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Abstract

How much do weather shocks matter? This paper analyzes the role of weather shocks in the generation and propagation of business cycles. We develop and estimate an original DSGE model with a weather-dependent agricultural sector. The model is estimated using Bayesian methods and quarterly data for New Zealand over the sample period 1994:Q2 to 2016:Q4. Our model suggests that weather shocks play an important role in explaining macroeconomic fluctuations over the sample period. A weather shock – as measured by a drought index – acts as a negative supply shock characterized by declining output and rising relative prices in the agricultural sector. Increasing the variance of weather shocks in accordance with forthcoming climate change leads to a sizable increase in the volatility of key macroeconomic variables and causes significant welfare costs up to 0.58% of permanent consumption.

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Keywords: Business Cycles, Climate Change, Weather Shocks, DSGE.

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1 Introduction

The prospect of considerable climate change and its potentially large impacts on economic well-being are central concerns for the scientific community and policymakers. Along with a forecast increase in global mean temperature of 1 to 4 degrees Celsius above 1990 levels, the Intergovernmental Panel on Climate Change (IPCC) forecasts a rise in both variability and frequency of extreme events, such as droughts (IPCC, 2014). The intensification of extreme drought events is currently emerging as one of the most important facets of global warming, which may have large macroeconomic implications, particularly for the agricultural sector.

Many efforts have been made to assess the potential economic impact of climate change (Nordhaus, 1994; Tol, 1995; Fankhauser and Tol, 2005), especially its consequences on agricultural systems (Adams et al., 1998; Fischer et al., 2005; Deschenes and Greenstone, 2007). As climatic factors enter into the production function as direct inputs, any important variation in weather conditions has a large effect on agricultural production. From a policymaker perspective, the evaluation of the economic costs incurred from climate shocks has become a crucial element in the decision-making process to implement measures that would offset potential harmful effects on the economy and in turn on social welfare. These very specific macroeconomic costs, generated by variable weather conditions, are particularly challenging for agriculture-based economies, as well as for developing countries, and may undermine world food security (IPCC, 2014).

Given the remaining uncertainties around the economic costs of variable weather conditions, the main objective of this paper is to provide a quantitative evaluation of the effects of weather shocks on the business cycles of an economy. We develop an original real business cycle model that includes a weather-sensitive agricultural sector. Then, we apply Bayesian techniques to determine the implications of weather shocks on business cycles. Once estimated, the model is amenable to the analysis of climate change. As climate is assumed to be a stationary process in our study, an analysis of changes in the mean of the climate variable is irrelevant. However, changes in the variance of the climate variable and the underlying impacts on the business cycles can be examined.

In recent literature, many efforts have been made to propose models linking macroeconomic variables and the weather. The first strand of the literature is related to integrated assessment models (IAMs) pioneered by Nordhaus (1991). These types of models are now used by governments to provide an evaluation of the social costs of carbon emissions. 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. In contrast, in our approach we measure the short run implications of the weather on aggregate fluctuations. The second strand of the literature exemplified by Barro (2006, 2009) or Gourio (2008) investigates the implications of rare economic disasters on asset prices and welfare. The term "risk disaster" encompasses a very large range of events such as wars, economic depression and most importantly with respect to our paper: natural disasters. It should, however, be noted that our analysis does not account for the dimension of the risk. In addition the scope of the natural disaster is narrow here, as we do not consider tsunamis, tornadoes or earthquakes. Instead, we focus on the role of weather conditions, more specifically droughts, on agricultural production and their implications for macroeconomic fluctuations. Finally, the last strand of the literature employs empirical models to examine the short-run effects of the weather on economic activity. 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. De Winne and Peersman (2016) estimate the dynamic effects of global food commodity supply shocks on the U.S. economy. They find that unfavorable commodity market shock rises agricultural price and lead to a persistent decline in real GDP and consumer expenditures. Bloesch and Gourio (2015) originally assess the effect of winter weather on US business activity for the US economy; they find that the weather has a very short-lived effect on economic activity. Auray et al. (2016) assess the short run role of temperatures and precipitations on the productivity cycles of England during the pre-industrial period. They find that a temporary rise in temperature induces a reduction of 11% of TFP implying a large contraction of output and a welfare cost.

We contribute to this literature by measuring the short-run effects of weather variables on economic activity using an original extension of the RBC model including an agricultural sector. The analysis conducted here allows us not only to measure short run effects of the weather as in the empirical literature, but also to contrast the long run effect induced by climate change as in the integrated assessment literature. The fit exercise is conducted using New Zealand data as this country is small enough to have a relatively homogeneous weather at a macro level. Large countries such as the US have too large cross-state divergences in terms of the weather to have a single weather indicator. A regional approach of our setup could, however, be applied to large economies.

Regarding the methodology employed in the paper, it comprises three steps. First, we estimate a VAR model for New Zealand to provide some preliminary empirical evidence on the impact of weather shocks on macroeconomic variables. Second, we build and estimate a DSGE model and we compare the results with the estimated VAR. Third, we increase the variance of weather shocks, consistently with climate change projections, to assess the effects of climate change on the welfare and the macroeconomic volatility of New Zealand.

The main result of the paper suggests 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, accompanied by a very weak decline of hours worked. Our business cycle decomposition exercises also show that weather shocks are an important driver of agricultural production and, in a much smaller proportion, of the GDP. Finally, we use our model for an analysis of climate change by increasing the variance of weather shocks consistently with projections up to 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 significant welfare costs incurred by weather-driven business cycles, as today households are willing to pay 0.40% 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 remainder of this paper is organized as follows: Section 2 provides some empirical evidences 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 discusses the propagation of a weather shock, assesses the consequences of a drought and its implication in terms of business cycles statistics, presents the historical variance decomposition of the main aggregates (gross domestic product and agricultural production), 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 7 concludes.

2 Business cycles evidence

This section provides some preliminary empirical evidence on the impact of weather shocks on macroeconomic variables. The weather acts as a direct input in agricultural production, thus making agricultural output sensitive to poor weather conditions. A country whose GDP significantly depends on its agricultural sector may therefore be exposed to the variations of the weather. New Zealand is one of these countries, with an agricultural sector that represented around 7% of total output during the past years, according to the World Bank. Although New Zealand has a temperate climate that is well suited for agriculture, it also frequently faces weather accidents. In particular, New Zealand has been subject to more or less severe droughts during the last decade. Such weather shocks may create production shortages that may in turn induce significant macroeconomic fluctuations. In the literature, only a few studies have examined the role of climate on business cycles. Buckle et al. (2007) showed in an empirical article that the weather acts as an important source of business cycles, along with international output and trade price variations. Bloor and Matheson (2010) also found evidence of the importance of the weather, more particularly the occurrence of El Niño events, on agricultural production and total output in New Zealand. Finally, Kamber et al. (2013) showed that food prices and goods and services prices are affected by drought events. They also found that relative to a period in which a drought occurs, the exchange rate and the interest rate would be lower than they would have been without the drought.

Before setting-up the theoretical model, we investigate how the weather, especially droughts, may induce economic fluctuations in New Zealand. To that end, we estimate a VAR (vector autoregressive) model on New Zealand quarterly data that are seasonally adjusted and cover the period 1994Q2 to 2016Q4.

The VAR model has to reflect the small open economy assumption. That is, New Zealand's 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.[1] 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.[2]

[1] More details can be found in the online appendix.

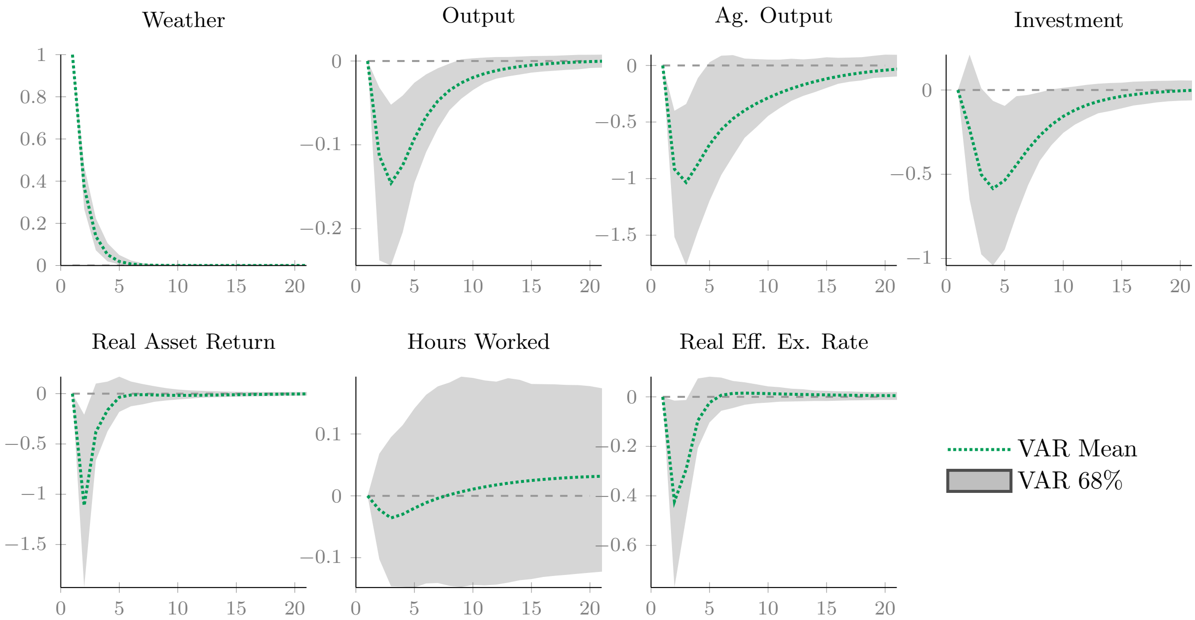
[2] As the historical data only cover a restricted period of time, we assume that human activities do not significantly affect the occurrence of droughts.

The VAR model writes:

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

where $t = 1, \ldots, T$ is the time subscript and p is the lag length, X_t is the matrix of the variables from the three bloc, *i.e.*, domestic, foreign, and weather blocs; A_t is the matrix of the coefficients to estimate, as well as the coefficients set to zero to insure the exogeneity restrictions between the three blocs; and η_t is the error term with zero mean and variance σ^η.

The VAR model is estimated with one lag, as suggested by both Hannan-Quinn and Schwarz criteria. It relies on 8 variables. Six of them represent the domestic block: GDP, agricultural production, investments, hours worked,[3] real effective exchange rate, and the share return of the NZSX50. The foreign block contains a measure of GDP for the rest of the world.[4] All these variables are expressed in terms of percentage deviation from their HP trend. Finally, the weather block contains a drought index constructed from soil moisture deficit observations, as in Kamber et al. (2013). Positive values of this index depict prolonged episodes of dryness.



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

To investigate the effects of an adverse weather shock, we examine the impulse responses to a one-standard-deviation of the drought variable. The Choleski decomposition of the error variance-covariance matrix is used to derive the orthogonal impulse

[3]Unfortunately, there is no data regarding hours worked in the agricultural sector and the non-agricultural sector, so we consider hours worked in the whole economy.

[4]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.

responses. The results are depicted in Figure 1, where each panel represents the response of one of the variables to the weather shock. Time horizon is plotted on the x-axis while the percent deviation from the steady state is plotted on the y-axis. 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 contraction 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 model

This section is devoted to a formal presentation of the DSGE model. Our model is a two-sector, two-good economy in a small open economy setup in a flexible exchange rate regime.[5] The home economy, *i.e.,* New Zealand, is populated by households and firms. The latter operate in the agricultural and the non-agricultural sectors. Households consume both home and foreign varieties of goods, thus creating a trading channel adjusted by the real exchange rate. However, the home country is a small open economy facing the business cycle developments of the foreign country. The general structure of the model is summarized in Figure 2. The remainder of this section presents the main components of the model.

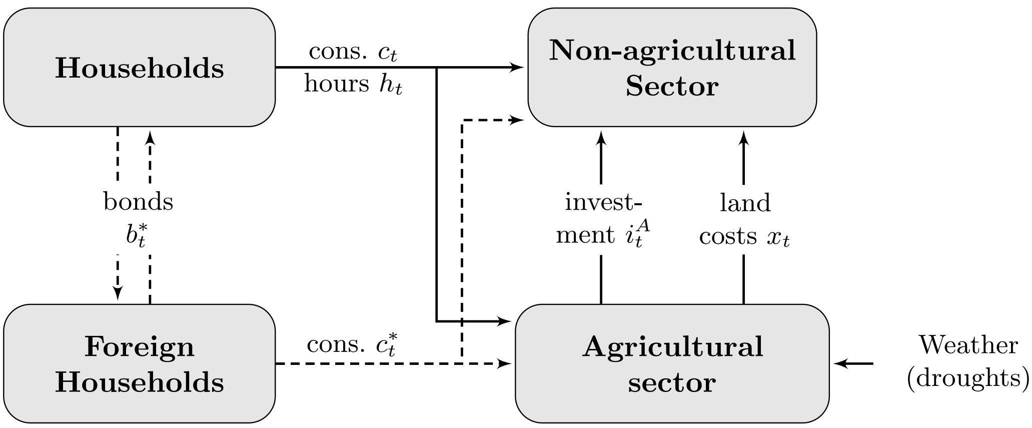


Figure 2: The theoretical model.

[5]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.

3.1 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 $\beta \in (0,1)$:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\sigma_C} C_{jt+\tau}^{1-\sigma_C} - \frac{\chi}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right] C_{t-1+\tau}^{b\sigma_C}, \tag{2}$$

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 σ_C and σ_H 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. In addition, the habit formation is multiplicative in consumption as in Galí (1994), and affects the labor supply. This utility function mutes the role of consumption habits and magnifies in turn the wealth effect of consumption over the labor supply. Under this specification, labor supply becomes weakly cyclical during an adverse weather event, consistently with empirical evidence.

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:

$$h_{jt} = \left[\left(h_{jt}^{N}\right)^{1+\iota} + \left(h_{jt}^{A}\right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{3}$$

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:

$$\sum_{s=N,A} w_t^s h_{jt}^s + r_{t-1} b_{jt-1} + rer_t r_{t-1}^{*} b_{jt-1}^{*} - T_t \geq C_{jt} + b_{jt} + rer_t b_{jt}^{*} + p_t^N rer_t \Phi(b_{jt}^{*}). \tag{4}$$

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 real exchange rate rer_t (an increase in rer_t can be interpreted as an appreciation of the foreign exchange rate). 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 $p_t^N = P_t^N/P_t$.[6] The pa-

[6]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.

rameter $\chi_B > 0$ denotes the magnitude of the cost paid by domestic households when purchasing foreign bonds.

The first-order conditions solving the household's optimization problem are obtained by maximizing the welfare index in Equation 2 under the budget constraint in Equation 4 given the labor sectoral reallocation cost in Equation 3. First, the marginal utility of consumption is determined by:

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

where λ_t^c denotes the Lagrange multiplier associated with the household budget constraint.[7] The stochastic discount factor $\Lambda_{t,t+1}$ is determined by:

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

The Euler condition on domestic real bonds reads as follows:

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

The first-order condition determines the household labor supply in each sector:

$$\chi h_{jt}^{\sigma_H} = C_{jt}^{-\sigma_C} w_t^s \left(\frac{h_{jt}^s}{h_{jt}}\right)^{-\iota}, \text{ for } s = N, A \tag{8}$$

Finally, the Euler condition on foreign bonds can be expressed as the real exchange rate determination under incomplete markets:

$$E_t \left\{ \frac{rer_{t+1}}{rer_t} \right\} = \frac{r_t}{r_t^*}(1 + p_t^N \Phi'(b_{jt}^*)), \tag{9}$$

where $\Phi'(b_{jt}^*)$ is the derivative of the bonds and risk-premium cost function.

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:

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}} (C_{jt}^N)^{\frac{\mu-1}{\mu}} + \left(\varphi \varepsilon_t^A\right)^{\frac{1}{\mu}} (C_{jt}^A)^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}}, \tag{10}$$

where $\mu \geq 0$ denotes the substitution elasticity between the two types of consumption goods, $\varphi \in [0,1]$ is the fraction of agricultural goods in the household's total consumption basket, and ε_t^A is a preference shock that affects the units of consumption of agricultural goods. The corresponding consumption price index P_t reads as follows:

$$P_t = \left[(1-\varphi)\left(P_{C,t}^N\right)^{1-\mu} + \varphi (P_{C,t}^A)^{1-\mu}\right]^{\frac{1}{1-\mu}}, \tag{11}$$

[7] In equilibrium, the marginal utility of consumption equals the Lagrange multiplier λ_t^c associated with the household budget constraint.

where $P_{C,t}^N$ and $P_{C,t}^A$ are consumption price indexes of non-agricultural and agricultural goods, respectively. The preference shock ε_t^A is represented by an autoregressive process:

$$\log(\varepsilon_t^A) = \rho_A \log(\varepsilon_{t-1}^A) + \sigma_A \eta_t^A, \qquad \eta_t^A \sim \mathcal{N}(0,1), \tag{12}$$

where $\rho_A \in [0,1)$ denotes the root of the shock process and $\sigma_A \geq 0$ its standard deviation. This shock captures variations in the consumption of agricultural goods which are not directly driven by the sectoral substitution between the two types of goods available in the economy.

Second, each indexes C_{jt}^N and C_{jt}^A are also a composite consumption subindexes composed of domestically and foreign produced goods:

$$C_{jt}^s = \left[(1-\alpha_s)^{\frac{1}{\mu_S}} (c_{jt}^s)^{\frac{(\mu_S-1)}{\mu_S}} + (\alpha_s)^{\frac{1}{\mu_N}} (c_{jt}^{s*})^{\frac{(\mu_S-1)}{\mu_s}}\right]^{\frac{\mu_S}{(\mu_S-1)}} \text{ for } s = N, A \tag{13}$$

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:

$$P_{C,t}^s = \left[(1-\alpha_s)(P_t^s)^{1-\mu_s} + \alpha_s (e_t P_t^{s*})^{1-\mu_s}\right]^{\frac{1}{(1-\mu_s)}}, \tag{14}$$

where 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:

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

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

3.2 Non-agricultural sector

There exists a continuum of perfectly competitive non-agricultural firms indexed by $i \in [0,n]$, with n 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:

$$\log(\varepsilon_t^Z) = \rho_Z \log(\varepsilon_{t-1}^Z) + \sigma_Z \eta_t^Z, \quad \text{with } \eta_t^Z \sim \mathcal{N}(0,1) \tag{18}$$

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.[8]

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.

The real profits are given by:

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

where 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 investments costlier, it follows an AR(1) shock process:

$$\log(\varepsilon_t^I) = \rho_I \log(\varepsilon_{t-1}^I) + \sigma_I \eta_t^I, \quad \text{with } \eta_t^I \sim \mathcal{N}(0,1) \tag{21}$$

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

Firms maximize the discounted sum of profits:

$$\max_{\{h_{it}^N, i_{it}^N, k_{it}^N\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+s} d_{it+\tau}^N \right\}. \tag{22}$$

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:

$$w_t^N = (1-\alpha)\, p_t^N \frac{y_{it}^N}{h_{it}^N}, \tag{23}$$

$$q_t^N = p_t^N + \kappa p_t^N \varepsilon_t^i \left(\varepsilon_t^i \frac{i_{it}^N}{i_{it-1}^N} - 1 \right) - E_t \left\{ \Lambda_{t,t+1} \frac{\kappa}{2} p_{t+1}^N \left[\left(\varepsilon_{t+1}^i \frac{i_{it+1}^N}{i_{it}^N} \right)^2 - 1 \right] \right\}, \tag{24}$$

$$q_t^N = E_t \left\{ \Lambda_{t,t+1} \left[\alpha p_{t+1}^N \frac{y_{it+1}^N}{k_{it}^N} + (1-\delta_K)\, q_{t+1}^N \right] \right\}. \tag{25}$$

3.3 Agricultural sector and the weather

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,

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

this variable captures variations in soil moisture that affect the production process of farmers. The measure used in the estimation is based on soil moisture deficit observations calculated from the daily water balance.[9] We assume that the aggregate drought index follows an univariate stochastic exogenous process:

$$\log(\varepsilon_t^W) = \rho_W \log(\varepsilon_{t-1}^W) + \sigma_W \eta_t^W, \qquad \eta_t^W \sim \mathcal{N}(0,1) \tag{26}$$

where $\rho_W \in [0,1)$ is the estimated persistence of the weather shock and $\sigma_W \geq 0$ its standard deviation. Shock processes are all normalized to one in 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, as shown by the restricted VAR in Section 2.

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:

$$\ell_{it} = (1-\delta_\ell)\,\Omega\left(\varepsilon_t^W\right)\ell_{it-1} + x_{it}, \tag{27}$$

where $\delta_\ell \in (0,1)$ is the rate of decay of land efficiency, $\Omega\left(\varepsilon_t^W\right)$ is a damage function incurred by weather variations, and x_{it} is the amount of non-agricultural goods necessary to maintain the level of land productivity. From a farmer perspective, x_{it} can be interpreted as spending on pesticides, herbicides, seeds, fertilizers and water applied to maintain the productivity of the field. A drought shock is assumed to reduce the fields crop production ℓ_{it}. In response to such an adverse shock, the farmer can optimally offset the soil dryness by increasing field irrigation, which materializes in our setup by a rise in x_{it}. From a breeder perspective, land efficiency is also critical for livestock systems, as the feed rationing of cattle is based on the use of local forage produced by country pastures. An unexpected drought is therefore expected to increase the feed budget through the deterioration of pasture supply combined with the need for more water for the dairy cattle.

In addition to this modeling choice, a damage function $\Omega(\cdot)$ is introduced in the spirit of integrated assessment models (IAMs) pioneered by Nordhaus (1991). Agricultural production is tied up with exogenous weather conditions through a damage function $\Omega(\cdot)$ that alters land productivity. We opt for a simple functional form for this damage function:

$$\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}, \tag{28}$$

where θ is the elasticity of land productivity with respect to the weather variations. With a positive value for θ, a drought shock is costly for agricultural activities through a decline in the productivity of land.

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

[9] The soil moisture variable measures the net impact of rainfall entering the pasture root zone in the soil, which is then lost in this zone as a result of evapotranspiration or use of water by plants.

a conservative approach on both the values of the parameters of the damage function and its functional form. First, regarding the functional form of the damage function, 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. Second, concerning the values of the parameters, our results depend on a single parameter, θ, which is very agonistically estimated through a very diffuse prior.

Turning to the technology, the production component of agriculture is strongly inspired by Restuccia et al. (2008) to the extent that agricultural output is Cobb-Douglas in land, physical capital inputs, and labor inputs.[10] Each representative firm $i \in [n, 1]$ operating in the agricultural sector has the following production function:

$$y_{it}^A = \varepsilon_t^Z \ell_{it-1}^{\omega} \left[\left(k_{it-1}^A\right)^{\alpha} \left(\kappa_A h_{it}^A\right)^{1-\alpha} \right]^{1-\omega}, \tag{29}$$

where y_{it}^A is the production function of the intermediate agricultural good that combines an amount of land ℓ_{it-1}, physical capital k_{it-1}^A, and labor demand h_{it}^A. Production is subject to an economy-wide technology shock ε_t^Z, whose description of the process is given in Equation 18. 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 New Zealand, the agricultural sector heavily relies on mechanization. Physical capital is lagged here because of the "time to build" assumption that states that physical capital requires one quarter to be settled.

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

$$i_{it}^A = k_{it}^A - (1 - \delta_K) k_{it-1}^A. \tag{30}$$

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

The real profits d_{it}^A are given by:

$$d_{it}^A = p_t^A y_{it}^A - p_t^N \left(i_{it}^A + S\left(\varepsilon_t^i \frac{i_{it}^A}{i_{it}^A} \right) i_{it-1}^A \right) - w_t^A h_{it}^A - p_t^N v\left(x_{it}\right), \tag{31}$$

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 described in Equation 20. There is yet no micro-evidence about the functional form of land costs $v(x_{it})$. We adopt here an unopinionated approach by imposing the following cost function: $v(x_{it}) = \frac{\tau}{1+\phi} x_{it}^{1+\phi}$ where $\tau > 0$ and $\phi \geq 0$. For $\phi \to 0$, land costs exhibit 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. Finally, variable ε_t^i is an investment shock which has been detailed in the previous subsection in Equation 21.

[10] 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.

Since the sector is competitive, the size of an individual farmer is indeterminate. We therefore assume that a representative farmer is price taker. The profit maximization problem of the farmers can be cast as choosing the input levels under land efficiency and capital law of motions as well as technology constraint:

$$\max_{\left\{h_{it}^{A}, i_{it}^{A}, k_{it}^{A}, \ell_{it}\right\}} E_t \sum_{\tau=0}^{\infty} \left\{\Lambda_{t,t+\tau} d_{it+\tau}^{A}\right\}. \tag{32}$$

The cost-minimization problem ensures that the real agricultural wage is directly driven by the marginal product of labor:

$$w_t^A = (1-\omega)(1-\alpha) p_t^A \frac{y_{it}^A}{h_{it}^A}. \tag{33}$$

The shadow value of capital goods, q_t^A, is determined by combing the first order condition on investment and capital:

$$q_t^A = p_t^N + \kappa p_t^N \varepsilon_t^i \left(\varepsilon_t^i \frac{i_{it}^A}{i_{it-1}^A} - 1\right) - E_t \left\{\Lambda_{t,t+1} \frac{\kappa}{2} p_{t+1}^N \left[\left(\varepsilon_{t+1}^i \frac{i_{it+1}^A}{i_{it}^A}\right)^2 - 1\right]\right\}. \tag{34}$$

Agricultural firms invest in physical capital until the marginal cost of physical capital reaches its expected marginal product:

$$q_t^A = E_t \left\{\Lambda_{t,t+1} \left[\alpha (1-\omega) p_{t+1}^A \frac{y_{it+1}^A}{k_{it}^A} + (1-\delta_K) q_{t+1}^A\right]\right\}. \tag{35}$$

Finally, the optimal demand for intermediate expenditures maintaining the level of land productivity is given by the following condition:

$$p_t^N v'(x_{it}) = E_t \left\{\Lambda_{t,t+1} \left[\omega p_{t+1}^A \frac{y_{it+1}^N}{\ell_{it}} + (1-\delta_\ell) \Omega\left(\varepsilon_{t+1}^W\right) p_{t+1}^N v'(x_{it+1})\right]\right\}. \tag{36}$$

The left-hand side of the equation captures the 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 affects the expected marginal benefit of lands through the damage function. 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.*, $v'(x_{it}) < 0$, generates a negative response of land expenditures and a decline in the relative price of agricultural goods, which is inconsistent with the data. A linear or convex cost function with $\phi \geq 0$ is then preferred to feature an increase in spending x_{it} following a drought shock.

3.4 Foreign economy

For the foreign economy block, our modeling strategy is rather close to the estimated small open economy models exemplified by Adolfson et al. (2007) and Adolfson et al. (2008) who use an exogenous VAR to model the foreign economy. Here, the foreign consumption is determined exogenously modeled by an AR(1) shock process. We complete this equation with two other structural equations that aim at capturing standard business cycle patterns of the foreign economy. 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.

First, foreign consumption follows an AR(1) process:

$$\log\left(c_{jt}^{*}\right) = (1-\rho_{*})\log\left(\bar{c}_{j}^{*}\right) + \rho_{*}\log\left(c_{jt-1}^{*}\right) + \sigma_{*}\eta_{t}^{*}, \qquad \eta_{t}^{*} \sim \mathcal{N}\left(0,1\right), \tag{37}$$

where the $0 \leq \rho_{*} < 1$ is the root of the process, $\bar{c}_{j}^{*} > 0$ is the steady state foreign consumption and $\sigma_{*} \geq 0$ is the standard deviation of the shock. The parameters σ_{*} and ρ_{*} are estimated in the fit exercise to capture variations of the foreign output gap. A rise in foreign output gap triggers an increase in the demand for home goods, followed by an appreciation of the foreign exchange rate, boosting the exports of the home country.

The welfare index of foreign households is similar to that of households residing in the home country but includes inelastic hours because of the endowment economy assumption. The objective of the foreign household j is thus given by:

$$\max_{\left\{c_{jt}^{*},b_{jt}^{*}\right\}} \sum_{\tau=0}^{\infty}\beta^{\tau}E_{t}\left\{\frac{1}{1-\sigma_{C}^{*}}\left(c_{jt+\tau}^{*}\right)^{1-\sigma_{C}^{*}}\left(c_{t-1+\tau}^{*}\right)^{\sigma_{C}^{*}b^{*}}\right\}, \tag{38}$$

where $b^{*} \in [0,1)$ is a parameter that accounts for external foreign consumption habits, and σ_{C}^{*} denotes foreign consumption risk aversion.

In addition, the foreign household is allowed to consume, or postpone consumption through risk-free bonds b_{jt}^{*} remunerated at a predetermined real rate r_{t-1}^{*}. The associated budget constrained is given by:

$$r_{t-1}^{*}b_{jt-1}^{*} = c_{jt}^{*} + b_{jt}^{*}. \tag{39}$$

The first order condition determines the real interest rate on bonds:

$$\beta E_{t}\left\{\lambda_{t+1}^{*}/\lambda_{t}^{*}\right\}r_{t}^{*} = 1, \tag{40}$$

$$\left(c_{jt}^{*}\left(c_{t-1}^{*}\right)^{-b^{*}}\right)^{-\sigma_{C}^{*}} = \lambda_{t}^{*}, \tag{41}$$

where λ_{t}^{*} is the Lagrange multiplier associated with the budget constraint.

Finally, in the absence of specific sectoral shocks, all sectoral prices of the foreign economy are perfectly synchronized, *i.e.*, $P_{t}^{*} = P_{t}^{A*} = P_{t}^{N*}$. In addition, the small size of the domestic economy implies that the import/exports flows from the home to the foreign country are negligible, thus implying that $P_{t}^{*} = P_{C,t}^{A*} = P_{C,t}^{N*}$.

3.5 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}. The public spending are assume 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:

$$\log(\varepsilon_{t}^{G}) = \rho_{G}\log(\varepsilon_{t-1}^{G}) + \sigma_{G}\eta_{t}^{G}, \qquad \eta_{t}^{G} \sim \mathcal{N}\left(0,1\right), \tag{42}$$

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 on intermediate markets.

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

$$G_t + r_{t-1} b_{t-1} = b_t + T_t. \tag{43}$$

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:

$$nY_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{P_t^N}{P_{C,t}^N}\right)^{-\mu_N}\left(\frac{P_{C,t}^N}{P_t}\right)^{-\mu} C_t + \alpha_N \left(\frac{1}{e_t}\frac{P_t^N}{P_{C,t}^{N*}}\right)^{-\mu_N}\left(\frac{P_{C,t}^{N*}}{P_t^*}\right)^{-\mu} C_t^*\right] + G_t + I_t + v(x_t) + \Phi(b_t^*) \tag{44}$$

where the total supply of home non-agricultural goods is given by $\int_0^n y_{it}^N \,\mathrm{d}i = nY_t^N$, and total demands from both the home and the foreign economy read as $\int_0^1 c_{jt} \,\mathrm{d}j = C_t$ and $\int_0^1 c_{jt}^* \,\mathrm{d}j = C_t^*$, respectively, with $1-\alpha_N$ and α_N the fraction of home and foreign home-produced non-agricultural goods, respectively.

Aggregate investment, with $\int_0^n i_{it}^N \,\mathrm{d}i = nI_t^N$ and $\int_n^1 i_{it}^A \,\mathrm{d}i = (1-n)\, I_t^A$, is given by:

$$I_t = (1-n)\, I_t^N + nI_t^A. \tag{45}$$

Turning to the labor market, the market clearing condition between household labor supply and demand from firms in each sector is $\int_0^1 h_{jt}^N \mathrm{d}j = \int_0^n h_{it}^N \mathrm{d}i$ and $\int_0^1 h_{jt}^A \mathrm{d}j = \int_n^1 h_{it}^A \mathrm{d}i$. This allows us to write the total amount of hours worked:

$$H_t = nH_t^N + (1-n)\, H_t^A. \tag{46}$$

Aggregate real production is given by:

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

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

$$(1-n) Y_t^A = \varphi \left[(1-\alpha_A)\left(\frac{P_t^A}{P_{C,t}^A}\right)^{-\mu_A}\left(\frac{P_{C,t}^A}{P_t}\right)^{-\mu} C_t + \alpha_A \left(\frac{1}{e_t}\frac{P_t^A}{P_{C,t}^{A*}}\right)^{-\mu_A}\left(\frac{P_{C,t}^{A*}}{P_t^*}\right)^{-\mu} C_t^*\right], \tag{47}$$

where $\int_n^1 y_{it}^A \,\mathrm{d}i = (1-n)\, Y_t^A$. 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.

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

$$b_t^* = r_{t-1}^* \frac{rer_t}{rer_{t-1}} b_{t-1}^* + tb_t, \tag{48}$$

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

$$tb_t = p_t^N \left[nY_t^N - G_t - I_t - v(x_t) - \Phi(b_t^*) \right] + p_t^A (1-n) Y_t^A - C_t. \tag{49}$$

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.[11] 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. In the following fit exercise, we solve the model using a linear approximation to the policy function, and employ the Kalman filter to form the likelihood function. For a detailed description, we refer the reader to the original papers.

4.1 Data

The Bayesian estimation relies on New Zealand quarterly data over the sample period 1994Q2 to 2016Q4. Therefore, each observable variable is composed of 91 observations. The dataset includes 6 times series: output, investment, hours worked, agricultural production, foreign production, and the drought index.

Concerning the transformation of the series, the point is to map non-stationary data to a stationary model. The 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, their trend is removed using the HP filter. The detrending method is not critical here, as similar results are obtained using a linear trend. For hours worked, the correction method of Smets and Wouters (2007) is applied. It consists of multiplying the amount of paid hours by the employment rate. However the resulting hour index exhibits an upward trend. We therefore take it in log and then remove its trend using the HP filter. 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.[12] The local values of the index are then

[11] See Appendix A for more details on the series used in the estimation.

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

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. In our fit exercise, we neglect trends by using the HP filter. The introduction of trends could affect our estimation results. However for tractability reasons, we have chosen to focus on short run macroeconomic fluctuations and to neglect long run effects involved by trends.

With respect to the VAR model presented in Section 2, the real asset return and the real exchange rate have been discarded from the estimation exercise. Assets returns variable was necessary for the VAR to identify the response of investment. Similarly, the real exchange rate captures the business cycle patterns of an open economy.

The vector of observable is given by:

$$\mathcal{Y}_t^{obs} = 100\left[\hat{y}_t, \quad \hat{\imath}_t, \quad \hat{h}_t, \quad \hat{y}_t^A, \quad \hat{y}_t^*, \quad \hat{w}_t\right]',$$

where $\hat{y}_t$ is the output gap, $\hat{\imath}_t$ is the investment gap, $\hat{h}_t$ is a hours worked index, $\hat{y}_t^A$ is the agricultural production gap, $\hat{y}_t^*$ is the foreign production gap and finally $\hat{w}_t$ is the drought index.

The corresponding measurement equations are given by:

$$\mathcal{Y}_t = \left[\log(Y_t/\bar{Y}), \quad \log(p_t^N I_t/\bar{I}), \quad \log(H_t/\bar{H}), \quad \log(p_t^A Y_t^A/\bar{Y}^A), \quad \log(C_t^*/\bar{C}^*), \quad \log(\varepsilon_t^W)\right]', \tag{50}$$

where the bar above the variables' names denote the steady state value of the corresponding variable.

4.2 Calibration and prior distributions

Table 3 summarizes our calibration and Table 4 displays the steady state moments 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.

Regarding open economy parameters, the home and foreign risk aversion parameters σ_C and σ_C^* are both weakly identified, we set this coefficient to 1.5 consistently with the empirical findings of Smets and Wouters (2007) for the US economy. On the same basis, we fix the foreign habit parameter b^* to 0.7 as it strongly interacts with the AR coefficient of the foreign shock ρ^*. The portfolio adjustment cost on foreign debt is set close to that in Schmitt-Grohé and Uribe (2003), with $\chi_B = 0.007$.[13] 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 Liu (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 parameterization, the share of agricultural goods in the consumption basket of households is set to $\varphi = 15\%$, as observed over the sample

[13]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.

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 last two remaining parameters σ and δ_ℓ are trickier to calibrate. The share of land σ 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. We assume that New Zealand agriculture technology is similar enough to other developed economies by setting $\sigma=0.15$. Finally, regarding the decay rate of land δ_ℓ, we apply the method of Christiano et al. (2005) by minimizing a measure of the distance between the model weather shock and VAR weather shock response. We find a value close to 10% implying an annual decay rate on land productivity equal to 40 percents. We fix the parameter $\delta_\ell=0.10$ accordingly prior to the Bayesian estimation of the model.

The rest of the parameters are estimated using Bayesian methods. Table 5 and Figure 3 report the prior (and posterior) distributions of the parameters for New Zealand.[14] Overall, our prior distributions are either relatively uninformative 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 0.10 and a standard deviation of 0.5, which is a rather loose prior. Substitution parameters μ, μ_N, and μ_A are assumed to follow a gamma distribution with a mean of 1.5 and a standard deviation of 0.8. The labor sectoral cost also has a positive support by following a Gamma distribution with a mean of 2 and a standard deviation of 1. The land cost parameter ϕ is given a Gamma distribution, instead of a Normal one, to impose a convex cost function. The prior mean and standard deviation are set to 1 and 0.6, respectively, so that the response of output is consistent with that of the VAR model. For the estimation of the key parameter θ bridging agricultural fluctuations to weather conditions, we adopt an agnostic approach using very uninformative prior with a uniform distribution with zero mean and standard deviation 10.

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 3. According to Figure 3, the data were fairly informative, as their posterior distributions did not stay very close to their priors, except for ϕ which seems weakly identified. We investigate the possible sources of non-identification for this parameter using methods developed by Iskrev (2010). Using the brute force search method, we find that the shape of the land cost function ϕ strongly interacts with the labor utility curvature parameter σ_H. The reason for the existence of this correlation link is rather straightforward, both ϕ and σ_H shape the response of hours (and in turn

[14] 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 height 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).

output) following a drought shock. However, parameter σ_H affects the response of the model to all shocks, thus making the scope of this parameter more critical than ϕ. It is therefore not surprising to find σ_H better identified than ϕ. Overall, these identification methods show that sufficient and necessary conditions for local identification are fulfilled by our model.

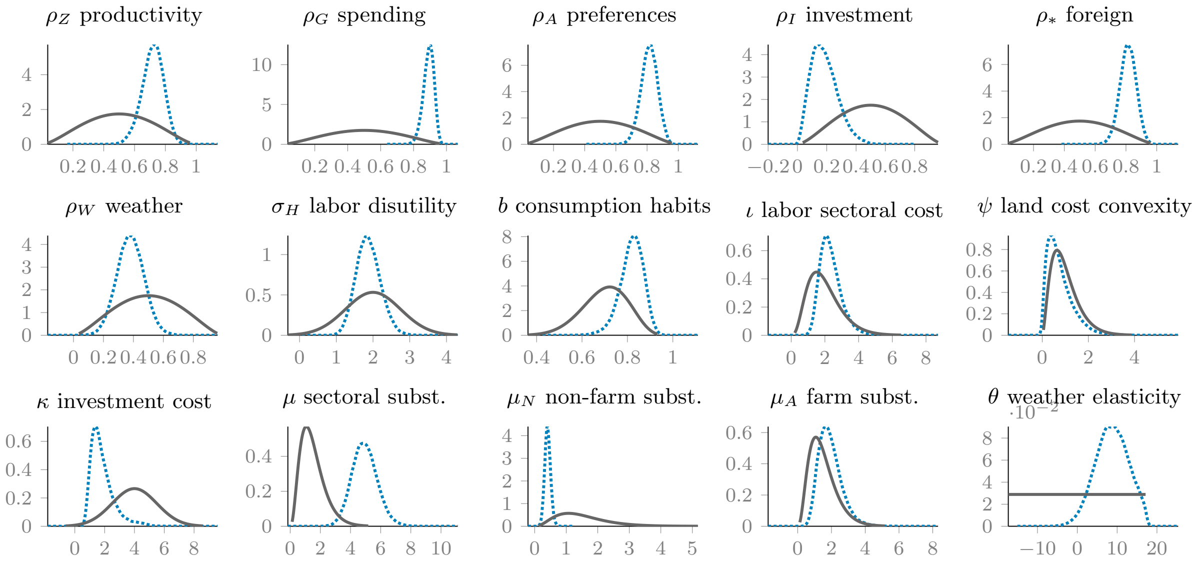


Figure 3: Prior and posterior distributions of structural parameters for New Zealand (excluding shocks).

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 Liu (2006) for New Zealand), several observations are worth making regarding the means of the posterior distributions of structural parameters. The land-weather elasticity parameter θ has a high posterior value that is clearly different from 0. This suggests that even with uninformative priors, the model suggests that variable weather conditions matter for generating macroeconomic fluctuations consistently with empirical evidence of Kamber et al. (2013). The land expenditure cost ϕ suggests that the model favor slightly increasing returns to scale for weather-induced damages. However, the high uncertainty around this parameter does not allow us to clearly conclude on the shape of the cost function. Substitution 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 remarkably low. Finally, the labor reallocation between agriculture and non-agriculture is rather costly, and is in line with the findings of Iacoviello and Neri (2010).

Since we used the VAR as a guideline for building our DSGE model, we report in Figure 4 the estimated response of the DSGE model (taken at posterior mean) following a 1% weather shock and the corresponding response of the VAR model.[15] The gray areas represent 68 and 95 percent probability intervals. Figure 4 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

[15]The IRFs of the DSGE model are obtained from the measurements equations in Equation 50 which makes them comparable with the VAR's IRFs.

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 roughly 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.

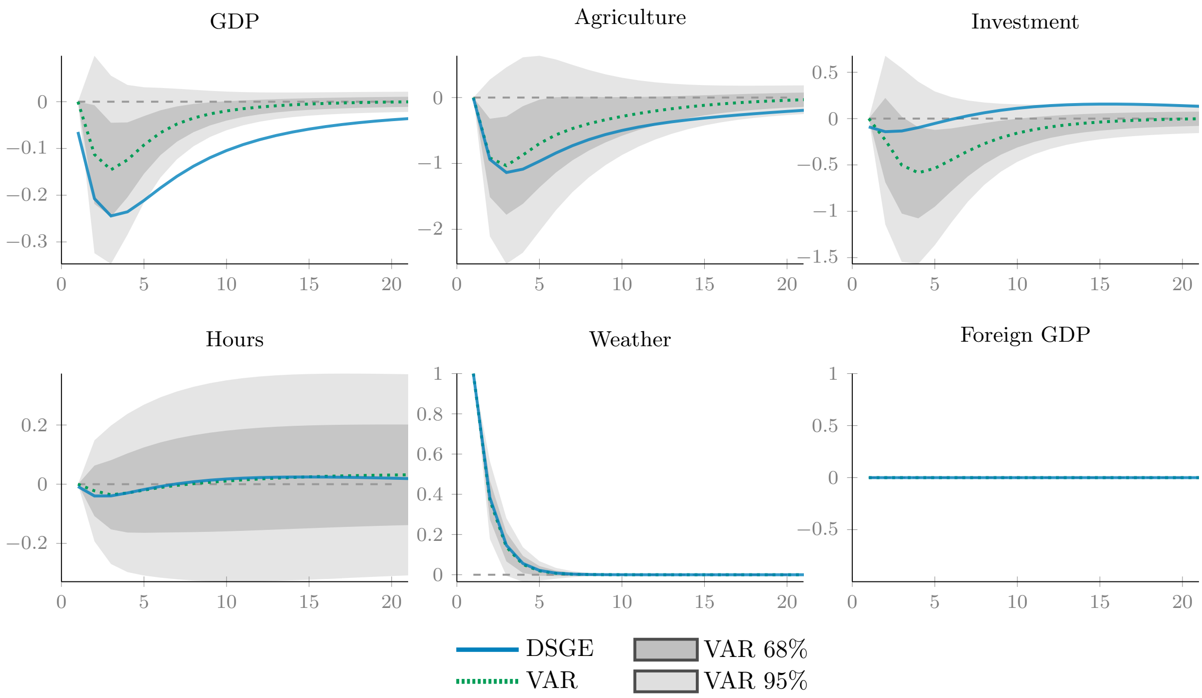


Figure 4: Comparison of the DSGE and the VAR impulse responses to a 1% weather shock (drought) in New Zealand.

4.4 Do weather shocks matter?

A natural question to ask at this stage 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. The model previously presented, denoted $M\ (\theta \neq 0)$, is compared to a constrained version $M\ (\theta = 0)$. In this constrained version, the weather-induced damages are removed by imposing $\theta = 0$ in Equation 28. Table 1 reports for the two nested 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 an uninformative prior distribution over models (*i.e.* 50% prior probability for each model), we compute both posterior odds ratios and model probabilities taking the model $M\ (\theta = 0)$, *i.e.*, the one with no weather damages as the benchmark.[16] We conduct a formal com-

[16]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 $M\ (\theta \neq 0)$ will not inevitably be favored to the other model.

	No Weather-Driven Business Cycles $\mathcal{M}(\theta = 0)$	Weather-Driven Business Cycles $\mathcal{M}(\theta \neq 0)$
Prior probability	1/2	1/2
Laplace approximation	-1016.853	-1012.835
Posterior odds ratio	1.000000	55.626
Posterior model probability	0.018	0.982

Table 1
Prior and posterior model probabilities

parison between models and refer to Geweke (1999) for a presentation of the method to perform the standard Bayesian model comparison employed in Table 1 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 $\mathcal{M}(\theta \neq 0)$ on $\mathcal{M}(\theta = 0)$ using Laplace-approximated marginal data densities. The posterior odds of the null hypothesis of no significance of weather-driven fluctuations is 55.6:1 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.

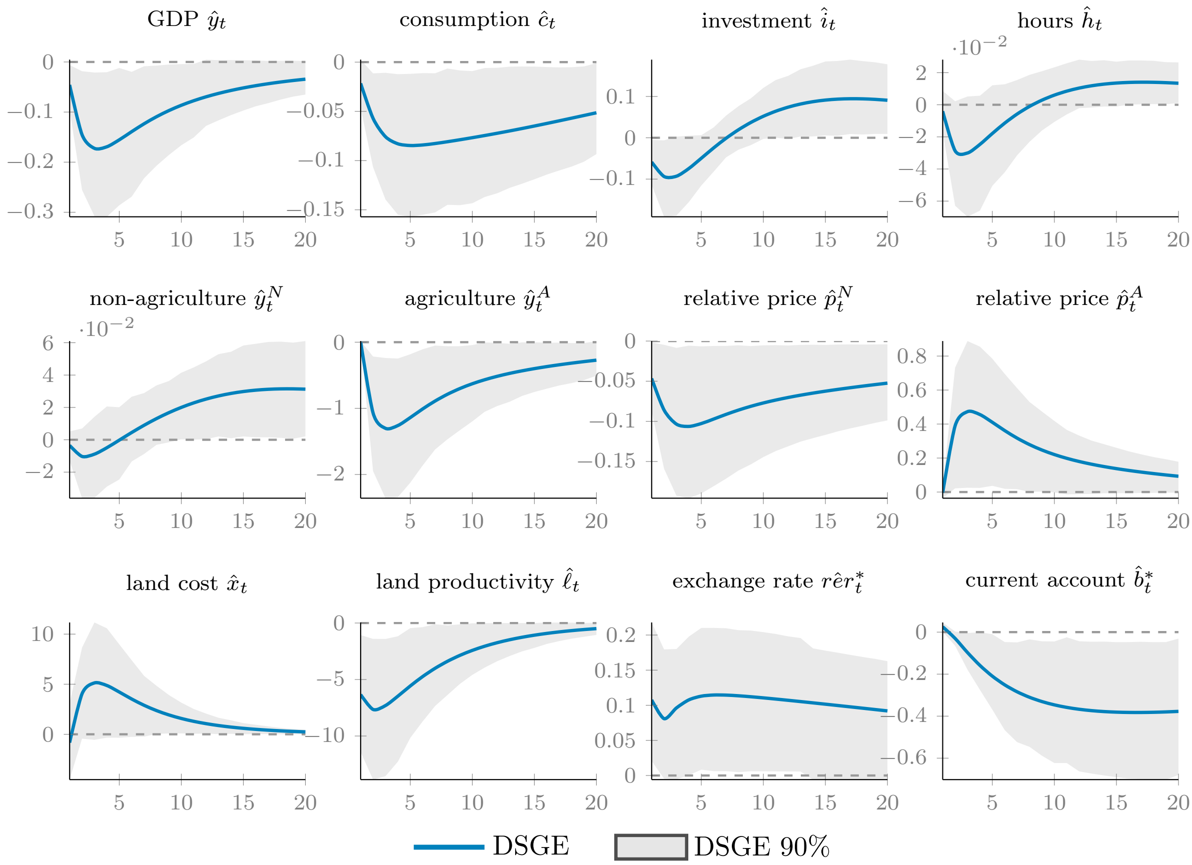
5 Weather shocks as drivers of aggregate fluctuations

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

5.1 Propagation of a weather shock

In the model, the measure of drought is assumed to be a stochastic exogenous process driven by a Gaussian shock η_t^W. To evaluate how an average drought event in New Zealand propagates in the economy, we first report the simulated Bayesian system responses of the main macroeconomic variables following a standard weather shock in Figure 5. 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 3. Contrary to the VAR model, the DSGE model allows one to explain the underlying theoretical mechanisms which explain how a weather shock propagates in the economy.

From a business cycle perspective, this shock acts as a standard (sectoral) negative supply shock through a combination of rising relative prices and falling output. A drought event strongly affects business cycles through a large decline in agricultural output (1.2%), as weather affects the land input in the production process of agricultural goods. The 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



Notes: Blue lines are the means of the distributions of the Impulse Response Functions (IRFs) generated when parameters are drawn from the posterior distribution, as reported in Figure 3. Gray areas are the 90 percent highest posterior density interval. IRFs are reported in percentage deviations from the deterministic steady state.

Figure 5: System response to an estimated weather shock η_t^W measured in percentage deviations from the steady state.

rainfall and pastures to support the agricultural sector. A drought shock decreases land productivity by 6% in the model. To compensate for this loss, farmers can use more non-agricultural goods as inputs to reestablish 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 27, 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 price structure between sectors. 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 demand and a supply effect. Since relative prices are negatively correlated, the price of non-agricultural goods decline in response.

From an international standpoint, the decline in domestic agricultural production generates current account deficits. Two factors might explain this. First, almost fifty percents of New Zealand's exports are accounted for by agricultural commodities. 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 1.

5.2 The contributions of weather shocks on aggregate fluctuations

Figure 6 reports the forecast error variance decomposition for two variables of interest, *i.e.*, aggregate real production (Y_t) and agricultural production (Y_t^A). Five different time horizons are considered, ranging from one quarter ($Q1$) to ten years ($Q40$) 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 and shock), demand shocks (government spending, household preferences and investment shocks), foreign shocks, and weather shocks.

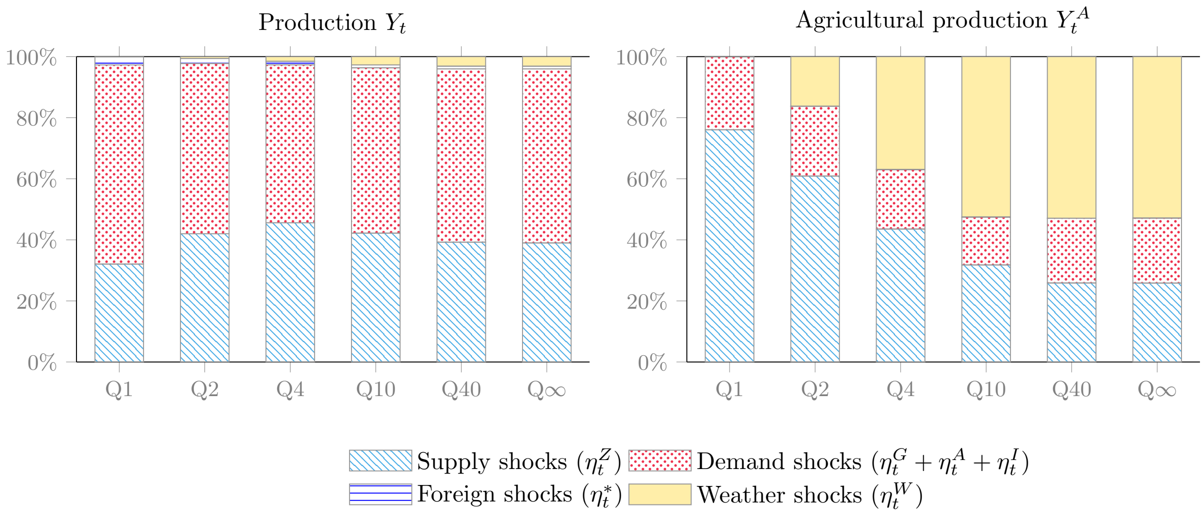


Figure 6: Forecast error variance decomposition at the posterior mean for different time horizons (one, two, four, ten, forty and unconditional).

As observed for aggregate production (Y_t), demand and supply shocks are the main drivers of the variance in both the short and the longer term. However, by increasing the time horizon, the contribution of weather shocks grows, starting from 0.14% at one-quarter horizon to 5.5% on a forty-quarter horizon. Foreign shocks play a modest role. They account for 2.8% of New Zealand's production in the short run, and less than 1% in the long run.

Turning to agricultural production, supply shocks account for most fluctuations in the short run. They are responsible for 70% of the variance of agricultural production at one-quarter horizon. Their importance declines in the long run, although remaining non-negligible, explaining 21% of agricultural production at a 10-quarter horizon. Weather shocks remarkably drive the variance of agricultural production after a time lag of one quarter. In addition, increasing the time horizon magnifies this result. Not less than 59% of the unconditional variance of agricultural production is driven by weather shocks.

Overall, we find that weather variations cause important macroeconomic fluctuations. The prospect of the increasing variance of drought events caused by climate change is a challenging issue for New Zealand policymakers, as it can have large implications for stabilization policies.

5.3 Historical decomposition of business cycles

An important question one can ask of the estimated model is how important the weather shocks were in shaping the recent New Zealand macroeconomic experience. Figure 7 provides an answer by reporting the time paths of aggregate output, and agricultural production on a quarter-to-quarter basis. The solid line depicts the time path of the ratio of the deviation from the steady state, while the bars depict the contribution of the shocks in the corresponding point deviation (at the mean of the estimated parameters). The shocks are gathered in the same way as in the forecast error variance decomposition exercise of subsection 5.2.

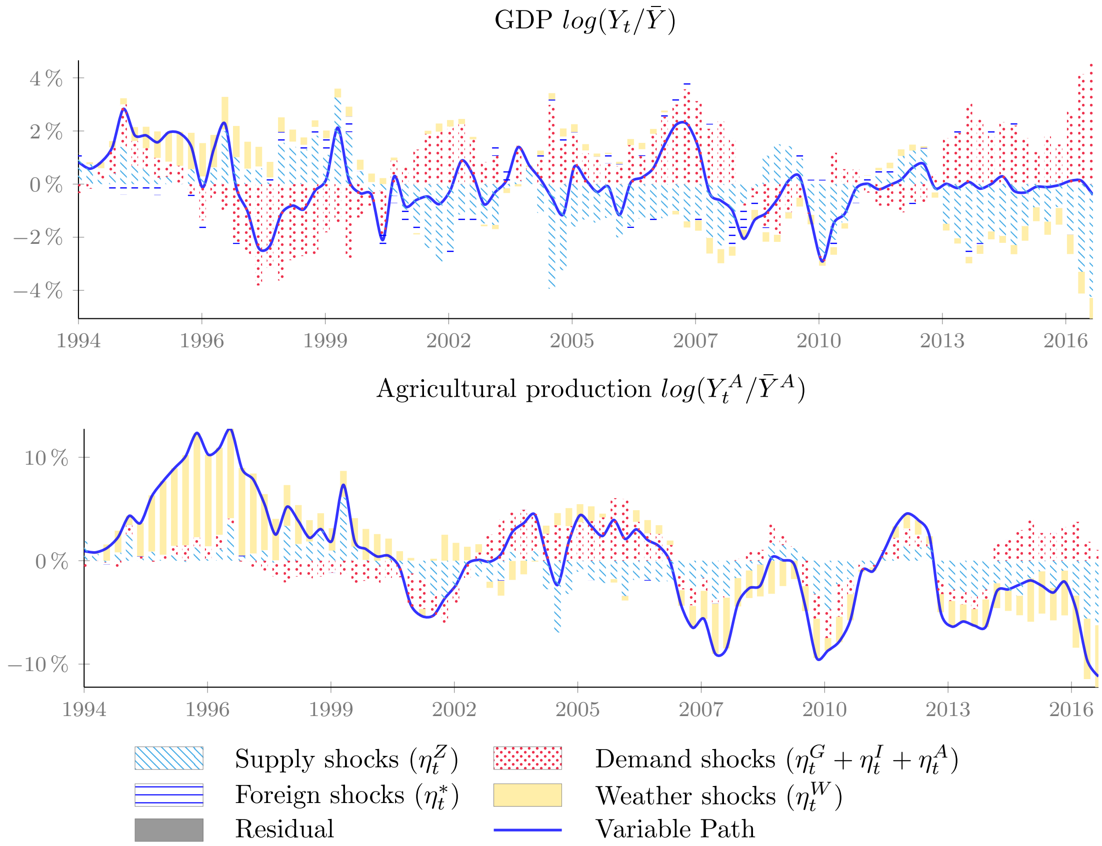


Figure 7: Historical decomposition of aggregate output and agricultural production.

In Figure 7, we can distinguish between two time periods for output (Y_t) and agricultural production (Y_t^A). First, up to 2006-2007, variations in aggregate production were positively driven by weather shocks. Over this period, New Zealand did not experience any significant drought events, with important soil moisture surpluses favoring agricultural production. In fact, during this period, around 46% of the increase in agricultural output was driven by positive weather shocks, on average. However, major drought events in 2008, 2010, 2013 and 2015 contributed negatively to output fluctuations accompanied by an important supply shock. After 2008, 40% of the decline in agricultural output is driven by adverse weather drought shocks.

6 Climate change implications for macroeconomic volatility and welfare

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 set-up irrelevant for analyzing changes in mean weather values. However, it allows for changes in the variance of climate. 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.

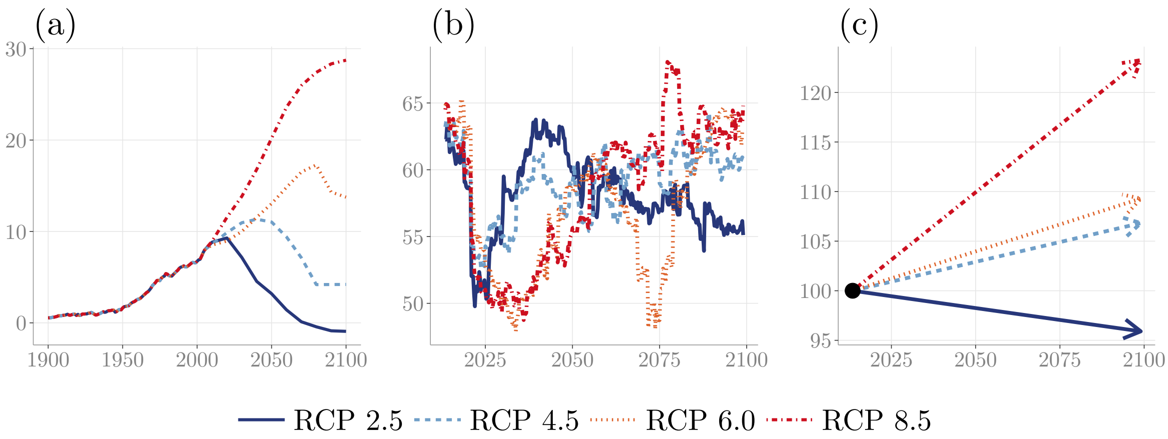
6.1 Building projections up to 2100 for weather shocks

To investigate the potential impact of climate change on aggregate fluctuations, we assume that the volatility the weather (η_t^W) (Equation 26) 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 8 shows emissions and projections of the emissions of one of the major greenhouse gases, *i.e.*, CO_2, up to 2100.[17]

For these four scenarios, soil moisture deficit data are not available. We therefore use a strongly correlated variable as a proxy: total rainfall. 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.

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

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 8 illustrates the evolution of the standard error for each scenario. It is then possible to compute the average growth rate of the standard error over the century depending on the climate scenario.[18] The results are displayed in the right panel of Figure 8. 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 8: Estimations of the increase of the standard error of the weather shock under four different climate scenarios.

6.2 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 standard error 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

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

		1994-2016 Benchmark	RCP 2.5	2100 (projections) RCP 4.5	RCP 6.0	RCP 8.5
sd(η_t^W)	Weather shock	100	95.90	106.82	109.30	123.25
sd(y_t)	GDP	100	99.82	100.15	100.23	100.72
sd(y_t^A)	Agriculture	100	96.89	102.54	103.86	111.53
sd(c_t)	Consumption	100	99.94	100.05	100.07	100.22
sd(i_t)	Investment	100	99.98	100.01	100.02	100.07
sd(h_t)	Hours	100	99.99	100.00	100.01	100.03
sd(r_t)	Real interest rate	100	100.00	100.00	100.00	100.00
sd(rer_t)	Exchange rate	100	99.86	100.12	100.18	100.57
E(W_t)	Welfare	-158.02	-158.00	-158.04	-158.06	-158.13
λ (%)	Welfare cost	0.4023	0.3562	0.4417	0.4623	0.5873

Notes: The model is first simulated as described in Section 4. Theoretical standard errors of each variable are then estimated and normalized to 100. Then, standard errors 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, -4.10%; RCP 4.5, $+6.82\%$; RCP 6.0, $+9.30\%$; RCP 8.5, $+23.25\%$). New simulations are estimated using the modified standard errors of these shocks, and the theoretical standard errors of the variables of interest are then compared to those of the reference period.

Table 2
Changes in Standard-Errors of Simulated Observables Under Climate Change Scenarios.

under historical weather conditions (for the 1989–2014 period) to their volatility under future climate scenarios (for the 2015–2100 period), normalizing the values of the historical period of each variable to 100.

Table 2 report these variations for some key variables. The first scenario is clearly optimistic, as the standard deviation of drought events is declining by 4.1%. As a result, macroeconomic fluctuations in the country naturally decrease. Agriculture output is particularly affected by this structural change, with a 3.11% decrease of its standard deviation. In contrast, the other scenario for which the rise in the standard deviation of the weather shock ranges between 6.82% for the less pessimistic scenario to 23.25% for the most pessimistic one, exhibit a strong increase in the volatility of macroeconomic variables. As a matter of facts, the standard error of total output rises by 0.15% under the RCP 4.5 scenario, and by 0.72% under the RCP 8.5 scenario. Agricultural production volatility experiences an important shift of 11.5% under the worst-case scenario. We also observe an increase in the real exchange rate of 0.57% and consumption of 0.22%, while for other macroeconomic variables the changes are very modest.

One would think that the volatility changes incurred by climate change are rather negligible, however, for developing economies this facet of climate change could be very critical. 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, and reducing the intensity of the capital, would critically exacerbate the results reported in Table 2.

6.3 The welfare cost of weather variability under climate change

Another important challenge for economists is to provide a metric that would price the cost of climate change. The final goal of this metric would be to evaluate the effectiveness of a policy designed to offset the potential costs of climate change. In the IAM literature, these costs are usually expressed in terms of output loss or utility-based consumption, but many uncertainties remain as the result of these models critically depends on the model's assumptions. For instance, Nordhaus (1993) evaluates the cost of climate change to roughly one percent of the GDP. Meanwhile, Dietz and Stern (2015) relaxes some key assumptions about the functional form of the damage function of Nordhaus and find much higher costs.

The literature mentioned before focuses on the very long run effects of climate change. In our setup, we take into account how the short term variability induced by weather may generate a social cost for households. To do so, we employ the method of Lucas (2003) to measure the welfare cost of weather-driven business cycles as detailed in Appendix B. In a nutshell, we compute the welfare of the household using an alternative version of the model with no weather shocks and compare this welfare with our estimated model. We then convert the welfare costs between these two regimes into unconditional consumption percentage, denoted λ. The parameter λ can be interpreted as the percentage of permanent consumption that the household is willing to abandon to stay in an economy free of weather shocks. The last two rows of Table 2 report the corresponding welfare mean and welfare cost.

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. The simulations show that today, New Zealanders would be willing to give up to 0.40% of their unconditional consumption in order to live in an economy free of drought events. The magnitude of this cost is not negligible.[19] Under the optimistic scenario, they would only abandon only 0.35% of their permanent consumption. In the worst-case scenario, this fraction would reach 0.58%. With respect to the benchmark situation over the 1994-2016 period, the welfare cost under the worst-case scenario has increased of 44% for a 23% rise of the variability of the weather shock. This suggests that there is a strong non-linear relationship between the variance of the shock and the welfare cost.

Our results show that short-run fluctuations incurred by weather matter as well, and could be embedded into integrated assessment models to evaluate the costs of climate change.

7 Conclusion

In this paper, we have investigated the business cycle evidence on weather shocks. We have developed and estimated a DSGE model for a small open economy, New Zealand.

[19]For instance, our model evaluates the welfare costs of business cycles induced by productivity shocks to 0.05%, -0.002 for spending shocks, -0.05% for investment shocks, 0.50% for preference shocks and 0.002% for foreign shocks. On average, these costs lie in the ballpark of estimates obtained in the RBC literature, see for example Otrok (2001) except for the preference shock. The latter generates important welfare costs as it directly affects the relative price structure of consumption goods which strongly affects the household's utility.

Our model includes an agricultural sector that faces exogenous weather variations affecting the 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, accompanied by a very weak decline of hours worked. Our business cycle decomposition exercises also show that weather shocks are an important driver of agricultural production and, in a much 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 0.40% 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 on 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 Data

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.
- **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.
- **Share Prices:** New Zealand All Ordinaries Index (NZSE:IND). *Source:* Bloomberg.
- **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.

B 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.[20]

[20]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.

We define the welfare index for regime a, *i.e.*, the regime associated with an economy without weather shocks ($\sigma_W = 0$ in Equation 26) as $\mathcal{W}_t^a$. Similarly, we define a second regime, denoted b, that includes weather shocks. The corresponding welfare index of this regime is given by $\mathcal{W}_t^b$. Recall that the welfare index is given by:

$$\mathcal{W}_t = E_t \sum_{\tau=0}^{\infty} \beta^\tau \left[\frac{1}{1-\sigma_C} C_{jt+\tau}^{1-\sigma_C} - \frac{\chi}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right] C_{t-1+\tau}^{b\sigma_C}., \tag{51}$$

The no-arbitrage condition between *scenarii* a and b reads as follows:

$$E_t \sum_{\tau=0}^{\infty} \beta^\tau \mathcal{U} \left((1-\lambda) C_{t+\tau}^a, C_{t-1+\tau}^a, h_{t+\tau}^a \right) = E_t \sum_{\tau=0}^{\infty} \beta^\tau \mathcal{U} \left(C_{t+\tau}^b, C_{t-1+\tau}^b, h_{t+\tau}^b \right), \tag{52}$$

where λ is the welfare cost, *i.e.*, the fraction of consumption the household is willing to give up to live in an economy free of weather fluctuations.

Rewriting Equation 52, the welfare cost is given by:

$$\lambda = 1 - \left[\frac{E\left[\mathcal{W}_t^b\right] + E\left[\mathcal{V}_t^a\right]}{E\left[\mathcal{W}_t^a\right] + E\left[\mathcal{V}_t^a\right]} \right]^{\frac{1}{1-\sigma_C}} \tag{53}$$

where $E[\cdot]$ denotes the asymptotic mean generated by a large sample of artificial series and $\mathcal{V}_t$ is an auxiliary variable. It is given by: $\mathcal{V}_t = \frac{\chi}{1+\sigma_H} E_t \sum_{\tau=0}^{\infty} \beta^\tau h_{jt+\tau}^{1+\sigma_H} C_{t-1+\tau}^{b\sigma_C}$.

We employ a second order approximation to the model's policy function using perturbation methods as in Collard and Juillard (2001). This solution method is standard in the macroeconomic literature as it provides an accurate evaluation of the welfare by avoiding spurious welfare reversals.

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 good in consumption basket	0.15
$\bar{H}^N = \bar{H}^A$	Hours worked	1/3
σ_C	Risk aversion	1.5
$\bar{\ell}$	Land per capita	0.40
ω	Share of land in agricultural output	0.15
δ_ℓ	Rate of decay of land efficiency	0.10
α_N	Openness of non-agricultural market	0.25
α_A	Openness of agricultural market	0.45
χ_B	International portfolio cost	0.007
σ_C^*	Foreign risk aversion	1.5
b^*	Foreign consumption habits	0.7

Table 3
Calibrated parameters.

Variable	Interpretation	Model	Data
$\bar{C}/\bar{Y}$	Ratio of consumption to GDP	0.56	0.57
$\bar{I}/\bar{Y}$	Ratio of investment to GDP	0.22	0.22
$400 \times (\bar{r} - 1)$	Real interest rate	4.74	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 4
Steady state ratios (empirical ratios are computed using data between 1990 to 2017).

		Prior distributions			Posterior distribution	
		Shape	Mean	Std.	Mean [5%:95%]	
SHOCK PROCESS $AR(1)$						
Economy-wide TFP sd	σ_Z	$\mathcal{W}$	0.1	0.5	1.74	*[1.48:1.99]*
Spending sd	σ_G	$\mathcal{W}$	0.1	0.5	4.04	*[3.45:4.57]*
Investment sd	σ_I	$\mathcal{W}$	0.1	0.5	5.15	*[4.07:6.21]*
Preferences sd	σ_A	$\mathcal{W}$	0.1	0.5	11.03	*[7.75:14.26]*
Weather sd	σ_W	$\mathcal{W}$	0.1	0.5	0.81	*[0.71:0.91]*
Foreign demand sd	σ_*	$\mathcal{W}$	0.1	0.5	0.59	*[0.52:0.66]*
Economy-wide (AR term)	ρ_Z	$\mathcal{B}$	0.5	0.2	0.72	*[0.61:0.83]*
Spending (AR term)	ρ_G	$\mathcal{B}$	0.5	0.2	0.89	*[0.84:0.94]*
Investment (AR term)	ρ_I	$\mathcal{B}$	0.5	0.2	0.18	*[0.04:0.32]*
Preferences (AR term)	ρ_A	$\mathcal{B}$	0.5	0.2	0.81	*[0.73:0.9]*
Weather (AR term)	ρ_W	$\mathcal{B}$	0.5	0.2	0.38	*[0.23:0.52]*
Foreign demand (AR term)	ρ_*	$\mathcal{B}$	0.5	0.2	0.81	*[0.73:0.9]*
STRUCTURAL PARAMETERS						
Labor disutility	σ_H	$\mathcal{B}$	2	0.75	1.87	*[1.32:2.4]*
Consumption habits	b	$\mathcal{B}$	0.7	0.10	0.82	*[0.74:0.9]*
Labor sectoral cost	ι	$\mathcal{G}$	2	1	2.32	*[1.36:3.31]*
Investment cost	κ	$\mathcal{N}$	4	1.50	1.83	*[0.77:2.91]*
Substitutability by type of goods	μ	$\mathcal{G}$	1.5	0.8	4.93	*[3.53:6.26]*
Substitutability home/foreign	μ_N	$\mathcal{G}$	1.5	0.8	1.91	*[0.86:2.94]*
Substitutability home/foreign	μ_A	$\mathcal{G}$	1.5	0.8	0.41	*[0.26:0.56]*
Land expenditures cost	ϕ	$\mathcal{G}$	1	0.60	0.76	*[0.02:1.51]*
Land-weather elasticity	θ	$\mathcal{U}$	0	10	8.62	*[2.3:15.78]*
Marginal log-likelihood					-1012.83	

Notes: The column entitled "Shape" indicates the prior distributions using the following acronyms: N describes a normal distribution, G a Gamma one, B a Beta one, and W a Weibull one.

Table 5

Prior and posterior distributions of structural parameters and shock processes.

Online Appendix

Weather Shocks, Climate Change and Business Cycles

2017

Contents

1 Measuring 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 2015 period. Then, we follow Narasimhan and Srinivasan

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

(2005) to create the soil moisture deficit index. In a nutshell, for each $m = \{1, \dots, 12\}$ month in each $t = \{1980, \dots, 2015\}$ year, we compute monthly soil water deficit (expressed in percent) as:

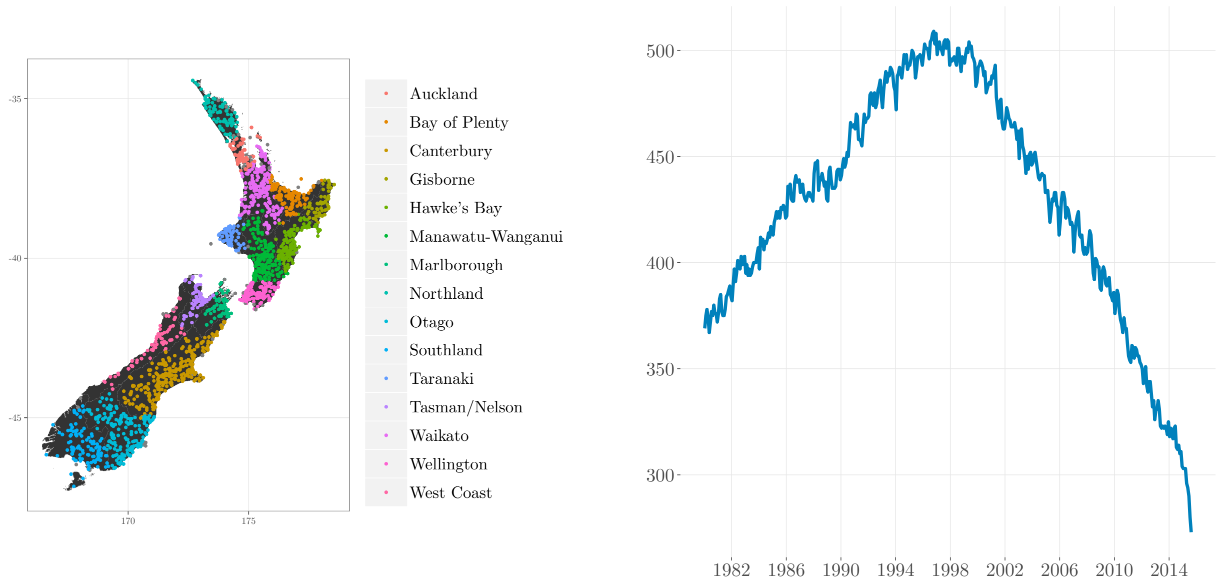
$$SD_{t,m} = \frac{SW_{t,m} - Med(SW_m)}{Med(SW_m)}. \tag{1}$$

The index for any given month is then computed as:

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

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

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] 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 4. The VAR model needs to reflect the small open economy assumption. That is, New Zealand's 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

[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.

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:

$$\begin{bmatrix} X_t^D \\ X_t^W \\ X_t^* \end{bmatrix} = \sum_{l=1}^{p} \begin{bmatrix} A_l^{11} & A_l^{12} & A_l^{13} \\ 0 & A_l^{22} & 0 \\ 0 & 0 & A_l^{33} \end{bmatrix} \begin{bmatrix} X_{t-l}^D \\ X_{t-l}^W \\ X_{t-l}^* \end{bmatrix} + \begin{bmatrix} \eta_t^D \\ \eta_t^W \\ \eta_t^* \end{bmatrix}, \tag{3}$$

where $t = 1, \ldots, T$ is the time subscript, p is the lag length,[3] X_t^D, X_t^W and X_t^* are column vectors of variables for the small open economy, the weather block and the rest of the world, respectively. The error terms η_t^D, η_t^W and η_t^* are exogenous and independent with zero mean and variance σ^{η^D}, σ^{η^W}, and σ^{η^*}, respectively. The coefficients in B_l^{11} to B_l^{33}, and C 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.

For our New Zealand economy model, the domestic block is:

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

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, $\hat{q}_t$ is real asset return, and $\widehat{rer}_t$ is real effective exchange rate. 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. Finally, the international economy block writes:

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

where $\hat{y}_t^*$ stands for foreign real output growth.

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 $X_t = \begin{bmatrix} X_t^D & X_t^W & X_t^* \end{bmatrix}'$ is the $n \times 1$ vector of endogenous variables at time t, $A_l = \begin{bmatrix} A_l^{11} & A_l^{12} & A_l^{13} \\ 0 & A_l^{22} & 0 \\ 0 & 0 & A_l^{33} \end{bmatrix}$, for $l = 1, \ldots, p$ are the $n \times n$ matrices of lagged parameters to be estimated, and $\eta_t = \begin{bmatrix} \eta_t^D & \eta_t^W & \eta_t^* \end{bmatrix}'$, 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 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.

[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 domestic weather block

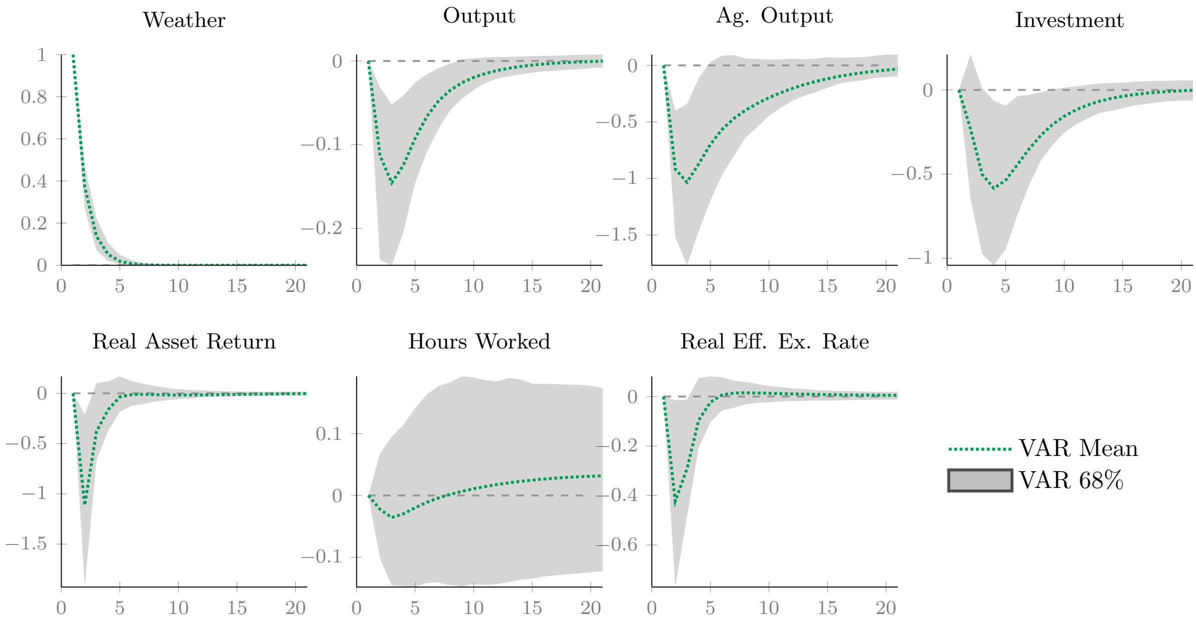
The estimated VAR model contains a domestic weather block to study the impact of weather conditions on business cycle fluctuations. We rely on the same weather variable as in the DSGE model whose construction is explained in section 1. When it takes positive values, the weather variable depicts a prolonged episode of dryness. It is the only variable in the exogenous domestic weather block.

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, real asset return q_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.[4] 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.



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.

[4]We focus on the shock to the weather variable. The complete set of IRFs is available upon request.

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:

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

With a damage function:

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

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

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

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:

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

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

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

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

3.4 The foreign economy

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

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

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

$$\left(c_{jt}^*\left(c_{t-1}^*\right)^{-b^*}\right)^{-\sigma_C^*} = \lambda_t^*, \tag{31}$$

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:

$$nY_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{p_t^N}{p_{C,t}^N}\right)^{-\mu_N}\left(p_{C,t}^N\right)^{-\mu} C_t + \alpha_N\left(\frac{p_t^N}{rer_t}\right)^{-\mu_N} C_t^*\right] + G_t + I_t + v\left(X_t\right) + \Phi(b_t^*) \tag{32}$$

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

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

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

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

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

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

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:

$$tb_t = p_t^N\left[nY_t^N - G_t - I_t - v\left(x_t\right) - \Phi(b_t^*)\right] + p_t^A(1-n)Y_t^A - C_t. \tag{37}$$

And domestic shocks:

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

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

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

$$\log(\varepsilon_t^A) = \rho_A\log(\varepsilon_{t-1}^A) + \sigma_A\eta_t^A, \text{ with } \eta_t^A \sim \mathcal{N}\left(0,1\right), \tag{41}$$

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

4 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 3.

4.1 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:

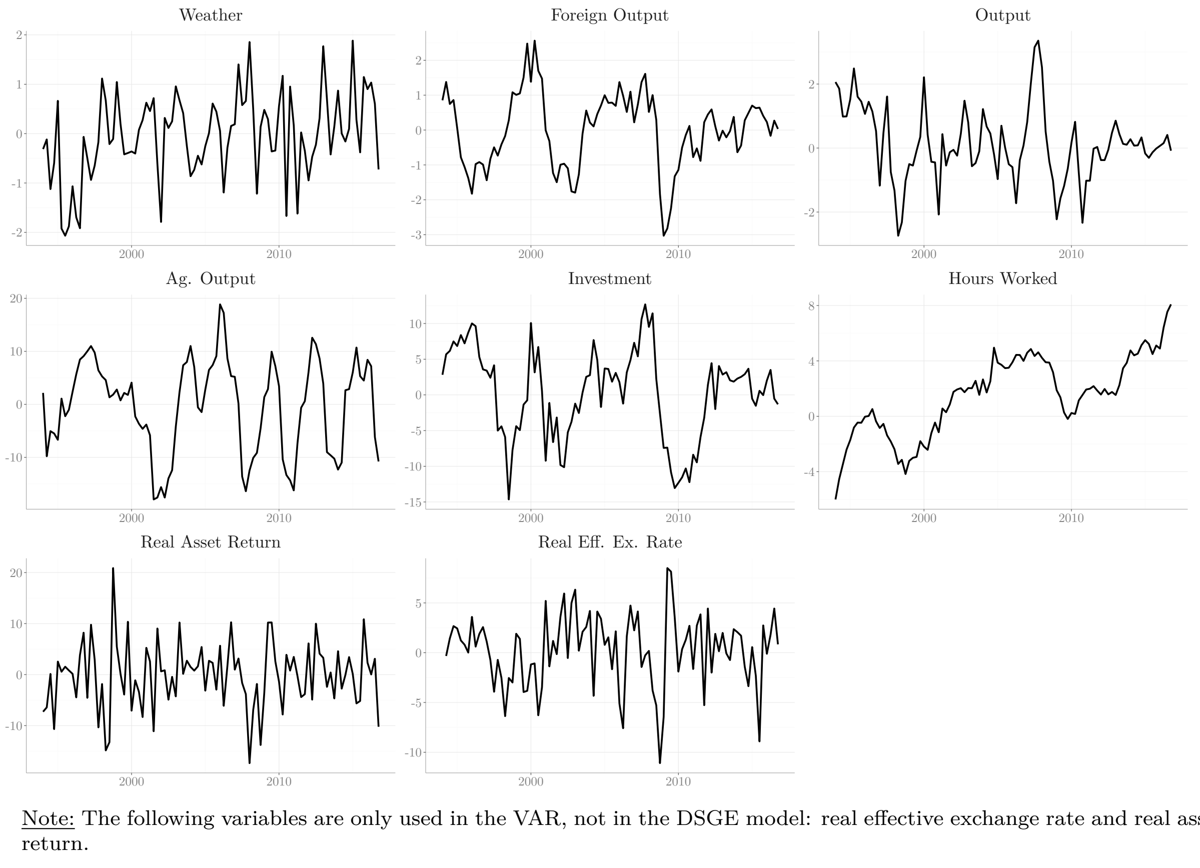
$$\hat{y}_t = \log\left(\frac{Y_t}{P_t N_t}\right) - HP\left(\frac{Y_t}{P_t N_t}\right),$$

where $HP(.)$ is the HP filter on a quarterly basis (*i.e*, setting the smoothing coefficient to 1600).

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

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

Finally, the data are demeaned because trends are not incorporated in our model. We are aware that the introduction of trends could affect our estimation results. However for tractability reasons, we have chosen to focus on short run macroeconomic fluctuations and to neglect long run effects involved with trends. Such an approach has also been chosen by Smets and Wouters (2003).



Note: The following variables are only used in the VAR, not in the DSGE model: real effective exchange rate and real asset return.

Figure 3: Observable variables used in the VAR and the DSGE estimations.

4.2 Measurement equations of the DSGE model

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

$$\begin{bmatrix} 100^*\hat{y}_t, \\ 100^*\hat{\imath}_t, \\ 100^*\hat{h}_t, \\ 100^*\hat{y}_t^A, \\ 100^*\hat{y}_t^*, \\ 100^*\hat{\eta}_t \end{bmatrix} = \begin{bmatrix} \log(Y_t/\bar{Y}), \\ \log(p_t^N I_t/\bar{I}), \\ \log(H_t/\bar{H}), \\ \log(p_t^A Y_t^A/\bar{Y}^A), \\ \log(C_t^*/\bar{C}^*), \\ \log(\eta_t^W) \end{bmatrix}.$$

5 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° × 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.[5] 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.

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:

$$\overline{\Delta\sigma_{i,\eta W}} = (1 + \sigma_{i,\eta^W})^q - 1, \tag{43}$$

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.

[5] 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 ($\overline{\Delta\sigma_{i,\eta^W}}$)
RCP 2.6	-0.1218964×10^3	-4.095090
RCP 4.5	0.1923896×10^3	6.820885
RCP 6.0	0.2591393×10^3	9.294213
RCP 8.5	0.6096352×10^3	23.249574

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}), and the corresponding average growth rate over the whole 1989–2100 period ($\overline{\Delta\sigma_{i,\eta^W}}$).

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

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