Online Appendix
(not for publication)

Weather Shocks

2019

Contents

1 Data

1.1 Data source

The sample period begins in 1994:Q3 and extends to 2016:Q4. All data are log deviations from their trend, except share prices and the weather.

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

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

1.2 Measuring the Weather

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

The measure of weather reads as follows:

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

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

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

$$MD_{t,m} = \begin{cases} \frac{D_{t,m} - Med(D_m)}{Med(D_m) - Min(D_m)} & \text{if } D_{t,m} = Med(D_m) \\ \frac{D_{t,m} - Med(D_m)}{Max(D_m) - Med(D_m)} & \text{if } D_{t,m} > Med(D_m) \end{cases}, \tag{1}$$

   where $Med(\cdot)$, $Min(\cdot)$ and $Max(\cdot)$ are the median, minimum and maximum functions, respectively.

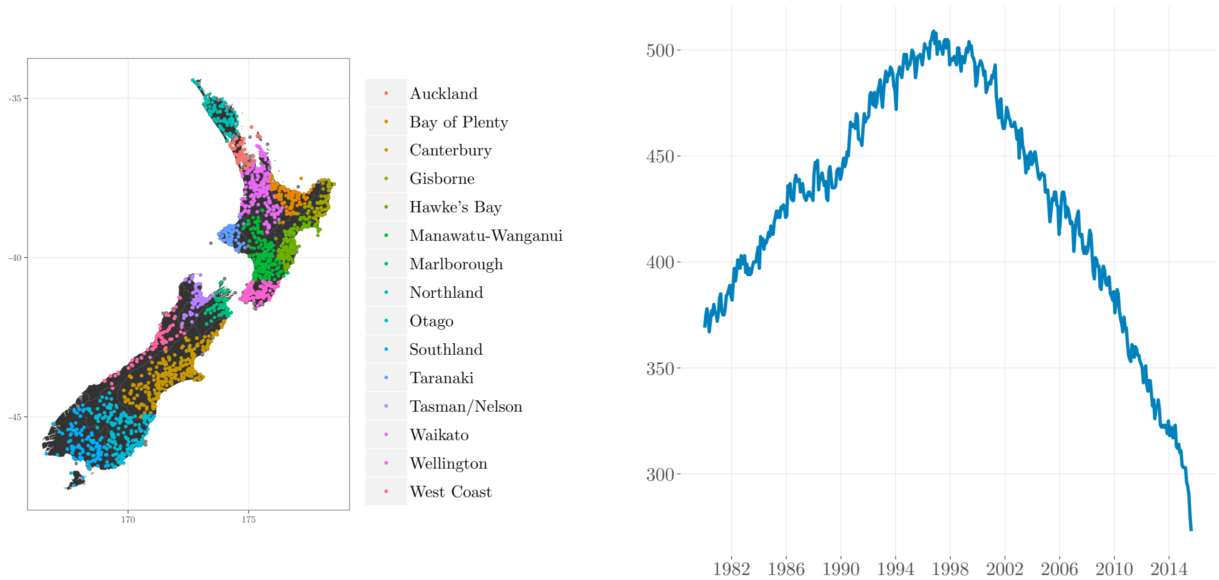
3. The index for any given month is then computed as:

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

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

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

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



(a) Spatial covering

(b) Temporal covering

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

[2]The 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.

2 The SVAR 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.

We estimate a SVAR (structural vector autoregressive) model on New Zealand data presented in section 6. To do so, we first estimate a restrictive VAR model to reflect the small open economy assumption. Then, we build on this restricted VAR and estimate an SVAR model to impose some restrictions on the contemporaneous effects.

2.1 A Restricted VAR

Let us first define a reduced-form VAR(p) model as:

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

where X_t is the $n \times 1$ vector of endogenous variables at time t, which are assumed to be a linear function of their past values X_{t-l} with l the number of lags $l = 1, \ldots, p$, A_l are the $n \times n$ matrices of lagged parameters, C is a n vector of constants and finally $\eta_t \sim N(0, \Sigma_\eta)$ is a $n \times 1$ vector of Gaussian structural disturbances.

The small open economy assumption reflects the idea that 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 for the weather variable, so that it can affect the domestic macroeconomic variables, and so that neither domestic nor foreign macroeconomic variables can affect the weather variable. We therefore have three blocks: one for the domestic economy, another for the weather, and another for the rest of the world.

The model writes:

$$\begin{bmatrix} X_t^W \\ X_t^\star \\ X_t^D \end{bmatrix} = C + \sum_{l=1}^{p} \begin{bmatrix} A_l^{11} & 0 & 0 \\ 0 & A_l^{22} & 0 \\ A_l^{31} & A_l^{32} & A_l^{33} \end{bmatrix} \begin{bmatrix} X_{t-l}^W \\ X_{t-l}^\star \\ X_{t-l}^D \end{bmatrix} + \begin{bmatrix} \eta_t^W \\ \eta_t^\star \\ \eta_t^D \end{bmatrix}, \tag{4}$$

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

The weather block writes:

$$X_t^W = \left[\hat{\omega}_t\right]', \tag{5}$$

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

$$X_t^\star = \left[\hat{y}_t^\star\right]', \tag{6}$$

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

$$X_t^D = \left[\hat{y}_t \quad \hat{y}_t^A \quad \hat{h}_t \quad \hat{c}_t \quad \hat{\imath}_t \quad \widehat{rer}_t\right]', \tag{7}$$

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

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

For clarity purposes, Equation 4 can be rewritten in the following compact form:

$$X_t = C + \sum_{l=1}^{p} A_l X_{t-l} + \eta_t, \tag{8}$$

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

2.1.1 The domestic weather block

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

2.1.2 The foreign economy block

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

2.1.3 The domestic economy block

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

2.2 A Structural VAR

Once the restricted VAR is estimated, we further impose some restrictions on the contemporaneous effects of the covariates.

Using the same matrix notation as in Equation 8, the SVAR model writes:

$$A_0 X_t = C + \sum_{l=1}^{p} A_l X_{t-l} + \eta_t, \tag{9}$$

where the lower triangular matrix A_0 imposes restrictions on the contemporaneous relationships between the variables. These restrictions on the A_0 matrix allow us to identify the orthogonal structural disturbances contained in vector η_t. The restrictions placed on the A_0 matrix are the following:

$$A_0 X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & 1 & 0 & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 & 0 & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & 1 & 0 & 0 \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & 1 & 0 \\ b_{81} & b_{82} & b_{83} & b_{84} & b_{85} & b_{86} & b_{87} & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{\omega}_t \\ \hat{y}_t^\star \\ \hat{y}_t \\ \hat{y}_t^A \\ \hat{h}_t \\ \hat{c}_t \\ \hat{\imath}_t \\ \widehat{rer}_t \end{bmatrix}. \tag{10}$$

The weather variable $\hat{\omega}_t$ and the foreign real output $\hat{y}_t^\star$ are contemporaneously affected by themselves only, in accordance with the exogeneity assumptions made previously. Domestic real GDP $\hat{y}_t$ is considered as the most exogenenous of the domestic variables,[4] as we assume that none of the other domestic variables have a contemporaneous effect. With the exception of the foreign output variable, the weather variable is assumed to have a potentially non-zero contemporary effect on all other variables in the system. All domestic variables are assumed to be able to respond in a contemporary way to changes in foreign production. Agricultural real output $\hat{y}_t^A$ is assumed to be contemporaneously affected by the domestic GDP. We assume that domestic GDP and agricultural output have a contemporaneous effect on hours worked $\hat{h}_t$. Consumption $\hat{c}_t$ is assumed to respond contemporaneously to domestic GDP, agricultural output, and hours worked. Investment i_t is supposed to be influenced by domestic GDP and agricultural output, hours worked and consumption. Lastly, the real effective exchange rate $\widehat{rer}_t$ is assumed to be contemporaneously affected by all variables. It is therefore the most endogenous variable in the model.

2.3 Estimation Results

The coefficients of the restricted VAR model described in Equation 8 are depicted in Table 1.

The estimation $\hat{A}_0$ of the A_0 matrix from Equation 9 is the following:

$$\hat{A}_0 X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.00 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.11 & 0.10 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0.13 & 0.10 & 0.08 & 1 & 0 & 0 & 0 & 0 \\ 0.13 & 0.10 & 0.10 & 0.08 & 1 & 0 & 0 & 0 \\ 0.09 & 0.20 & 0.10 & 0.06 & 0.12 & 1 & 0 & 0 \\ 0.11 & 0.13 & 0.08 & -0.13 & 0.12 & 0.10 & 1 & 0 \\ 0.11 & 0.10 & 0.11 & 0.10 & 0.19 & 0.05 & 0.10 & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{\omega}_t \\ \hat{y}_t^\star \\ \hat{y}_t \\ \hat{y}_t^A \\ \hat{h}_t \\ \hat{c}_t \\ \hat{\imath}_t \\ \widehat{rer}_t \end{bmatrix}. \tag{11}$$

Does the introduction of a weather variable in the autoregressive model lead to a better fit? To answer this question, we consider in the manner of Sims (1972) both bivariate and full-fledged VAR models. As explained by Sims (1980), the estimated pattern of causality as measured by Granger in macroeconomic time series is not stable over the inclusion of macroeconomic variables. We thus investigate the causality in the easiest way by considering a bi-variate case with the weather and one other macroeconomic variable. We also investigate causality patterns within the multivariate SVAR model. In addition to the number of variables in the VAR, we also control for the role of contemporaneous effects in driving causality patterns which may be

[4]This assumption is standard, for instance Sims (1980) assumes that output is the most exogenous variables (after money supply). In the case of VAR applied to commodities, Kamber et al. (2016) also use this identification strategy.

	Dependent variables							
	$\hat{\omega}_t$	$\hat{y}^\star_t$	$\hat{y}_t$	$\hat{y}^A_t$	$\hat{h}_t$	$\hat{c}_t$	$\hat{\imath}_t$	$\widehat{rer}_t$
Intercept	-0.02	-0.01	-0.01	-0.16	0.13	0.01	-0.11	0.16
	(0.09)	(0.06)	(0.08)	(0.49)	(0.07)	(0.10)	(0.37)	(0.37)
$L(\hat{\omega}_t)$	0.37^{***}		-0.10	-1.24^{*}	0.02	-0.05	-0.41	-0.40
	(0.10)		(0.10)	(0.61)	(0.09)	(0.12)	(0.46)	(0.46)
$L(\hat{y}^\star_t)$		0.84^{***}	0.10	-0.86	0.18^{*}	0.14	1.20^{**}	-0.73
		(0.06)	(0.09)	(0.53)	(0.08)	(0.10)	(0.40)	(0.40)
$L(\hat{y}_t)$			0.43^{**}	-2.68^{***}	-0.09	-0.15	0.56	0.42
			(0.13)	(0.76)	(0.11)	(0.15)	(0.57)	(0.57)
$L(\hat{y}^A_t)$			0.01	0.76^{***}	-0.01	0.04^{**}	0.01	0.01
			(0.01)	(0.07)	(0.01)	(0.01)	(0.05)	(0.05)
$L(\hat{h}_t)$			0.02	0.20	0.96^{***}	-0.01	0.13	0.05
			(0.04)	(0.21)	(0.03)	(0.04)	(0.16)	(0.16)
$L(\hat{c}_t)$			-0.01	1.24^{*}	-0.08	0.35^{**}	0.35	-0.66
			(0.09)	(0.56)	(0.08)	(0.11)	(0.42)	(0.42)
$L(\hat{\imath}_t)$			0.02	0.32^{*}	0.02	0.01	0.62^{***}	-0.03
			(0.02)	(0.13)	(0.02)	(0.03)	(0.10)	(0.10)
$L(\widehat{rer}_t)$			0.07^{**}	0.16	0.04	-0.00	0.30^{**}	0.18
			(0.02)	(0.15)	(0.02)	(0.03)	(0.11)	(0.11)
R^2	0.14	0.71	0.42	0.75	0.94	0.41	0.69	0.19
Adj. R^2	0.12	0.70	0.36	0.72	0.94	0.34	0.66	0.10
Num. obs.	89	89	89	89	89	89	89	89
RMSE	0.81	0.59	0.77	4.59	0.68	0.91	3.46	3.43

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. The estimated standard deviations are given in brackets.

Table 1: Estimated coefficients for the restricted VAR model.

more informative than past values in the VAR model. This causality differ from the standard Granger causality as it anslo includes contemporaneous variables in the regression equation. Given the joint roles of the number of variables and contemporaneous effects, we contrast up to three situations:

1. A first situation in which we look at whether the weather variable “Granger” causes another variable in a bi-variate setup.
2. In the second situation, we examine Granger causality by comparing the prediction of the VAR with and without the weather variable. This translates into setting the term A_1^{11} to 0 in the matrix of coefficients of lagged variables A_1 of the model, under the null hypothesis.
3. In the third situation, we look at whether removing the weather variable from the equation in Equation 9 decreases the forecasting performance of the model. This can be interpreted as investigating whether both past and contemporaneous effects of the weather statistically affects the errors of prediction by imposing coefficients to be of all zeros both in the lag matrix A_l^{31} and contemporaneous effects matrix b_{31}, b_{41}, b_{51}, b_{61}, b_{71} and b_{81}.

In all three cases, a Fisher test is performed, under which the null hypothesis consists in considering the simultaneous nullity of the coefficients associated with the weather variable and its lagged values.

	Situation (1)		Situation (2)		Situation (3)	
VAR-type:	bivariate		multivariate		multivariate	
Causality-type:	past only		past only		past + current	
Independant Variable	F	Pr(>F)	F	Pr(>F)	F	Pr(>F)
$\hat{y}_t$	0.40	0.67	0.98	0.46	0.66	0.75
$\hat{y}_t^A$	2.05	0.13	4.14	0.00***	2.51	0.01***
$\hat{h}_t$	0.50	0.61	0.04	1.00	0.44	0.93
$\hat{c}_t$	1.01	0.37	0.19	0.99	1.00	0.46
$\hat{i}_t$	0.01	0.99	0.81	0.60	0.08	1.00
$\widehat{rer}_t$	1.75	0.18	0.77	0.63	1.66	0.08**

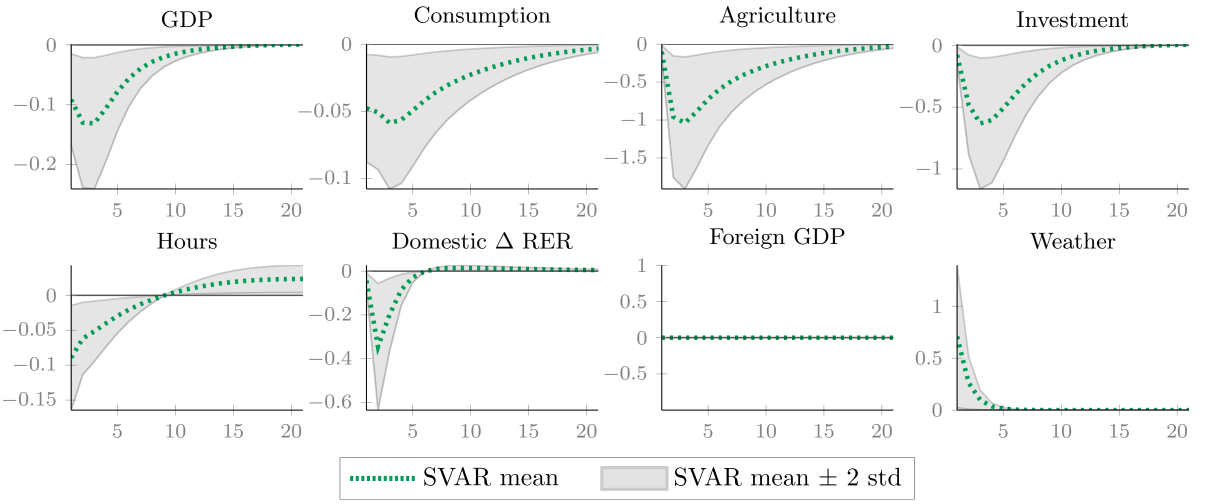
Notes: The Fisher tests presented consider three complete model alternatives in which the independent variable indicated in the rows is regressed: on its lagged values and on the (lagged) weather variable (Situation 1), on its lagged valued and the lagged values of the other variables of the model from Equation 8 (Situation 2), on the contemporaneous and lagged variables of the model from Equation 9 (Situation 3). In all three cases, the corresponding restricted model is one in which the weather variable has been removed.

Table 2: Inclusion tests of the (lagged) weather variable (F-test for nested models).

The results of the tests are presented in Table 2, considering a one-period lag model. The weather variable does not Granger cause the other variables as all p-values in the situation (1) column are all above 10%, the null hypothesis is not rejected. This underlines the fact that past values of the weather are not informative to predict any other macrovariable. However, once all the other variables are considered, the addition of the weather variable to the model improves the adjustment of the equations of domestic agricultural production whether we consider contemporaneous effects (situation 3) or not (situation 2). When contemporaneous effects are considered, the addition of the weather variable in the equation of the real effective exchange rate also improves the fit. This result underlines that most of the information regarding the weather that is relevant for predicting agricultural output and real effective exchange rate is driven by contemporaneous effects. Intuitively, the weather instantaneously affects agricultural output and the real exchange rate within the quarter at which the weather shock realizes. Thus in this situation, the weather can be informative for forecasters to adjust their nowcasts of agricultural output and the real exchange rate along the number of days of droughts they observe within the predicted quarter.

2.4 Macroeconomic response to weather shocks

We now present the empirical results of the impulse responses to a one standard deviation shock to the weather variable, *i.e.*, the drought indicator to assess the macroeconomic response following this shock. These IRFs are reported in Figure 2. The solid green lines are the responses while the gray areas are the 95% error bands obtained from $10,000$ Monte-Carlo simulations. The responses are computed for 20 periods. We focus on the shock to the weather equation. The complete set of IRFs is reporteded in Figure 3 and Figure 4: each column represents the response of the system to a specific shock.



Notes: The green dashed line is the Impulse Response Function. The gray band represents 95% error band obtained from the 10,000 Monte-Carlo simulations. The response horizon is in quarters.

Figure 2: SVAR 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 mechanism is triggered by the large fall in agricultural production accompanied by a decrease in investment, 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 mechanism of the weather shock between the model and the SVAR.

3 The non-linear model

We provide here the non-linear equations of the model prior using perturbations methods as in Collard and Juillard (2001) to get the model's dynamics in the neighborhood of the deterministic steady state. A first order approximation is applied to the model's equilibrium conditions as in Smets and Wouters (2007) to extract the sequence of shocks through the Kalman filter and construct the likelihood function for an estimation of structural parameters.

3.1 Households

The marginal utility of consumption is given by:

$$\lambda_t^c = (C_t - bC_{t-1})^{-\sigma_C}, \tag{12}$$

The stochastic discount reads as:

$$\Lambda_{t,t+1} = \beta E_t \left\{ \frac{\lambda_{t+1}^c}{\lambda_t^c} \right\}. \tag{13}$$

The Euler equation is given by:

$$E_t \left\{ \Lambda_{t,t+1} \right\} r_t = 1. \tag{14}$$

The real exchange rate is obtained by:

$$E_t \left\{ \frac{rer_{t+1}^*}{rer_t^*} \right\} = \frac{r_t}{r_t^*} (1 + p_t^N \Phi'(b_{jt}^*)). \tag{15}$$

The labor supply equation in each sector is:

$$\chi h_t^{\sigma_H} = C_t^{-\sigma_C} w_t^N \left(\frac{h_t^N}{h_t} \right)^{-\iota}, \tag{16}$$

$$\chi h_t^{\sigma_H} = C_t^{-\sigma_C} w_t^A \left(\frac{h_t^A}{h_t} \right)^{-\iota}. \tag{17}$$

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

$$h_t = \left[\left(h_t^N \right)^{1+\iota} + \left(h_t^A \right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{18}$$

The CES consumption bundle is determined by:

$$C_t = \left[(1-\varphi)^{\frac{1}{\mu}} (C_t^N)^{\frac{\mu-1}{\mu}} + \left(\varphi \varepsilon_t^A \right)^{\frac{1}{\mu}} (C_t^A)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \tag{19}$$

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

$$1 = \left[(1-\varphi) \, (p_{C,t}^N)^{1-\mu} + \varphi (p_{C,t}^A)^{1-\mu} \right]^{\frac{1}{1-\mu}}, \tag{20}$$

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:

$$p_{C,t}^N = \left[(1-\alpha_N) \, (p_t^N)^{1-\mu_N} + \alpha_N {rer_t}^{1-\mu_N} \right]^{\frac{1}{(1-\mu_N)}}, \tag{21}$$

$$p_{C,t}^A = \left[(1-\alpha_A) \, (p_t^A)^{1-\mu_A} + \alpha_A {rer_t}^{1-\mu_A} \right]^{\frac{1}{(1-\mu_A)}}. \tag{22}$$

3.2 Non-agricultural Firms

Technology is given by:

$$Y_t^N = \varepsilon_t^Z \left(K_{t-1}^N \right)^{\alpha} \left(H_t^N \right)^{1-\alpha}, \tag{23}$$

Law of motion of physical capital is:

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

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:

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

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

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

3.3 Farmers

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

$$\ell_t = \left[(1-\delta_\ell) + \frac{\tau}{\phi} X_t^\phi, \right] \Omega\left(\varepsilon_t^W\right) \ell_{t-1} \tag{28}$$

With a damage function:

$$\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}, \tag{29}$$

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

$$Y_t^A = \ell_{t-1}^\omega \left[\varepsilon_t^Z \left(K_{t-1}^A \right)^\alpha \left(\kappa_A H_t^A \right)^{1-\alpha} \right]^{1-\omega}, \tag{30}$$

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

$$I_t^A = K_t^A - (1-\delta_K) K_{t-1}^A. \tag{31}$$

First order conditions are given by:

$$w_t^A = (1-\omega)(1-\alpha) p_t^A \frac{Y_t^A}{H_t^A}, \tag{32}$$

$$q_t^A = p_t^N + \kappa p_t^N \varepsilon_t^i \left(\varepsilon_t^i \frac{I_t^A}{I_{t-1}^A} - 1 \right) - E_t \left\{ \Lambda_{t,t+1} \frac{\kappa}{2} p_{t+1}^N \left[\left(\varepsilon_{t+1}^i \frac{I_{t+1}^A}{I_t^A} \right)^2 - 1 \right] \right\} \tag{33}$$

$$q_t^A = E_t \left\{ \Lambda_{t,t+1} \left[\alpha (1-\omega) p_{t+1}^A \frac{Y_{t+1}^A}{K_t^A} + (1-\delta_K) q_{t+1}^A \right] \right\} \tag{34}$$

$$\frac{p_t^N}{\tau X_t^{\phi-1} \ell_{t-1} \Omega\left(\varepsilon_t^W\right)} = E_t \left\{ \Lambda_{t,t+1} \left(\omega \frac{Y_{t+1}^A}{\ell_t} + \frac{p_{t+1}^N}{\tau X_{t+1}^{\phi-1} \ell_t} \left[(1-\delta_\ell) + \frac{\tau}{\phi} X_{t+1}^\phi \right] \right) \right\} \tag{35}$$

3.4 The foreign economy

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

$$\log\left(c_t^*\right) = (1-\rho_*) \log\left(\bar{c}_j^*\right) + \rho_* \log\left(c_{t-1}^*\right) + \sigma_* \eta_t^* \tag{36}$$

$$\beta E_t \left\{ \lambda_{t+1}^* / \lambda_t^* \right\} r_t^* = 1, \tag{37}$$

$$1/c_t^* = \lambda_t^*, \tag{38}$$

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:

$$(1-n_t)\,Y_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{p_t^N}{p_{C,t}^N}\right)^{-\mu_N}\left(p_{C,t}^N\right)^{-\mu} C_t + \alpha_N\left(\frac{p_t^N}{rer_t}\right)^{-\mu_N} C_t^*\right] + Y_t^N g\varepsilon_t^G + I_t + n_t X_t + 0.5\chi_B (B_t^*)^2. \tag{39}$$

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

$$n_t Y_t^A = \varphi\left[(1-\alpha_A)\left(\frac{p_t^A}{p_{C,t}^A}\right)^{-\mu_A}\left(p_{C,t}^A\right)^{-\mu} C_t + \alpha_A\left(\frac{p_t^A}{rer_t}\right)^{-\mu_A} C_t^*\right], \tag{40}$$

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

$$H_t = (1-n_t)\,H_t^N + n_t H_t^A \tag{41}$$

$$I_t = (1-n_t)\,I_t^N + n_t I_t^A \tag{42}$$

$$Y_t = (1-n_t)\,p_t^N Y_t^N + n_t p_t^A Y_t^A \tag{43}$$

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

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

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

$$tb_t = p_t^N\left[(1-n_t)\,Y_t^N - Y_t^N g\varepsilon_t^G - I_t - n_t X_t - 0.5\chi_B (B_t^*)^2\right] + p_t^A n_t Y_t^A - C_t. \tag{44}$$

And a set of structural disturbances:

$$\log(\varepsilon_t^Z) = \rho_Z \log(\varepsilon_{t-1}^Z) + \sigma_Z/100\eta_t^Z, \quad \text{with } \eta_t^Z \sim \mathcal{N}(0,1), \tag{45}$$

$$\log(\varepsilon_t^G) = \rho_G \log(\varepsilon_{t-1}^G) + \sigma_G/100\eta_t^G, \quad \text{with } \eta_t^G \sim \mathcal{N}(0,1), \tag{46}$$

$$\log(\varepsilon_t^I) = \rho_I \log(\varepsilon_{t-1}^I) + \sigma_I/100\eta_t^I, \quad \text{with } \eta_t^I \sim \mathcal{N}(0,1), \tag{47}$$

$$\log(\varepsilon_t^H) = \rho_H \log(\varepsilon_{t-1}^H) + \sigma_H/100\eta_t^H, \quad \text{with } \eta_t^A \sim \mathcal{N}(0,1), \tag{48}$$

$$\log(\varepsilon_t^W) = \rho_W \log(\varepsilon_{t-1}^W) + \sigma_W/100\eta_t^W, \quad \text{with } \eta_t^W \sim \mathcal{N}(0,1), \tag{49}$$

$$\log(\varepsilon_t^N) = \rho_N \log(\varepsilon_{t-1}^N) + \sigma_N/100\eta_t^N, \quad \text{with } \eta_t^N \sim \mathcal{N}(0,1), \tag{50}$$

$$\log(\varepsilon_t^C) = \rho_C \log(\varepsilon_{t-1}^C) + \sigma_C/100\eta_t^C, \quad \text{with } \eta_t^C \sim \mathcal{N}(0,1), \tag{51}$$

$$\log(\varepsilon_t^E) = \rho_E \log(\varepsilon_{t-1}^E) + \sigma_E/100\eta_t^E, \quad \text{with } \eta_t^E \sim \mathcal{N}(0,1). \tag{52}$$

4 Steady state

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

$$\bar{r} = 1/\beta. \tag{53}$$

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

$$\bar{h} = \left[\left(\bar{h}^N\right)^{1+\iota} + \left(\bar{h}^A\right)^{1+\iota}\right]^{1/(1+\iota)}. \tag{54}$$

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

$$\bar{z} = \bar{r} - (1 - \delta). \tag{55}$$

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

$$\bar{K}^N = \bar{h}^N \left(\frac{\bar{z}}{\alpha}\right)^{(1/(\alpha-1))}, \tag{56}$$

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

$$\bar{Y}^N = \left(\bar{K}^N\right)^{\alpha} \left(\bar{h}^N\right)^{1-\alpha}. \tag{57}$$

While investment per firm is given by:

$$\bar{I}^N = \delta \bar{K}^N. \tag{58}$$

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

$$\bar{W}^N = (1 - \alpha) \frac{\bar{Y}^N}{\bar{h}^N}. \tag{59}$$

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

$$\bar{W}^A = \bar{W}^N. \tag{60}$$

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

$$\bar{Y}^A = \frac{\bar{h}^A \bar{W}^A}{(1 - \omega)(1 - \alpha)}. \tag{61}$$

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

$$\bar{K}^A = (1 - \omega) \alpha \frac{\bar{Y}^A}{\bar{z}}. \tag{62}$$

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

$$\kappa_A = \left[\left(\frac{\bar{Y}^A}{\bar{\ell}^{\omega}}\right)^{1/(1-\omega)} \left(\bar{K}^A\right)^{-\alpha}\right]^{1/(1-\alpha)} \frac{1}{\bar{h}^A}. \tag{63}$$

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

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

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

$$\bar{X} = \delta_\ell \phi \bar{\varrho}. \tag{64}$$

Name	Steady state	Name	Steady state	Name	Steady state
$\bar{r}$	1.0118	n	0.0715	C	0.5319
$\bar{h}^N$	0.3333	$\bar{K}^N$	8.7921	$\bar{I}^N$	0.2198
$\bar{h}^A$	0.3333	$\bar{K}^A$	8.7921	$\bar{I}^A$	0.2198
$\bar{z}$	0.0368	κ_A	1.3062	$\bar{h}$	0.3991
$\bar{Y}^N$	0.9815	$\bar{\ell}$	0.4	$\overline{tb}$	0
$\bar{Y}^A$	1.1150	$\bar{\varrho}$	5.8521	χ	1150.6
$\bar{W}^N$	1.9728	τ	2.4547	$\overline{gdp}$	0.9676
$\bar{W}^A$	1.9728	$\bar{X}$	0.3278	$\Omega\left(\bar{\varepsilon}^s\right)$	1

Table 3: Steady state values for the estimated model.

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

$$\tau = \frac{1}{\bar{\varrho}\bar{\ell}\bar{X}^{\phi-1}}. \tag{65}$$

The stock of physical capital per farmer is given by:

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

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

$$\left(1-\bar{n}\right)\bar{Y}^N = \left(1-\varphi\right)\bar{C} + \bar{Y}^N g + \left(1-\bar{n}\right)\bar{I}^N + \bar{n}\bar{I}^A + \bar{n}X, \tag{66}$$

$$\bar{n}\bar{Y}^A = \varphi\bar{C}. \tag{67}$$

We obtain the following equation:

$$\left(1-\bar{n}\right)\left(\bar{Y}^N - \bar{I}^N\right) = \bar{n}\left(\frac{\left(1-\varphi\right)}{\varphi}\bar{Y}^A + \bar{I}^A + \bar{X}\right) + \bar{Y}^N g \tag{68}$$

From the latter equation, it's straightforward to pin down the value of $\bar{n}$:

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

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

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

5 The welfare cost of weather-driven business cycles

To get a welfare perspective on climate change, we compute how much consumption households are willing to abandon to stay in an equilibrium free of weather shocks.[5] Consider the following utility function:

$$U_t = \frac{1}{1-\sigma}\left(C_{jt+\tau} - bC_{t-1+\tau}\right)^{1-\sigma} - \frac{\chi\varepsilon^H_{t+\tau}}{1+\sigma_H}h^{1+\sigma_H}_{jt+\tau}, \tag{69}$$

[5] 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.

Abstracting from the exogenous shock ε_t^H, the taylor expansion up to second order of the left term of the utility function is given by:

$$E\left[U_{C,t}\right] \simeq \frac{1}{1-\sigma}\left(C-bC\right)^{1-\sigma}-\frac{1}{2}\sigma\left(C-bC\right)^{-\sigma-1}E\left[\left(c_t-c\right)^2\right]+\frac{1}{2}\sigma b^2\left(C-bC\right)^{-\sigma-1}E\left[\left(c_{t-1}-c\right)^2\right] \tag{70}$$

While for the right term of the utility function:

$$E\left[U_{H,t}\right] \simeq -\frac{\chi}{1+\sigma_H}h^{1+\sigma_H}-\frac{1}{2}\sigma_H\chi h^{\sigma_H-1}E\left[\left(h_t-h\right)^2\right] \tag{71}$$

Expressed in terms of variances (i.e., $v\left(x_t\right)=E[\left(x_t-x\right)^2]$), the utility function up to second order is given by:

$$E\left[U_t\right] \simeq \bar{U}-\frac{1}{2}\sigma\left(1-b^2\right)\left(C-bC\right)^{-\sigma-1}v\left(c_t\right)-\frac{1}{2}\sigma_H\chi h^{\sigma_H-1}v\left(h_t\right) \tag{72}$$

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

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

$$E\left[W_t\right]=\frac{\bar{U}}{1-\beta}-\frac{1}{2}\sigma\left(1-b^2\right)\frac{\left(\bar{C}-b\bar{C}\right)^{-\sigma-1}}{1-\beta}v\left(c_t\right)-\frac{1}{2}\sigma_H\chi\frac{h^{\sigma_H-1}}{1-\beta}v\left(h_t\right) \tag{73}$$

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

$$\left(1+\lambda\right)^{1-\sigma}=\frac{U_C-\gamma_C v\left(c_t^A\right)+\gamma_H\left[v\left(h_t^B\right)-v\left(h_t^A\right)\right]}{\left[U_C-\gamma_C v\left(c_t^B\right)\right]} \tag{74}$$

where $U_C=\left(1-\sigma\right)^{-1}\left(\bar{C}-b\bar{C}\right)^{1-\sigma}$, $\gamma_C=0.5\sigma\left(1-b^2\right)\left(\bar{C}-b\bar{C}\right)^{-\sigma-1}$ and $\gamma_H=0.5\sigma_H\chi h^{\sigma_H-1}$. The closed-form expression of the welfare index is given by:

$$\lambda=\left[\frac{U_C-\gamma_C v\left(c_t^A\right)+\gamma_H\left[v\left(h_t^B\right)-v\left(h_t^A\right)\right]}{\left[U_C-\gamma_C v\left(c_t^B\right)\right]}\right]^{1/(1-\sigma)}-1 \tag{75}$$

6 Estimation of the DSGE Model

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

6.1 Macroeconomic time series transformation

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

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

$$\hat{y}_t = \log\left(\frac{Y_t}{P_t N_t}\right) - \Gamma\left(\log\left(\frac{Y_t}{P_t N_t}\right)\right), \tag{76}$$

where $\Gamma(.)$ is the quadratic trend (linearized through the log).

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

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

as the mean of $SMDI_t$ is one as a result from the soil moisture index, the mean of the observable variable $\hat{\omega}_t$ is thus zero.

6.2 Measurement equations of the DSGE model

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

$$\begin{bmatrix} 100 \times \hat{\omega}_t \\ 100 \times \hat{y}_t^* \\ 100 \times \hat{y}_t \\ 100 \times \hat{y}_t^A \\ 100 \times \hat{h}_t \\ 100 \times \hat{c}_t \\ 100 \times \hat{\imath}_t \\ 100 \times \Delta\widehat{rer}_t^* \end{bmatrix} = 100 \times \begin{bmatrix} \log(\varepsilon_t^W) \\ \log(Y_t^*/\bar{Y}^*) \\ \log(Y_t/\bar{Y}) \\ \log(n_t p_t^A Y_t^A / \left(\bar{Y}^A \bar{n}\right)) \\ \log(H_t/\bar{H}) \\ \log(C_t/\bar{C}) \\ \log(p_t^N I_t/\bar{I}) \\ \log(RER_t/RER_{t+1}) \end{bmatrix}. \tag{77}$$

Note that the right hand side of measurement equations has a zero mean, so the left hand side has it mean removed accordingly, prior the estimation of the model.

For any shock process, note that we also divide by 100 the standard deviation of the stochastic disturbance:

$$\log(\varepsilon_t^m) = \rho_m \log(\varepsilon_{t-1}^m) + \sigma_m/100\eta_t^m, \quad \text{with } \eta_t^m \sim \mathcal{N}(0,1).$$

where $m = \{Z, G, I, H, W, N, C, E\}$.Under this transformation, our priors on standard deviation of shocks σ_m are expressed as Smets Wouters in percentages as well as our observable variables.

6.3 Comparing the SVAR and the DSGE models

Since we used the SVAR as a guideline for building our DSGE model, we report in Figure 6 the estimated response of the DSGE model (taken at posterior mean) following a 1% weather shock and the corresponding response of the SVAR model.[6] The gray areas represent the 95 percent probability intervals (*i.e.*, 2 standard-deviation from the mean). Figure 6 shows that the model does very well at reproducing the estimated effects of weather shocks, including the hump-shape response of real GDP, real agricultural production and the muted response of hours. Another challenging aspect of the fit exercise is to capture the higher persistence of the response of macro-variables compared to the weather shock process. In particular, the weather requires five quarters to vanish while output, investment and hours take more than fifteen periods to go back to steady state. The introduction of an endogenous land input successfully captures this hysteresis effects. However, the model does overstate the contraction of output and its persistence while it does understate the decline in investment.

[6]The IRFs of the DSGE model are obtained from the measurements equations in Equation 77 which makes them comparable with the SVAR's IRFs.

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

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

Table 4: Estimations of growth rates of standard errors of the weather process under different scenarios.

7 Building long run scenarios of weather shocks

To estimate the variability of the weather process η_t^W, we rely on simulated weather data from a circulation climate model, the Community Climate System Model (CCSM). We consider the data simulated under the four well-employed Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). They are given on a 0.9° × 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.[7] 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:

$$\overline{\Delta\sigma_{i,\eta_W}} = (1 + \sigma_{i,\eta^W})^q - 1, \tag{78}$$

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. Table 4 summarizes the estimates.

[7] 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.

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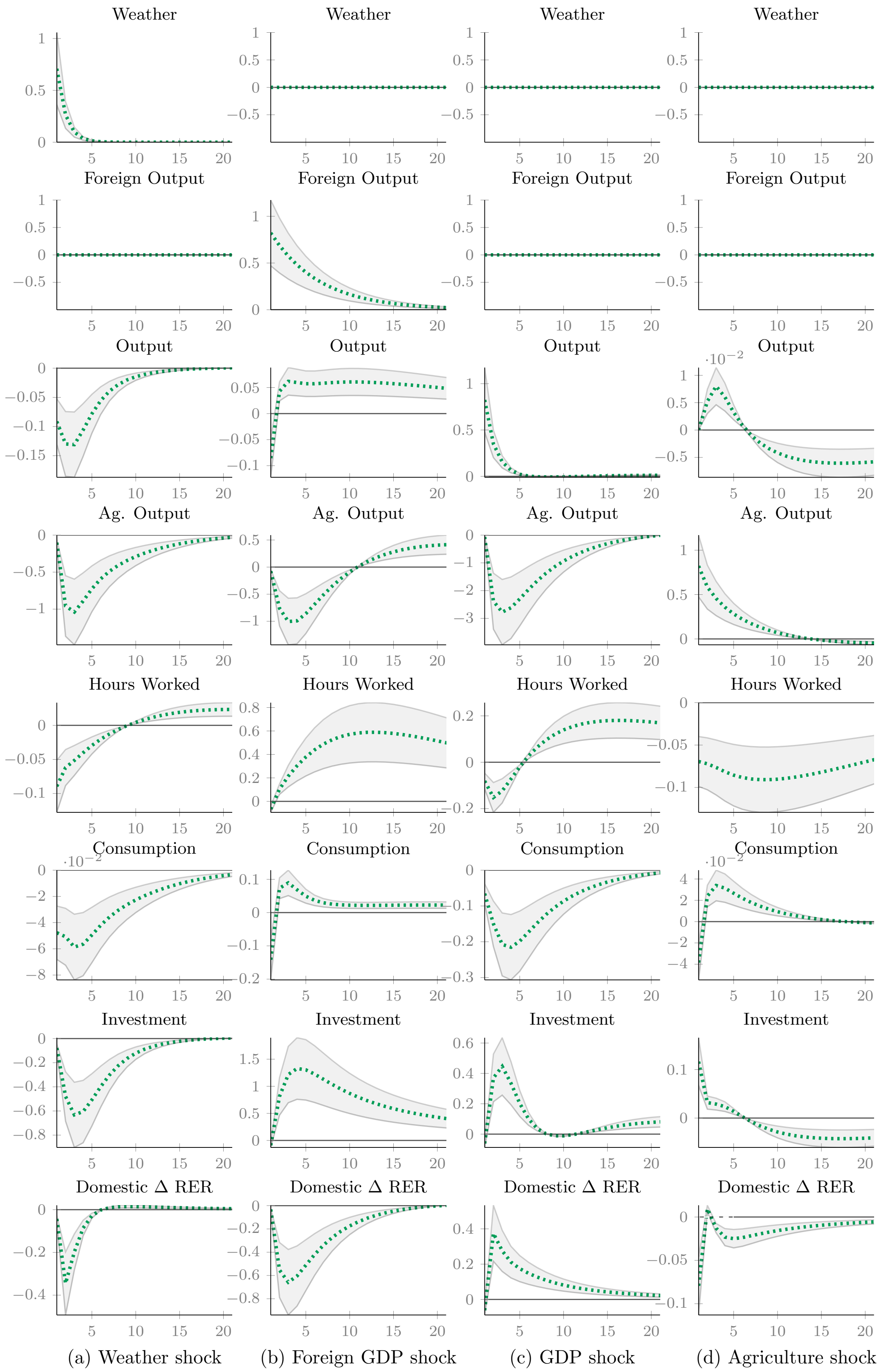
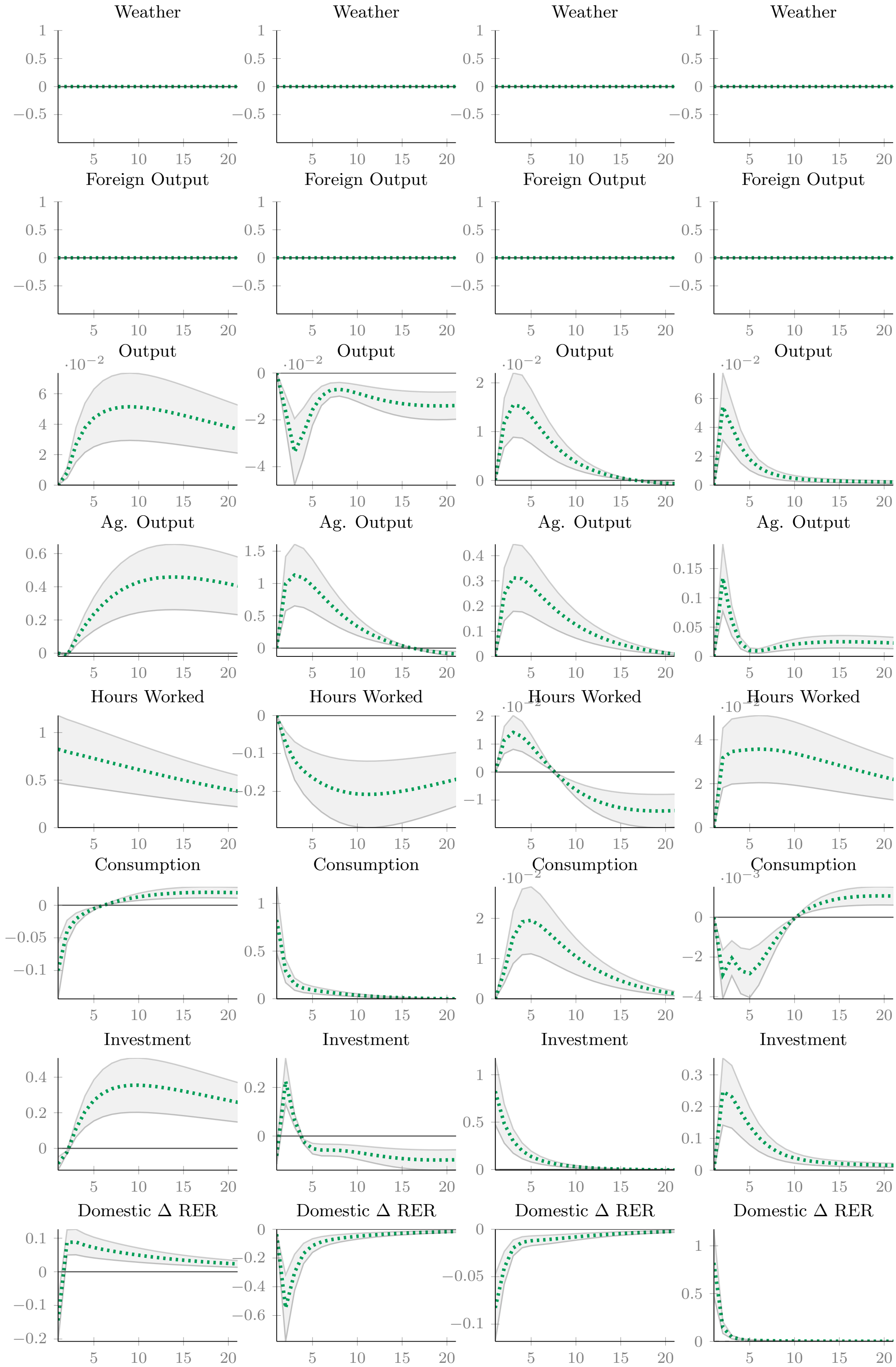


Notes: Each column represents the response of the system to a 1% weather shock (column 1), world output shock (column 2), output shock (column 3), and agricultural output shock (column 4). The green dashed line is the Impulse Response Function. The gray band represents 95% error band obtained from 10,000 Monte-Carlo simulations. The response horizon is in quarters.

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



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

Notes: Each column represents the response of the system to a 1% investment shock (column 1), consumption shock (column 2), hours worked shock (column 3), and real effective exchange rate shock (column 4). The green dashed line is the Impulse Response Function. The gray band represents 95% error band obtained 10,000 Monte-Carlo simulations. The response horizon is in quarters.

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

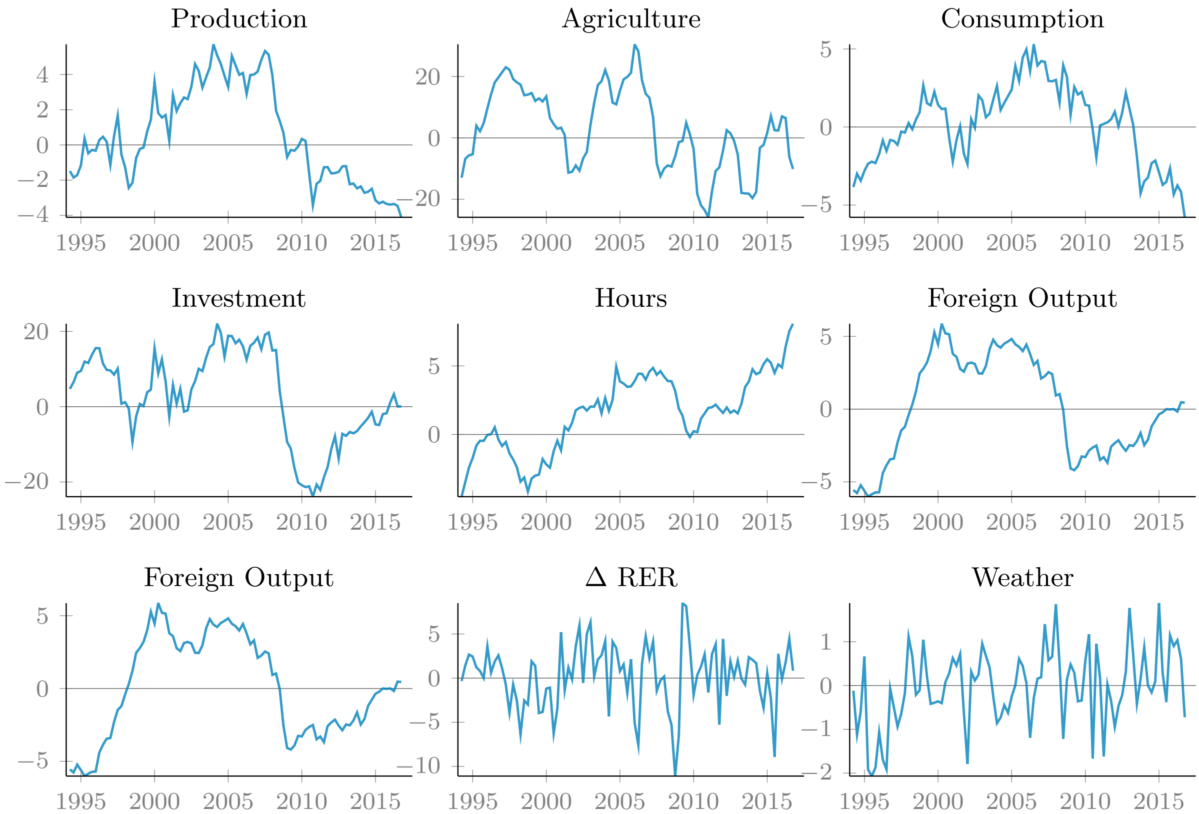


Figure 5: Observable variables used in the SVAR and the DSGE estimations.

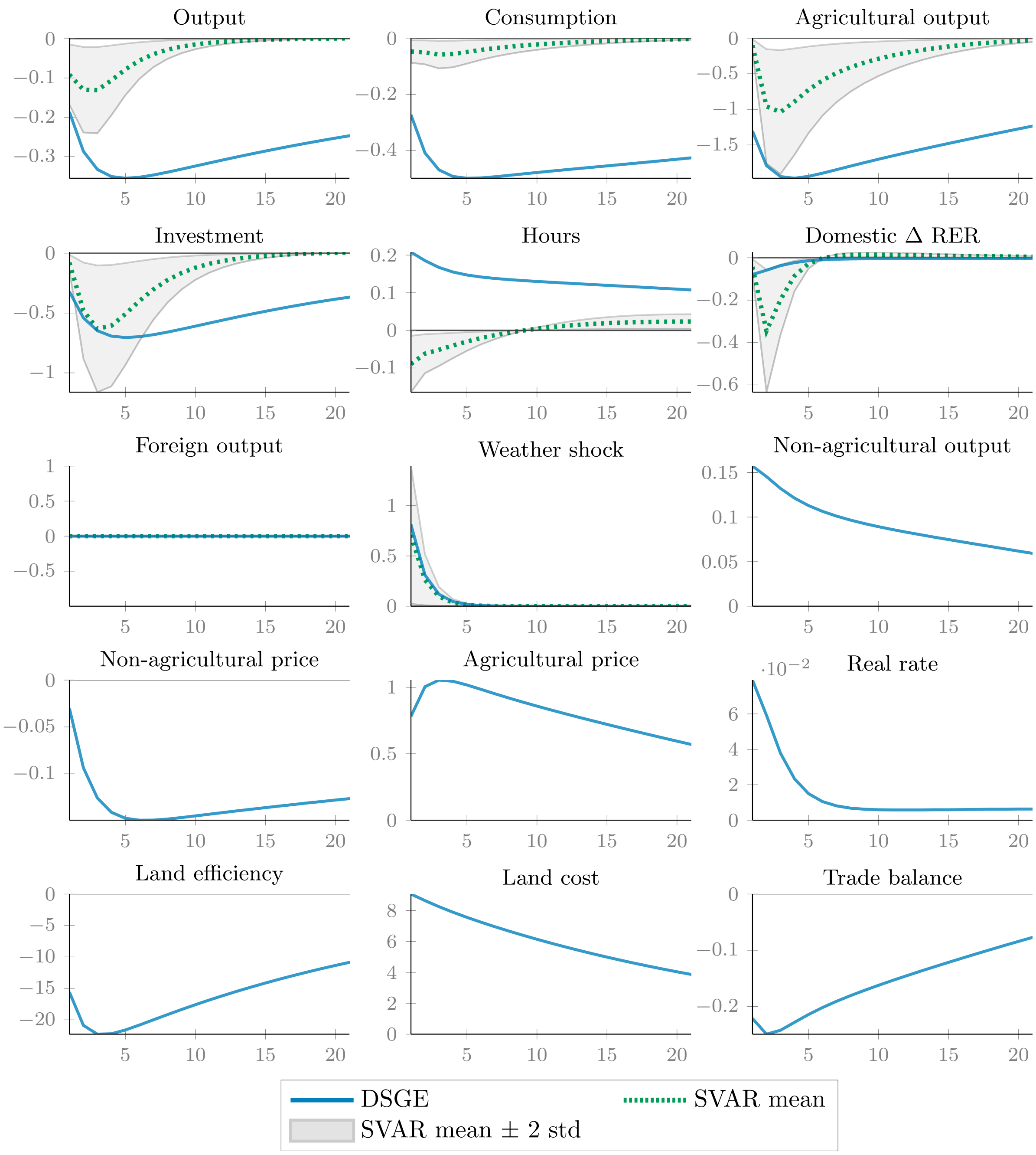


Figure 6: Comparison of the DSGE and the SVAR impulse responses to a 1% weather shock (drought) in New Zealand.