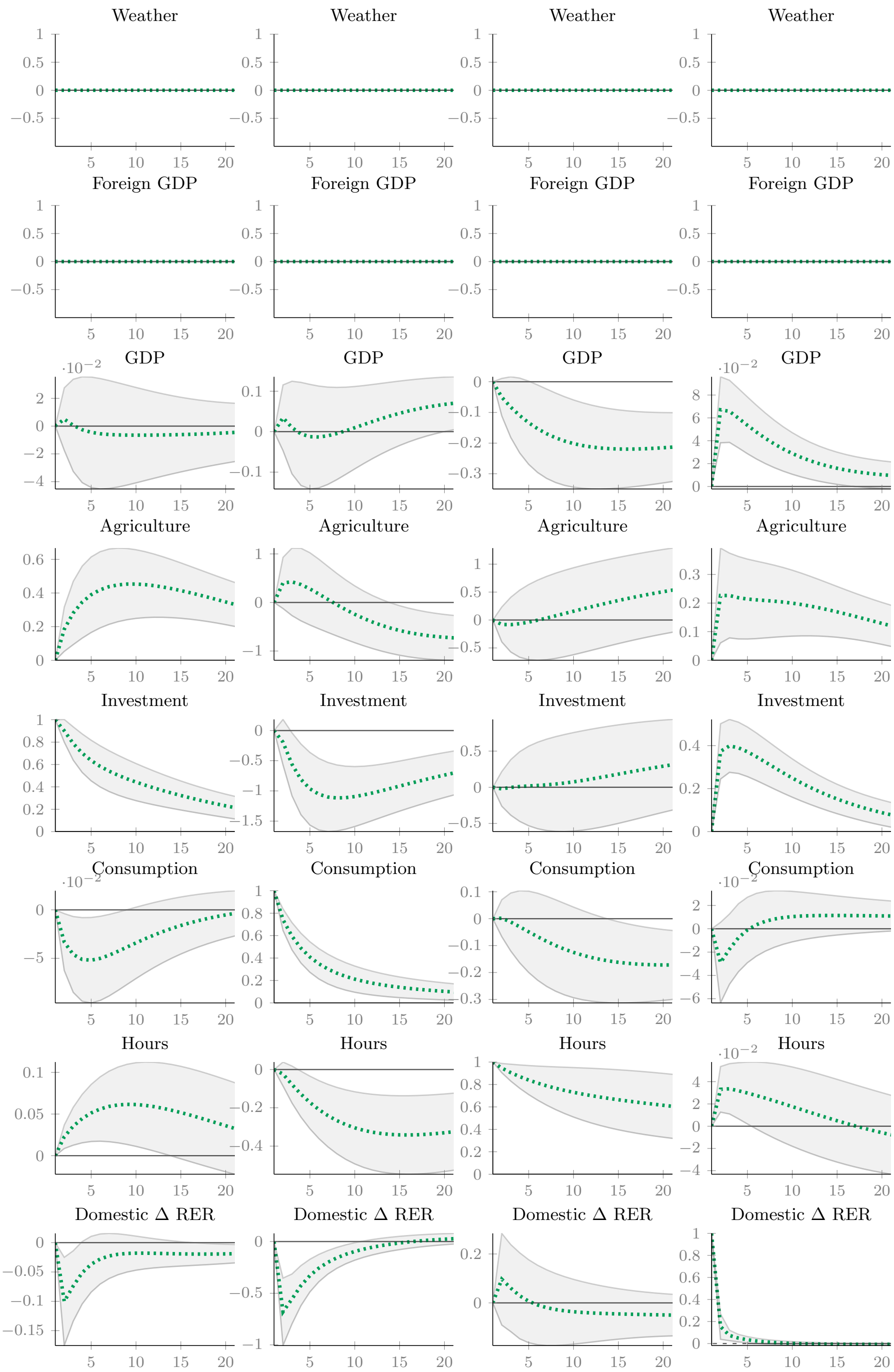


(a) Weather shock (b) Foreign GDP shock (c) GDP shock (d) Agriculture shock

Notes: Each column represents the response of the system to a 1% weather shock (column 1), world output shock (column 2), output shock (column 3), and agricultural output shock (column 4). The green dashed line is the Impulse Response Function. The gray band represents 68% error band obtained from the 250 bootstrap runs. The response horizon is in quarters.

Figure 3: VAR impulse responses to a 1% shock (1/2)



(e) Invest. shock (f) Consumption (g) Hours shock (h) RER shock

Notes: Each column represents the response of the system to a 1% investment shock (column 1), consumption shock (column 2), hours worked shock (column 3), and real effective exchange rate shock (column 4). The green dashed line is the Impulse Response Function. The gray band represents 68% error band obtained from the 250 bootstrap runs. The response horizon is in quarters.

Figure 4: VAR impulse responses to a 1% shock (2/2)

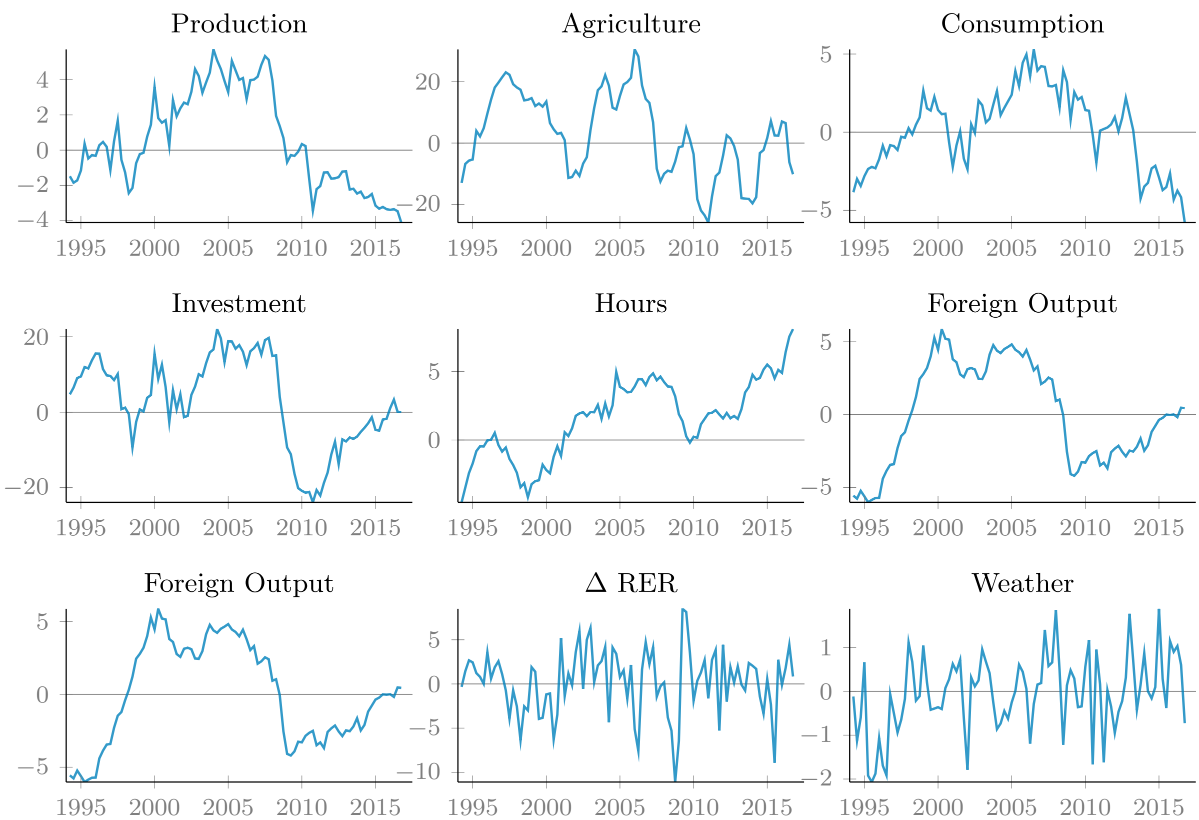


Figure 5: Observable variables used in the VAR and the DSGE estimations.

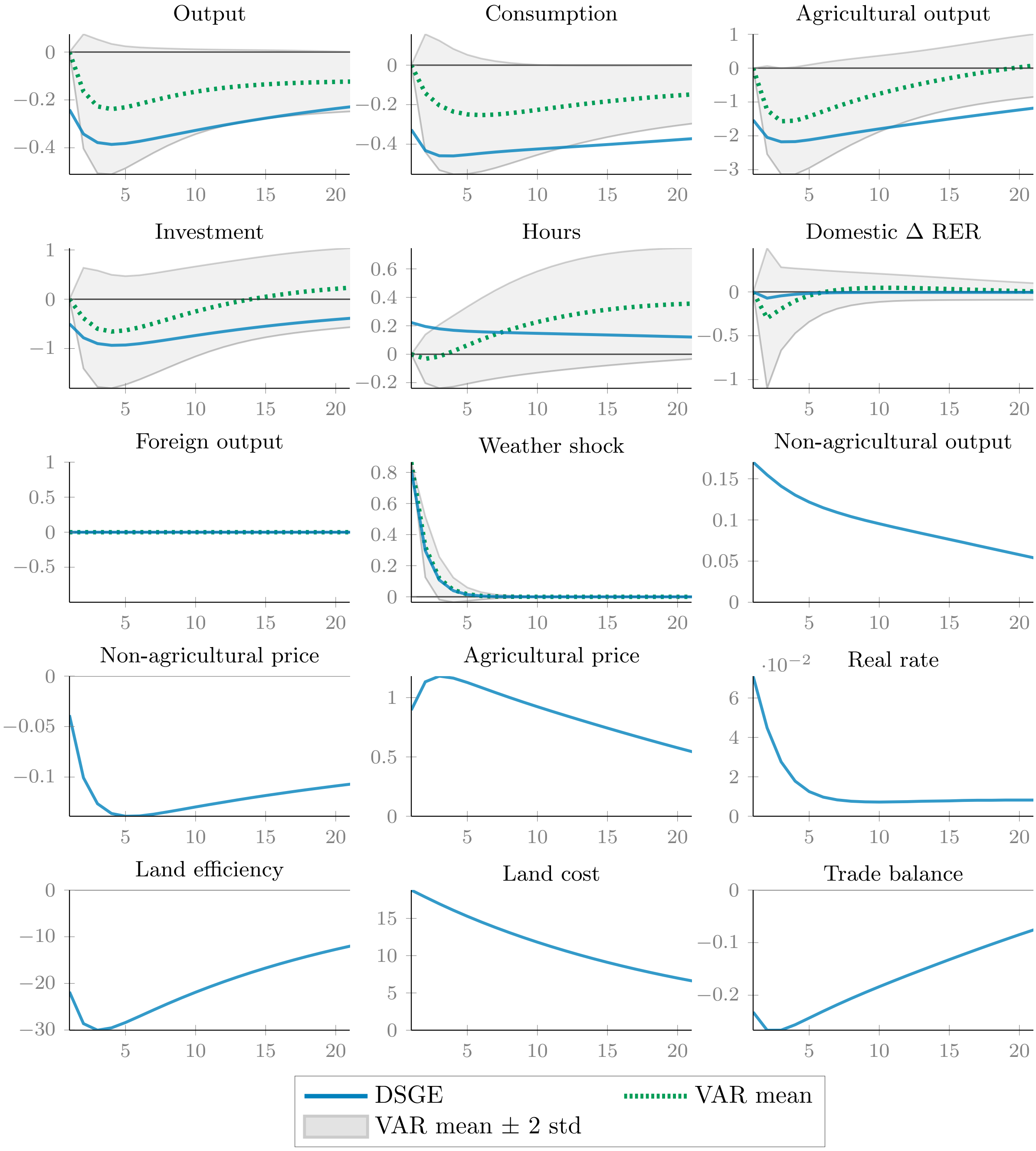


Figure 6: Comparison of the DSGE and the VAR impulse responses to a 1% weather shock (drought) in New Zealand.