Southeast Asian Journal of Economics Vol.12(1), April 2024: 77-124
Received: 17 June 2023
Revision: 31 August 2023
Accepted: 31 October 2023

Economic Impacts of Climate Change in Thailand: Theory and Evidence

Chestapan Jaipiam

Faculty of Economics, Chulalongkorn University, Bangkok, Thailand

Corresponding author: Chestapan.J@gmail.com

Abstract

Climate change, characterized by not only rising average temperatures but also intensifying extreme weather events such as floods and droughts, poses substantial risks to the production of goods and services. This study investigates the implications of these extreme weather conditions on Thailand's macroeconomy, utilizing the Standardized Precipitation-Evapotranspiration Index (SPEI) to measure drought conditions. Through the analysis of both the Dynamic Stochastic General Equilibrium (DSGE) and Structural Vector Autoregression (SVAR) models, extreme weather conditions have a significant negative impact on short-run macroeconomic performance, causing disruptions in production and domestic demand while simultaneously driving up agricultural prices. Notably, the counterfactual analyses reveal that policy measures designed to adapt to climate change and enhance labor mobility across sectors markedly alleviate the detrimental economic consequences of climatic extremes. Consequently, this underscores the pivotal role of adaptive climate and labor migration policies in mitigating the adverse impacts of climate change on Thailand's macroeconomy.

Keywords: business cycle, climate change, climate shocks, DSGE models, small open economy, structural VAR models

1. Introduction

"Unlike many of the wolf cries, this one [climate change], in my opinion, should be taken very seriously." – Nobel Laureate William Nordhaus in the American Economic Review in 1977

In Aesop's fable "The Boy Who Cried Wolf," the boy lies to the villagers, claiming that a wolf is attacking. However, climate scientists are not deceiving us. Currently, there is a solid scientific consensus that the wolf [climate change] is truly at the gate, posing an imminent threat to humanity. The 2021 Intergovernmental Panel on Climate Change (IPCC) report is referred to as "the code red for humanity." Climate change affects every aspect of human life, including the economy. Extreme weather events, such as floods and droughts, can disrupt the production of goods and services, especially in the agricultural sector.

This paper examines the economic impacts of climate change in Thailand. According to the Global Climate Risk Index (Eckstein et al., 2021), Thailand is ranked ninth globally in terms of countries most affected by climate risks for the years 2000–2019. Moreover, Thailand, one of the world's largest food producers and still a developing country, has approximately one-third of its population working in the agricultural sector. This situation implies that the country is highly vulnerable to climate change since droughts and floods can pose significant threats to agricultural production.

The literature on macroeconomic modeling of climate change is dominated by the integrated assessment models (IAMs) pioneered by Nordhaus (1991). These models assume that economic activities generate greenhouse gases, which consequently lead to an increase in temperature. Subsequently, a rise in temperature negatively affects economic activity through a damage function. Despite their prevalent use and policy influence, the IAMs have faced widespread criticism, ranging from philosophers to mainstream economists. The models are deterministic by nature and, as a result, do not adequately address the uncertainty associated with climate change. Furthermore, the models heavily rely on a calibration exercise, especially in the choice of the damage function. Pindyck (2013) pointed out that the models are "close to useless" and "completely ad hoc, with no theoretical or empirical foundation."

This paper aims to directly address this problem. Two approaches are utilized, including both theoretical and empirical models, to quantify the economic impacts of climate change. To address Pindyck's critique, both models are estimated using an observable climate variable, the Standardized Precipitation-Evapotranspiration Index (SPEI), which captures the degree of floods and droughts in a specific area. The SPEI index is one of the most novel drought indices and is widely used in the geography literature. Additionally, a Global SPEI Database is available, covering all parts of the world, and is easily accessible.

First, the dynamic stochastic general equilibrium (DSGE) model is employed to establish the theoretical foundation of the transmission mechanism of climate shocks in a small open economy setting. Unlike the IAMs, this model is inherently stochastic and explicitly includes shocks to account for uncertainty. Moreover, this model enables experiments to be conducted to observe how the impulse response changes under different calibrations of the structural parameters. Nevertheless, most environmental DSGE models investigate the effects of climate change policies, such as optimal taxes on fossil fuels (Golosov et al., 2014), while only a few studies examine climate shocks. For instance, Hashimoto and Sudo (2022) developed the DSGE model of the Japanese economy using flood events, and Gallic and Vermandel (2020) built the DSGE model of the New Zealand economy using the Soil Moisture Deficit Index (SMDI). The latter assumed that climate shocks affect the economy through the agricultural sector. In this paper, Gallic and Vermandel's (2020) DSGE model is modified to suit the structure of the Thai economy and is estimated using the SPEI index instead. Thailand is still a developing country, whereas New Zealand is already a developed country. Moreover, even though the SPEI index reflects wet/dry weather conditions worse than the SMDI index (Hou et al., 2022), it is available globally, including Thailand. In addition, a counterfactual experiment was conducted on the damage function parameter, which was not done by Gallic and Vermandel (2020).

Second, the structural vector autoregression (SVAR) model is used to validate the theoretical results obtained from the DSGE model. The SVAR model relaxes the strong economic restrictions in the DSGE model and reveals the reduced-form relationship between variables within the model. The identification technique for the SVAR model for a small open economy was initially developed by Cushman and Zha (1997). Subsequently, Buckle et al. (2007) proposed an empirical framework based on this technique to estimate the impacts of various shocks influencing the business cycle, including climate shocks. Recent empirical studies have focused on investigating the roles of climate shocks in agricultural countries such as New Zealand (Kamber et al., 2013; Gallic & Vermandel, 2020) and Thailand (Jirophat et al., 2022). In this paper, the SVAR model is constructed similarly in spirit to Kamber et al. (2013), Gallic and Vermandel (2020), and Jirophat et al. (2022).

This paper follows the framework proposed by Gallic and Vermandel (2020), which seeks to reconcile these two approaches in the literature of macroeconomic modeling of climate change. Since the DSGE model is estimated using the Bayesian technique introduced by Smets and Wouters

(2007), it can be compared to the SVAR model (Sims, 2012). Unlike the SVAR model, which treats the economy as a single black box, the DSGE model provides a structural relationship between all economic agents and their optimizing behaviors (Sims, 2012). This means that the DSGE model yields a more detailed understanding of the propagation mechanisms of climate shocks, allowing for the execution of counterfactual experiments. However, the SVAR model is still essential in this paper for three reasons. First, the SVAR model typically fits the data better than the DSGE model (Sims, 2012). Second, unlike the DSGE model, which restricts the direct impacts of climate change on the economy to agriculture, the SVAR model permits direct impacts through other channels, including all other domestic variables in the model, which appears to be more realistic. Third, the results from the SVAR model can be directly compared with the previous study in Thailand by Jirophat et al. (2022).

This paper makes two significant contributions to the understanding of the Thai economy. First, to the best of our knowledge, this is the first study on the effects of climate change using the DSGE model in Thailand. Most DSGE studies in Thailand have predominantly focused on monetary policy (Tanboon, 2008; Phrommin, 2018; Kubo & Hirao, 2020; Amatyakul et al., 2021; Luangaram & Wongpunya, 2022), with only a few exploring other topics, such as tourism (Wannapan et al., 2018). Second, while Jirophat et al. (2022) previously examined the macroeconomic impacts of climate shocks in Thailand using the SVAR model and the SPEI index, we enhance the credibility of the results by utilizing a different SPEI dataset with finer spatial resolution and more extensive data required for estimation. In addition, a different set of macroeconomic variables is incorporated and detrended using a distinct method to align with the DSGE model. The concurrent use of both theoretical and empirical models also provides a more comprehensive analysis.

Two main results are obtained from the two aforementioned models. First, climate shocks significantly reduce output in both models. Despite differences in the magnitude of effects (0.11 percent in the DSGE model versus 0.38 percent in the SVAR model) and the time climate shocks take to dissipate (more than 25 quarters in the DSGE model versus 13 quarters in the SVAR model), both models demonstrate a similar transmission mechanism of climate shocks. The mechanism includes both a supply-side decline in agricultural output and a demand-side drop in consumption and investment. Second, the price significantly increases only in the agricultural sector for the DSGE model, and climate shocks lead to food inflation in the SVAR model. However, the price does not significantly change in the non-agricultural sector for the DSGE model, and climate shocks do not affect headline inflation for the SVAR model.

Regarding policy implications, in addition to climate mitigation policy aimed at reducing the size of climate shocks, the findings from counterfactual experiments underscore the necessity of implementing climate adaptation and labor migration policies to effectively mitigate the impacts of climate shocks. The former helps reduce the decline in land productivity after climate shocks, resulting in a smaller decrease in agricultural output. The latter facilitates labor migration from the agricultural sector, which is highly susceptible to climate change, to the non-agricultural sector. This, in turn, enables the non-agricultural sector to better absorb the impacts of climate shocks.

The remainder of the paper is organized as follows. Section 2 discusses the climate change measurement used in this paper. Sections 3 to 4 introduce the theoretical model, the DSGE model, to examine the transmission mechanism of climate shocks. Section 5 presents the empirical evidence from the SVAR model, confirming the theoretical results. Section 6 concludes the paper.

2. Climate measurement

The stream of literature usually focuses on two main measures of climate change—temperature and precipitation—as they directly impact economic activities. However, using each variable separately does not provide a comprehensive view of climate conditions. Therefore, the decision was made to utilize the drought index, which combines the effects of changing temperature and precipitation. The most recent and commonly used drought index[1] is the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano (2010). It has been used to model the macroeconomic impacts of climate change in a panel of countries (Generoso et al., 2020) as well as in Thailand (Jirophat et al., 2022).

2.1 SPEI characteristics

The SPEI index is calculated as the difference between precipitation and potential evapotranspiration (PET), representing a climatic water balance. It can be computed at various time scales, ranging from weeks to months. The index is standardized, meaning it indicates the deviation of weather conditions from the historical norm, which has a value of zero. A positive value implies wetter-than-normal weather conditions, while a negative value implies drier-than-normal weather conditions.

2.2 SPEI data collection

The SPEI index was obtained from https://spei.csic.es/, where there are 2 SPEI datasets: SPEI Global Drought Monitor and Global SPEI Database. Each dataset contains grids of monthly time series covering all global land. The key features of each dataset are summarized in Table 1.

[1] Other commonly used drought indices include the Palmer Drought Severity Index (PDSI) (Palmer, 1965) and Standardized Precipitation Index (SPI) (McKee et al., 1993).

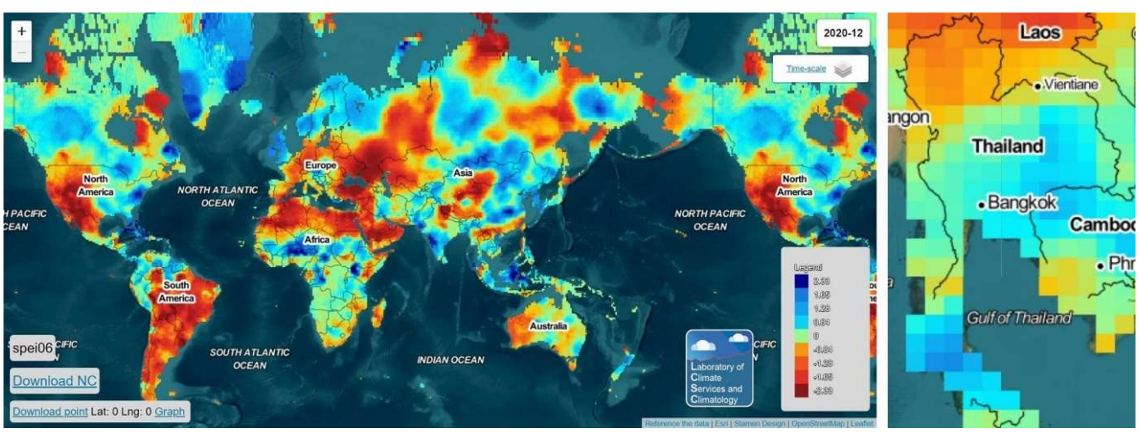
Table 1. SPEI datasets

Characteristics	SPEI Global Drought Monitor	Global SPEI Database
Availability	January 1950–Present	January 1901–December 2020
Spatial Resolution	1 degree	0.5 degrees
Number of Grids for Thailand	60 grids	200 grids
PET Estimation Method	Thornthwaite equation (1948)	FAO 56 Penman-Monteith equation (1998)
Data Requirements	Small (temperature and duration of daylight)	Large (temperature, wind speed, relative humidity, and solar radiation)
Advantage	Near real-time SPEI	Robust method of SPEI estimation
Recommended Usage	Drought monitoring and early warning	Long-term climatological analysis

Notes: Global SPEI Database refers to version 2.7. The newer version has greater data availability.

Due to its superior features, the Global SPEI Database version 2.7[2] (see Figure 1) was chosen instead of the SPEI Global Drought Monitor used by Jirophat et al. (2022).

Figure 1. Map of SPEI grids from the Global SPEI Database



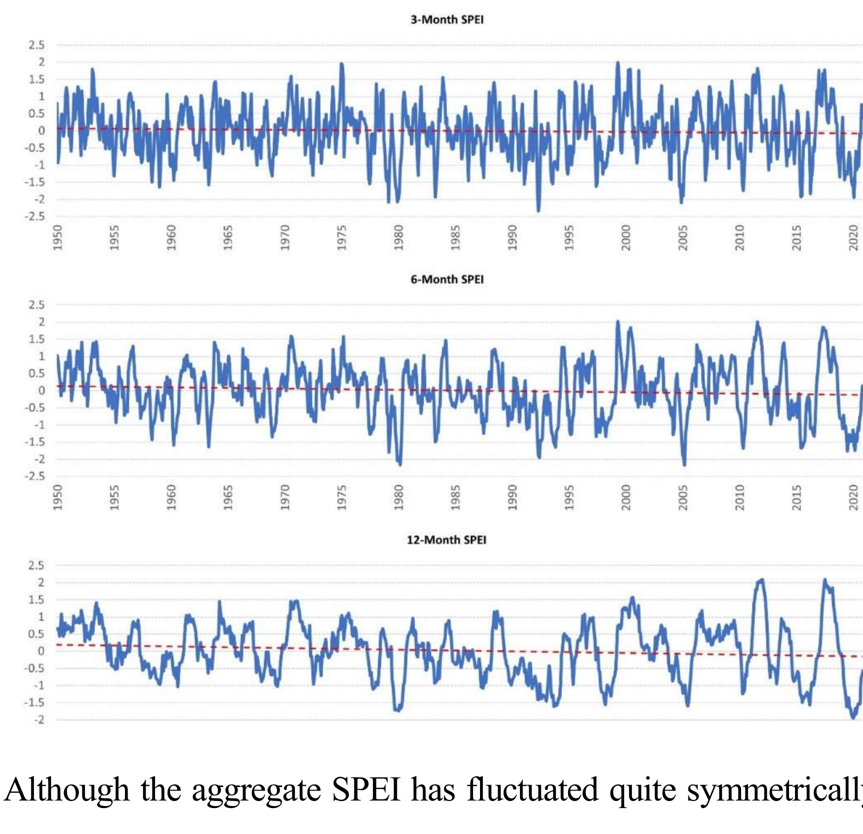
Notes: The figure on the left is the world map, while the figure on the right is the map of Thailand.

[2] The dataset is stored in NetCDF format, which can be dealt with using the R package called "ncdf4".

2.3 Time-series patterns of climate change in Thailand

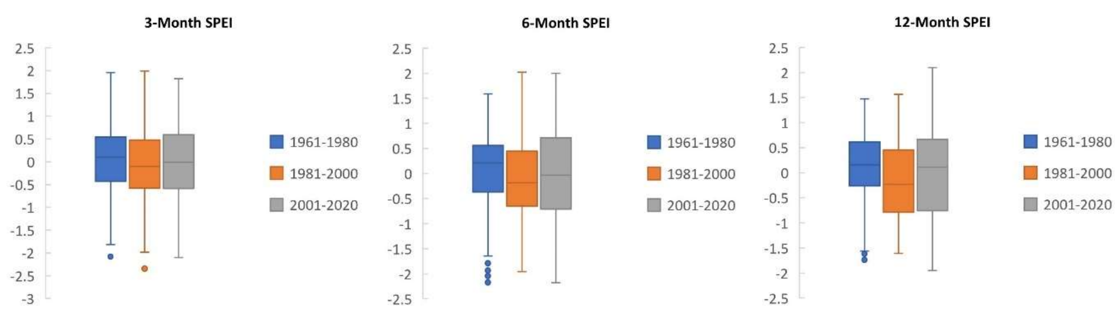
Following Jirophat et al. (2022), weather conditions in Thailand were analyzed using the 3-month, 6-month, and 12-month SPEI indices. The monthly averages of 200 SPEI grids in Thailand are depicted in Figure 2. All three SPEI indices effectively capture extreme weather events in Thailand. For example, the aggregate SPEI index for the 2011 Great Flood is approximately 2, while the index for the 1979–1980 Great Drought is about -2. Although there are negative trends in all SPEI indices, these trends are not statistically significant. Hence, it cannot be concluded that weather conditions in Thailand have become drier over time, as found by Jirophat et al. (2022).

Figure 2. Average of SPEI grids—Time-series



Although the aggregate SPEI has fluctuated quite symmetrically around zero, which is the historical norm by construction, the range of fluctuations has widened over time. This pattern is also evident in the box plots associated with the 6-month and 12-month SPEI indices but not the 3-month SPEI index (Figure 3). In Figure 3, each vertical bar represents all possible values of the SPEI index within a 20-year interval. It is apparent that these vertical bars have become wider over time for both the 6-month and 12-month SPEI indices. This suggests that weather conditions in Thailand are becoming more volatile over time, which is consistent with the narrative of climate change and similar to the findings of Jirophat et al. (2022).

Figure 3. Average of SPEI grids—Box plots



2.4 Weather index

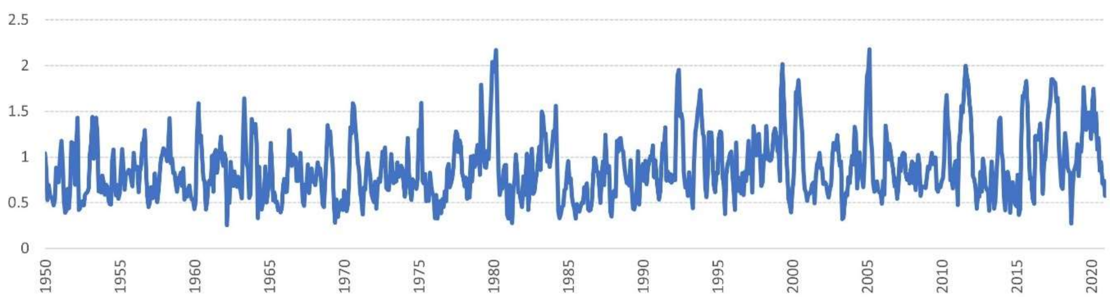
The 6-month SPEI index was utilized, in line with Generoso et al. (2020), because it effectively captures medium-term weather trends that mainly affect economic activities, such as agriculture. Next, the weather index was calculated using the absolute deviation of SPEI grids, following the approach of Jirophat et al. (2022) and Bremus et al. (2020):

$$Weather_t = \frac{1}{N} \times \sum_{i=1}^{N} |SPEI_{it}| \tag{1}$$

where N is the 200 SPEI grids, and $SPEI_{it}$ is the 6-month SPEI index of grid *i* at time *t*.

This calculation enabled a focus solely on the magnitude of the weather conditions' deviation from the historical norm and treated both wetter-than-average and drier-than-average weather conditions symmetrically (Figure 4). It also helped avoid the issue where the economic effects of positive SPEI values and negative SPEI values cancel each other out in the model during parameter estimation.

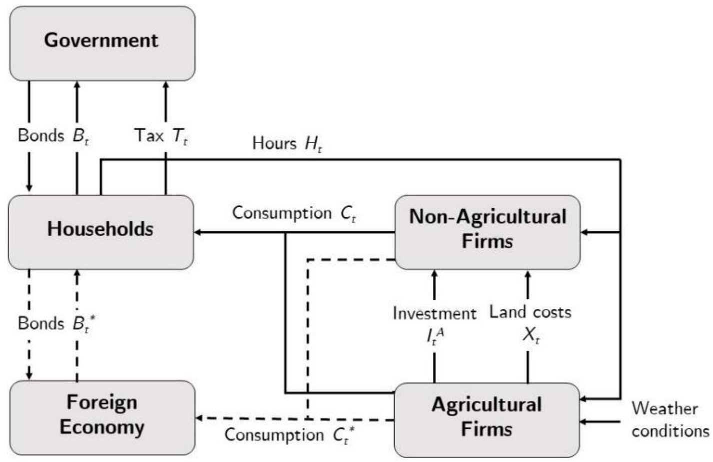
Figure 4. Weather index: Absolute deviation of SPEI grids



3. Structure of DSGE model

Gallic and Vermandel's (2020) DSGE model for a small open economy under a flexible exchange rate regime was adopted. The home economy comprises two groups of infinite living agents: households and firms. Among the firms, there are two types: agricultural firms and non-agricultural firms. Both types of firms produce for domestic consumption as well as foreign consumption. To simplify the model, climate shocks were assumed to only affect agricultural firms. The structure of the DSGE model is summarized in Figure 5.

Figure 5. Structure of the DSGE model



Notes: This diagram is adapted from Gallic and Vermandel (2020).

In this economy, a continuum of firms exists indexed by $i \in [0,1]$. A fraction n_t represents agricultural firms, and the remaining fraction $1 - n_t$ represents non-agricultural firms. It was assumed that the fraction of agricultural firms is subject to an exogenous shock: $n_t = n \times \varepsilon_t^N$, where ε_t^N follows an AR(1) shock process.[3]

To model the economic impacts of climate change, the climate shock ε_t^W, was introduced, which captures deviations in weather conditions, whether wet or dry, from the historical norm. This climate shock directly affects the production of agricultural goods. Unlike the IAMs pioneered by Nordhaus (1991), which assumes a feedback loop between economic activity and climate change, it was assumed that weather conditions are strictly exogenous. Consequently, ε_t^W also follows an AR(1) shock process.[4] This approach is considered conservative in comparison to the IAMs since parameters determining the strength of the feedback loop are unknown (Pindyck, 2013).

[3] Specifically, $log(\varepsilon_t^N) = \rho_N log(\varepsilon_{t-1}^N) + \sigma_N \eta_t^N,\ \eta_t^N \sim \mathcal{N}(0,1)$

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

3.1 Agricultural firms

The representative agricultural firm $i \in [0, n_t]$ has the Cobb-Douglas production function in which agricultural output y_{it}^A depends on three inputs including land ℓ_{it-1}, subject to the weather $\Omega(\varepsilon_t^w)$, physical capital k_{it-1}^A, and labor h_{it}^A:

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

where $\omega \in [0,1]$ is the share of land in agricultural production, $\alpha \in [0,1]$ is share of capital in output, and κ_A is technology parameter endogenously determined in the steady state. The production function is subject to an economy-wide total factor productivity (TFP) shock ε_t^Z , assumed to follow an AR(1) shock process.[5]

Weather conditions were assumed to affect the production of agricultural goods by reducing land productivity. The damage function $\Omega(\varepsilon_t^w)$ associated with land ℓ_{it-1} is given by:

$$\Omega(\varepsilon_t^w) = (\varepsilon_t^w)^{-\theta} \tag{3}$$

where θ is the elasticity of land with respect to climate. When $\theta = 0$, the climate shock will have no effect on macroeconomic fluctuations.

Finally, the real profit of the representative agricultural firm is given by:

$$\pi_{it}^A = p_t^A y_{it}^A - p_t^N \left(i_{it}^A + S\left(\varepsilon_t^I \frac{i_{it}^A}{i_{it-1}^A}\right) i_{it-}^A \right) - w_t^A h_{it}^A - p_t^N x_{it} \tag{4}$$

where i_{it}^A is the investment of the representative agricultural firm, $p_t^A = P_t^A/P_t$ is the relative production price of agricultural goods, and w_t^A is the real wage in the agricultural sector. The investment adjustment cost function $S(x) = 0.5\kappa(x-1)^2$ is subject to investment shock ε_t^I, which can make investment more or less

[5] Specifically, $log(\varepsilon_t^Z) = \rho_Z log(\varepsilon_{t-1}^Z) + \sigma_Z \eta_t^Z,\ \eta_t^Z \sim \mathcal{N}(0,1)$

expensive. The investment shock is assumed to follow an AR(1) shock process.[6]

Assumed to be a price taker, the representative agricultural firm solves the profit maximization problem:

$$\max_{\{h_{it}^A, i_{it}^A, k_{it}^A, \ell_{it}^A, x_{it}^A\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} \pi_{it+\tau}^A \right\} \tag{5}$$

subject to land productivity accumulation (Equation 6) and physical capital accumulation (Equation 7) constraints. Here, the parameter $\Lambda_{t,t+\tau}$ denotes the household stochastic discount factor between t and $t + \tau$.

The law of motion of land productivity is given by:

$$\ell_{it} = [(1 - \delta_\ell) + v(x_{it})]\Omega(\varepsilon_{t-1}^W)\ell_{it-1} \tag{6}$$

with the land expenditure cost function: $v(x_{it}) = \frac{\tau}{\phi} x_{it}^{\phi}$. Land productivity decreases by δ_ℓ, which is the land productivity decay rate, and increases by $v(x_{it})$, where x_{it} is the land expenditure on land productivity enhancers such as fertilizers and pesticides.

The law of motion of physical capital is given by:

$$i_{it}^A = k_{it}^A - (1 - \delta_k)k_{it-1}^A \tag{7}$$

where $\delta_k \in [0,1]$ is the depreciation rate of capital.

3.2 Non-agricultural firms

The representative non-agricultural firm $i \in [n_t, 1]$ has the Cobb-Douglas production function in which non-agricultural output y_{it}^N depends only on two inputs, including physical capital k_{it-1}^N and labor h_{it}^N:

$$y_{it}^N = \varepsilon_t^Z (k_{it-1}^N)^\alpha (h_{it}^N)^{1-\alpha} \tag{8}$$

where $\alpha \in [0,1]$ is the share of capital in output.

---

[6] Specifically, $log(\varepsilon_t^I) = \rho_I log(\varepsilon_{t-1}^I) + \sigma_I \eta_t^I,\ \eta_t^I \sim \mathcal{N}(0,1)$

Similar to agricultural firms but without land expenditure, the real profit of the representative non-agricultural firm π_{it}^{N} is given by:

$$\pi_{it}^{N} = p_t^N y_{it}^N - p_t^N \left(i_{it}^N + S\left(\varepsilon_t^I \left(\frac{i_{it}^N}{i_{it-1}^N} \right) i_{it-}^N \quad \right) \right) - w_t^N h_{it}^N \tag{9}$$

where i_{it}^N is the investment of the representative non-agricultural firm, $p_t^N = P_t^N / P_t$ is the relative production price of non-agricultural goods, and w_t^N is the real wage in the non-agricultural sector.

Assumed to be a price taker, the representative non-agricultural firm solves the profit maximization problem:

$$\max_{\{h_{it}^N, i_{it}^N, k_{it}^N\}} E_t \left\{ \sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau} \, \pi_{it+\tau}^N \right\} \tag{10}$$

subject to physical capital accumulation constraint (Equation 11).

The law of motion of physical capital is given by:

$$i_{it}^N = k_{it}^N - (1 - \delta_k) k_{it-1}^N \tag{11}$$

where $\delta_k \in [0,1]$ is the depreciation rate of capital.

3.3 Households

The representative household $\mathrm{j} \in [0,1]$, who can choose to work in either agricultural firms $\mathrm{h}_{\mathrm{jt}}^{\mathrm{A}}$ to receive a real wage $\mathrm{w}_{\mathrm{jt}}^{\mathrm{A}}$ or non-agricultural firms $\mathrm{h}_{\mathrm{jt}}^{\mathrm{N}}$ to receive a real wage $\mathrm{w}_{\mathrm{jt}}^{\mathrm{N}}$, faces the utility function:

$$U_{jt} = \frac{1}{1-\sigma} \left(C_{jt} - bC_{jt-1} \right)^{1-\sigma} - \frac{\chi \varepsilon_t^H}{1+\sigma_H} h_{jt}^{1+\sigma_H} \tag{12}$$

where C_{jt} is the consumption index, $\mathrm{b} \in [0,1]$ is consumption habit parameter, h_{jt} is the labor disutility index, and $\sigma > 0$ and $\sigma_H > 0$ are the consumption risk aversion parameter and the labor disutility curvature parameter, respectively. There is imperfect substitutability of labor supply between the agricultural sector and the non-agricultural sector, so we imposed the CES labor disutility index: $\mathrm{h_{jt}} = \left[\left(\mathrm{h_{jt}^N}\right)^{1+\iota} + \left(\mathrm{h_{jt}^A}\right)^{1+\iota}\right]^{\frac{1}{1+\iota}}$ where ι is the labor sector reallocation cost parameter. Moreover, the labor supply is subject to the labor supply shock ε_t^H, which can make hours worked more costly or less costly in terms of welfare. The labor supply shock is assumed to follow an AR(1) process.[7]

Moreover, the representative household can choose to invest in risk-free home bonds $\mathrm{b_{jt}}$ and risky foreign bonds $\mathrm{b_{jt}^*}$. Therefore, he or she solves the utility maximization problem:

$$\max_{\{C_{jt},b_{jt},b_{jt}^*,h_{jt}^A,h_{jt}^N\}} E_t\left\{\sum_{\tau=0}^{\infty} \beta^\tau\, U_{jt+\tau}\right\} \tag{13}$$

subject to the budget constraint (Equation 14).

The representative household's budget constraint is given by:

$$\sum_{s=N,A} w_{jt}^s h_{jt}^s + r_{t-1}b_{jt-1} + rer_t^* r_{t-1}^* b_{jt-1}^* - t_{jt} \geq C_{jt} + b_{jt} + rer_t^* b_{jt}^* + p_t^N rer_t^* \Phi\left(b_{jt}^*\right) \tag{14}$$

with the real exchange rate: $\mathrm{rer_t^*} = \mathrm{e_t^* P_t^*/P_t}$. The income of the representative household consists of the real wage in each sector $\mathrm{w_{jt}^s}$, the real interest rate from domestic bond $\mathrm{r_{t-1}}$, and the real interest rate from foreign bond $\mathrm{r_{t-1}^*}$. Furthermore, the government charges each household a lump-sum tax $\mathrm{t_{jt}}$. The expenditure of the representative household consists of consumption $\mathrm{C_{jt}}$, the purchase of domestic bond b_{jt}, and the purchase of foreign bond $\mathrm{b_{jt}^*}$. Additionally, each household needs to pay a risk premium cost $\Phi\left(b_{jt}^*\right) = 0.5\chi_B\left(b_{jt}^*\right)^2$ in terms of domestic non-agricultural goods.

The allocation of the total consumption between non-agricultural goods and agricultural goods and between home-produced and foreign-produced goods

[7] Specifically, $\log(\varepsilon_t^H) = \rho_H \log(\varepsilon_{t-1}^H) + \sigma_H \eta_t^H, \quad \eta_t^H \sim \mathcal{N}(0,1)$

are explained next. The representative household allocates his or her total consumption C_{jt} into non-agricultural goods C_{jt}^{N} and agricultural goods C_{jt}^{A}. The CES consumption bundle is given by:

$$C_{jt} = \left[(1-\varphi)^{\frac{1}{\mu}}\left(C_{jt}^{N}\right)^{\frac{\mu-1}{\mu}} + (\varphi)^{\frac{1}{\mu}}\left(C_{jt}^{A}\right)^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}} \tag{15}$$

where $\mu \geq 0$ is the substitution elasticity between agricultural and non-agricultural goods, and $\varphi \in [0,1]$ is the share of agricultural goods in consumption bundle. Hence, the corresponding consumption price index becomes $P_t = \left[(1-\varphi)\left(P_{C,t}^{N}\right)^{1-\mu} + \varphi\left(P_{C,t}^{A}\right)^{1-\mu}\right]^{\frac{1}{1-\mu}}$, where $P_{C,t}^{N}$ and $P_{C,t}^{A}$ are the consumption price indices of non-agricultural and agricultural goods, respectively.

In each type of goods, both non-agricultural goods and agricultural goods, the representative household also allocates consumption between home-produced goods c_{jt}^{s} and foreign-produced goods c_{jt}^{s*}. The composite consumption subindex is given by:

$$C_{jt}^{s} = \left[(1-\alpha_s)^{\frac{1}{\mu_s}}\left(c_{jt}^{s}\right)^{\frac{\mu_s-1}{\mu_s}} + (\alpha_s)^{\frac{1}{\mu_s}}\left(c_{jt}^{s*}\right)^{\frac{\mu_s-1}{\mu_s}}\right]^{\frac{\mu_s}{\mu_s-1}}; \quad s = N, A \tag{16}$$

where $\mu_s \geq 0$ is the substitution elasticity between home and foreign goods in sector s, and $\alpha_s \in [0,1]$ is the share of imported goods in the consumption bundle in sector s. Hence, the corresponding consumption price index becomes $P_t = [(1-\alpha_s)(P_t^{s})^{1-\mu_s} + \alpha_s(e_t^{*}P_t^{s*})^{1-\mu_s}]^{\frac{1}{1-\mu_s}}; \quad s = N, A$, where P_t^{s} is the production price index of home-produced goods in sector s and P_t^{s*} is the price of foreign-produced goods in sector s.

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

$$C_{jt}^{N} = (1-\varphi)\left(\frac{P_{C,t}^{N}}{P_t}\right)^{-\mu} C_{jt} \quad \text{and} \quad C_{jt}^{A} = \varphi\left(\frac{P_{C,t}^{A}}{P_t}\right)^{-\mu} C_{jt} \tag{17}$$

$$c_{jt}^{s} = (1-\alpha_s)\left(\frac{P_t^{s}}{P_{C,t}^{s}}\right)^{-\mu_s} C_{jt}^{s} \quad \text{and} \quad c_{jt}^{s*} = \alpha_s\left(e_t^{*}\frac{P_t^{s*}}{P_{C,t}^{s}}\right)^{-\mu_s} C_{jt}^{s}; \quad s = N, A \tag{18}$$

3.4 Government

The government spends a fixed fraction of non-agricultural goods g subject to the public spending shock ε_t^G, assumed to follow an AR(1) shock process.[8] Hence, the public spending is given by:

$$G_t = \varepsilon_t^G g Y_t^N \tag{19}$$

The government also issues the total amount of bonds $\int_0^1 b_{jt}\,dj = B_t$ at the real interest rate r_t and charges the total amount of lump-sum taxes $\int_0^1 t_{jt}\,dj = T_t$. Thus, the government's budget constraint is given by:

$$G_t + r_{t-1}B_{t-1} = B_t + T_t \tag{20}$$

3.5 Foreign economy

The representative foreign household $j \in [0,1]$ faces the utility function:

$$U_{jt}^{*} = \varepsilon_t^E \frac{1}{1-\sigma^*}\left(c_{jt}^{*} - b^* c_{jt-1}^{*}\right)^{1-\sigma^*} \tag{21}$$

where c_{jt}^{*} is the foreign consumption index, $b^* \in [0,1]$ is the foreign consumption habit parameter, and $\sigma^* > 0$ is the foreign consumption risk aversion parameter. The utility function is subject to a foreign time-preference shock ε_t^E, assumed to follow an AR(1) shock process.[9]

In a small open economy setup, the foreign economy is affected by only its own consumption shock, not the shocks from the home economy. So, the

---

[8] Specifically, $\log(\varepsilon_t^G) = \rho_G \log(\varepsilon_{t-1}^G) + \sigma_G \eta_t^G, \quad \eta_t^G \sim \mathcal{N}(0,1)$

[9] Specifically, $log(\varepsilon_t^E) = \rho_E log(\varepsilon_{t-1}^E) + \sigma_E \eta_t^E, \quad \eta_t^E \sim \mathcal{N}(0,1)$

exogenous foreign consumption is given by:

$$log\left(c_{jt}^{*}\right) = (1-\rho_C)log\left(\overline{c_j^{*}}\right) + \rho_C log\left(c_{jt-1}^{*}\right) + \sigma_C \eta_t^C; \quad \eta_t^C \sim \mathcal{N}(0,1) \tag{22}$$

where $\overline{c_j^{*}}$ is the steady state foreign consumption.

Moreover, the representative foreign household can buy only its own bonds but not home economy bonds. Thus, he or she solves the utility maximization problem:

$$\max_{\{c_{jt}^{*}, b_{jt}^{*}\}} E_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \, U_{jt+\tau}^{*} \right\} \tag{23}$$

subject to the budget constraint (Equation 24).

The representative foreign household's budget constraint is given by:

$$r_{t-1}^{*} b_{jt-}^{*} \geq c_{jt}^{*} + b_{jt}^{*} \tag{24}$$

The income of the representative household consists of the real interest rate from foreign bond r_{t-1}^{*}, while the expenditure of each consists of its consumption c_{jt}^{*} and the purchase of foreign bond b_{jt}^{*}.

3.6 Aggregation and equilibrium conditions

All agents in the economy were aggregated so that the total supply of home non-agricultural goods becomes $\int_{n_t}^{1} y_{it}^{N} \, di = (1-n_t)Y_t^N$ and the total supply of home-agricultural goods becomes $\int_{0}^{n_t} y_{it}^{A} \, di = n_t Y_t^A$. Therefore, the aggregate output is given by:

$$Y_t = (1-n_t)Y_t^N + n_t Y_t^A \tag{25}$$

Similarly, the aggregate investment is given by: $I_t = (1-n_t)I_t^N + n_t I_t^A$, and the aggregate hours worked is given by: $H_t = (1-n_t)H_t^N + n_t H_t^A$.

The market clearing conditions were imposed on all markets to deduce the general equilibrium conditions of the model. First, the equilibrium in the non-agricultural goods market is given by:

$$(1-n_t)Y_t^N = (1-\varphi)\left[(1-\alpha_N)\left(\frac{P_t^N}{P_{C,t}^N}\right)^{-\mu_N}\left(\frac{P_{C,t}^N}{P_t}\right)^{-\mu} C_t \right.$$

$$\left. + \alpha_N\left(\frac{1}{e_t^*}\frac{P_t^{N*}}{P_{C,t}^{N*}}\right)^{-\mu_N}\left(\frac{P_{C,t}^{N*}}{P_t^*}\right)^{-\mu} C_t^*\right] + G_t + I_t + n_t X_t + \Phi(B_t^*) \quad (26)$$

where the total demand from the home economy is $\int_0^1 C_{jt}\, dj = C_t$, the total demand from the foreign economy is $\int_0^1 C_{jt}^*\, dj = C_t^*$, and the total land expenditure is $\int_0^{n_t} x_{it}\, di = n_t X_t$.

Second, the equilibrium in the agricultural goods market is given by:

$$n_t Y_t^A = \varphi\left[(1-\alpha_A)\left(\frac{P_t^A}{P_{C,t}^A}\right)^{-\mu_A}\left(\frac{P_{C,t}^A}{P_t}\right)^{-\mu} C_t + \alpha_A\left(\frac{1}{e_t^*}\frac{P_t^{A*}}{P_{C,t}^{A*}}\right)^{-\mu_A}\left(\frac{P_{C,t}^{A*}}{P_t^*}\right)^{-\mu} C_t^*\right] \quad (27)$$

In both equilibrium conditions (Equations 26 and 27), the left-hand side denotes the aggregate supply of a certain type of goods, while the right-hand side denotes the aggregate demand for a certain type of goods in both home and foreign economies.

Since the land expenditure is considered an intermediate input in the model, the gross domestic product (GDP) is given by:

$$GDP_t = Y_t - p_t^N n_t X_t \quad (28)$$

The law of motion of real foreign debt and the trade balance are given by:

$$B_t^* = r_{t-1}^* \frac{rer_t^*}{rer_{t-1}^*} B_{t-1}^* + TB_t \quad (29)$$

$$TB_t = p_t^N[(1-n_t)Y_t^N - G_t - I_t - n_t X_t - \Phi(B_t^*)] + p_t^A n_t Y_t^A - C_t \quad (30)$$

In conclusion, the DSGE model consists of the five components mentioned earlier: agricultural firms, non-agricultural firms, households, the government, and the foreign economy (Figure 5). Climate shocks were assumed to negatively impact land productivity, resulting in a reduction in agricultural output by agricultural firms. This reduction should affect the overall output of the economy. Subsequently, in accordance with the equilibrium conditions, a decrease in supply is expected to lead to a decrease in demand, potentially affecting either domestic demand, foreign demand, or both.

4. Estimation of DSGE model

The DSGE model was estimated using Bayesian methods on Thailand's quarterly data, following the seminal paper of Smets and Wouters (2007).In brief, Bayesian methods compute the posterior distribution of the DSGE parameters by using Bayes' rule:

$$p(\theta|y^T, M) \propto p(y^T|\theta, M)p(\theta|M) \tag{31}$$

where $p(\theta|y^T, M)$ is the posterior distribution of the parameters given the observable data and the model, $p(y^T|\theta, M)$ is the likelihood density of the observable data given the parameters and the model, and $p(\theta|M)$ is the prior distribution of the parameters given the model.

The likelihood density was computed by the Kalman filter, and the prior distribution was selected based on pre-experimental knowledge of the parameters. After calculating the mode of the posterior distribution, the Markov chain Monte Carlo (MCMC) method, namely the Metropolis-Hasting algorithm, was employed to trace the shape of $p(\theta|y^T, M)$ and calculate the highest posterior density (HPD) interval. The model was estimated using Dynare.[10] The first-order conditions used to estimate the model are shown in the Appendices.

[10] Gallic and Vermandel's (2020) Dynare code was adapted to create a model using 4 parallel chains, each consisting of 1,000,000 simulations. The first 100,000 simulations from each chain were discarded as a burn-in. The parameter mh_jscale was configured to attain an acceptance ratio close to 24%. To evaluate the convergence of these simulations, multivariate convergence statistics proposed by (Brooks & Gelman, 1998) were employed.

4.1 Data

The sample spanning from 1993Q1 to 2020Q4 was used, dictated by the availability of Thailand's GDP and the SPEI index. It is worth noting that real exchange rate data is available from 1994, and hours worked data is available from 2005. However, both variables can still be incorporated into the DSGE model estimation, thanks to the flexibility of Bayesian methods in handling missing values. Table 2 provides a summary of the eight observable variables in the DSGE model, along with their respective data sources.

Table 2. Data used in estimation of DSGE and SVAR models

Variable	Data	Source
DSGE Estimation		
Output	GDP, CVM (reference year = 2002), sa	NESDC
Consumption	Household PFCE, CVM (reference year = 2002), sa	NESDC
Investment	Private GFCF, CVM (reference year = 2002), sa	NESDC
Hours Worked	Number of employed persons classified by hours worked per week	National Statistical Office
Agricultural Output	Agriculture GDP, CVM (reference year = 2002), sa	NESDC
Foreign Output	OECD Real GDP Index (reference year = 2015), sa	OECD
Real Exchange Rate	Real effective exchange rate index: Trade weight broad 25	Bank of Thailand
Weather Condition	6-Month Standardized Precipitation-Evapotranspiration Index	Global SPEI Database Version 2.7
SVAR Estimation (Additional)		
VIX Index	CBOE volatility index	Chicago Board Options Exchange
Commodity Price	CRB Commodity Index, spot (reference year = 1967)	Commodity Research Bureau
Inflation	Headline Consumer Price Index (reference year = 2019)	Ministry of Commerce
Food Inflation	Raw food Consumer Price Index (reference year = 2019)	Ministry of Commerce
Interest Rate	3-Month government bond yield	Bank of Thailand

Notes: NESDC stands for Office of the National Economic and Social Development Council.

The non-stationary data was transformed to map with the stationary model as follows: Output, consumption, investment, and agricultural output were divided by the working-age population.[11] Then, the natural logarithm of these variables was taken. Finally, the Hodrick-Prescott (HP) filter was applied with the smoothing parameter $\lambda = 1600$ to detrend them. Foreign output was log-transformed with the same HP filter applied for detrending. For the real exchange rate, the first difference of the logarithm was taken. For hours worked, the weighted average of hours worked per week[12] was initially calculated. Next, the correction method was applied (Smets & Wouters, 2007), which involves multiplying it by the employment rate. To ensure the data was seasonally adjusted, the STL method (Cleveland et al., 1990) was utilized. Finally, the data was log-transformed with the same HP filter applied for detrending. For the weather condition, the natural logarithm of the weather index was taken, as constructed in Section 2.4.

4.2 Measurement equations

The vector of observable variables is given by:

$$y_t^{obs} = 100 \times \left[\hat{y}_t \quad \hat{c}_t \quad \hat{\iota}_t \quad \hat{h}_t \quad \widehat{y_t^A} \quad \widehat{y_t^*} \quad \Delta\widehat{rer}_t \quad \widehat{\omega_t}\right]^T \tag{32}$$

where $\hat{y}_t$ is the output gap, $\hat{c}_t$ is the consumption gap, $\hat{\iota}_t$ is the investment gap, $\hat{h}_t$ is the hours worked gap, $\widehat{y_t^A}$ is the agricultural output gap, $\widehat{y_t^*}$ is the foreign output gap, $\Delta\widehat{rer}_t$ is the real exchange rate growth, and $\widehat{\omega_t}$ is the weather condition.

[11] Working-age population data was obtained from the National Statistical Office. Before 1996, the working-age population referred to adults older than 13. From 1996 onward, the working-age population refers to adults older than 15. Missing values are imputed using linear interpolation.
[12] From 2011 onward, employed persons working 50–59 hours, 60–69 hours, 70–79 hours, 80–89 hours, and 90 hours and over are considered as working 50 hours and over to maintain consistency with the data from previous years.

The corresponding vector of measurement equations is given by:

$$y_t = 100 \times \left[\widetilde{GDP_t} \quad \widetilde{C_t} \quad \widetilde{p_t^N} + \widetilde{I_t} \quad \widetilde{h_t} \quad \widetilde{n_t} + \widetilde{p_t^A} + \widetilde{Y_T^A} \quad \widetilde{C_t^*} \quad -\Delta\widetilde{rer_{t+1}^*} \quad \widetilde{\varepsilon_t^W}\right]^T \quad (33)$$

where all variables are in percentage deviations from their steady state: $\widetilde{x_t} = log(x_t/\bar{x})$. In the model, the real exchange rate is the price of foreign currency, so the negative of its growth rate was taken to obtain the real exchange rate growth of Thailand.

4.3 Parameter calibration and estimation

Table 3 summarizes the calibration of the model. Most of the calibration is inspired by the DSGE model of the Bank of Thailand (Tanboon, 2008). The remaining parameters were estimated using the previously mentioned Bayesian methods. Table 4 reports the prior and posterior distributions of the estimated parameters with the 90% HPD interval.

Table 3. Calibrated parameters

Parameter	Description	Value	Source
β	Discount factor	0.3	Tanboon (2008) calculated from 3% real interest rate
δ_K	Capital depreciation rate	0.0105	Tanboon (2008)
α	Share of capital in output	0.3	Tanboon (2008)
g	Share of public spending in GDP	0.2	Tanboon (2008)
φ	Share of agricultural goods in consumption basket	0.2	Share of raw food in CPI consumption basket
$\overline{H^N} = \overline{H^A}$	Hours worked	1/3	Standard
$\bar{\ell}$	Land per capita	0.25	FAO's arable land (hectares per person) in Thailand (1993–2020)
α_N	Share of imported non-agricultural goods in consumption basket	0.21	Luangaram and Wongpunya (2022)
α_A	Share of imported agricultural goods in consumption basket	0.21	Luangaram and Wongpunya (2022)
χ_B	International portfolio cost	0.0007	Schmitt-Grohé and Uribe (2003)

σ^*	Foreign consumption risk aversion	1	Gallic and Vermandel (2020)
b^*	Foreign consumption habits	0	Gallic and Vermandel (2020)

Table 4: Estimated parameters: Prior and posterior distribution

		Prior			**Posterior**	
Description	**Parameter**	**Distri-bution**	**Mean**	**Std.**	**Mean**	**90% HPD Interval**
AR(1) Shock Process						
Persistence in economy-wide TFP shock	ρ_Z	$\mathcal{B}$	0.5	0.2	0.62	[0.5:0.75]
Persistence in labor supply shock	ρ_H	$\mathcal{B}$	0.5	0.2	0.2	[0.05:0.33]
Persistence in public spending shock	ρ_G	$\mathcal{B}$	0.5	0.2	0.72	[0.62:0.82]
Persistence in investment shock	ρ_I	$\mathcal{B}$	0.5	0.2	0.14	[0.03:0.24]
Persistence in labor sector reallocation shock	ρ_N	$\mathcal{B}$	0.5	0.2	0.36	[0.2:0.51]
Persistence in climate shock	ρ_W	$\mathcal{B}$	0.5	0.2	0.4	[0.26:0.54]
Persistence in foreign time-preference shock	ρ_E	$\mathcal{B}$	0.5	0.2	0.18	[0.06:0.28]
Persistence in foreign consumption shock	ρ_C	$\mathcal{B}$	0.5	0.2	0.52	[0.39:0.64]
Std. in economy-wide TFP shock	$\sigma_Z \times 100$	$\mathcal{W}$	1	2	2	[1.69:2.29]
Std. in labor supply shock	$\sigma_H \times 100$	$\mathcal{W}$	1	2	4.77	[3.38:6.12]
Std. in public spending shock	$\sigma_G \times 100$	$\mathcal{W}$	1	2	6.6	[5.81:7.34]
Std. in investment shock	$\sigma_I \times 100$	$\mathcal{W}$	1	2	8.18	[6.82:9.49]
Std. in labor sector reallocation shock	$\sigma_N \times 100$	$\mathcal{W}$	1	2	5.14	[4.12:6.11]
Std. in climate shock	$\sigma_W \times 100$	$\mathcal{W}$	1	2	0.31	[0.27:0.34]
Std. in foreign time-preference shock	$\sigma_E \times 100$	$\mathcal{W}$	1	2	5.79	[4.71:6.83]
Std. in foreign consumption shock	$\sigma_C \times 100$	$\mathcal{W}$	1	2	1.26	[1.12:1.4]
Structural Parameters in Agricultural Sector						
Land expenditure cost	ϕ	$\mathcal{N}$	1	1	1.87	[1.14:2.73]
Share of land in agricultural production	ω	$\mathcal{B}$	0.2	0.1	0.15	[0.03:0.27]
Land productivity decay rate	δ_ℓ	$\mathcal{B}$	0.1	0.05	0.13	[0.04:0.22]
Elasticity of land w.r.t. climate	θ	$\mathcal{U}$	0	500	7.16	[-7.48:22.2]
Other Structural Parameters						
Consumption risk aversion	σ	$\mathcal{N}$	2	0.35	0.56	[0.37:0.74]
Labor disutility curvature	σ_H	$\mathcal{N}$	2	0.75	3.13	[2.12:4.13]
Consumption habits	b	$\mathcal{B}$	0.7	0.1	0.63	[0.54:0.72]

Investment adjustment cost	κ	$\mathcal{N}$	4	1.5	0.68	[0.42:0.93]
Substitutability agri/non-agri goods	μ	$\mathcal{G}$	2	1	5.71	[3.63:7.74]
Substitutability home/foreign agri goods	μ_A	$\mathcal{G}$	2	1	1.19	[0.5:1.85]
Substitutability home/foreign non-agri goods	μ_N	$\mathcal{G}$	2	1	1.04	[0.82:1.25]
Labor sector reallocation cost	ι	$\mathcal{N}$	1	0.75	2.16	[1.26:3.05]

Notes: The prior distributions use the following acronyms: $\mathcal{B}$ denotes a Beta distribution, $\mathcal{W}$ denotes a Weibull distribution, $\mathcal{N}$ denotes a Normal distribution, $\mathcal{U}$ denotes a Uniform distribution, and $\mathcal{G}$ denotes a Gamma distribution.

The prior distributions were directly adopted from Smets and Wouters (2007) for the persistence of AR(1) shock processes, the consumption risk aversion σ, the labor disutility curvature σ_H, the consumption habits b, and the investment adjustment cost κ parameters. Nevertheless, the standard deviation of AR(1) shock processes was assumed to follow a Weibull distribution with a mean of 1 and a standard deviation of 2 because it provides a better fit compared to the Inverse Gamma distribution used in Smets and Wouters (2007) (Gallic & Vermandel, 2020).

The prior distribution was specified for the land productivity decay rate parameter δ_ℓ as a Beta distribution with a mean of 0.1 and a standard deviation of 0.05. Although this prior is stricter than the one in Gallic and Vermandel (2020), it still allows the land productivity decay rate to range from 0 to 0.25. This range reflects the previously estimated parameter value of 0.07 in Gallic and Vermandel (2020).

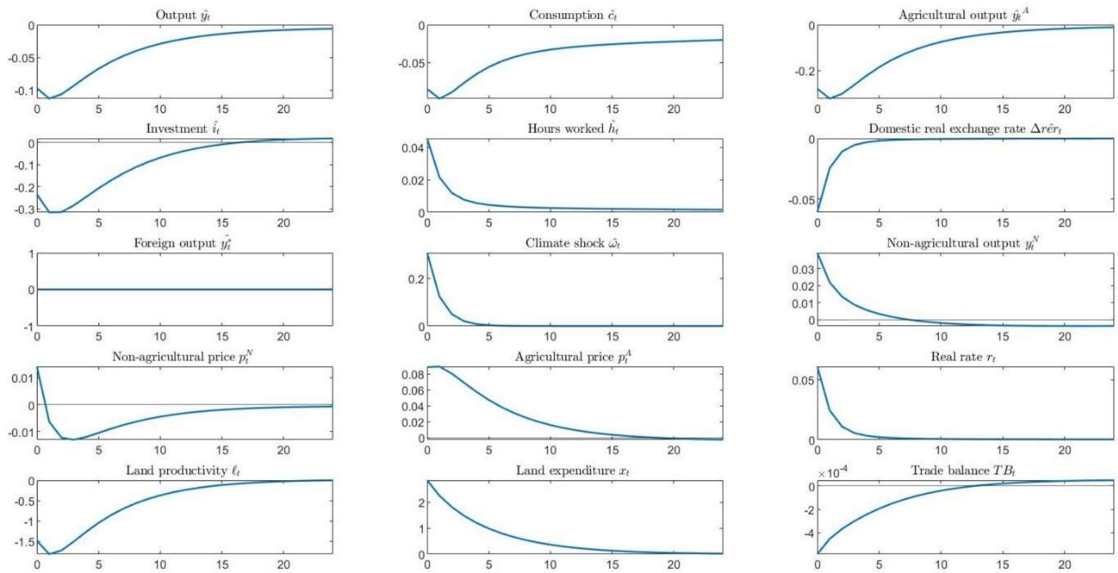
The prior distributions were also taken directly from Gallic and Vermandel (2020) for other parameters, including the labor sector reallocation cost ι, the land expenditure cost ϕ, $t$he share of land in agricultural production ω, and the elasticity of land with respect to climate θ parameters. In short, these choices are based on existing literature and the researcher's discretion regarding the plausible value ranges.

One key feature of the prior selection is the use of a non-informative prior for the damage function parameter θ. A uniform distribution was employed with zero mean and a standard deviation of 500. This choice intentionally refrained from imposing specific constraints on the parameter, allowing the data to dictate its value. This approach is adopted to avoid controversy in climate change modeling. Notably, Pindyck (2013) highlighted that introducing an arbitrary damage function based on the author's judgment within the IAMs can undermine the model's reliability.

4.4 Transmission mechanism of climate shocks

Figure 6 displays the impulse response of climate shocks ε_t^W. These shocks lead to a reduction in output of around 0.11 percent. Their effects are so persistent that it takes over 25 quarters for them to fully dissipate. In this model, the main channel through which climate shocks affect output is through a contraction in agricultural output by about 0.32 percent as a result of a decline in land productivity in the model. Consequently, agricultural firms must increase land expenditure to restore land productivity to its steady state. This reduction in supply and higher production costs mechanically leads to an increase in the agricultural price relative to the overall price. Climate shocks also have demand-side effects, causing a decrease in consumption and investment by approximately 0.1 percent and 0.32 percent, respectively. However, from an international perspective, climate shocks have a relatively small impact, as reflected by only slight deteriorations in the trade balance and the real exchange rate. Note that the limited impact on the trade balance might be unrealistic and could be attributed to the model's limitations, particularly its exclusion of observable trade balance data in the estimation process.

Figure 6. Impulse response of climate shocks ε_t^W



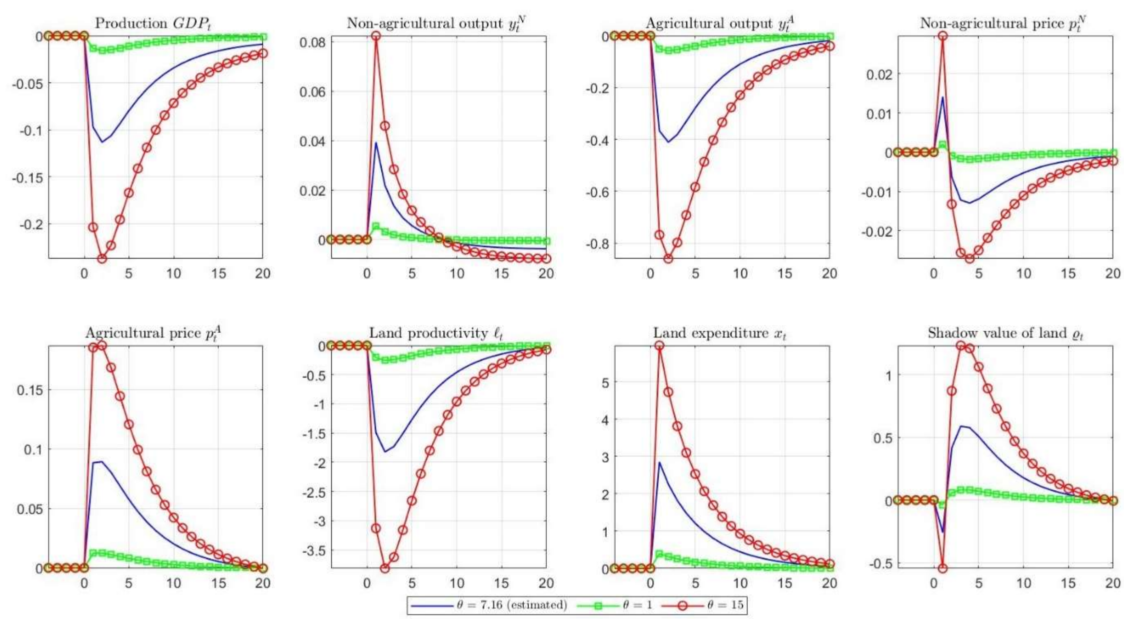
Notes: Impulse responses are reported in percentage deviations from the steady state of the estimated DSGE model. They are generated from the mean posterior distributions of parameters. The first eight variables are observable variables from the real-world data in Equation 32, while the rest of the variables are theoretical variables from the theoretical model.

4.5 Climate adaptation policy

There are two types of climate change policy: climate mitigation and climate adaptation. The former involves efforts to reduce greenhouse gas emissions or removing them from the atmosphere, ultimately reducing the size of climate shocks examined in Section 4.4. In contrast, climate adaptation policy focuses on building resilience to climate change. For example, governments may construct dams to protect regions from droughts and plant mangroves to prevent floods. This measure will directly minimize the negative impacts of climate shocks on the macroeconomy.

To assess the role of climate adaptation policy, a counterfactual experiment was conducted on the damage function parameter θ (Equation 3). This parameter represents the elasticity of land with respect to climate. Impulse responses were compared in three scenarios: under the estimated value ($\theta = 7.16$), under low damage ($\theta = 1$), and under high damage ($\theta = 15$) (Figure 7). As θ increases, land productivity experiences a greater decline, resulting in a more significant drop in agricultural output. This, in turn, necessitates a larger increase in land expenditure to offset the productivity loss. Therefore, GDP is negatively affected by two distinct mechanical processes: a decrease in agricultural output and an increase in land expenditure, which is treated as an immediate input. Therefore, climate adaptation policy that reduces the damage function parameter θ is beneficial to the macroeconomy because it can mitigate the extent of GDP reduction when facing climate shocks of the same magnitude.

Figure 7. Impulse response of climate shocks ε_t^W varying damage function parameter θ



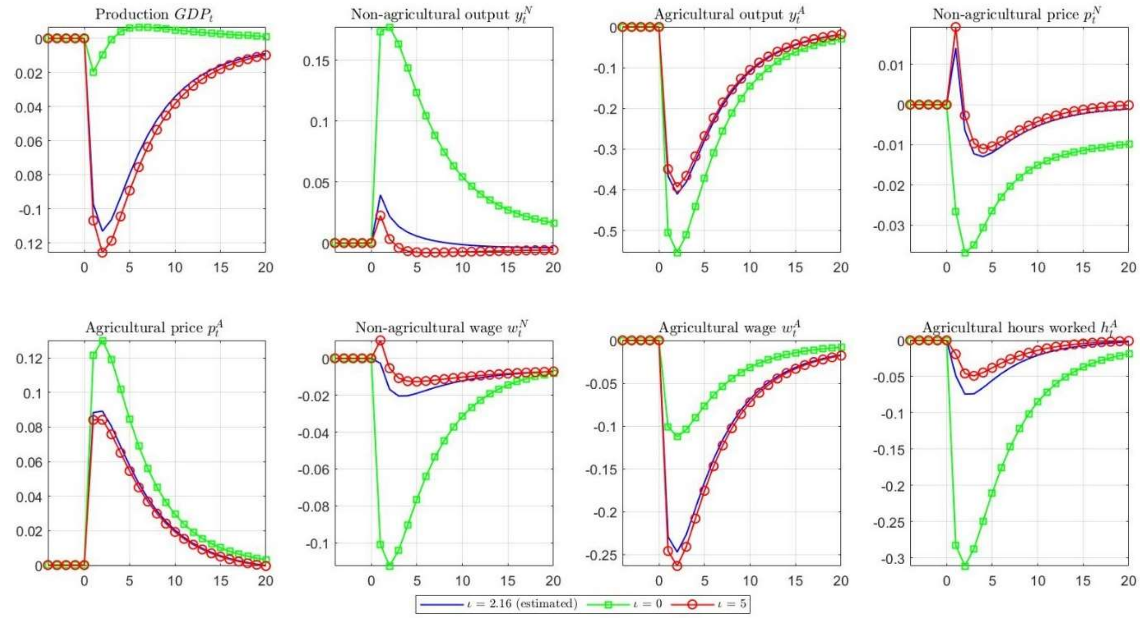
Notes: Impulse responses are reported in percentage deviations from the steady state of the estimated DSGE model. The climate shock occurs in period 1. Prior to that is the deterministic steady state of the model.

4.6 Labor migration policy

The labor migration policy aims to facilitate the movement of labor from the agricultural sector, which still employs approximately one-third of the Thai workforce, to the non-agricultural sector. For instance, the government can promote training programs to equip farmers with the necessary skills for employment in non-agricultural fields.

To assess the impact of labor migration policy, a counterfactual experiment was conducted on the labor disutility curvature parameter ι (Equation 12). This parameter determines the cost of labor substitution across two sectors. Impulse responses were compared in three scenarios: under the estimated value ($\iota = 2.16$), under the linear substitution ($\iota = 0$), and under the costly substitution ($\iota = 5$) (Figure 8). Under the perfect labor substitution scenario, climate shocks induce more labor migration from the agricultural sector to the non-agricultural sector. This leads to a smaller drop in the agricultural wage but a larger decline in the non-agricultural wage. Moreover, it results in a larger drop in agricultural output, partially offset by a larger spike in non-agricultural output. Consequently, GDP experiences a smaller decline under the perfect labor substitution scenario. Therefore, a labor migration policy that reduces the labor disutility curvature parameter ι is beneficial to the macroeconomy because it can mitigate the extent of GDP reduction when facing climate shocks of the same magnitude.

Figure 8. Impulse response of climate shocks ε_t^W varying labor disutility curvature parameter ι



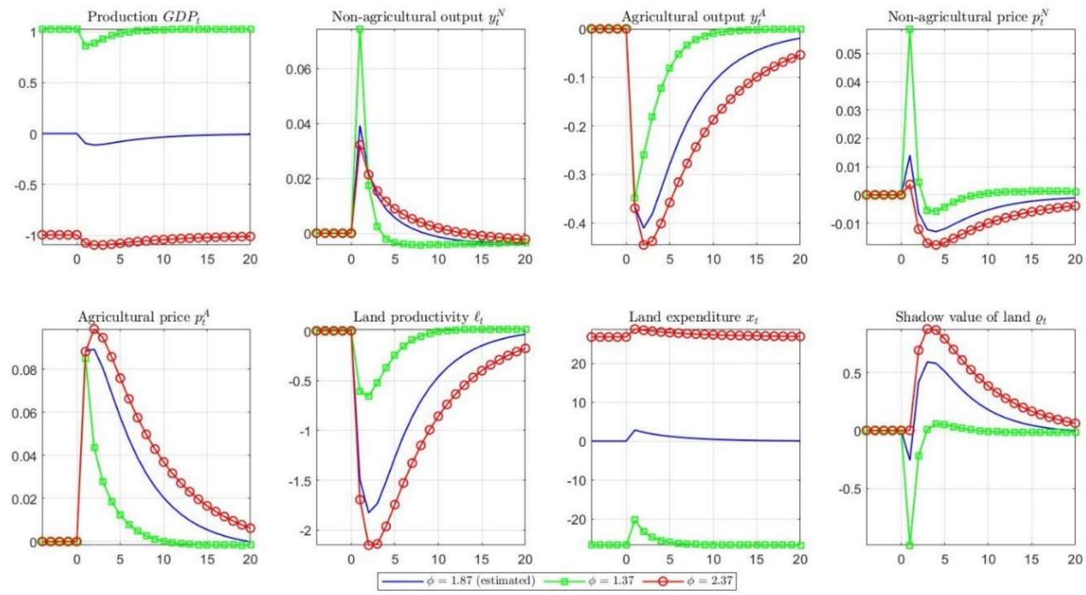
Notes: Impulse responses are reported in percentage deviations from the steady state of the estimated DSGE model. The climate shock occurs in period 1. Prior to that is the deterministic steady state of the model.

4.7 Sensitivity analysis of other key structural parameters

This section examines the impulse responses of climate shocks ε_t^W under different calibrations of two other key structural parameters (Gallic & Vermandel, 2020). Both parameters control the dynamics of land in the agricultural sector (Equation 6).

First, the land expenditure cost parameter ϕ (Equation 6) was considered. This parameter determines the returns to scale of land expenditure. Impulse responses were compared in three cases: under the estimated value ($\phi = 1.87$), under lowly increasing returns ($\phi = 1.37$), and under highly increasing returns ($\phi = 2.37$) (see Figure 9). As ϕ increases, land expenditure also rises to harness the benefits of increasing returns, mechanically reducing GDP because land expenditure is treated as an intermediate input. However, under the high ϕ case, climate shocks lead to a more substantial fall in land productivity, resulting in a larger drop in agricultural output and a larger rise in the agricultural price.

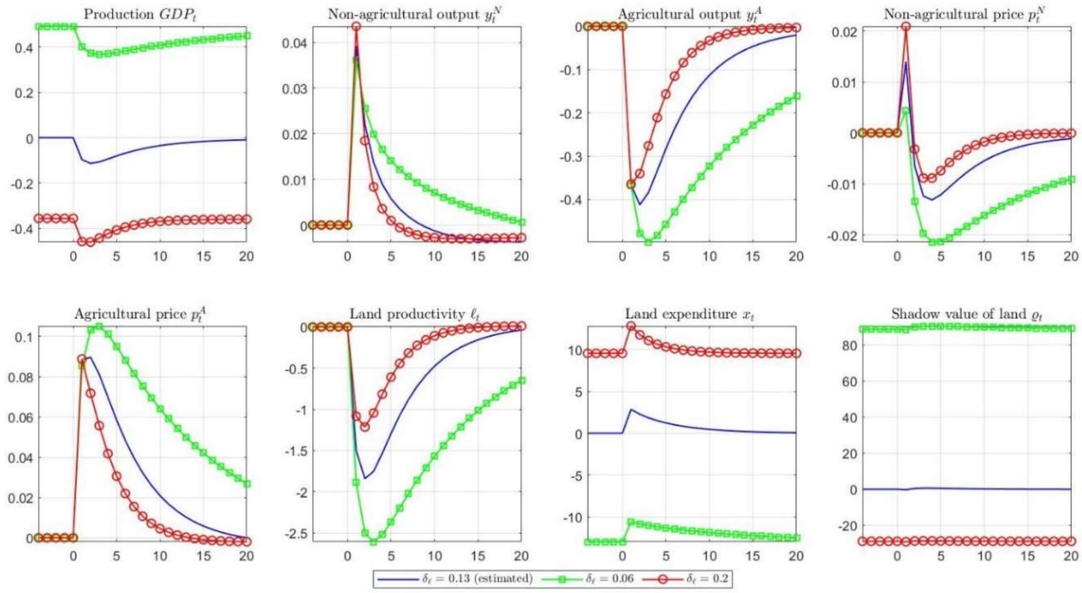
Figure 9. Impulse response of climate shocks ε_t^W varying land expenditure cost parameter ϕ



Notes: Impulse responses are reported in percentage deviations from the steady state of the estimated DSGE model. The climate shock occurs in period 1. Prior to that is the deterministic steady state of the model.

Second, the land productivity decay rate parameter δ_ℓ (Equation 6) was considered. Impulse responses were compared in three cases: under the estimated value ($\delta_\ell = 0.13$), under low productivity decay rate ($\delta_\ell = 0.06$), and under high productivity decay rate ($\delta_\ell = 0.2$) (Figure 10). As δ_ℓ increases, land expenditure also rises to compensate for a faster decline in land productivity, similarly reducing GDP, as observed with the increase in ϕ. Nevertheless, under the high δ_ℓ case, climate shocks lead to a smaller reduction in land productivity, resulting in a smaller decrease in agricultural output and a larger increase in agricultural prices.

Figure 10. Impulse response of climate shocks ε_t^W varying land productivity decay rate parameter δ_ℓ



Notes: Impulse responses are reported in percentage deviations from the steady state of the estimated DSGE model. The climate shock occurs in period 1. Prior to that is the deterministic steady state of the model.

5. SVAR model

The SVAR model was modified to estimate the impacts of climate shocks in the small open economy of Kamber et al. (2013), Gallic and Vermandel (2020), and Jirophat et al. (2022) to be consistent with the DSGE model estimation.

5.1 Identification strategy

The estimating equation is given by:

$$\begin{bmatrix} Y_t^W \\ Y_t^* \\ Y_t^D \end{bmatrix} = C + \begin{bmatrix} B_{11} & 0 & 0 \\ 0 & B_{22} & 0 \\ B_{31} & B_{32} & B_{33} \end{bmatrix} \begin{bmatrix} Y_{t-1}^W \\ Y_{t-1}^* \\ Y_{t-1}^D \end{bmatrix} + \epsilon_t \tag{34}$$

where C is a column vector of constants, and Y_t^W, Y_t^*, and Y_t^D are column vectors of variables for the climate block, the global block, and the domestic block, respectively. The climate block consists of the weather condition constructed in

Section 2.4. The global block comprises foreign output, VIX index, and commodity price. The domestic block consists of output, agricultural output, consumption, investment, inflation, food inflation, government bond yield, and real exchange rate.

These three blocks are ordered based on their exogeneity, with the climate and global blocks affecting the domestic block, but not vice versa, due to imposed restrictions on the VAR coefficient matrix.

5.2 Data

The same dataset was used as the DSGE model (summarized in Table 2) with identical preprocessing procedures. Nonetheless, some additional variables were introduced into the model: VIX index, commodity price, inflation, food inflation, and interest rate. These additions were intended to improve the representation of the economy within the reduced-form relationship. For the commodity price, inflation, and food inflation, the previous preprocessing method was followed, involving taking the natural logarithm and applying the HP filter with the smoothing parameter $\lambda = 1600$ for detrending.

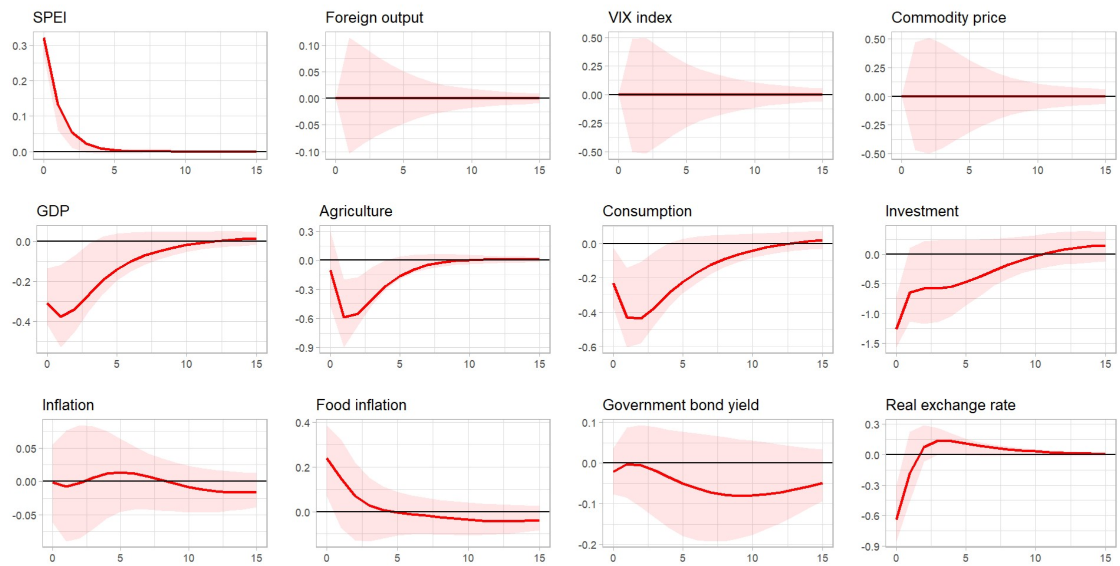
Due to the availability constraints pertaining to government bond yield data, the sample period was restricted to cover the years from 1996Q1 to 2020Q4 instead. Note that hours worked have been excluded from the model, as data for this variable is available only from 2005 onward.

5.3 Transmission mechanism of climate shocks

Figure 11 illustrates the impulse response of climate shocks based on weather conditions constructed from the 6-Month Standardized Precipitation-Evapotranspiration Index. These climate shocks result in a 0.38 percent reduction in GDP, and it takes approximately 13 quarters for these effects to dissipate. This outcome is driven by a combination of supply-side and demand-side factors.

Specifically, agriculture drops around 0.59 percent, while consumption and investment decrease by approximately 0.44 percent and 1.26 percent, respectively. Although climate shocks do not notably impact headline inflation, their effect on food inflation is both positive and significant in the first quarter at 0.24 percent. These shocks negatively impact the real exchange rate, with a statistically significant reduction of 0.64 percent in the first quarter.

Figure 11. Impulse response of climate shocks: 6-month SPEI index



Notes: Impulse responses are reported as a percentage change from the baseline of the SVAR model. Shaded areas are 68% confidence intervals obtained from the 10,000 Monte-Carlo simulations.

Now, the results are compared with the previous study on climate shocks in Thailand that used the SVAR model, as conducted by Jirophat et al. (2022). In both studies, climate shocks lead to a reduction in GDP, and the shocks take approximately 13 quarters to dissipate. However, the magnitude of the impact in this paper is about half of that reported by Jirophat et al. (2022). Additionally, this paper reveals impacts on both the demand side and supply side, whereas Jirophat et al. (2022) only found the impacts on the supply side. Although Jirophat et al. (2022) suggested that the impacts on headline inflation and food inflation are positive but not statistically significant, this paper demonstrates that these impacts are positive and statistically significant for food inflation. This emphasizes the implications of climate change for monetary policy, as highlighted by Jirophat et al. (2022), in a clearer manner.

5.4 Comparison between DSGE and SVAR models

The impulse response generated from the SVAR model (Figure 11) exhibits similarities to the one produced by the DSGE model (Figure 6) in terms of the direction of the effects. In both models, climate shocks have adverse impacts on output via both the production side (agriculture) and the expenditure side (consumption and investment). Although the magnitude of these effects in the DSGE is approximately one-third of those in the SVAR model, climate shocks take more than twice as long to dissipate in the DSGE model. Therefore, the cumulative effects over time in these two models should be relatively comparable. Furthermore, the DSGE model reveals a significant increase in the price within the agricultural sector but not in the non-agricultural sector. This theoretical result aligns with the empirical findings of the SVAR model, where only food inflation experiences a significant increase, whereas headline inflation does not.

6. Conclusion

This paper investigates the economic effects of climate change in Thailand by constructing two models: the theoretical model and the empirical model. The findings indicate that climate shocks negatively affect output via both the supply side, specifically agricultural output, and the demand side, specifically consumption and investment, in both the DSGE model and the SVAR model. Nonetheless, the impacts of climate shocks in the DSGE model are smaller but longer-lasting than those of the SVAR model. This is in line with the observation made by Nelson et al. (2014) that results from climate change models are usually similar in terms of direction but different in terms of magnitude due to variations in model structures. Furthermore, climate shocks result in increased prices in the agricultural sector in the DSGE model, which is consistent with the rise in food inflation observed in the SVAR model. However, the effects on non-agricultural price in the DSGE model and headline inflation in the SVAR model are comparatively limited. The overall findings closely resemble those of Jirophat et al.'s (2022) previous study conducted in Thailand, with some nuanced differences that allow this paper to make more extensive claims. These differences pertain particularly to the effects on the demand side and food inflation.

This paper contains two main caveats. First, in Table 4, the parameter in the damage function is not significantly different from zero. This suggests that the SPEI data may not fit the model as well as the SMDI data did in Gallic and Vermandel (2020). Second, the incorporation of trade balance data into the DSGE model estimation is recommended to enhance the model's representation of the real world.

Finally, the findings from this paper call for three actions from policymakers to mitigate the potential negative impacts of climate change on the Thai economy. First, climate mitigation policies are needed to reduce the magnitude of climate shocks. Second, climate adaptation policies are needed to reduce the damage caused by climate shocks. Third, structural policies that facilitate labor mobility between the agricultural sector and the non-agricultural sector are needed to enable the non-agricultural sector, which is less susceptible to climate change, to help absorb the impacts of climate shocks.

Acknowledgements

I gratefully acknowledge my research advisor, Pongsak Luangaram, for his tremendous support and guidance throughout the process of writing this paper. I thank Gauthier Vermandel for providing programming codes on the DSGE model. I also thank the editor, Vasileios Zikos, and two anonymous referees for comments that substantially improved this paper.

References

Amatyakul, P., Apaitan, T., Hiruntiaranakul, S., & Nookhwun, N. (2021). *Revisiting Thailand's monetary policy model for an integrated policy analysis* (Discussion Paper 164). Puey Ungphakorn Institute for Economic Research. Retrieved from https://www.pier.or.th/dp/164/

Bremus, F., Dany-Knedlik, G., & Schlaak, T. (2020). Price stability and climate risks: Sensible measures for the European Central Bank. *DIW Weekly Report*, *10*(14), 206-213. https://doi.org/10.18723/diw_dwr:2020-14-1

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*(4), 434-455. https://doi.org/10.1080/10618600.1998.10474787

Buckle, R. A., Kim, K., Kirkham, H., McLellan, N., & Sharma, J. (2007). A structural VAR business cycle model for a volatile small open economy. *Economic Modelling*, *24*(6), 990-1017. https://doi.org/10.1016/j.econmod.2007.04.003

Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on Loess. *Journal of Official Statistics*, *6*(1), 3-73.

Cushman, D. O., & Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary Economics*, *39*(3), 433-448. https://doi.org/10.1016/S0304-3932(97)00029-9

Eckstein, D., Künzel, V., & Schäfer, L. (2021). *The global climate risk index 2021*. Bonn: Germanwatch.

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

Generoso, R., Couharde, C., Damette, O., & Mohaddes, K. (2020). The growth effects of El Niño and La Niña: Local weather conditions matter. *Annals of Economics and Statistics*, *140*, 83-126. https://doi.org/10.15609/annaeconstat2009.140.0083

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, *82*(1), 41-88. https://doi.org/10.3982/ECTA10217

Hashimoto, R., & Sudo, N. (2022). *Transmission of flood damage to the real economy and financial intermediation: Simulation analysis using a DSGE model* (22-E-5). Bank of Japan. Retrieved from https://www.boj.or.jp/en/research/wps_rev/wps_2022/wp22e05.htm

Hou, M., Yao, N., Li, Y., Liu, F., Biswas, A., Pulatov, A., & Hassan, I. (2022). Better drought index between SPEI and SMDI and the key parameters in denoting drought impacts on spring wheat yields in Qinghai, China. *Agronomy*, *12*(7). https://doi.org/10.3390/agronomy12071552

Jirophat, C., Manopimoke, P., & Suwanik, S. (2022). *The macroeconomic effects of climate shocks in Thailand* (Discussion Paper 188). Puey Ungphakorn Institute for Economic Research. Retrieved from https://www.pier.or.th/dp/188/

Kamber, G., McDonald, C., & Price, G. (2013). *Drying out: Investigating the economic effects of drought in New Zealand* (Reserve Bank of New Zealand Analytical Notes Series AN2013/02). Retrieved from https://www.rbnz.govt.nz/hub/publications/analytical-note/2013/an2013-02

Kubo, A., & Hirao, K. (2020). Do inflation targeters in Southeast and East Asia respond to exchange rate movements? *Southeast Asian Journal of Economics*, *8*(2), 25-42.

Luangaram, P., & Wongpunya, N. (2022). *Exploring the role of exchange rate in inflation targeting: Evidence from Thailand* (Discussion Paper 179). Puey Ungphakorn Institute for Economic Research. Retrieved from https://www.pier.or.th/dp/179/

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, *17*(22), 179-183. Retrieved from - https://www.droughtmanagement.info/literature/AMS_Relationship_Drought_Frequency_Duration_Time_Scales_1993.pdf

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., Kyle, P., Von Lampe, M., Lotze-Campen, H., Mason d'Croz, D., van Meijl, H., van der Mensbrugghe, D., Müller, C., Popp, A., Robertson, R., … Willenbockel, D. (2014). Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences*, *111*(9), 3274-3279. https://doi.org/10.1073/pnas.1222465110

Nordhaus, W. D. (1977). Economic growth and climate: The carbon dioxide problem. *The American Economic Review*, *67*(1), 341-346.

Nordhaus, W. D. (1991). To slow or not to slow: The economics of the greenhouse effect. *The Economic Journal*, *101*(407), 920-937. https://doi.org/10.2307/2233864

Palmer, W. C. (1965). *Meteorological drought* (Issue v. 30). U.S. Department of Commerce, Weather Bureau.

Phrommin, K. (2018). Monetary policy analysis under headline and core inflation targeting in Thailand. *Thailand and The World Economy*, *36*(2), 1-31.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature*, *51*(3), 860-872. https://doi.org/10.1257/jel.51.3.860

Schmitt-Grohé, S., & Uribe, M. (2003). Closing small open economy models. *Journal of International Economics*, *61*(1), 163-185. https://doi.org/10.1016/S0022-1996(02)00056-9

Sims, C. A. (2012). Statistical modeling of monetary policy and its effects. *American Economic Review*, *102*(4), 1187-1205. https://doi.org/10.1257/aer.102.4.1187

Smets, F., & Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review*, *97*(3), 586-606. https://doi.org/10.1257/aer.97.3.586

Tanboon, S. (2008). *The Bank of Thailand structural model for policy analysis* (Discussion Paper 12/2008). Monetary Policy Group, Bank of Thailand. Retrieved from https://www.bot.or.th/content/dam/bot/documents/th/research-and-publications/research/discussion-paper-and-policy-paper/dp122008th_surach.pdf

Vicente-Serrano, S. M., Beguería, S., & 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. https://doi.org/10.1175/2009JCLI2909.1

Wannapan, S., Chaiboonsri, C., & Sriboonchitta, S. (2018). Application of the Bayesian DSGE model to the international tourism sector: Evidence from

Thailand's economic cycle. *WIT Transactions on Ecology and the Environment*, *227*, 257-268.

Appendices

Appendix I: Agricultural firms' profit maximization problem

The Lagrange function associated with agricultural firms' profit maximization problem is given by:

$$\mathcal{L} = E_t\left\{\sum_{\tau=0}^{\infty}\Lambda_{t,t+\tau}\left[\pi_{t+\tau}^{A} + q_t^A\left(i_{it}^A + (1-\delta_K)k_{it-1}^A - k_{it}^A\right) + \varrho_t\left(\left((1-\delta_\ell) + v(x_{it})\right)\Omega(\varepsilon_t^W)\ell_{it-1} - \ell_{it}\right)\right]\right\} \quad (35)$$

The first-order condition with respect to h_{it}^A is given by:

$$w_t^A = (1-\omega)(1-\alpha)p_t^A\frac{y_{it}^A}{h_{it}^A} \quad (36)$$

The first-order condition with respect to i_{it}^A is given by:

$$q_t^A = p_t^N + \kappa p_t^N\varepsilon_t^I\left(\varepsilon_t^I\frac{i_{it}^A}{i_{it-1}^A} - 1\right) - E_t\left\{\Lambda_{t,t+1}\frac{\kappa}{2}p_{t+1}^N\left[\left(\varepsilon_{t+1}^I\frac{i_{it+1}^A}{i_{it}^A}\right)^2 - 1\right]\right\} \quad (37)$$

The first-order condition with respect to k_{it}^A is given by:

$$q_t^A = E_t\left\{\Lambda_{t,t+1}\left[\alpha(1-\omega)p_{it+1}^A\frac{y_{it+1}^A}{k_{it}^A} + (1-\delta_K)q_{t+1}^A\right]\right\} \quad (38)$$

The first-order condition with respect to ℓ_{it} is given by:

$$\varrho_t = E_t\left\{\Lambda_{t,t+1}\left[\omega p_{t+1}^A\frac{y_{it}^A}{\ell_{it}} + \varrho_{t+1}\left((1-\delta_\ell) + v(x_{it+1})\right)\Omega(\varepsilon_{t+1}^W)\right]\right\} \quad (39)$$

The first-order condition with respect to x_{it} is given by:

$$\varrho_t = \frac{p_t^N}{v'(x_{it})\Omega(\varepsilon_t^W)\ell_{it-1}} \quad (40)$$

Appendix II: Non-agricultural firms' profit maximization problem

The Lagrange function associated with non-agricultural firms' profit maximization problem is given by:

$$\mathcal{L} = E_t\left\{\sum_{\tau=0}^{\infty} \Lambda_{t,t+\tau}\left[\pi_{t+\tau}^N + q_t^N\left(i_{it}^N + (1-\delta_K)k_{it}^N - k_{it}^N\right)\right]\right\} \tag{41}$$

The first-order condition with respect to h_{it}^N is given by:

$$w_t^N = (1-\alpha)p_t^N \frac{y_{it}^N}{h_{it}^N} \tag{42}$$

The first-order condition with respect to i_{it}^N is given by:

$$q_t^N = p_t^N + \kappa p_t^N \varepsilon_t^I\left(\varepsilon_t^I \frac{i_{it}^N}{i_{it-1}^N} - 1\right) - E_t\left\{\Lambda_{t,t+1}\frac{\kappa}{2}p_{t+1}^N\left[\left(\varepsilon_{t+1}^I \frac{i_{it+1}^N}{i_{it}^N}\right)^2 - 1\right]\right\} \tag{43}$$

The first-order condition with respect to k_{it}^N is given by:

$$q_t^N = E_t\left\{\Lambda_{t,t+1}\left[\alpha p_{it+1}^N \frac{y_{it+1}^N}{k_{it}^N} + (1-\delta_K)q_{t+1}^N\right]\right\} \tag{44}$$

Appendix III: Households' utility maximization problem

The household's utility maximization problem can be simplified as:

$$\max_{\{c_{jt},b_{jt},b_{jt}^*,h_{jt}^A,h_{jt}^N\}} E_t\left\{\sum_{\tau=0}^{\infty} \beta^\tau U_{jt+\tau}\right\} \tag{45}$$

subject to

$$C_{jt} \leq \sum_{s=N,A} w_{jt}^s h_{jt}^s + r_{t-1}b_{jt-1} + rer_t^* r_{t-1}^* b_{jt-1}^* - t_{jt} - b_{jt} - rer_t^* b_{jt}^* - p_t^N rer_t^* \Phi\left(b_{jt}^*\right) \tag{46}$$

The marginal utility of consumption C_{jt} is given by:

$$\lambda_t^C = U_{C_{jt}} = \frac{\partial U_{jt}}{\partial C_{jt}} = \left(C_{jt} - bC_{jt-1}\right)^{-\sigma} \tag{47}$$

The household stochastic discount factor is given by:

$$\Lambda_{t,t+1} = \beta E_t \left\{ \frac{\lambda_{t+1}^C}{\lambda_t^C} \right\} \tag{48}$$

The marginal disutility of labor h_{it}^N is given by:

$$U_{h_{jt}^N} = \frac{\partial U_{jt}}{\partial h_{jt}^N} = \chi \varepsilon_t^H h_{jt}^{\sigma_H} \left(\frac{h_{jt}^N}{h_{jt}} \right) \tag{49}$$

The marginal disutility of labor h_{it}^A is given by:

$$U_{h_{jt}^A} = \frac{\partial U_{jt}}{\partial h_{jt}^A} = \chi \varepsilon_t^H h_{jt}^{\sigma_H} \left(\frac{h_{jt}^A}{h_{jt}} \right) \tag{50}$$

The first-order condition with respect to b_{jt} is given by:

$$E_t\{\Lambda_{t,t+1}\} r_t = 1 \tag{51}$$

The first-order condition with respect to b_{jt}^* is given by:

$$E_t \left\{ \frac{rer_{t+1}^*}{rer_t^*} \right\} = \frac{1}{E_t\{\Lambda_{t,t+1}\} r_t^*} \left(1 + p_t^N \Phi'\left(b_{jt}^*\right) \right) \tag{52}$$

The first-order condition with respect to h_{jt}^N is given by:

$$w_t^N U_{C_{jt}} = U_{h_{jt}^N} \tag{53}$$

The first-order condition with respect to h_{jt}^A is given by:

$$w_t^A U_{C_{jt}} = U_{h_{jt}^A} \tag{54}$$

Appendix IV: Foreign economy's utility maximization problem

The foreign economy's utility maximization problem can be simplified as:

$$\max_{\{c_{jt}^*, b_{jt}^*\}} E_t \left\{ \sum_{\tau=0}^{\infty} \beta^\tau U_{jt+\tau}^* \right\} \tag{55}$$

subject to

$$c_{jt}^* \leq r_{t-1}^* b_{jt-1}^* - b_{jt}^* \tag{56}$$

The marginal utility of consumption c_{jt}^{*} is given by:

$$\lambda_t^{C^*} = U_{c_{jt}^*} = \frac{\partial U_{jt}^*}{\partial c_{jt}^*} = \varepsilon_t^E \left(c_{jt}^* - b^* C_{jt-1}^*\right)^{-\sigma^*} \tag{57}$$

The household stochastic discount factor is given by:

$$\Lambda_{t,t+1}^* = \beta E_t \left\{ \frac{\lambda_{t+1}^{C^*}}{\lambda_t^{C^*}} \right\} \tag{58}$$

The first-order condition with respect to b_{jt}^{*} is given by:

$$E_t\{\Lambda_{t,t+1}^*\} r_t^* = 1 \tag{59}$$