Weather Shocks

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NGFS Workstream on Monetary Policy, Nov. 4, 2025

General Information

Paper : Gallic, E & Vermandel, G. (2020). **Weather Shocks**. *European Economic Review*, 124, 103409. doi : 10.1016/j.euroecorev.2020.103409

Replication materials : R and dynare with matlab [GitHub repository]

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Aims of the paper

Some macro questions at hand:

- What are the **transmission mechanisms** of a **weather shock** both at sectoral and international levels?
- What are the **short run** and **long run** implications of **weather shocks**?
- How costly are weather fluctuations for households in terms of **welfare**?

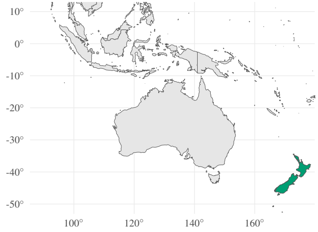
Methodology: 4 Steps

1. **Data pre-processing**
   - from daily weather **data** (grid/stations) to quarterly national values
   - **drought index** $\rightarrow$ narrow view of the weather (droughts and heat waves).
2. **Empirical Facts**
   - characterization a weather shock through the lens of a **VAR model**.
3. **Theoretical Model**
   - design and estimation of a **DSGE model** for a small open-economy
   - analysis of the **propagation** of a weather shock and its implications in terms of **business cycle statistics**.
4. **Scenarios**
   - we measure the implications of **climate change** on **aggregate fluctuations** by **increasing the variance of** **weather shocks**.

A Model for a Small Open Economy

In the paper, we focus on **New-Zealand**:

- New-Zealand has experienced **weather-driven recessions**:
  - 2013 – North Island + West of the South Island drought (cost: \$1.3 billion / 0.5% of GDP)
  - 2008 – national drought (cost: \$2.8 billion / 1.5% of GDP)
  - 2004 – lower North Island floods (cost: \$185–\$219 millions).
- New Zealand provides **very good quality data** (both for **weather** and **agriculture**).
- New Zealand is small enough to be subject to fairly homogeneous weather.



Outline

2. Building a Weather Index

Measuring the Weather

- **Challenge** : computing at a macro level a weather index strongly correlated with real agricultural production.
- **Solution** : create **soil moisture deficit index** :
  1. Collect **soil water deficit** data from weather stations (on a monthly basis).
  2. Compute **percentage deviation from monthly median** as in Narasimhan and Srinivasan (2005): $D_{t,m} = \frac{SWD_{t,m} - Med(SWD_m)}{Med(SWD_m)}$ and include persistence of deficits, $SMDI_{t,m} = 0.5 \times SMDI_{t,m-1} + \frac{D_{t,m}}{50}$ that captures the evatransporation.
  3. Aggregation: compute an average per region, get national index by a weighting each region by its relative size in national agricultural production.

The Upcoming Steps

1. Get a map of the country:
   - `data/map/map_nz.R`
2. Download weather stations data:
   - `data/climate_data/01_download_weather_data.R`
3. Build the **Soil Moisture deficit index**:
   - `data/climate_data/02_weather_metrics.R`

2.1. Getting a Map of the Country

Roadmap

Aim

Import a map of New Zealand in `R`.

In the Replication Codes

- Download the map file from stats.govt.nz.
- Extract the content (`2015 Digital Boundaries Generalised Clipped.gdb`) in the folder `data/map/`.
- Launch `data/map/map.Rproj` to open RStudio and set the working directory correctly.
- Run the `R` script: `map_nz.R`.

Map File of New Zealand

- Weather data arrive at the **station level**.
- Each station has **GPS coordinates** (longitude, latitude).
- To aggregate by **region**, we must know which region each station falls in.
- We therefore import a **map of NZ regions** into R.
- A suitable ESRI File Geodatabase (GDB) can be downloaded from stats.govt.nz.

What is a .gdb?

- A `.gdb` is a directory storing spatial tables (points/lines/polygons) + indexes/metadata.
- It supports multiple layers (e.g., **regions**, **districts**, **coastlines**) in one container.
- In `R`, it can be read with `sf::st_read()`, and the contents can be shown with `sf::st_layers()`.

Practice

data/map/map_nz.R

1. Import regional boundaries from the official 2015 ESRI **Geodatabase** (Statistics NZ).
2. Reproject geometries to the national CRS (`EPSG:4167`).
3. Simplify polygons (tolerance: 5 km) to reduce file size and improve plotting speed.
4. Define a **bounding box** and clip to New Zealand's extent.
5. Harmonize region names, merging "Tasman" and "Nelson" into a single "Tasman/Nelson" unit (because of agricultural data used later on).
6. **Export** the resulting spatial object as `nz_df_regions.rda`.

What is a Coordinate Reference System (CRS)?

- A **Coordinate Reference System (CRS)** defines how spatial data are projected onto the Earth's surface.
- It ensures that longitude/latitude coordinates and distances correspond to real geographic locations.
- There are two main types:
  - **Geographic CRS**: uses angles (latitude, longitude). Example: WGS84 (`EPSG:4326`).
  - **Projected CRS**: uses linear units (meters, km), optimized for a region. Example: NZGD2000 / New Zealand Transverse Mercator (`EPSG:4167`).
- In practice:
  - All spatial layers (`sf` objects) must share the same CRS before spatial joins or overlays.
  - Reprojection is done with `st_transform()` in `R`.

2.2. Download Weather Station Data

Roadmap

Aim

Download weather data from weather stations.

Warning

- This step no longer works, since the access to the National Climate Database (New Zealand) via the 'CliFlo' platform is deprecated.
- In the **second session**, we will show how to get data from a **grid dataset** instead of using data from weather stations.

In the Replication Codes

- R script: `data/climate_data/01_download_weather_data.R`.

Download Weather Data from Stations

- Among the available variables at the monthly level, we focus on:
  - 00: Total rainfall (monthly)
  - 66: Mean Deficit of Soil Moisture.
- Three-step procedure (implemented via `functions_weather_stations.R`):
  1. Gather station metadata (operating dates, GPS, available metrics).
  2. Download per-station monthly data via API (POST/GET, auth, paging).
  3. Tidy those and save yearly chunks as `.rda` files.
- The resulting files are saved in:
  - `data/climate_data/data_00` for rainfall,
  - `data/climate_data/data_66` for soil moisture.

Practice Time

Practice

- Launch RStudio by double-clicking on `data/climate_data/climate_data.Rproj`.
- In RStudio, open the `R` script `data/climate_data/01_download_weather_data.R`.
- Unfortunately, the code can no longer be run, but we can still have a look at the logic that can be adapter to another data provider.

2.3. The Drought Metric

Roadmap

Aim

Build drought/rainfall metrics at region-month, then aggregate to national.

In the Replication Codes

- R script: `data/climate_data/02_weather_metrics.R`.

In a Nutshell

- At this step, we have a map for the country (with the regions), and monthly weather data.
- The procedure:
  1. Assign stations to regions (map join).
  2. Aggregate raw measures to **region-month** (e.g., sum rainfall; mean SMD).
  3. Remove seasonality: subtract long-run monthly means (1980–2016).
  4. Build drought index **SMDI** following Narasimhan and Srinivasan (2005).
  5. Apply **agricultural GDP** region-year weights; sum to **national monthly**.
  6. Aggregate to **quarterly / annual** national series.

Practice Time

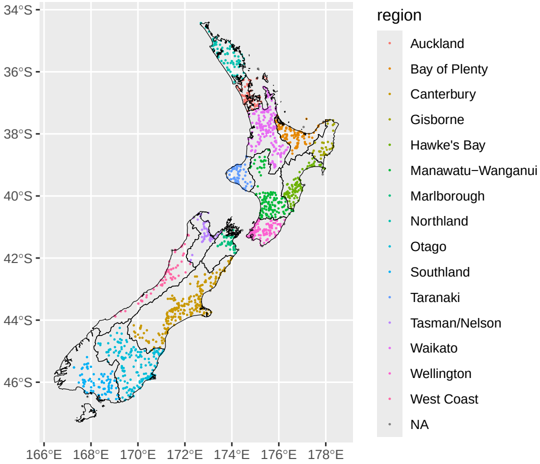
Practice

- RStudio has already been launched previously when you double-clicked on `data/climate_data/climate_data.Rproj`.
- In RStudio, open the `R` scripts:
  - `data/climate_data/02_weather_metrics.R`.
  - `data/climate_data/03_explanations-for-NGFS.R`.
- We will give you a link with sample data to run this part.
- Before creating the drought index, we will make a pause and go back to the slides to explain the procedure of the function doing so (`climate_variables()`).

Soil Moisture Deficit Index (SMDI): Motivation

- The **SMDI** measures relative dryness. It is based on soil moisture deficit levels.
- It accounts for both **long-term climatology** and **short-term persistence** of drought.
- It is computed at monthly frequency.
- The building steps are documented in Kamber et al. (2013).
- The next couple of slides recall these steps.

Step 1: Assign Stations to Regions



Weather Stations

Step 2: Aggregation at Region-Month Level

- For each region r, year y, and month m:

$$SMD_{r,ym} = \frac{1}{n_{\text{stations},r}} \sum_{i \in \mathcal{I}_r} SMD_{i,ym},$$

where:

- $SMD_{r,ym}$: soil moisture deficit in region r
- $\mathcal{I}_r$: set of stations in region r
- $SMD_{i,ym}$: soil moisture deficit in station i.

Step 3: Deseasonalized Soil Moisture Deficit

Aim

Compare current soil moisture to its long-term climatology.

$$\mathrm{SD}_{ym} = \begin{cases} \dfrac{SMD_{ym} - \mathrm{Med}(SMD_m)}{\mathrm{Med}(SMD_m) - \mathrm{Min}(SMD_m)} \times 100, & SMD_{ym} \leq \mathrm{Med}(SMD_m) \\ \dfrac{SMD_{ym} - \mathrm{Med}(SMD_m)}{\mathrm{Max}(SMD_m) - \mathrm{Med}(SMD_m)} \times 100, & SMD_{ym} > \mathrm{Med}(SMD_m) \end{cases}$$

- y: year index; m: month index (Jan–Dec).
- SMD_{ym}: observed mean soil moisture deficit.
- The long-term monthly statistics (Min, Max, Med) are computed over the whole sample here (1987–2021).

Step 4: Recursive Index Construction

Initialization:

$$SMDI_1 = \frac{SD_1}{25T + 25}$$

Recurrence:

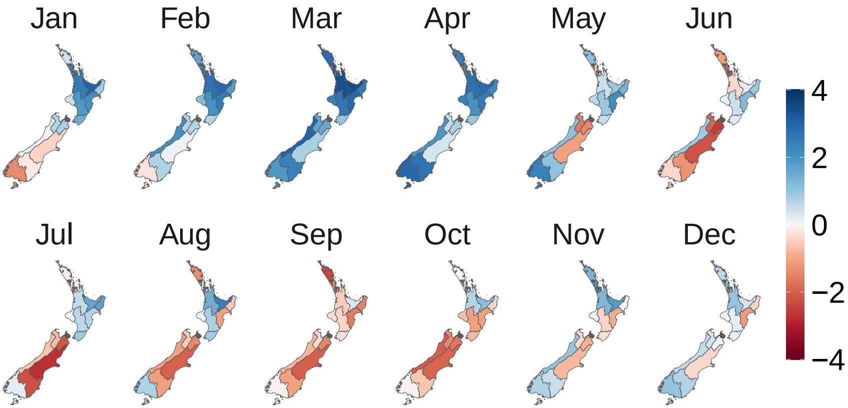
$$SMDI_t = \frac{SD_t}{25T + 25} - \frac{25}{25T + 25} SMDI_{t-1}$$

- T: temporal smoothing constant (typically $T = 1$).
- The index evolves recursively: prolonged dry or wet periods accumulate over time.
- $SMDI$ is bounded between -4 (extreme drought) and $+4$ (very wet).
- Each month's standardized deficit (SD_t) contributes partly to the new index, while the previous month's deficit decays exponentially.

Step 4: Implementation in R (sketch)

```
valeur_c <- function(t) -25 / (25 * t + 25)
# Recursive computation for one region
calcul_smdi <- function(x) {
  df_tmp <- df |> filter(region == x)
  index <- rep(NA, nrow(df_tmp))
  index[1] <- df_tmp$value_s[1] / (25 * val_T + 25)
  for (i in 2:nrow(df_tmp)) {
    index[i] <- df_tmp$value_s[i] / (25 * val_T + 25) -
                valeur_c(val_T) * index[i - 1]
  }
  df_tmp$index <- index
  df_tmp
}
```

Step 4: SMDI for Each Region-Month



SMDI in 2013 at the region-month level.

Step 5: Weights for Regional Agricultural Intensity

Why weighting?

- Different regions contribute unequally to New Zealand's agricultural output.
- Weight by **regional agricultural GDP shares**: representative national weather indicators.
- Regions with larger agricultural sectors have proportionally greater influence in national aggregates.

Data source:

- Statistics New Zealand: regional accounts for agricultural GDP.
  - `matrix_pond_agriculture.xls` (*sheet:* RNA434201_20150707_091730_92).

Step 5: Constructing Agricultural Weights

Yearly weights:

$$w_{r,y} = \frac{\text{AgriGDP}_{r,y}}{\sum_{r'} \text{AgriGDP}_{r',y}}$$

- Each year's weights sum to one: $\sum_r w_{r,y} = 1$.
- Represent the share of national agricultural value added in region r.

About the Complete Methodology

- The complete weighting methodology is slightly more complex, as the agricultural GDP data do not fully cover the entire weather data period.
- Further details are provided in the companion ebook for **Session 2**, in Chapter 5.

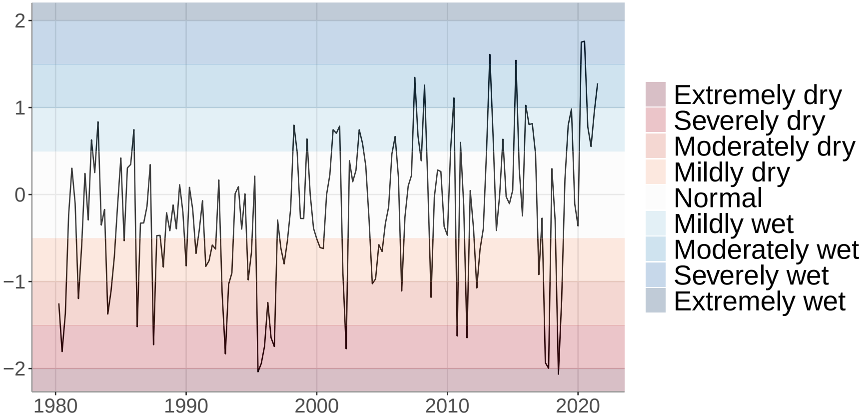
Step 6: Temporal Aggregation

- At the beginning of step, we have region-wise values for the SMDI, and regional weights representing agricultural intensity.
- We multiply the region's SMDI by its weight before summing.
- We obtain a **national monthly SMDI**.
- Then, we can average to quarterly or annual frequency.

The SMDI takes values in $[-4, 4]$:

- $SMDI \approx 0$: normal soil conditions.
- $SMDI < -1$: moderate drought.
- $SMDI < -2$: severe drought.
- $SMDI < -3$: extreme drought.

The Obtained Series for SMDI



SMDI on a quarterly basis for New-Zealand.

Measuring Droughts: Wrap-Up

- The **SMDI** captures both **intensity** and **duration** of drought.
  - It relies on **relative anomalies** (not absolute levels) of soil moisture.
  - Its recursive structure smooths short-term variability.
  - It is straightforward to compute once long-term climatology is available.
- Another metric, the **Standardized Precipitation-Evapotranspiration Index (SPEI)** (Vicente-Serrano et al., 2010) will be presented in **session 2**.

2.4. Macroeconomic Data

Rodmap

Aim

- Construct a quarterly macroeconomic dataset for New Zealand to be matched with the SMDI.
- Sample period: 1994Q3 to 2016Q4.
- All variables are log deviations from trend (HP filter), except share prices.

In the Replication Codes

- R scripts in the `data` folder (launch `data/data.Rproj`):
  - `variables_names.R`: variable name and better descriptions for graphs.
  - `01_data_world_new_oecd.R`: GDP for trading partners.
  - `02_1_seasonality.R`: Helper functions to detrend series.
  - `02_2_data_import.R`: Building the macroeconomic dataset.

Key Economic Variables

- **Gross Domestic Product (GDP)**: Real per capita output, expenditure approach, seasonally adjusted (Stats NZ).
- **Rest of World GDP**: Weighted average of major trading partners (OECD).
- **Agricultural Output**: Real agriculture, forestry, and fishing GDP (Stats NZ).
- **Consumption & Investment**: Household consumption and gross fixed capital formation (Stats NZ).
- **Labor Market**: Paid hours, employment, population (Stats NZ).
- **Prices and Exchange Rates**: CPI, GDP deflator (Stats NZ), REER (FRED).
- **Financial Variables**: Share prices (Bloomberg), interest rate (OECD)

Implementation Steps

1. Build Rest-of-World GDP.
2. Collect New Zealand series.
3. Merge all variables.
4. Detrend the data and express in real per-capita.

In the Replication Codes

- Step 1: `01_data_world_new_oecd.R`.
- Steps 2 to 4: `02_2_data_import.R`.

2.5. Rest of The World

Rest-of-World GDP

- We build a weighted aggregate of major **trading partners' GDP** to represent external economic conditions for New Zealand.
  - Australia, Germany, Japan, UK, USA

Variable	Source	Frequency	Purpose
Gross domestic product	OECD QNA	Quarterly	Economic conditions
Short-term interest rate	OECD EO100	Quarterly	Global monetary stance
Consumer Price Index (CPI)	OECD QNA	Quarterly	Inflation proxy
GDP Deflator	OECD	Quarterly QNA archive	Price base consistency
Population (15–64)	OECD Hist. pop. data	Annual $\rightarrow$ quarterly	Scaling variable

- Each series is harmonized and, if necessary, rebased to $2010 = 100$.
- For population data, quarterly values are estimated using the Denton–Cholette disaggregation method.

Weighted Aggregation

We compute each partner's share in total GDP:

$$\text{share}_{i,t} = \frac{\text{GDP}_{i,t}}{\sum_j \text{GDP}_{j,t}}$$

Then, we aggregate across countries:

$$\text{wgdp}_t = \sum_i \text{share}_{i,t} \times \frac{\text{GDP}_{i,t}}{\text{POP}_{i,t} \times \text{DEF}_{i,t}},$$

$$\text{wcpi}_t = \sum_i \text{share}_{i,t} \times \text{CPI}_{i,t}.$$

Resulting files

The resulting dataset is saved as: `economic_data/df_w.rda`

2.6. New Zealand Series

New Zealand Series

For the **domestic bloc** in the empirical estimation, we need the following variables:

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

In the Replication Codes

- The data ar in the sheets of `data/economic_data/data_nz.xls`
- The importation and harmonization are performed in `02_2_data_import.R`.

GDP and Agricultural GDP

- We use real shares to split nominal GDP:
  - $\mathbf{GDP}_t^{\mathbf{nom}}$: Expenditure-based GDP, **nominal**, SA
  - $\mathbf{GDP}_t^{\mathbf{real}}$: GDP, **chain-volume** (real), SA.
  - $\text{AGRI}_t^{\text{real}}$: Agriculture GDP, **chain-volume** (real), SA.
- **Agricultural share** in real terms:

$$\text{agri\_share}_t = \frac{\text{AGRI}_t^{\text{real}}}{\text{GDP}_t^{\text{real}}}.$$

- **Agricultural GDP**:

$$\text{GDP}_t^a = \text{agri\_share}_t \times \text{GDP}_t^{\text{nom}}.$$

- **Non-agricultural nominal GDP** by subtraction:

$$\text{GDP}_t = \text{GDP}_t^{\text{nom}} - \text{GDP}_t^a.$$

2.7. Merge

Merging All Data

Combine all macroeconomic, external, and weather variables into a single quarterly dataset.

- New Zealand blocks: GDP, consumption, investment, trade, labor, prices, population, interest rate, REER, oil, share prices.
- Rest of World aggregates: weighted GDP, CPI, deflator, rate (`df_w.rda`).
- Climate indicator: SMDI.

In the Replication Codes

- The merge is performed in `02_2_data_import.R`.

2.8. Real Per-Capita Transformations and Detrending

Real Per-Capita Transformations and Detrending

Aim

Express all macro variables in real per-capita terms and remove long-run trends (with HP filters).

In the Replication Codes

- The real per capita transformation and the detrending are performed in `02_2_data_import.R`.

Real Per-Capita Transformations

- We express the quarterly macro variables in real per-capita terms:

$$
\begin{aligned}
r_y &= \frac{Y}{POP \times PP}, & r_{y^a} &= \frac{Y_A}{POP \times P_A}, \\
r_c &= \frac{C}{POP \times PP}, & r_i &= \frac{I_{\text{private}}}{POP \times PP}, \\
r_h &= H \times E, & r_w &= \frac{W}{PP}.
\end{aligned}
$$

  - where POP is a population index, PP is the GDP deflator, and P_A is an agricultural price index, all rebased to 2010=100

Detrending

- We detrend some series using the Hodrick–Prescott (HP) filter with quarterly smoothing parameter $\lambda = 1600$.
- Then, we compute the log-deviation from trend.

In the Replication Codes

- The functions used to detrend the data are in `02_1_seasonality.R`.

```
myfilter <- function(x) {
  res <- hp_filter(x)
  log(x / res) * 100   # log deviation in percentage
}
```

Detrending

```r
#' Applies the HP filter on a quarterly time serie
#' @param x Series for which to retrieve the trend.
#' @returns The trend part of the series.
#' @importFrom mFilter hpfilter
hp_filter <- function(x) {
  serie <- x
  if (any(is.na(x))) serie <- x[!is.na(x)]
  res <- hpfilter(serie, freq = 1600, type = "lambda")$trend |>
    as.vector()
  if (any(is.na(x))) {
    x[!is.na(x)] <- res
    res <- x
  }
  res
}
```

Output

- At this point, all macro variables **expressed as log deviations from trend**.
  - **Macroeconomic**: `y_obs`, `c_obs`, `i_obs`, `h_obs`, `w_obs`, `p_obs`, `r_obs`, etc.
  - **Agriculture**: `y_a_obs`, `p_a_obs`.
  - **External**: `wy_obs`, `wp_obs`, `wr_obs`, `reer_obs`.
  - **Climate**: `smdi_obs`.

Resulting files

- The output table, `df_finale`, is exported in `data/df_finale.rda`
- And in a CSV file: `data/df_finale.csv`.

3. Empirical Evidence with a VAR

Gathering Empirical Evidence from a VAR

- **How does the weather affect the economy?**
- Some **empirical facts** collected from a restricted VAR with three blocks:
  1. **Weather block**: drought index ($\hat{\omega}_t$)
  2. **Foreign block**: rest-of-world GDP ($\hat{y}_t^\star$)
  3. **Domestic block**: $\{\hat{y}_t, \hat{y}_t^A, \hat{\imath}_t, \hat{h}_t, \hat{q}_t, \widehat{rer}_t\}$
- Some (fair) **assumptions**:
  - Small open economy: domestic variables $\nrightarrow$ foreign variables,
  - Weather is exogenous.
- **Data**: New Zealand 1994Q2 to 2016Q4 saved in `data/df_finale.rda`

Restricted VAR

The VAR reads as:

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

weather: $X_t^W = \hat{\omega}_t$; **foreign variable:** $X_t^\star = \hat{y}_t^\star$; **domestic block**:

$$X_t^D = \begin{bmatrix} \hat{y}_t & \hat{y}_t^A & \hat{\imath}_t & \hat{h}_t & \hat{q}_t & \widehat{rer}_t \end{bmatrix} \quad (2)$$

The **restrictions** reflect the assumptions (small open economy, exogeneity of weather).

Roadmap

1. Assemble the data.
2. Prepare the VAR restriction matrices + estimate the VAR
3. Identify the SVAR by imposing contemporaneous (lower-triangular) structure + Estimate the parameters.
4. Compute the Impulse Response Functions (IRFs).

In the Replication Codes

- Launch the Rstudio Project file `var_estimation/estimation.Rproj`.
- In RStudio, open `01_restricted_var.R`.
- Note: Some helper functions to compute the IRFs are written in `var_estimation/assets/irf_varest.R`.

VAR Restriction Matrices

Aim

Impose block exogeneity.

- We build a binary mask R for one lag: $R_{ij} = 1$ if regressor j is allowed in equation i, else 0.

$$\begin{bmatrix} A_l^{11} & 0 & 0 \\ 0 & A_l^{22} & 0 \\ A_l^{31} & A_l^{32} & A_l^{33} \end{bmatrix}$$

- This is contained in `A_l_restrict`.

Estimating the Restricted VAR

- The choice of lags can be made using an information criterion such as the AIC or the Hannan & Quinn criterion, with `VARselect()` from {vars}.

```
VARselect(data, lag.max = 4, type = "const")
L <-  1
```

- The, we estimate the restrained VAR with the lag restrictions with the `restrict()` function from {vars}

```
var_1 <- VAR(data, p = L, type = "const")
var_res <- restrict(var_1, method = "manual", resmat = A_l_restrict)
```

From Restricted to Structural VAR

- Once the restricted VAR is estimated, we further impose structure on the **contemporaneous relationships** among variables.
- The Structural VAR (SVAR) model is written as:

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

  where:

  - A_0 is a lower triangular matrix encoding contemporaneous restrictions,
  - η_t are the **orthogonal structural shocks**.
- These restrictions identify the structural innovations consistent with our **economic assumptions.**

The lower-triangular matrix A_0

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & 1 & 0 & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 & 0 & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & 1 & 0 & 0 \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & 1 & 0 \\ b_{81} & b_{82} & b_{83} & b_{84} & b_{85} & b_{86} & b_{87} & 1 \end{bmatrix}$$

- **Restricted VAR**: we enforce weather/foreign as exogenous blocks in the lag structure.
- A_0: adds contemporaneous exogeneity weather and foreign do not react within the quarter to domestic shocks, while domestic variables may react instantly to them.
  - Variables ordered earlier can contemporaneously affect variables ordered later, but not the other way around.
- **1s in the diagonal**: fixes the scale of each equation so that the shocks η_t are structural shocks, i.e., orthogonal and scaled, which is required to compute the IRFs.
  - to have 1 s.d. structural shock in the IRFs

The lower-triangular matrix A_0 in R and the SVAR Estimation

- The matrix A_0 is defined:

```
amat <- A_l_restrict
amat[amat == 1] <- NA
amat <- amat[, -which(colnames(amat) == "const")]
amat[upper.tri(amat)] <- 0
diag(amat) <- 1
```

- And the SVAR is estimated using the `SVAR()` function from {vars}:

```
svar_est <- SVAR(
    x = var_res, Amat = amat, Bmat = NULL, estmethod = "direct"
)
```

Impulse Response Functions

- We compute the IRFs to a **weather shock**
  - Horizon: 20 quarters; *10,000* Monte-Carlo draws,
  - 68%/95% bands.
- We adapted `vars:::irf.varest()` so that it works with a restricted VAR.

In the Replication Codes

- The functions to compute the IRFs are located in `car_estimation/assets/irf_varest.R`:
  - `irf_varest()`: compute IRF (wraper function),
  - `irf_internal()`: actually computes the IRFs given a VAR or SVAR model.
  - `boot_internal()`: generate empirical distributions of IRFs by resampling residuals.

Computing and Simulating Impulse Responses

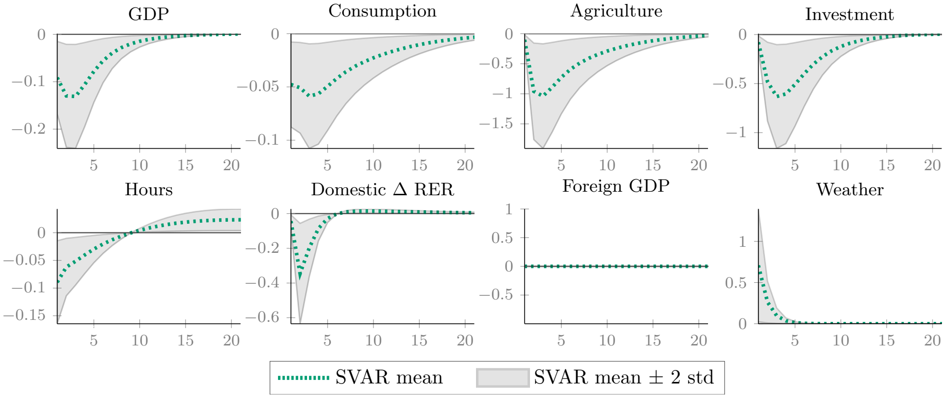
- We first compute the IRFs from the estimated SVAR:

```
irfs <- irf(
  svar_est, n.ahead = last_lag, boot = FALSE,
  cumulative = FALSE, ortho = TRUE, seed = 1
)
```

- Then, we run Monte Carlo simulation for uncertainty bands:
  - With the function `irfs_mc()` we draw many random shocks ($N = 10{,}000$) and rescales the IRF for each draw.
  - The simulated responses are summarized into 68% and 95% credible intervals:

$$\text{IRF}_h^{(s)} = \varepsilon_s \cdot \text{IRF}_h, \quad \varepsilon_s \sim \mathcal{N}(0,1)$$

Propagation of a Weather Shock (1/2)



Notes: Green line: **IRF**. Gray band: **95% error band** obtained from 10,000 Monte-Carlo simulations. Response horizon in quarters. Y-axis: percent deviation from the steady state.

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

Propagation of a Weather Shock (2/2)

Business cycles facts :

1. A **weather shock (a drought)** generates a recession...
2. But hours worked remains acyclical ($\neq$a sectoral TFP shock).
3. Internationally, **weather** depresses the domestic real exchange rate (NZ\$ $\searrow$).

Next step : build a macro-model which features these business cycle facts.

4. An Estimated DSGE Model

A Sketch of the Model (1/3)

- **DSGE model** in an RBC framework (no nominal effects+rational expectations)
- Small open economy (home vs world)
- **Two sectors**:
  - weather-dependent agricultural sector (**original feature**)
  - standard non-agricultural sector
- **Weather shocks** affect the agricultural sector (**original feature**)

A Sketch of the Model (2/3)

1. Farmers face **exogenous weather**.
2. They can **offset** bad weather conditions by purchasing goods in the non-agricultural sector.
3. This leads to **spillover effects** between the two sectors.

A Sketch of the Model (3/3)

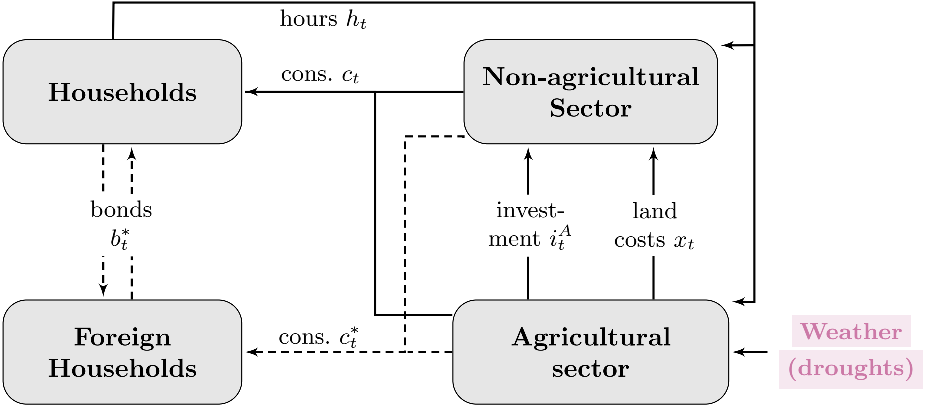


Figure 2: The Model.

Agricultural sector and the weather

- The weather follows an univariate stochastic exogenous process:

$$\log(\varepsilon_t^W) = \rho_W \log(\varepsilon_{t-1}^W) + \sigma_W \eta_t^W, \qquad \eta_t^W \sim \mathcal{N}(0,1) \tag{3}$$

  where $\varepsilon_t^W > 1$ features a **drought**.

- Each farmer $i \in [n, 1]$ has a **land endowment ℓ_{it}** whose time-varying productivity (or efficiency) writes:

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

  - $\delta_\ell \in (0,1)$ is the rate of decay of land efficiency;
  - x_{it} are intermediate goods to maintain land efficiency (crops, water, fertilizers...);
  - $\Omega\left(\varepsilon_t^W\right)$ is a **weather damage function** (discussed after).

Agricultural sector and the weather (1/3)

- We opt for a simple functional form for this **damage function**:

$$\Omega\left(\varepsilon_t^W\right) = \left(\varepsilon_t^W\right)^{-\theta}, \tag{5}$$

  where θ is the **elasticity of land productivity** with respect to the weather variations.

- Following IAMs models pioneered by Nordhaus (1991), the damage function bridges the weather with economic conditions.

- To avoid concerns from Pindyck (2017):

  1. Our setup is linear (i.e., we don't exploit the non-linearity of the damage function).
  2. θ is estimated agnostically (through a very diffuse prior).

Agricultural sector and the weather (2/3)

- **Profits of the farmer**:

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

- For the **land cost function** $v\left(x_{it}\right)$, we opt for an unopiniated form:

$$v\left(x_{it}\right) = \frac{\tau}{1+\phi} x_{it}^{1+\phi}$$

$\tau > 0$: scale parameter; ϕ: **elasticity of intermediate input to land**:

  - $\phi > 0$ land costs exhibits increasing returns, $\phi = 0$ linear returns and $\phi < 0$ decreasing returns.
  - Data favors $\phi \geq 0$ (as weather shocks generate recessions).

Agricultural sector and the weather (3/3)

- Lastly, the optimization of profits is given by:

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

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

$$s.t.\ i_{it}^A = k_{it}^A - (1-\delta_K)\, k_{it-1}^A$$

- FOC on land ℓ_{it}:

$$\underbrace{p_t^N v'\left(x_{it}\right)}_{\text{current marginal land cost}} = \underbrace{E_t \left\{ \Lambda_{t,t+1} \left[\omega p_{t+1}^A \frac{y_{it+1}^N}{\ell_{it}} + (1-\delta_\ell)\, \Omega\left(\varepsilon_{t+1}^W\right) p_{t+1}^N v'\left(x_{it+1}\right) \right] \right\}}_{\text{expected marginal gains}}$$

The DSGE Model and Replication Material

In the Replication Codes in git /scripts/dsge/

- **Model solved in Dynare v6.x (MATLAB environment)**
  Estimated with quarterly New Zealand data (`dataNZ_cubic_trend.m`)
- **Structure of the replication folder:**
  - `RBC_q0.mod` — Estimated model **without weather shocks**.
  - `RBC_q1.mod` — Baseline estimated model **with weather shocks**.
  - `COMPARE.mod` — Script comparing model fit across specifications.
  - `dataNZ_cubic_trend.m` — Input dataset (New Zealand macroeconomic data).
- **Core results:** these can be found in `thenotebook.mlx`

4.1. Estimation

Running the Estimated DSGE Model with Weather Shocks

MATLAB

- Set the working directory to `scripts/dsge/` where `RBC_q1.mod` is stored
- Make sure dynare is in set in path
- Write in Console window:

```
dynare RBC_q1
```

- This command:
  - Loads and solves the model at the **posterior mean** of estimated parameters.
  - Displays smoothed estimates for endogenous variables.
- The resulting estimated model can then be used for quantitative analysis.

Estimation

		Prior distributions			Posterior distribution	
		Shape	Mean	Std.	Mean	[5%:95%]
σ_H	Labor disutility	$\mathcal{B}$	2	0.75	1.87	*[1.32:2.40]*
b	Consumption habits	$\mathcal{B}$	0.7	0.10	0.82	*[0.74:0.90]*
ι	Labor sectoral cost	$\mathcal{G}$	2	1	2.32	*[1.36:3.31]*
κ	Investment cost	$\mathcal{N}$	4	1.50	1.83	*[0.77:2.91]*
μ	Subst. by type of goods	$\mathcal{G}$	1.5	0.8	4.93	*[3.53:6.26]*
μ_N	Subst. home/foreign	$\mathcal{G}$	1.5	0.8	1.91	*[0.86:2.94]*
μ_A	Subst. home/foreign	$\mathcal{G}$	1.5	0.8	0.41	*[0.26:0.56]*
ϕ	Land expenditures cost	$\mathcal{G}$	1	0.60	0.76	*[0.02:1.51]*
θ	Land-weather elasticity	$\mathcal{U}$	0	10	8.62	*[2.3:15.78]*
	Marginal log-likelihood				-1012.83	

Table 1: Prior and posterior distributions of structural parameters.

4.2. Business Cycle Analysis

The Live Script: `thenotebook.mlx`

- The MATLAB Live Script `thenotebook.mlx` provides a **self-contained and reproducible workflow** for the DSGE model.
- It can be executed cell-by-cell to generate all the key results of the paper:
  - **Table 6:** Steady-state ratios (c/y, i/y, openness, etc.)
  - **Table 7:** Business-cycle second moments
  - **Figure 7:** Impulse responses to weather shocks (η_s)
  - **Figure 8:** Historical decomposition ("All shocks" vs. "Weather only")
  - **Variance decomposition:** Forecast error variance by shock group (Q2–Q∞)
  - ...

Weather shock propagation

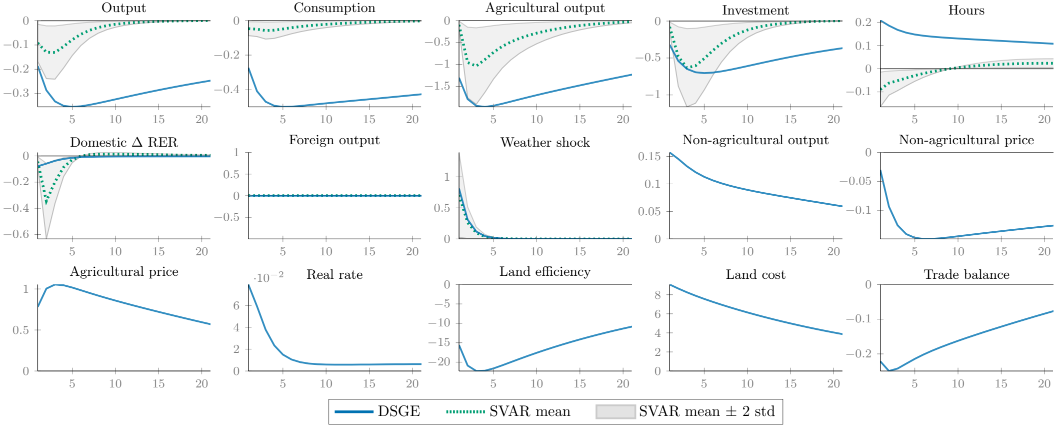


Figure 3: System response to an estimated weather shock η_t^W (pp dev ss).

Variance decomposition

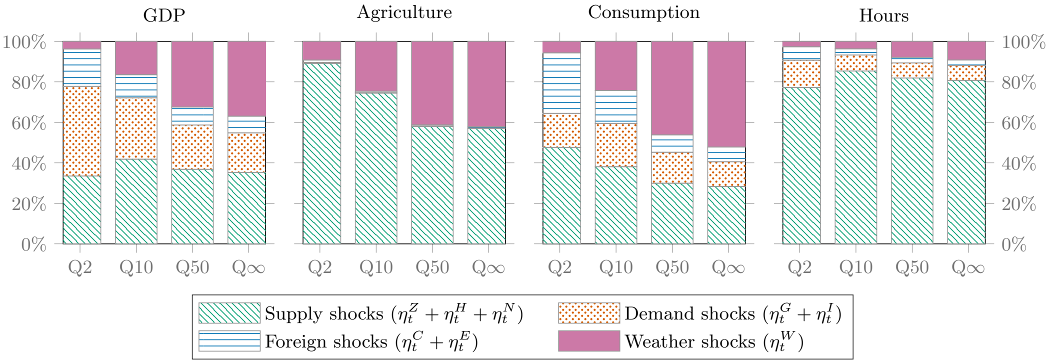


Figure 4: Forecast error variance decomposition at the posterior mean for different time horizons (one, ten, forty and unconditional) for four observable variables.

4.3. Climate Change

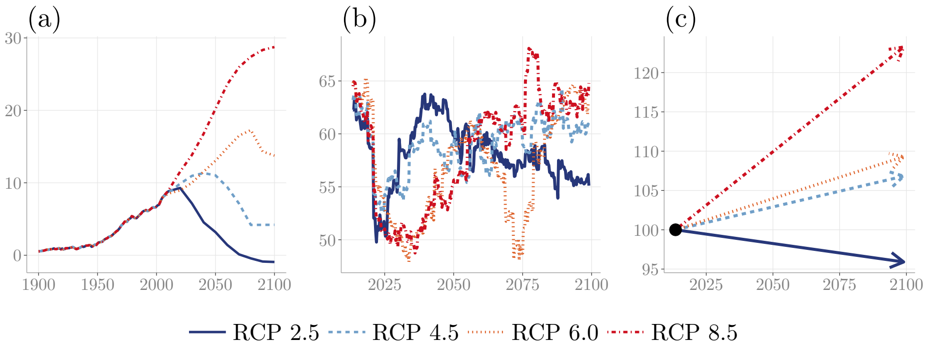
Climate change and Business Cycles

> "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)

- Climate is supposed to be stationary in our framework: our set-up is irrelevant for analyzing changes in **mean climate values**.
- However, it allows for changes in the **variance of climate**.

Climate change and business cycles

- How much is the weather variance expected to increase?



Notes: (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).

Climate Projections: Data & Aggregation

Aim

Approximate climate change by increasing the variance of weather shocks.

- We build quarterly, national precipitation series under four RCP scenarios and use them to study time-varying volatility.
- We rely on CMIP5, CCSM4, monthly data for precipitation (soil moisture is not available):
  - **Historical data**: 1850–2005 (we use data starting from 1960)
  - **Scenarios** (RCP 2.6/4.5/6.0/8.5): 2006–2100.
- We spatially aggregate the data at the national level using agricultural weights.
- And we temporally aggregate the monthly data at the quarterly level.

Roadmap

In the Replication Codes

- Launch the RStudio project file `data/climate_data/climate_data.Rproj`.
- In the RStudio window that appeared, open the R script `04_projections.R`

1. Download climate projections.
2. Aggregate data.
3. Compute the variance of the weather under different scenarios.

4.4. Download Data

Download Climate Scenarios and Model Output

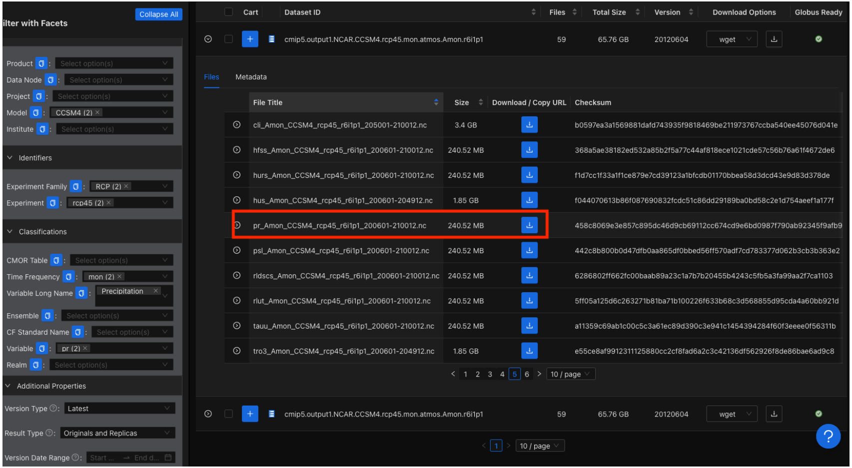
- Global climate models simulate the physical processes driving the Earth's climate.
- They are run under standardized **Representative Concentration Pathways** (RCPs), each describing a greenhouse gas concentration trajectory up to 2100:
  - **RCP 2.6**: strong mitigation (radiative forcing peaks at 2.6 W/m^2)
  - **RCP 4.5**: stabilization without overshoot (4.5 W/m^2)
  - **RCP 6.0**: intermediate scenario (6.0 W/m^2)
  - **RCP 8.5**: high-emission 'business-as-usual' (8.5 W/m^2)
- We use monthly precipitation projections simulated by the NCAR CCSM4 model under these RCP scenarios from 2006 to 2100.
- They can be downloaded here: ESGF MetaGrid, and saved in the `data/climate_data/projections` folder.

The NetCDF Files

- The files are (again) NetCDF files.
- We download one for each scenario, and one for historical data.
- The name of the file is informative. For example:
  `pr_Amon_CCSM4_rcp45_r6i1p1_200601-210012.nc`

`pr`	Variable: precipitation ($\mathrm{kg\,m^{-2}\,s^{-1}}$)
`Amon`	Atmospheric variable, monthly frequency
`CCSM4`	Model: *Community Climate System Model*, version 4 (NCAR)
`rcp45`	Scenario: RCP 4.5
`r6i1p1`	Ensemble member: run 6, initialization 1, physics 1
`200601-210012`	Time period: Jan. 2006 – Dec. 2100

ESGF MetaGrid



Example for RCP 4.5 🌐 https://aims2.llnl.gov/search/cmip5/

4.5. Aggregation

Aggregation

- As earlier, we use **regional weights** to aggregate the data at the national level:
  - the weights are representative of the agricultural intensity of each region over the period 1987–2014.
- For **temporal aggregation**, we simply sum the monthly national averages of precipitation over the 3-months that define the quarters.
- At the end of the day, we have **quarterly national values** for the **historical dataset** (1960Q1–2005Q4) and **each of the four RCP scenarios** (2006Q1–2100Q1).

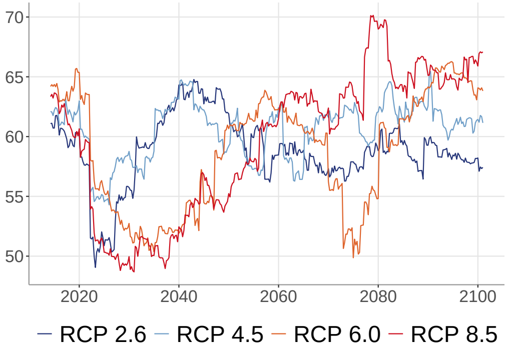
4.6. Variance of the weather

Rolling Estimation of Local Volatility

- We use a rolling window of **102 quarters** (25.5 years), matching the DSGE sample size.
- Within each window, we fit an AR(1) model:

$$P_\tau = \mu + \phi\, P_{\tau-1} + \varepsilon_\tau,$$

- And we store $\widehat{\sigma}_t = \mathrm{sd}(\widehat{\varepsilon}_\tau)$, giving a **time-varying standard deviation** of the weather shock.



Estimated time-varying standard deviation of precipitation.

Estimation of the Growth of Weather-Shock Volatility

- For each scenario, we estimate a log–linear trend in the rolling standard deviations:

$$\ln(\widehat{\sigma}_t) = \alpha + \beta t + u_t.$$

  - β: **instantaneous quarterly growth rate** of the volatility of precip. shocks.

- This translated to **long-run growth rates**:

$$\sigma_{i,\eta^W} = e^{\beta} - 1$$

- Average growth over 1989–2100:

$$\overline{\Delta\sigma_{i,\eta^W}} = (1 + \sigma_{i,\eta^W})^q - 1, \quad q = 347$$

Warning

The growth rates (object `growth_rates`) are a bit different than those reported in the paper: the region-wise aggregation is a bit different.

Values Obtained in R Used in MATLAB

- The values obtained in R (column `tot_growth`):

```
> 1 + growth_rates$tot_growth / 100
 RCP 2.6  RCP 4.5  RCP 6.0  RCP 8.5
1.002573 1.047109 1.114458 1.300868
```

In the Replication Codes (MATLAB)

- In `thenotebook.mlx`, these values can be set in `set_param_value('sig_s',the_sig_s*1.002573);`

Climate change and business cycles: Results (from the paper)

In the Replication Codes

See one of the last exercises of `thenotebook.mlx`

		1994-2016	2100 (projections)			
		Benchmark	RCP 2.6	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
E($\mathcal{W}_t$)	Welfare	-158.02	-158.00	-158.04	-158.06	-158.13
λ (%)	Welfare cost	0.4023	0.3562	0.4417	0.4623	0.5873

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

5. Next Time

Next Time

- **Next Session: Practical Implementation and Extensions**
  - **Weather data:** Extracting and processing New Zealand weather data in `R`.
  - **VAR model:** Building and estimating a Structural VAR including weather shocks in `R`.
  - **DSGE model:** Reviewing the Dynare code and running simulations in `MATLAB`.
  - Notebooks: https://3wen.github.io/weathershocks
- **Extended Applications:**
  - Constructing a **weather index** for another country using gridded datasets.
  - Exploring the **main building blocks of the DSGE model** and how to extend them (a minimalist example code will be provided).

6. Appendix

References I

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Narasimhan, B. and Srinivasan, R. (2005). Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology*, 133(1):69–88. doi:10.1016/j.agrformet.2005.07.012.

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The economic journal*, 101(407):920–937. doi:10.2307/2233864.

Pindyck, R. S. (2017). The use and misuse of models for climate policy. *Review of Environmental Economics and Policy*, 11(1):100–114. doi:10.1093/reep/rew012.

Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate*, 23(7):1696–1718.

Households (1/2)

There are j households maximizing welfare index:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\sigma_C} C_{jt+\tau}^{1-\sigma_C} - \frac{\chi}{1+\sigma_H} h_{jt+\tau}^{1+\sigma_H} \right] C_{t-1+\tau}^{b\sigma_C}, \tag{6}$$

With an imperfect substitutability of labor supplies between the agricultural and non-agricultural sectors:

$$h_{jt} = \left[\left(h_{jt}^{N} \right)^{1+\iota} + \left(h_{jt}^{A} \right)^{1+\iota} \right]^{1/(1+\iota)}. \tag{7}$$

And real budget constraint:

$$\sum_{s=N,A} w_t^s h_{jt}^s + r_{t-1} b_{jt-1} + rer_t r_{t-1}^{*} b_{jt-1}^{*} - T_t \geq C_{jt} + b_{jt} + rer_t b_{jt}^{*} + p_t^N rer_t \Phi(b_{jt}^{*}). \tag{8}$$

Households (2/2)

- The CES consumption bundle between non-agricultural and agricultural goods is determined by :

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}}(C_{jt}^{N})^{\frac{\mu-1}{\mu}} + \left(\varphi\varepsilon_{t}^{A}\right)^{\frac{1}{\mu}}(C_{jt}^{A})^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}}, \tag{9}$$

with $P_t = [(1-\varphi)(P_{C,t}^{N})^{1-\mu} + \varphi(P_{C,t}^{A})^{1-\mu}]^{1/(1-\mu)}$.

- In addition, each C_{jt}^{N} and C_{jt}^{A} are themselves sub-indexes between home and foreign goods:

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

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

Non-agricultural sector

- There is a continuum of firms indexed by $i \in [0, n]$ maximizing profits:

$$d_{it}^{N} = p_t^N y_{it}^N - p_t^N \left(i_{it}^N + S\left(\varepsilon_t^i \frac{i_{it}^N}{i_{it-1}^N}\right) i_{it-1}^N \right) - w_t^N h_{it}^N, \tag{10}$$

- Technology:

$$y_{it}^N = \varepsilon_t^Z \left(k_{it-1}^N\right)^{\alpha} \left(h_{it}^N\right)^{1-\alpha}, \tag{11}$$

- Law of motion of physical capital

$$i_{it}^N = k_{it}^N - (1 - \delta_K)\, k_{it-1}^N, \tag{12}$$

Foreign Economy

- Endowment economy with exogenous consumption:

$$\log\left(c_{jt}^{*}\right) = (1-\rho_{*})\log\left(\bar{c}_{j}^{*}\right) + \rho_{*}\log\left(c_{jt-1}^{*}\right) + \sigma_{*}\eta_{t}^{*},$$

- Foreign households solve:

$$\max_{\left\{c_{jt}^{*}, b_{jt}^{*}\right\}} \sum_{\tau=0}^{\infty} \beta^{\tau} E_t \left\{\mathcal{U}\left(c_{jt+\tau}^{*}, c_{t-1+\tau}^{*}\right)\right\},$$

$$s.t. \; : r_{t-1}^{*} b_{jt-1}^{*} = c_{jt}^{*} + b_{jt}^{*}$$

- So that foreign consumption shocks affect the domestic country through imports and the real exchange rate.

Market Clearing (1/3)

- Non agricultural sector clears:

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

where $I_t = nI_t^N + (1-n)\,I_t^A$..

Market Clearing (2/3)

- Agricultural sector clears:

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

- Total production reads as:

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

Market Clearing (3/3)

- The law of motion of motion of foreign debt is given by:

$$b_t^* = r_{t-1}^* \frac{rer_t}{rer_{t-1}} b_{t-1}^* + tb_t, \tag{13}$$

- And the trade balance reads as:

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

Calibration (1/2)

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.

Calibration (2/2)

Variable	Interpretation	Model	Data
$\bar{C}/\bar{Y}$	consumption-to-GDP	0.56	0.57
$\bar{I}/\bar{Y}$	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
$n\bar{Y}^A/\bar{Y}$	farming production-to-GDP	0.08	0.07

Table 4: Steady state ratios (empirical ratios are computed using data between 1990 to 2017).

Estimation (1/3)

The model is estimated using Bayesian techniques which combine likelihood estimation with prior information via Dynare.

- We estimate 6 sequences of shocks
- We estimate 21 structural parameters
- Parameters related to weather conditions are estimated agnostically with diffuse prior.

Estimation (2/3)

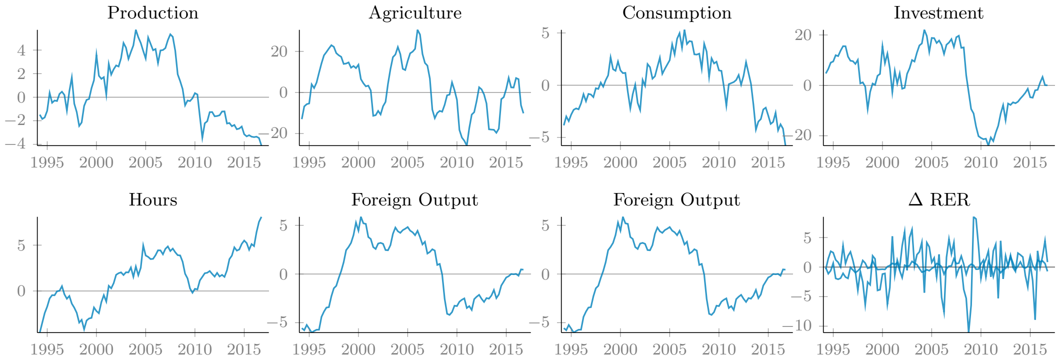

Figure 5: Observable variables used to estimate the DSGE model.

Estimation (3/3)

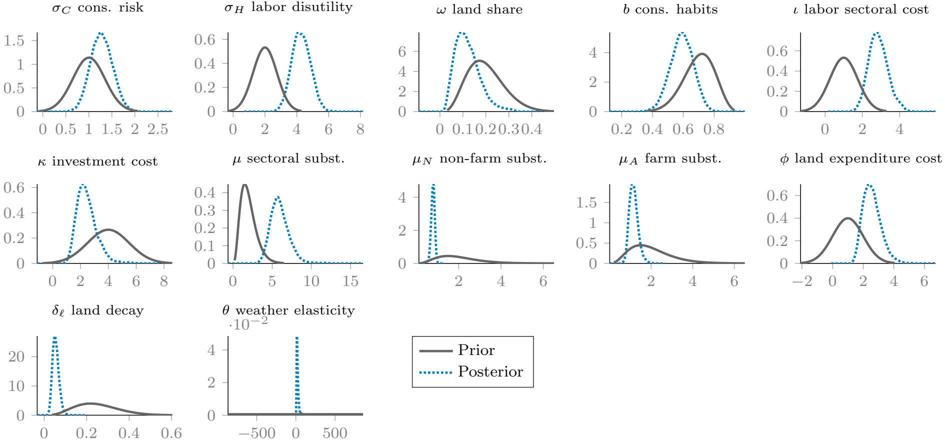

Figure 6: Prior and posterior distrib. of structural params for New Zealand (excluding shocks).

Do weather shocks matter?

	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 5: Prior and posterior model probabilities.