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The Macroeconomic Effects of Climate Shocks in Thailand

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Abstract

This paper studies the dynamic impact of climate shocks on economic activity and inflation in Thailand, a developing country susceptible to the effects of climate change. We utilize a Vector Autoregressive (VAR) analysis that accounts for the asymmetric and nonlinear impacts of climate change. Overall, climate shocks are significantly contractionary on output whereas their effect on inflation is rather muted. For output, the impact is more pronounced on the production rather than expenditure side of the economy, although highly persistent climate shocks can have significant effects on demand. Furthermore, we find that the macroeconomic impact of climate change varies significantly across sectors of production as well as components of inflation. Raw food prices, in particular vegetables, are sensitive to climate shocks, consistent with the agricultural sector being most vulnerable, with effects that are more pronounced in the short-run. This contrasts with industrial production and service sectors that experience more persistent effects. We also find that dry versus wet weather conditions deliver varying effects on output and inflation, and we also find that the impact of climate shocks are more severe if extreme weather events are large, as well as sustained for longer periods of time. Finally, utilizing a panel autoregressive distributed lag model (ARDL), we quantify significant differences in the impact of climate shocks on aggregate output across provinces, depending on the provincial level of income as well as its proportion of output tied to agricultural activities.

Keywords: climate shocks, climate change, macroeconomy, inflation, extremity, nonlinearity, sectors of production, output.

JEL Codes: E23, E52, O13, O53, Q56.

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1 Introduction

The Earth's climate has been changing at an unprecedented pace over past decades - with weather events that have becoming more volatile, frequent, and extreme. The adverse consequences of climate change are now not only concentrated in lower-income and developing countries that typically rely on agricultural activities (Dell et al., 2012; Acevedo et al., 2018), but have also been reported to severely affect advanced economies as well. Persistent changes in temperature or precipitation patterns including more volatile climate conditions can have both short and long-term macroeconomic consequences that work to lower output per capita through various channels such as reduced production and investment (Noy, 2009; Colacito et al. 2019; Acevedo et al, 2020), as well as create risks for price stability by exerting upward pressure or creating volatility in prices (Parker, 2018; Heinen et al., 2019; Faccia et al., 2021). Given that the severity of climate change is expected to accelerate in the future, central bankers around the world are thus expressing the urgency to incorporate the macroeconomic effects of climate change into their monetary and financial stability mandates to ensure that their policy frameworks are robust to such risks (Batten et al., 2020; Scott et al. 2017; Batten, 2018; Bremus et al. 2020).

This paper aims to contribute to the ongoing debate on the macroeconomic consequences of climate change and draw implications that are relevant to central banks.[1]. From a central bank perspective, policymakers are concerned about whether climate change can have significant and persistent effects on output and prices over horizons relevant to monetary policy. Therefore, our work investigates the dynamic impacts of climate shocks on output and inflation in Thailand, over both the short and medium run horizons. We view Thailand as a suitable candidate for this study given its high vulnerability to climate change due to its geography, economy, and level of development (Marks, 2018)[2]. In particular, Thailand is one of the world's largest food producers, and therefore droughts, flooding, and tropical storms pose serious threats to agricultural activities and livestock production. This risk is not only relevant to reduced output growth, but also to large income losses as well, as the agricultural sector employs approximately a third of Thailand's population. Furthermore, as a developing nation, fresh food products

[1] This is a vast literature and includes studies that assesses the impact of both physical and transition risk. The effect of physical risk, which is the focus of this study, arises from the interaction between higher average temperatures, more frequent weather extremes and the exposure and vulnerability of society and economic systems to these hazards. Physical risk can be divided into two categories: (i) gradual global warming and its associated physical changes, such as rising sea levels or changes in precipitation patterns; and (ii) natural disasters such as hurricanes, floods and heatwaves (Drudi et al, 2021). On the other hand, transition risk is the risk inherent in changing strategies, policies or investments to reduce its reliance on climate change related causes, e.g., use of carbon. This type of risk is more related to the strand of economics of trade and climate and economics of adaptation.

[2] According to ADB and World Bank (2021), Thailand has been cited as one of the ten most flood-affected countries in the world, with the Great Flood in 2011 leading to an estimated loss of 1,425 trillion (US$46.5 billion) in economic damages through disruptions in production and supply chains.

takes up approximately a fifth of Thailand's CPI basket, thus extreme or unpredictable weather events can raise challenges for price stability as food inflation becomes more volatile. Changing climate conditions is also a key concern towards the livelihood of coastal tourism, in which Thailand's economy is highly reliant upon.

To investigate the macroeconomic impacts of climate change for Thailand, we adopt two econometric approaches. First, we estimate a times-series vector autogressive (VAR) model similar to Kamber et al. (2013) that includes a system of macroeconomic variables to analyze the dynamic impact of climate shocks on output and inflation, while allowing its impact to have nonlinear and asymmetric effects. To better understand how the shocks propagate through various sectors of the economy, we also investigate its impact on the subcomponents of GDP (e.g. agriculture, industrial and service sectors for the production side, and consumption, investment, exports and imports for the expenditure side) and inflation (core, energy and disaggregated food components). Second, to analyze whether there are any differences in the cross-provincial impact of climate shocks on output that can be explained by factors such as provincial levels of income or reliance of agricultural activities, we estimate a panel autoregressive distributed lag model (ARDL) that is similar in spirit to the cross-country study of Kahn et al. (2019).

Despite a large literature that investigates the economic effects of climate-related shocks, the literature has documented mixed results - some suggesting limited or no effects while other reporting significant damages (Tol, 2009; Dell et al., 2014; Hsiang, 2016; for recent surveys). Our work helps shed light on these ongoing debates while offering the following contributions. First, we choose to adopt the Standardized Precipitation Evapotranspiration Index (SPEI) as our climate variable, which conveniently combines the effect of both changing precipitation and temperature patterns. As such, we are able to study how changing climate conditions holistically impact the economy, rather than following the usual approach of studying rainfall and temperature effects separately. In addition, the SPEI index measures climate conditions as standardized deviations from its historical norm, which as emphasized by Kahn et al. (2019), is an important departure from the literature. The focus on deviations helps capture changes in the distribution of weather patterns such as its variability, which arguably matters more for economic activity than just the average temperature or precipitation levels. Furthermore, by using deviations of the SPEI, we avoid spurious results that could occur from the common usage of trended variables, such as temperature levels, that are often employed in standard climate regressions (Mendelsohn, 2016; Kahn et al., 2019; Tol, 2021).

A distinguishing feature of our work is that it also provides a highly comprehensive within-country study of climate change. A long line of literature offers cross-country analyses to highlight heterogeneous country experiences, and emphasize the differences that stem from the level of income across nations (Sachs and Warner 1997; Gallup et al.

1999; Nordhaus 2006; Dell et al., 2012; Cashin et al., 2017; Burke and Tanutama, 2019; Kahn et al. 2019). However, results based on cross-sectional averages may not be entirely relevant to macroeconomic policy of a particular country, nor can it uncover the full scale of heterogeneity that might exist along various dimensions. For example, separate studies highlight that the economic effects of climate change could differ depending on the direction of shock (positive vs. negative), size (extreme vs. moderate), as well as degree of persistence (sudden vs. long-lasting) (see Cavallo, 2013; Burke et al., 2015; Kahn et al., 2019, Kim et al., 2021). Our study investigates whether climate shocks are significant for output and prices along all these dimensions at the same time as examining its heterogeneous impacts across sectors and provinces. Such an analysis is lacking for Thailand, especially at the macroeconomic level, as much of the existing studies have only focused on the impact of adverse weather conditions, particularly rainfall, on regional output (Sangkhaphan and Shu, 2020) or individual crop production (Pipitpukdee et al., 2020; Pakeechai et al., 2020).

Based on a preview of our results, climate shocks can have both significant short and medium run effects on output and inflation. The impact is nevertheless highly heterogenous depending on the sector affected, and it also crucially hinges upon the direction, persistence and size of the climate shock. In particular, we find that climate shocks mainly acts as a supply shock and it can be contractionary for real activity, with overall muted but mildly inflationary effects on prices. The agricultural sector in particular is highly vulnerable, consistent with raw food inflation especially vegetables being highly responsive to climate shocks. Finally, there are important cross-provincial differences in the effect of climate shocks depending on certain characteristics, such as output in poor provinces contracting more following climate change.

This paper is organized into five sections. Section 2 describes the climate data for our analyses and highlights important historical patterns of climate change in Thailand. Section 3 contains country-level analysis of climate change and discusses how climate shocks may affect aggregate output and inflation through various subcomponents and over different time horizons. Section 4 contains the cross-provincial results. The final section concludes and draws implication for monetary policy.

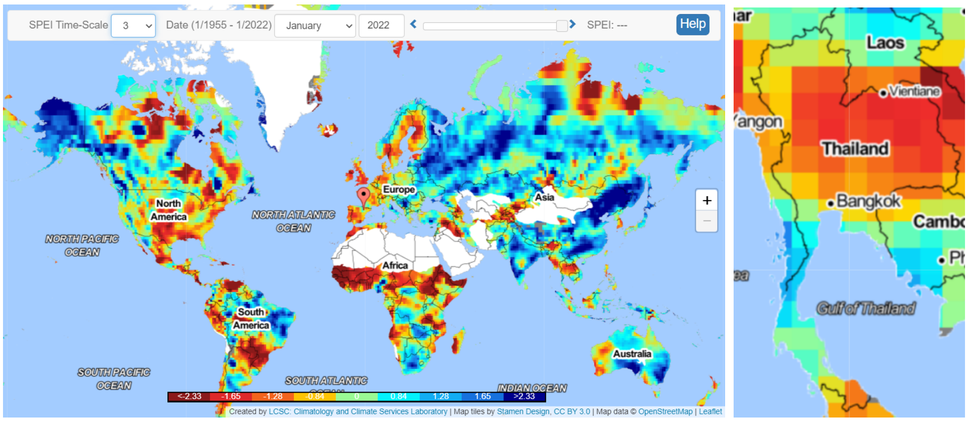
2 Climate Data and Climate Change Paterns

We utilize the Standardized Precipitation Evapotranspiration Index (SPEI) as a measure of weather conditions, which combines the effect of both changing preciptation and temperature patterns. The SPEI index was originally developed by Vicente-Serrano et al. (2010), and due to its attractive features, it has been frequently used to examine climate change in various countries (Couharde et al., 2019; Bremus et al., 2020). In this section, we describe the construction method of the SPEI index and document its key properties that reflect the historical patterns of climate change in Thailand.

2.1 SPEI Data Construction

Our empirical study requires a country-level SPEI index for the VAR estimation and provincial-level SPEI inidices for the panel ARDL analysis. Constructing the country-level SPEI index is straightforward, as it can be obtained from aggregating over SPEI indices that are calculated for individual grids that are available at https://spei.csic.es.[3] For Thailand, there are 57 individual grids (see Figure 1b), where each grid represents a 0.5 degree spatial resolution that is available at a monthly frequency from January 1950 to present.

Figure 1: Map of SPEI Grids



(a) World Map (b) Thailand Map Source: https://spei.csic.es

The SPEI index at the individual grid level are times series that represents the net supply of water available for a particular area, calculated as the difference between precipitation and potential evapotranspiration[4]. This water balance can be cumulated over different time periods, such as over 1, 3, 6, 9, 12, 24, 36, and 48 months, to capture varying degrees of persistence and severities in climate conditions. For example, the 3-month SPEI index (SPEI3M) represents the water balance cumulated over three months. The 12-month SPEI index (SPEI12M) represents the water balance cumulated over a year and captures more persistent and severe weather conditions.

A particularly attractive feature of the SPEI index is that it represents standardized deviations of climate conditions from its historical norm since the cumulated water

[3]For robustness checks, we also consider other aggregation methods. This includes the median value, first principal component, as well as aggregating only over cropland areas. All alternative measures of aggregation do not significantly differ from the average value, and the correlation between measures are high at levels exceeding 0.9.

[4]The potential evapotranspiration can be estimated by using different types of models, however, the simplest model is the Thornthwaite (1948) equation.

balance is fitted to a Log-logistic distribution function[5]. A standardized index allows for easy comparison across regions, as well as the convenience in aggregating SPEI indices across grids. Moreover, calculating the climate variable as deviations from their long-term norms offers various other benefits. First, as discussed in Kahn et al. (2019), it avoids the econometric pitfalls in previous studies that tend to use trended variables such as temperature levels in output growth equations when studying the impact of climate change which could lead to spurious results. Second, it allows us to consider the directional effects of climate change, where a positive value in the SPEI index indicates wetter-than-normal weather conditions and a negative value implies drier-than-normal weather conditions. Finally, it offers for easy classification of climate conditions - from normal, to moderate, and to exceptionally extreme. For example, according to the National Oceanic and Atmospheric Administration (NOAA) classification as shown in Table 1, a SPEI value greater than 1.6 indicates weather conditions that are extremely moist. This feature allows us to study the nonlinear impact of climate conditions on the macroeconomy based on the extremity of weather conditions as indicated by various ranges of the SPEI index.

Table 1: Classification of Weather Conditions

Weather condition	SPEI range
Exceptionally moist	$SPEI \geq 2$
Extremely moist	1.6 $\leq$ SPEI $<$ 2
Very moist	1.3 $\leq$ SPEI $<$ 1.6
Moderately moist	0.8 $\leq$ SPEI $<$ 1.3
Slightly moist	0.5 $\leq$ SPEI $<$ 0.8
Near Normal	-0.5 $\leq$ SPEI $<$ 0.5
Slightly dry	-0.8 $\leq$ SPEI $<$ -0.5
Moderately dry	-1.3 $\leq$ SPEI $<$ -0.8
Very dry	-1.6 $\leq$ SPEI $<$ -1.3
Extremely dry	-2 $\leq$ SPEI $<$ -1.6
Exceptionally dry	$SPEI <$ -2

Source: NOAA's National Centres for Environmental Information

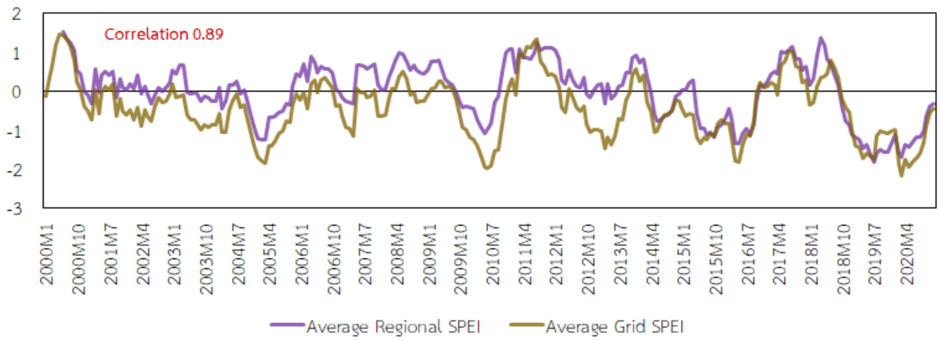
Next, we discuss the construction of the provincial SPEI index. Given that the grids in Figure 1b do not exactly align with the 77 provinces in Thailand, we need to construct provincial SPEI indices from raw monthly precipitation and temperature data that we obtain from the Hydro-Informatics Institute. With this dataset, we construct provincial SPEI indices for the 2001-2020 period by utilizing the official R package called 'SPEI'[6], which utilizes the Thornthwaite (1948) equation to estimate potential evapotranspiration

[5]In constructing the long-term norm, the norm is different in each month. For example, if we consider the data from 1950 to 2020, the SPEI index for Jan 2020 compares the cumulative water balance in Jan 2020 with the long-term norm for all months of January, i.e. the norm for Jan 1950, Jan 1951,...,Jan 2020. The same idea applies to other months. Therefore, due to this characteristic, we can utilize the SPEI index without seasonal adjustment.

[6]For more information about the package see https://cran.r-project.org/web/packages/SPEI/index.html

levels. We check the robustness of our provincial SPEI indices by taking the simple average of all provincial series, and comparing it to the previously calculated country-level SPEI. As shown in Figure 2, both indices move together well, with a high correlation of 0.89.

Figure 2: Aggregated SPEI Indices based on Grid-Level and Provincial-Level Data



Note: Average Regional SPEI is calculated from taking the average of individual SPEI indices across 88 individual provinces. The Average Grid SPEI is calculated by taking the average of individual SPEI indices across 57 individual grids.

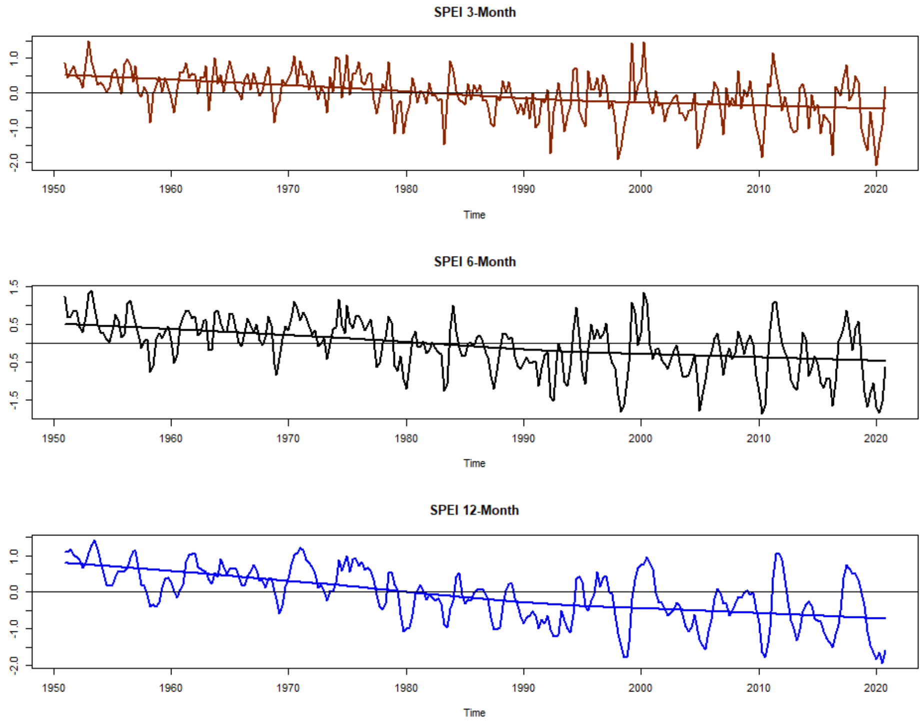
2.2 Historical Patterns of Climate Change

We analyze weather conditions in Thailand via the SPEI index over the 3, 6, and 12 month horizons (SPEI3M, SPEI6M, and SPEI12M). Figure 3 contains a plot of these series, alongside their fitted trends. As shown, all SPEI indices appear to capture key weather events in Thailand well. For example, the great drought (July 1979 - March 1980) generated a sharp decline in all SPEI indices, while the great flood that spanned over six months in the second half of 2011 caused all SPEI indices to increase dramatically. It is also evident that climate conditions in Thailand has become drier than what is considered normal over time as evident by negative and statistically significant trends for all SPEI indices. The slope that becomes slightly steeper as the SPEI horizon increases is also indicative of climate shocks that are becoming more extreme.[7] Another interesting observation is that the trend for all Thai SPEI indices dropped below zero around 1980, signifying permanent drier than normal weather conditions. According to Nita et al. (2022) among others, this is a global phenomenon as global temperatures have been reported to rise sharply since the early 1980s.

Alongside a drier trend, we also find that weather conditions in Thailand are becoming more volatile and extreme. Figure 4 shows the box plots associated with the SPEI3M, SPEI6M, and SPEI12M time series. Each horizontal bar represents all possible values

[7] According to Mann Kendall statistical test that has been widely applied in the trend detection of hydrometeorological time series, we find that the test statistics to the fitted trends of 3, 6, and 12 month SPEI indices are -0.36, -0.38 and -0.43 with corresponding p-values of 0.00. This indicates statistically significant monotonic downward trends.

Figure 3: SPEI Indices and Drier Trends

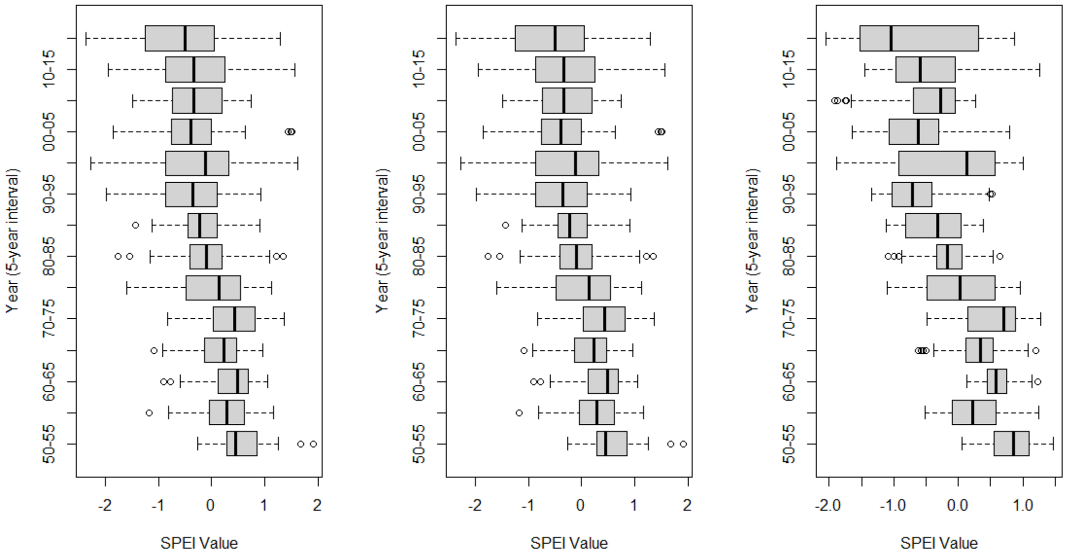


Note: Country-level SPEI indices obtained from aggregating over individual grids. The solid line represents the long-term trend.

of the SPEI index that fall within a 5-year interval. The fact that this horizontal bar has become wider over time indicates more extreme weather events. The inner rectangle that represents the interquartile range has also become wider over time, signifying more volatile climate deviations from what is considered as normal. Given that the most recent box for the SPEI12M index is particularly wide, this means that weather conditions are not only becoming more volatile, but also more persistent. The thick black vertical line marks the median SPEI value for each 5-year interval which has been gradually shifting leftwards. This confirms our earlier observation of drier weather conditions over time for Thailand.

Finally, we examine whether extreme weather conditions have been occurring more frequently over time. We use the classification in Table 1 to calculate the proportion of grids with SPEI values that fall into what is considered to be extremely moist, normal and extremely dry at each point in time. Figure 5 illustrates the results over the full 1950-2020 sample over 5-year increments. As shown, it is clear that Thailand has become more susceptible to more frequent and extremely dry weather conditions. This observation stands out in the most recent period (2015-2020), where the severe drought in 2019-2020 significantly widened the box plot and increased the SPEI median. Meanwhile, it has become less likely that extremely wet or even normal weather conditions would occur. This reaffirms our earlier findings that over past decades, climate conditions in Thailand is becoming more dry and severe over time.

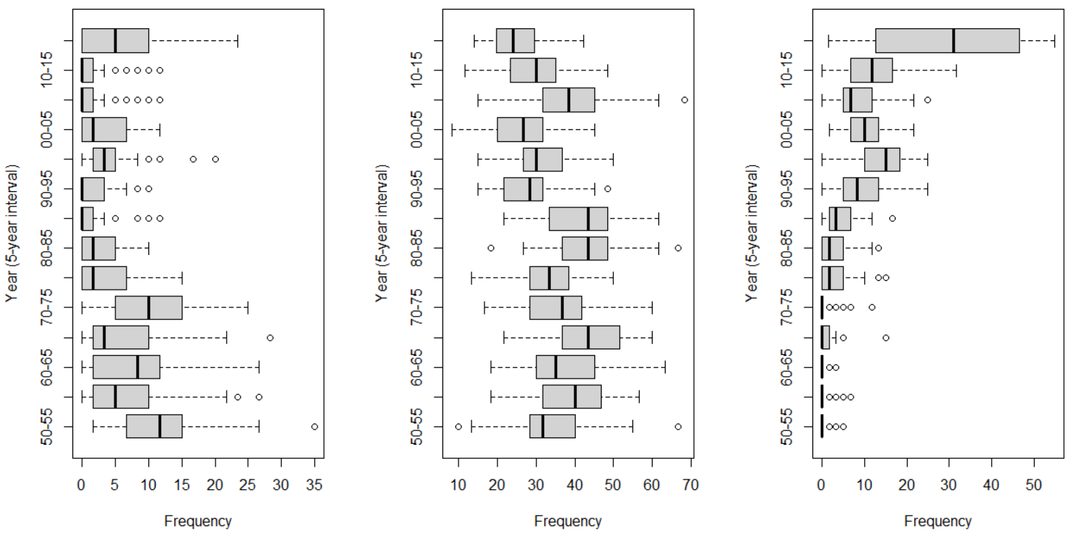
Figure 4: Box plots of SPEI Indices



(a) SPEI 3-Month (b) SPEI 6-Month (c) SPEI 12-Month

Note: Box plots of country-level SPEI indices over various frequencies and five-year time intervals, where the solid line represents the median value, the box is the IQR range, and dots are outliers.

Figure 5: Frequency of Extreme Climate Conditions



(a) Extremely Moist Condition (b) Normal Condition (c) Extremely Dry Condition

Note: Box plots of the frequency of occurrences of extreme (SPEI values in excess of 2 and -2) and normal (SPEI values between -0.5 and 0.5) climate conditions are based on the SPEI6m country-level index. The solid line represents the median value, the box is the IQR range, and dots are outliers, where box plots are calculated over five year intervals.

3 Country-level Macroeconomic Impact of Climate Shocks

3.1 Data and Model Specification

For our empirical analysis, we adapt the structural vector autoregression (VAR) model of Buckle et al. (2007) and Kamber et al. (2013) to suit a small open economy such as Thailand. It is specified as:

$$\begin{pmatrix} Climate_t \\ Global_t \\ Domestic_t \end{pmatrix} = A_0 + \begin{pmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{pmatrix} \times \begin{pmatrix} Climate_{t-1} \\ Global_{t-1} \\ Domestic_{t-1} \end{pmatrix} + \epsilon_t \tag{1}$$

where A_0 denotes a column vector containing constant terms of each equation, and ϵ_t is the white noise error term. $Climate_t$, $Global_t$, and $Domestic_t$ are three separate blocs that contain climate, global, and domestic variables respectively. These blocs are ordered according to their degree of exogeneity, where we impose restrictions on the coefficient matrix of their lag terms so that climate and global blocs are not affected by domestic variables. This approach is standard in the small open economy literature.

We describe the three blocs in the above specification in turn. First, the climate bloc, which is the most exogenous, includes our measurement variable of climate, which is the SPEI index. In the baseline specification, we follow Bremus et al. (2020) and utilize the absolute value of the SPEI index to provide a measure of overall weather conditions:

$$Overall_t = 1/N \times \sum_{i=1}^{N} |SPEI_{i,t}| \tag{2}$$

where N is the 57 SPEI grids and $SPEI_{i,t}$ is the SPEI index of grid i at time t. As shown, the overall SPEI index captures the average climate of the country based on the absolute SPEI values in the grids. Note that measured in this way, the climate variable treats both wet (positive SPEI values) and dry (negative SPEI values) climate conditions symmetrically.[8]

Next, the global bloc ($Global_t$) consists of variables aiming to capture global economic conditions, in order to control for the effect of the global economy on Thailand's small open economy. We include the real GDP of OECD countries to capture global output, the VIX index to capture global sentiment and risk aversion, and real global oil and non-fuel

[8] This means that in the VAR analysis, the impulse response function will represent how variables respond to a one standard deviation increase in the average absolute value of climate shocks, which does not differentiate between increasingly wet or dry conditions. For reference, a one standard deviation increase in the absolute SPEI index is equivalent to the recent drought in Thailand as experienced during 2019-2020.

prices to capture fluctuations in commodity prices. Lastly, the domestic bloc contains key macroeconomic variables for Thailand, including real GDP, the consumer price index (CPI), the 2-year government bond yield, and the nominal effective exchange rate (NEER). All macroeconomic variables are at the quarterly frequency and are expressed as the percentage change differences from the same period in the previous year. They are obtained from disparate sources - Thai GDP from the Office of the National Economic and Social Development Council of Thailand (NESDC); CPI inflation, the 2-year government bond yield, and the NEER from CEIC; OECD real GDP from the OECD database, and VIX from the FRED. The sample spans 2001-2020, where the beginning of the sample is determined based on the availability of government bond yield data, as well the adoption of an inflation targeting regime in Thailand during 2001.

We are also interested in investigating the effects of climate change on sectoral variables to better understand the channels in which shocks propagate. To do so, we place each disaggregated component of real output and CPI inflation in the VAR after either aggregate output or inflation respectively. For real output, we analyze both disaggregated components based on sectors of production as well as the expenditure side components of real output. On the production side, the three main sectors are agriculture, industrial, and service sectors, with average shares of 7.4%, 34.2%, and 58.4% respectively.[9] As for the expenditure share components, consumption, investment, exports and imports take up 54.5%, 25.1%, 73.1%, and 68% of real output respectively.

Aside from the effects of climate change on output, inflation is another key variable that can be directly affected by extreme changes in weather conditions. In particular, global warming or extreme weather events can adversely impact global food production, leading to food price inflation in many countries that rely on imported food. Thailand is a developing economy that has a sizable portion of the consumption basket tied to food, and therefore it is particularly vulnerable to changing weather conditions. Also, being a small open economy, its fluctuations in inflation can be exposed to spillover effects from international commodity trade (Heinen et al., 2019; Parker 2018; Peersman, 2018) as well as global food price and energy shocks. We therefore investigate the impact of climate shocks on inflation and its subcomponents, which include c, raw food and energy, which take up a percentage share of 67, 20 and 12 precent of the CPI consumption basket.

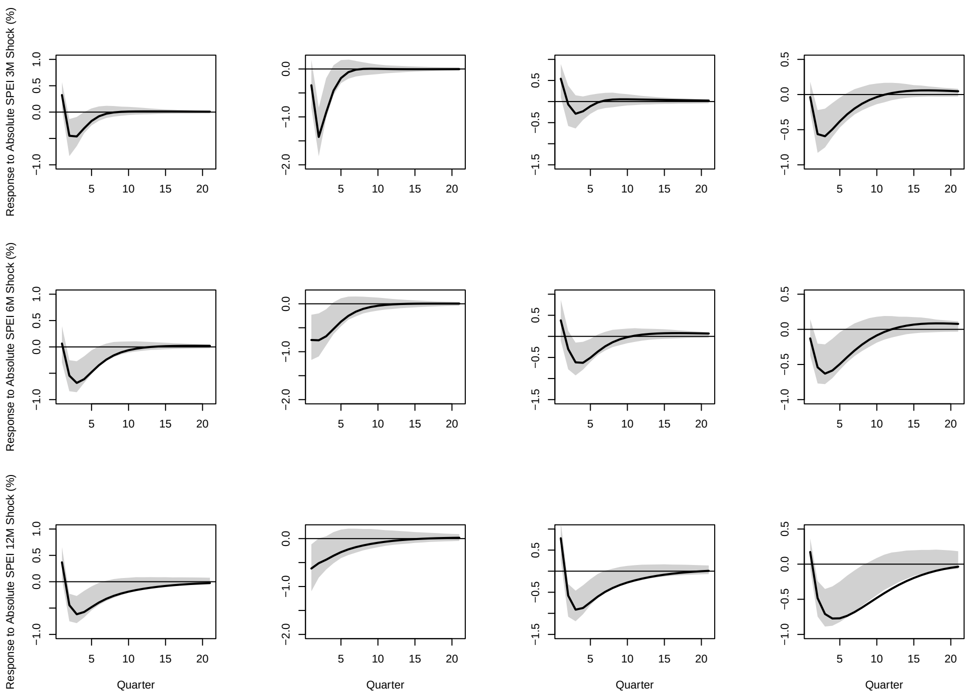
3.2 Impact on Output and Components

We start with the empirical analysis on the overall effects of a climate shock on output growth in Thailand. We present the analyses based on SPEI indices at 3, 6, and 12 month

[9]These shares have remained relatively constant over the full sample, with only minor increases in the share size of the industrial sector in the 2010s, but the increase was only temporary. On the other hand, the share size of the service sector saw a slight and steady increase from 57.5 62.7 percent over 2011 to 2020.

horizons. At the aggregated level, it is clear from the first column of Figure 6a that a one standard deviation increase in overall climate conditions significantly reduces real GDP growth, with the largest contraction occurring around 3 months. The magnitude of impact is similar for all three SPEI indices, occurring within the range of -0.5 to -0.7 percent. However, the results are more divergent with respect to the persistence of the climate shock. As shown, a shock to the SPEI3M takes approximately 7 quarters to dissipate, but a shock to the SPEI12M index takes as long as 15 quarters. Therefore, in line with Kahn et al. (2019), our findings suggest that the overall impact of a climate shock on output growth is largely contractionary, with more persistent climate shocks delivering more long-lasting effects.

Figure 6: Impulse Response of Climate Shocks on the Growth of Real Output and Key Production Components



(a) Real GDP (b) Agriculture (c) Industrial (d) Service

Note: Impulse response analyses based on the baseline VAR specification on real output growth and its components. Shaded areas are 68% confidence intervals

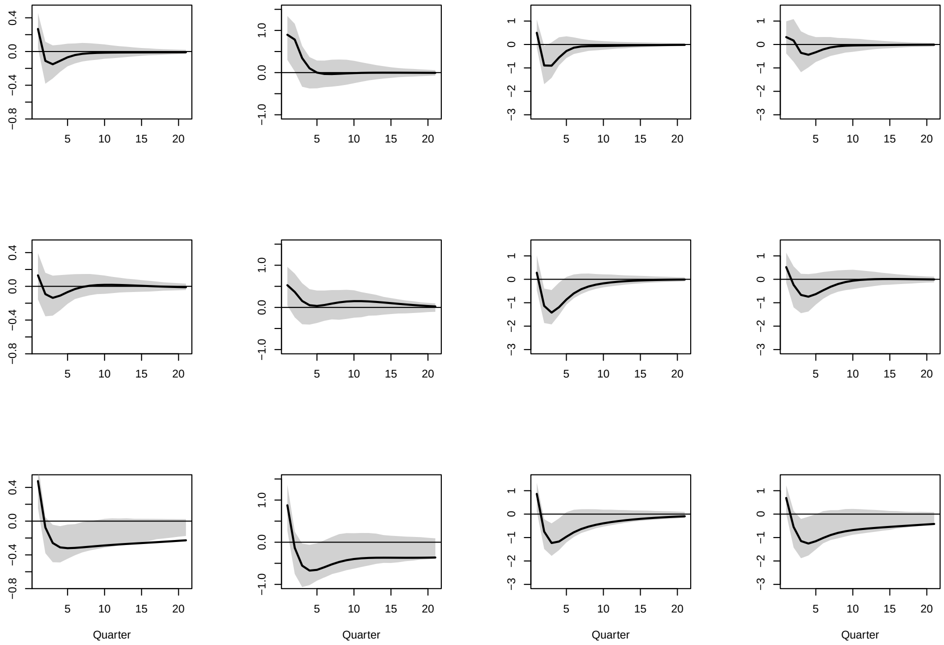
The main channels in which climate shocks could affect output is through impacts on physical capital, land, and agriculture and labor inputs. The early literature tends to identify the impact of a weather event as a supply side shock, where natural disasters and extreme weather conditions would most likely disrupt output such as capital stock, putting upward pressure on prices, lowering future potential growth. However, recent studies such as Batten et al. (2020), Ciccarelli and Marotta (2021) and Drudi et al. (2021) emphasize the demand-side adjustments to a climate shock as well. On the demand size, extreme weather events such as floods and storms could lead to losses in household and firm balance sheets, ultimately reducing private consumption, investments, and exports.

Longer term adjustments in consumer behavior as well as investments in infrastructures could also come about through heightened climate awareness as well.

To better understand how climate change could alter output through changes in both supply and demand, we investigate its impact on both production and expenditure sides of real output. On the production side, we investigate the impact of a climate shock on agriculture, industrial and service sectors. As shown in columns 2-4 of Figure 6a, it is evident that the contractionary effects of climate shocks carry over to each of the main sectors of real GDP growth. Not surprisingly, the agricultural sector is most impacted through destroyed crop yields. The impact of the shock on this sector is extremely sudden and causes real GDP growth to contract to its lowest point within a year. For less persistent climate shocks (SPEI3M), GDP growth contracts to -1.5% while more persistent climate shocks (SPEI12M) contracts to about -0.6%. By contrast, the impact of a climate shock on the service and industrial sectors are smaller in comparison (less than 1 percent), but takes longer to dissipate. For example, a shock from the SPEI12M takes about 15-20 quarters to disappear for both sectors.

Despite the significant contractionary effects of climate shocks on the production side of the economy, we find less clear-cut evidence for the expenditure components of real GDP growth (see Figure 7). First, for some components, the response is even expansionary in the short-term, before experiencing a decline in later stages. For investment, this increase is particularly pronounced, which may signify a short-term increase in investment following natural disasters such as severe floods. Second, the contractionary effects of a climate shocks on the components of real output are not statistically significant in some cases. However, more persistent climate shocks (SPEI12M) tend to deliver slightly more significant effects, with the decline in output being largest for imports and exports. Interestingly, we observe the effect of shocks to be slightly more persistent on the expenditure side compared to production sectors. These observations confirm our interpretation of a climate shock on expenditure components as demand shocks, whereas the relatively pronounced yet short-lived effects of the climate shock on production components are consistent with the supply-side story.

Figure 7: Impulse Response of Climate Shocks on Real GDP Expenditures



(a) Consumption (b) Investment (c) Exports (d) Imports

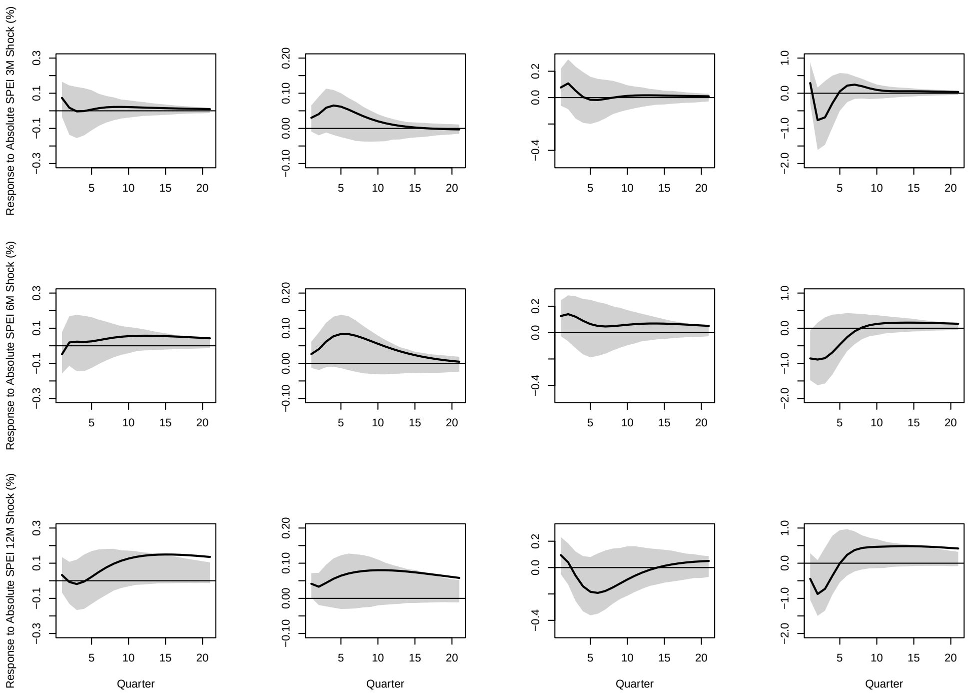
Note: Impulse response analyses based on the baseline VAR specification on real output growth and its components. Shaded areas are 68% confidence intervals.

3.3 Impact on Inflation and Components

Next, we turn to investigate the impact of climate shocks on inflation and its components. Compared to the literature that focuses on the effects of climate change on economic growth, much less is known about its impact on prices. However, physical losses incurred during an extreme weather event could create temporary shortages in goods and services, translating to higher prices. However, the empirical findings from the few studies that investigate the inflationary costs of climate disasters are rather mixed. Parker (2018) finds negligible effects of natural disasters on the inflation rates of advanced economies, but moderately longer-lasting effects on developing ones. Kim et al. (2021) shows that for the US, severe weather conditions have a time-varying effect, with only more recent impacts that are statistically significant. On the other hand, Heinen et al. (2016) studies the impact of hurricane and floods on Caribbean islands and finds significant price increases due to natural disasters. Finally, using detailed supermarket prices and quantities, Cavallo et al. (2014) documents that despite a significant decline in product availability following earthquake episodes in Chile and Japan, prices remained extremely sticky.

We analyze the impact of a climate shock on headline CPI inflation in Thailand. According to the first column of Figure 8a, we find that the overall impact is positive, but its magnitude is small at around 0.1% and is not statistically significant. An exception is the longer term impact of a persistent weather shock based on the SPEI12M on headline inflation which is positive and statistically significant beyond the 15 month horizon. As for the main components of inflation, the impact of a weather shock is not statistically significant either (see Figures 8b-8d). Based on their direction however, the estimated impact of a climate shock is positive for core and food components, while being contractionary for energy.

Figure 8: Impulse Response of Climate Shocks on Aggregate Inflation and Its Major Components

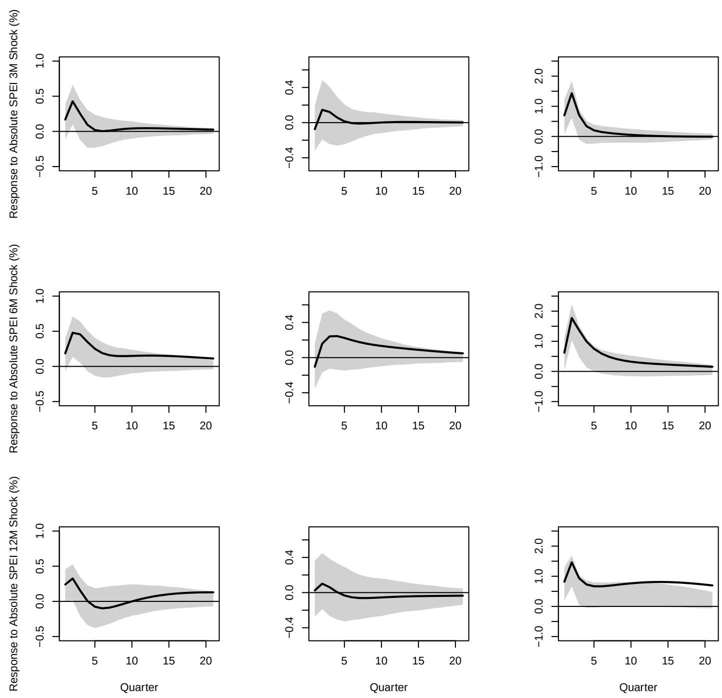


(a) Headline (b) Core (c) Food (d) Energy

Note: Impulse response analyses based on the baseline VAR specification with the addition of major components of headline CPI inflation. Shaded areas are 68% confidence intervals

Analyzing the impact on food inflation further, the impact of extreme weather events should be mainly concentrated on crops and agricultural products, leading to an elevation in food prices. However, we find that the impacts of extreme weather events on food inflation for SPEI3M and SPEI6M while positive, is statistically insignificant. For SPEI12M, there appears to be some evidence of negative price pressures on food inflation in the medium run. This finding is more or less in line with Faccia et al. (2021), where they show that while food can initially receive upward price pressures due to supply shortages following a climate shock in the short run, it can later put downward pressure on demand and result in a negative response in the medium- to long-term. Once we drill down to the disaggregated raw food sectors of the CPI, we find that there are actually clear and sizable increases in the price of vegetables following a climate shock, in contrast to meat products that are not statistically significant (Figure 9b). In Figure 9c, vegetable inflation increases by 1.5 percent, and interestingly, for more persistent climate shocks such as the SPEI12M, the impact of the shock can be exceptionally long-lasting. This finding highlights the heterogenous effects of climate shocks for the disaggregated components of inflation.

Figure 9: Impulse Response of Climate Shocks on Selected Sub-Components of Inflation



(a) Raw Food (b) Meat (c) Vegetable

Note: Impulse response analyses for the baseline specification with the addition of food subcomponents. Shaded areas are 68% confidence intervals

3.4 Asymmetries and Nonlinearities

We account for asymmetries and nonlinearities in our empirical investigation of climate shocks by replacing the climate variable in Eq. 1 with appropriate climate variables. First, to explore directional asymmetry, it is important to differentiate between positive (wet) and negative (dry) weather conditions via the following climate specification:

$$Positive_t = \begin{cases} \overline{SPEI}_{i,t}, & \overline{SPEI}_{i,t} > 0 \\ 0, & \overline{SPEI}_{i,t} \leq 0 \end{cases} \tag{3}$$

$$Negative_t = \begin{cases} 0, & \overline{SPEI}_{i,t} \geq 0 \\ |\overline{SPEI}_{i,t}|, & \overline{SPEI}_{i,t} < 0 \end{cases} \tag{4}$$

where $Positive_t$ and $Negative_t$ captures wet and dry climates respectively and $\overline{SPEI}_{i,t}$ denotes the average of SPEI values. For size reference, a one standard deviation shock to the $Positive_t$ index is equivalent to one-forth of the size of the 2011 Great flood episode in Thailand, while a one standard deviation shock to the $Negative_t$ index is equivalent to the size of 2019-2020 drought.

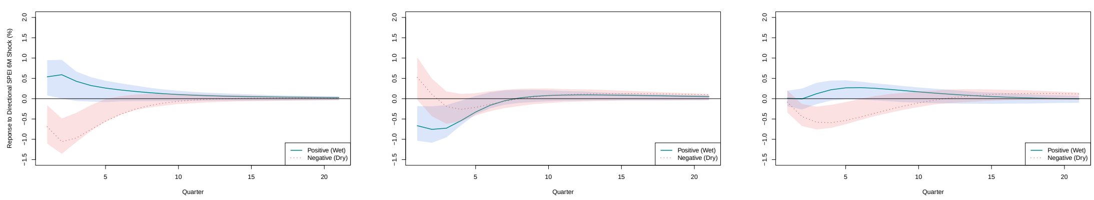
Next, to explore the impact of extreme weather conditions in our analysis, we define the climate variable as:

$$Extremity_t = 1/N \times \sum_{i=1}^{N} [SPEI_{i,t} \times I(threshold)_{i,t}] \tag{5}$$

where $Extremity_t$ is an index that captures extreme climate conditions as measured at time t. $I(threshold)_{i,t}$ is the index function with the value being 1 if the $SPEI_{i,t}$ falls within a certain specified threshold of interest, and 0 otherwise. We consider two types of extremities, moderately and very moist (dry), where the thresholds are defined by $0.8 \leq SPEI_{i,t} < 1.6$ ($-1.6 \leq SPEI_{i,t} < -0.8$), and extremely and exceptionally moist (dry), where the thresholds are defined by $SPEI_{i,t} \geq 1.6$ ($SPEI_{i,t} \leq -1.6$) (see Table 1).

We now turn to discuss the results from our empirical analysis that accounts for the asymmetric and nonlinear impacts of climate shocks. Starting with the asymmetric effects of climate shocks on real GDP growth, we first ask whether positive versus negative SPEI shocks generate the same impact on real activity[10]. As shown in Figure 10, there are clear differences between positive and negative climate conditions on real activity. For example, given that precipitation brings moisture and minerals into the soil which is crucial for crops to grow, a positive SPEI shock leads to growth in the output of agriculture sector, as shown in Figure 10a. Meanwhile, negative SPEI shocks, representing droughts which are harmful for crops, decrease agricultural output.

Figure 10: Directional Asymmetry of Climate Shocks on Major Sectors of Production



(a) Agriculture (b) Industrial (c) Service

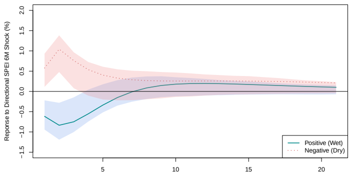
Note: Impulse response analyses based on the baseline VAR specification that takes into account directional asymmetry for climate conditions. Shaded areas represent 68% confidence intervals

Meanwhile, opposite effects can be observed for some activities in industrial and service sectors. Overall results are mainly driven by mining and construction sectors (see Figure 11a and 11b) where wet conditions make it more difficult to engage in these outdoor activities and vice versa. Finally, we observe that activities in the service sector is contractionary for dry conditions but expansionary for wet conditions. We conjecture that the results are mainly driven by tourism activities where accommodation (Figure

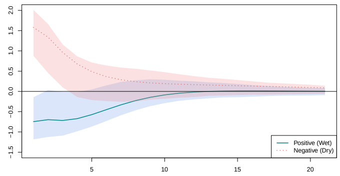
[10]Due to space considerations, going forward we will only present the results based on the SPEI6M index. The results based on alternative SPEI horizons generate similar qualitative responses and are available upon request.

11c) and transportation (Figure 11d), gets an expansionary boost during wet conditions, and is reduced during dry conditions. This is most likely seasonally related as tourists tend to avoid hot summer months.

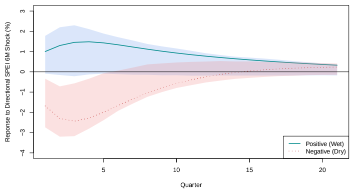
Figure 11: Directional Asymmetry of Climate Shocks on Selected Sectors of Production



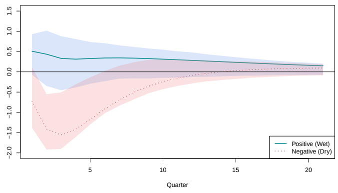
(a) Mining



(b) Construction



(c) Accommodation



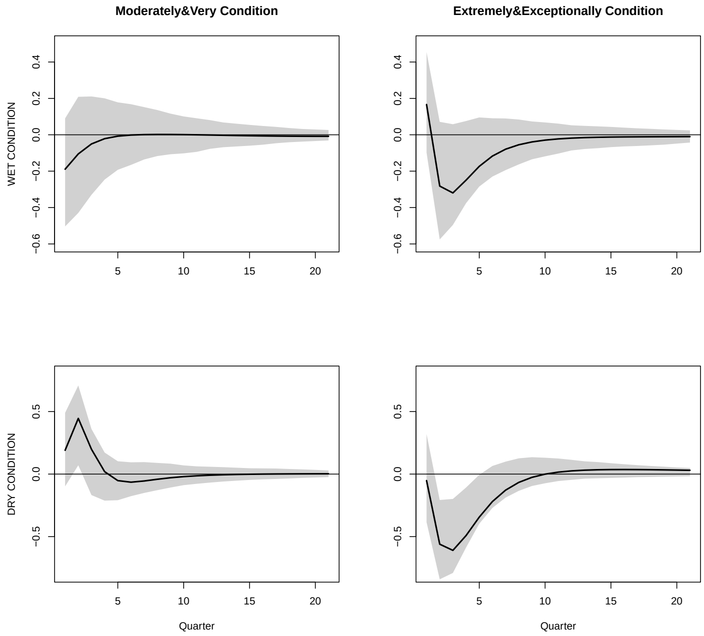
(d) Transportation

Note: Impulse response analyses based on the baseline VAR specification that takes into account directional asymmetry for climate conditions. Shaded areas are 68% confidence intervals.

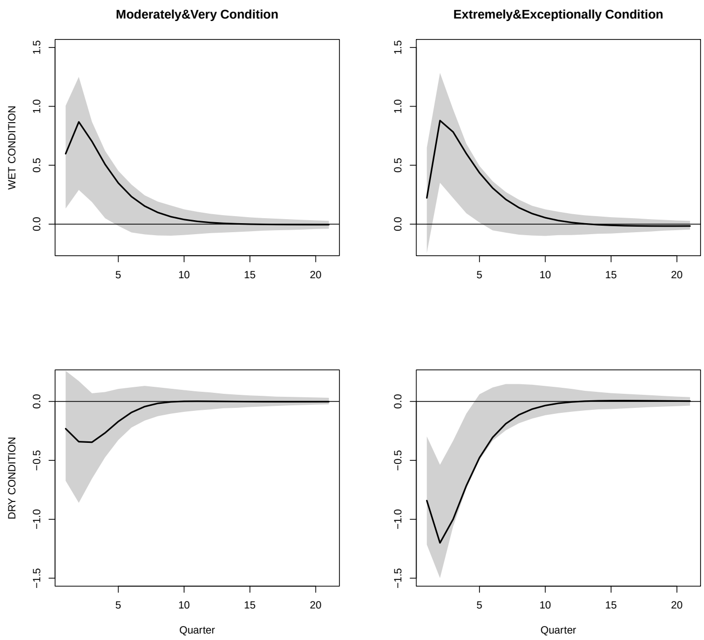
Apart from the directional impact of climate shocks that may invite varying responses from real activity, the extremity of the shock also matters. For real GDP for example, the impulse response in the case of exceptionally wet conditions are two times the impact of the moderate case (Figure 12a). For the agricultural sector, this difference is even more pronounced. We find that when there is a strong drought, the impact is almost three times as large as the moderate case (Figure 12b). However, for industrial and service sectors, we do not observe any differentiated responses based on extremities of shocks. Overall however, our results indicate that there are important asymmetries and non-linearities in the impact of climate shocks on certain components of real output that should be taken into careful consideration.

The importance of asymmetric and non-linear impacts of climate shocks carry over to inflation. In terms of directional asymmetry, we find that there are some differences between the impact of wet versus dry climate shocks on some inflation components. According to Figure 13c, more wet conditions pushes up energy prices while dry climate shocks act in the opposite direction. Parker (2018) arrives at an opposite conclusion based on a cross-country panel regression, where they explain that energy prices receive downward pressure following floods as plentiful rainfall reduces the cost of hydroelectric power generation. However, the source of electricity in Thailand mainly comes from natural gases. As such, we conjecture that during wet conditions when mining activities are affected, upward pressure is placed on prices. This is consistent with our finding for

Figure 12: The Impact of Extreme Climate Shocks for Output Growth and Agriculture



(a) Real GDP



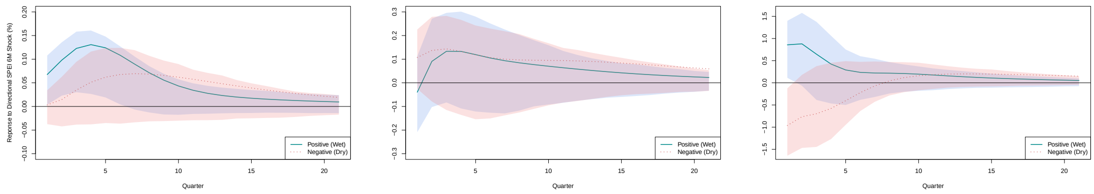
(b) Agriculture

Note: Impulse response analyses based on the baseline VAR specification that takes into account the different effects of extremities for climate conditions. Shaded areas are 68% confidence intervals

mining activities in Figure 11a.

In Figure 13b, we do not observe any directional asymmetries on food inflation. However, they become prominent at the subcomponent level (see Figure 14). Raw food, rice, and vegetable inflation in particular, decline in response to wet conditions due to over-

Figure 13: Directional Asymmetry of Climate Shocks on Inflation and Components

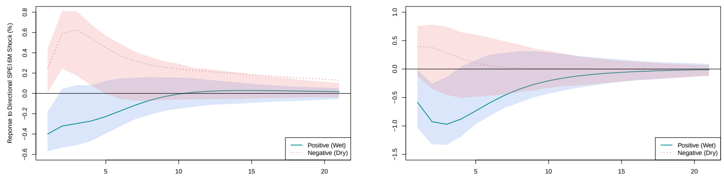


(a) Core (b) Food (c) Energy

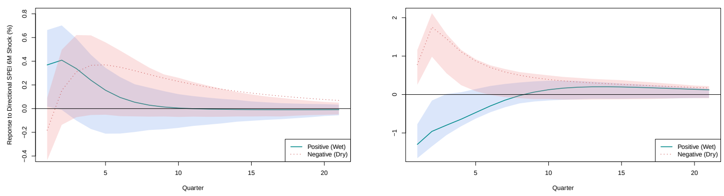
Note: Impulse response analyses based on the baseline VAR specification that takes into account directional asymmetry for climate conditions. Shaded areas are 68% confidence intervals

supply, whereas dry conditions conversely leads to higher inflation. As for the response of meat inflation, we observe slight differences in direction only in the short term. The response of meat inflation to a dry weather shock coincides with the findings of Kamber et al. (2013) where, initially after drought, an increasing in livestock slaughters put downward pressure on meat prices due to higher supply, but later decreases as subsequent slaughters reduces supply and increases meat inflation.

Figure 14: Directional Asymmetry of Climate Shocks on Food Inflation



(a) Raw Food (b) Rice

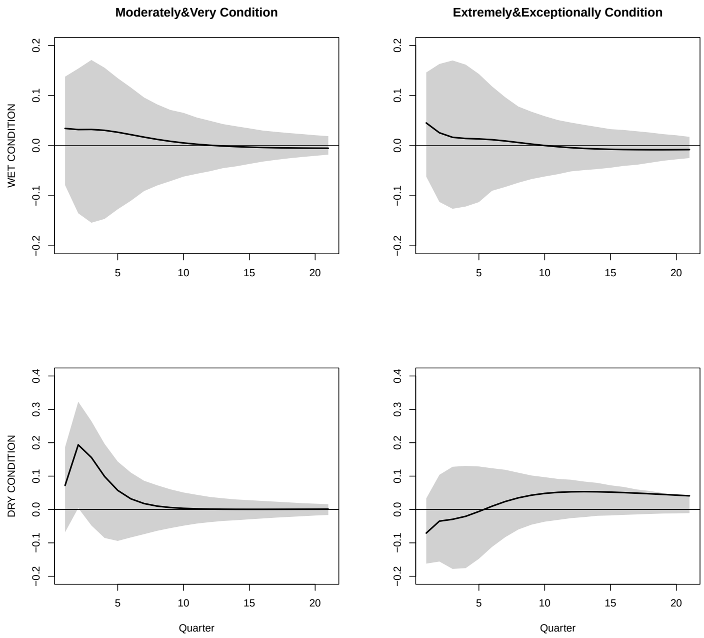


(c) Meat (d) Vegetable

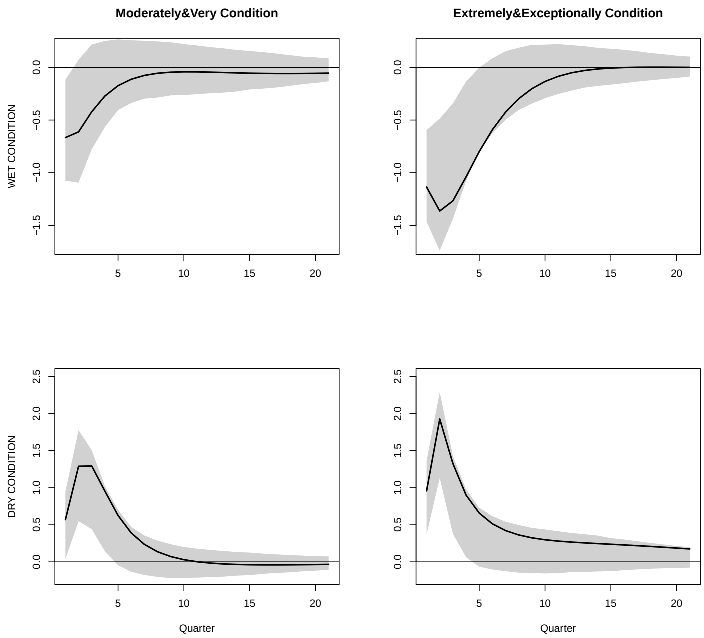
Note: Impulse response analyses based on the baseline VAR specification that takes into account directional asymmetry for climate conditions. Shaded areas are 68% confidence intervals

Finally, we find little evidence of differentiated responses to extreme weather conditions for headline CPI inflation (Figure 15a). The overall impact of both moderate and extreme weather shocks are not statistically significant. However, the degree of climate shocks do matter at the subcomponent level. The impact of extreme weather shocks on vegetable inflation in particular is particularly pronounced (Figure 15b), where prices respond by about two to three times higher. As such, while there is little threat to price stability from climate shocks, especially on headline inflation, it would be important to monitor price movements in certain subcomponents especially in the raw food category, especially as climate shocks in the future become more frequent and severe.

Figure 15: The Impact of Extreme Climate Shocks for Headline and Vegetable Inflation



(a) Headline



(b) Vegetable

Note: Impulse response analyses based on the baseline VAR specification that takes into account the effects of weather extremities for climate conditions. Shaded areas are 68% confidence intervals

4 Cross-provincial Macroeconomic Impacts of Climate Shocks

This section will examine the cross-provincial impacts of climate shocks along various dimensions. First, a large literature emphasizes that the impact of climate change varies across the rich and the poor, thus we investigate the extent in which the impact of climate change may depend on the gross provincial product (GPP) per capita. Second, in previous sections, we find that the effect of climate shocks on real output is heterogenous across sectors, and agricultural and tourism activities in particular, are disproportionately affected. Given that these two sectors are key engines to economic growth in Thailand - not only in terms of production, but also towards employment - we also investigate the extent in which the impact of climate change may vary based on each province's reliance on agricultural and tourism activities.

4.1 Data and Model Specification

To study the cross-provincial differences in the impact of climate change on real output, we utilize a similar panel autoregressive distributed lag model (ARDL) to Kahn et al. (2019), as outlined below[11]:

$$\Delta y_{i,t} = \alpha_1 \Delta SPEI_{i,t} + \alpha_2 \Delta SPEI_{i,t-1} + \alpha_3 \Delta SPEI_{i,t-2} + \beta_1 \Delta y_{i,t-1} + \beta_2 \Delta y_{i,t-2} + \gamma_i + a_t + \epsilon_{i,t}. \tag{6}$$

In the above specification, $\Delta y_{i,t}$ is the real Gross Provincial Product (GPP) per capita growth rate in province i at time t; $\Delta SPEI_{i,t}$ is the 12-month average of differences of SPEI in province i at time t that is weighted by the population in province i; γ_i is the province fixed effect; a_i is the time fixed effect and $\epsilon_{i,t}$ is the unexplained residual.[12] With the inclusion of fixed effect estimators, we implicitly assume that the climate variables are strictly exogenous, thus ruling out any reverse causality from economic growth to climate variables. This is a consistent assumption with the majority of literature, see for example, Dell et al. (2012) and Auffhammer et al. (2020).

We estimate the panel ARDL model above by feasible generalized least squares (FGLS) to ensure heteroskedastic-robust results (see Bai et al., 2020).[13] In doing so, apart from being able to quantify the short term effects of climate change on real GPP

[11] We opt for a panel ARDL model rather than a panel VAR because we only have provincial data on output and not inflation.

[12] Note that alternatively, population growth can be included as a control variable in similar regressions (Odusola and Abidoye, 2015 ; Zeb, 2013).

[13] Panel heteroskedasticity tests, i.e., the Breusch–Pagan/ Cook–Weisberg tests were undertaken to investigate the stationary variance of the error term where all the models exhibited heteroskedasticity. In addition, the Im–Pesaran–Shin (CIPS) panel unit root test was conducted to confirm that all macroeconomic variables in the regression are indeed stationary to avoid spurious results.

per capita growth through estimates of the beta coefficients, a key advantage of the panel ARDL specification is that we can also quantify the medium-run effects of climate change.[14]. In particular, the medium-run impact of changes in the climate variables on real GPP per capita growth (Θ) can be calculated from the OLS estimates of the short-run coefficients in equation (6) where:

$$\Theta = \frac{\sum_{j=1}^{l} \alpha_j}{1 - \sum_{k=1}^{p} \beta_k}.$$

To investigate the cross-provincial differences based on level of income and reliance on agricultural and tourism activities, we interact the current and lagged climate variable $\Delta SPEI_{i,t}$ that appears in Equation (6) with dummy variables. More specifically, we first generate a "Poor" dummy variable (P_t) that takes on the value of 1 if the GPP per capita in that province is below or equal to the 25th percentile of GPP per capita on average during the sample, and 0 otherwise. This approach identifies 20 provinces in the northern and northeastern region as being "Poor"[15]. As per the Thai GPP data that we use, it is available at an annual frequency and is obtained from NESDC. The sample is available over 2001-2019, and therefore we have a panel of 19 years for 77 provinces nationwide. Table 2 shows the summary statistics of GPP per capita and population as it varies across various Thai regions.

Table 2: Summary Statistics of Thai regional related data

	Northeastern	Northern	Southern	Eastern	Western	Central	Bangkok & Vicinities	Whole Country
Real GPP Per Capita Growth (%)								
Mean	4.45	3.08	1.67	2.54	2.45	2.55	1.59	2.87
Median	4.28	2.70	1.97	1.64	2.37	1.65	2.57	2.83
SD	4.38	5.03	5.56	7.75	5.15	7.14	4.62	5.34
Max	32.38	26.20	21.11	41.08	17.67	21.91	17.26	41.08
Min	-10.15	-14.49	-24.56	-25.05	-19.29	-16.16	-20.41	-25.05
Population (1,000 persons) as of 2019	18,523	11,373	9,590	6,056	3,665	3,176	16,932	69,315

*Notes: The whole country has 77 provinces. According to the Office of the National Economic and Social Development Council, the provinces are as follows: 1) Bangkok & Vicinities (6): Bangkok, Samut Prakan, Pathum Thani,Samut Sakhon, Nakhon Pathom, and Nonthaburi 2) Central (6): Saraburi, Singburi, Chai Nat, Ang Thong, Lop Buri, and Phra Nakhon Sri Ayuthaya 3) East (8): Chon Buri, Chachoengsao, Rayong, Trat, Chanthaburi, Nakhon Nayok, Prachin Buri, Sa Kaew 4) Northeast (20): Khon Kaen, Udon Thani, Loei, Nong Khai, Mukdahan, Nakhon Phanom, Sakon Nakhon, Kalasin, Nakhon Ratchasima, Chaiyaphum, Yasothon, Ubon Ratchathani, Roi Et, Buri Ram, Surin, Maha Sarakham, Si Sa Ket, Nongbua Lamphu, Amnat Chareon, and Bueng Kan 5) North (17): Chiang Mai, Lampang, Uttaradit, Mae Hong Son, Chiang Rai, Phrae, Lamphun, Nan, Phayao, Nakhon Sawan, Phitsanulok, Kam Phaeng Phet, Uthai Thani, Sukhothai, Tak, Phichit, and Phetchabun 6) West (6): Ratchaburi, Kanchanaburi, Phachuap Khiri Khan, Phetchaburi, Suphan Buri, and Samut Songkhram 7) South (14): Phuket, Surat Thani, Ranong, Phangnga, Krabi, Chumphon, Nakhon Si Thammarat, Songkhla, Satun, Yala, Trang, Narathiwat, Phathalung, Pattani,

Source: Office of the National Economic and Social Development Council of Thailand (NESDC)

Second, we utilize NESDC data to further differentiate between agricultural versus

[14]While the literature may define this as a long-run impact, we opt for a calling it a medium-run effect since the coverage is a 3-year horizon.

[15]These 20 poor provinces are Amnat Charoen, Buri Ram, Chaiyaphum, Kalasin, Mae Hong Son, Maha Sarakham, Mukdahan, Nakhon Phanom, Nan, Narathiwat, Nong Bua Lam Phu, Phatthalung, Phrae, Roi Et, Sakon Nakhon, Si Sa Ket, Sukhothai, Surin, Ubon Ratchathani and Yasothon.

non agricultural reliant provinces by defining an "Agricultural" dummy variable (A_t) that takes on the value of 1 if the proportion of agricultural output is more than 5 percent of its GPP on average during the year 2001 to 2019, and a 0 otherwise. In doing so, we identify 62 agricultural provinces in Thailand[16]. According to Table 3, while the agricultural sector contributes a rather small share of 6.14% to total GDP, but its importance is significant in certain regions such as the South where it accounts for almost a fifth of its regional output. We also choose to investigate the impact of climate shocks on agricultural provinces because of its coverage of workforce, where the agricultural sector employs around one-third of the country's labor force over a widespread area (see Figure 16). Most importantly, this sector is highly vulnerable to climate shocks as shown in the empirical findings of the previous section.

Table 3: Real Gross Regional Product (GRP) classified by Sectors, as of 2019

% of GRP	Northeastern	Northern	Southern	Eastern	Western	Central	Bangkok & Vicinities	Whole Kingdom (% of GDP)
Agriculture	16.20	16.54	21.66	4.72	17.07	4.97	0.51	6.14
Industrial	23.96	24.18	15.38	64.79	34.26	63.17	22.21	31.80
Mining and quarrying	0.72	3.20	3.15	8.69	1.52	1.79	0.04	2.09
Manufacturing	20.20	18.06	9.16	50.49	23.14	54.88	20.32	26.41
Electricity, gas, steam and air conditioning supply	3.13	2.90	3.10	5.33	9.12	5.90	1.28	2.85
Water supply; sewerage, waste management and remediation activities	0.34	0.47	0.23	0.40	0.40	0.27	0.64	0.51
Services	59.60	62.15	65.08	31.10	48.67	32.32	77.58	63.14
Construction	4.67	5.14	3.82	1.84	4.38	1.65	2.08	2.67
Wholesale and retail trade and repair of motor vehicles and motorcycle	12.51	13.46	9.35	10.12	10.43	9.20	19.72	15.40
Transportation and storage	2.89	3.66	8.08	4.04	3.19	3.50	8.96	6.78
Accommodation and food service activities	1.72	3.39	18.85	3.97	5.11	0.61	7.06	6.39
Information and communication	2.05	2.68	2.28	0.86	2.01	1.16	9.14	5.54
Financial and insurance activities	8.38	7.81	5.33	2.34	4.97	2.82	9.31	7.22
Real estate activities	7.40	7.35	5.21	2.26	5.66	3.13	3.17	3.93
Professional, scientific and technical activities	0.09	0.24	0.23	0.24	0.12	2.40	3.40	1.98
Administrative and support service activities	0.32	0.80	1.87	0.85	0.90	0.61	2.45	1.72
Public administration and defence; compulsory social security	4.89	5.40	4.59	2.21	4.94	3.43	5.71	4.84
Education	9.95	7.10	4.82	1.06	4.07	1.90	1.77	3.04
Human health and social work activities	3.69	4.47	2.77	1.02	2.86	1.61	1.99	2.22
Arts, entertainment and recreation	0.43	0.52	0.54	0.18	0.56	0.20	1.70	1.06
Other service activities	1.14	1.28	0.86	0.60	0.74	0.63	2.37	1.64

Source: Office of the National Economic and Social Development Council of Thailand (NESDC)

Third, we generate a "Tourism-related" province (T_t) that takes on the value of 1 if, according to the Ministry of Tourism and Sports, that province heavily relies on Tourism, and a 0 otherwise[17]. Tourism takes up a large share of the services sector in Thailand, which according to Table 3, it is mostly concentrated in Bangkok, Northern and Southern regions.

[16]These 62 agricultural-related provinces are Amnat Charoen, Bueng Kan, Buri Ram, Chai Nat, Chaiyaphum, Chanthaburi, Chiang Mai, Chiang Rai, Chumphon, Kalasin, Kamphaeng Phet, Kanchanaburi, Khon Kaen, Krabi, Lampang, Lamphun, Loei, Lop Buri, Maha Sarakham, Mukdahan, Nakhon Nayok, Nakhon Pathom, Nakhon Phanom, Nakhon Ratchasima, Nakhon Sawan, Nakhon Si Thammarat, Nan, Narathiway, Nong Bua Lam Phu, Nong Khai, Pattani, Phang-nga, Phatthalung, Phayao, Phetchaburi, Phichit, Phitsanulok, Phrae, Prachuap Khiri Khan, Ranong, Ratchaburi, Roi Et, Sa Kaeo, Sakon Nakhon, Samut Sakhon, Satun, Si Sa Ket, Songkhla, Sukhothai, Suphan Buri, Surat Thani, Surin, Tak, Trang, Trat, Ubon Ratchathani, Udon Thani, Uthai Thani, Uttaradit, Yala, and Yasothon.

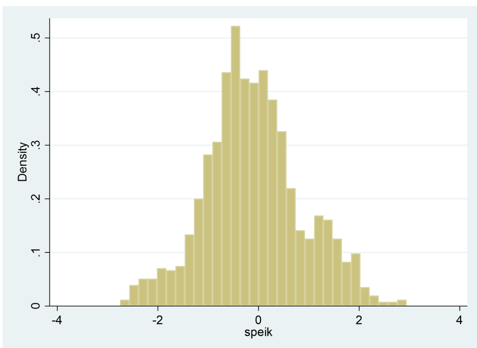
[17]These 13 tourism-related provinces are Bangkok, Phuket, Phang-nga, Krabi, Prachuap Khiri Khan, Surat Thani, Chiang Mai, Chiang Rai, Chonburi, Trat, Phra Nakhon Si Ayutthaya, Songkhla and Rayong.

Figure 16: Agricultural area in Thailand (shown in green shade)

Source: Food and Agriculture Organisation of the United Nations (FAO)

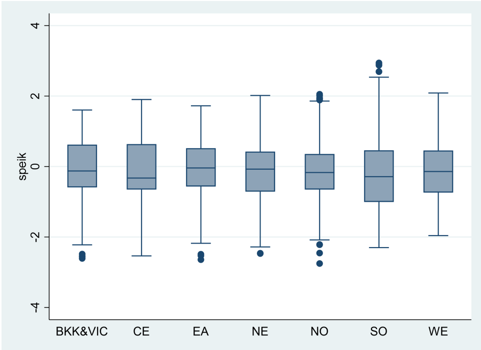
Finally, for the climate variable in estimation, we use the 12-month SPEI index to be consistent with GPP growth data that is available at an annual frequency. As mentioned earlier, we construct the provincial SPEI index from temperature and rainfall data in each province. To get a sense of this climate data that we use to estimate Equation (6), we show in Figure 17 that the distribution of the annual change in the 12-month SPEI index during the 2001-2019 period is left-skewed, reflecting drier conditions across most of the regions. Negative median box plots in Figure 18 across regions also confirm drier conditions in Thailand over the sample period.

Figure 17: Yearly Changes in SPEI, 2001-2019



Obs	Mean	Std. Dev.	Min	Max
1,386	-.0975537	.9718246	-2.752729	2.941706

Figure 18: Yearly Changes in SPEI across regions, 2001-2019



4.2 Empirical Findings

We estimate equation (6) to obtain baseline results, where we focus on the medium run impacts of climate change. As shown in Panel (a) of Table 4, we find that a change in the climate variable generates a statistically significant negative impact on real GPP per capita growth in the medium-run. More specifically, we find that if the SPEI12M increases by 1 unit annually, average per capita real GPP growth in the medium run will be statistically significantly lower by 2.28 percent per year. In terms of the direction of impact, this finding is in line with our previous country-level VAR results that the impact of a SPEI shock on real GDP is in general contractionary.

Table 4: Effects of a change in 12-month average SPEI on Real GPP per capita growth across provincial characteristics, 2001 - 2019

Dependent Variable is Real GPP per capita growth ($\Delta y_{i,t}$)	Feasible Generalised Least Squares (FGLS)			
	(a)	(b)	(c)	(d)
$\hat{\theta}_{\Delta SPEI_{i,t}}$	-0.0228*** (0.0064)	-0.0207*** (0.0064)	-0.0282*** (0.0070)	-0.0234*** (0.0064)
$\Delta y_{i,t-1}$	0.0103 (0.0278)	0.0126 (0.0278)	0.0112 (0.0278)	0.0106 (0.0278)
$\Delta y_{i,t-2}$	0.0745*** (0.0268)	0.0791*** (0.0268)	0.0750*** (0.0268)	0.0745*** (0.0269)
$\Delta SPEI_{i,t} * P_t$	-	-0.0074*** (0.0025)	-	-
$\Delta SPEI_{i,t} * A_t$	-	-	0.0063** (0.0031)	-
$\Delta SPEI_{i,t} * T_t$	-	-	-	0.0019 (0.0029)
No. of Observations	1222	1222	1222	1222

*Notes: 1. Standard errors in parentheses; 2. Time and provincial fixed effects were included (coefficient not reported); 3. Asterisks indicate statistical significance at the 1% (***), 5% (**) , and 10% (*) levels; 4. The long-run effects, θ, are calculated from the OLS estimates of the short-run coefficients.

Next, we investigate whether the climate change effect on regional output differs across groups of provinces as classified by certain characteristics by the inclusion of dummy variables as described earlier. Based on the estimation results in Table 4, there

Table 5: Effects of a directional change in 12-month average SPEI on Real GPP per capita growth across provincial characteristics, 2001 - 2019

Dependent Variable is Real GPP per capita growth ($\Delta y_{i,t}$)	Feasible Generalised Least Squares (FGLS)		
	(e)	(f)	(g)
$\hat{\theta}_{\Delta SPEI_{i,t}^+}$	-0.0193** (0.0091)	-0.0178** (0.0089)	-0.0336*** (0.0105)
$\hat{\theta}_{\Delta SPEI_{i,t}^-}$	0.0156* (0.0084)	0.0082 (0.0083)	0.015 (0.0093)
$\Delta y_{i,t-1}$	0.0126 (0.0269)	0.0009 (0.027)	0.008 (0.027)
$\Delta y_{i,t-2}$	0.0842*** (0.0262)	0.0774*** (0.0262)	0.081*** (0.0263)
$\hat{\theta}_{\Delta SPEI_{i,t}^+} * P_t$	-	0.0034 (0.0038)	-
$\hat{\theta}_{\Delta SPEI_{i,t}^+} * A_t$	-	-	0.0145*** (0.005)
$\hat{\theta}_{\Delta SPEI_{i,t}^-} * P_t$	-	0.0154*** (0.0033)	-
$\hat{\theta}_{\Delta SPEI_{i,t}^-} * A_t$	-	-	-0.0024 (0.0042)
No. of Observations	1298	1298	1298

*Notes: 1. Standard errors in parentheses; 2. Time and provincial fixed effects were included (coefficient not reported); 3. Asterisks indicate statistical significance at the 1% (***), 5% (**) , and 10% (*) levels; 4. The long-run effects, θ, are calculated from the OLS estimates of the short-run coefficients.

are important climate change impacts across provinces. According to the results in column (b), we find that climate change tends to affect poor provinces more since the effect of lagged SPEI variation has a negative and statistically significant impact on the medium-run economic growth of poor provinces, which differs from non-poor provinces by 0.74 percent. These results are in line with the literature, for example, Jones and Olken (2010), World Bank (2012), and Mehar et al. (2016). The literature states that, in addition to the limited economic resources and coping mechanisms, the destruction of critical infrastructure has a disproportionate negative impact on the well-being and opportunities of the poor. Next, turning to examine column (c), the study finds that the medium-run impact of climate change also depends on whether the province relies on agricultural activities. We find that, although the net effect to agricultural provinces is negative, climate shocks tend to affect these provinces less (benefit more) by 0.63 percent which is in line with the findings of rainfall effects on agricultural sector by Akram (2012) and the rainfall effects on cassava yields by Phatcharopaswatanagul (2018). However, in column (d), there are no significant differences in climate change based on whether the province is reliant on tourism. This contrasts with the results of Sangkhaphan and Shu (2020), studying Thailand case, and Becken and Wilson (2013), studying New Zealand case.

Finally, we investigate whether positive and negative SPEI shocks can impact real GPP growth per capita in different ways. In doing so, we separate $\Delta SPEI_{i,t}$ into positive and negative values, and interact them with current and lagged climate variables in equation (6) to account for the potential asymmetrical effects of climate change on economic growth[18]. As shown in Table 5, there is clear cut evidence of directional asymmetry for climate change. In fact, the directional impact of weather conditions also depends on provincial characteristics, such as whether they are poor or non-poor provinces or whether they are engaged heavily in agricultural activities. For example, in column (g), given an increase in positive or wet climate conditions, the real GPP per capita growth of agricultural provinces tends to be higher than non-agricultural ones by 1.45 percent per year, although the net effect to these provinces are still negative. In other words, wet or moist weather conditions less affect (benefit more) economic activity growth in agricultural provinces which is in line with, for example, Loayza et al. (2012) and Birthal and Hazrana (2019). On the other hand, in column (f), if SPEI conditions become increasingly dry, real GPP per capita growth of poorer provinces improve by more than non-poor ones by 1.54 percent per year, which is in contrast with Sangkhaphan and Shu (2019). This again highlights the importance of accounting for heterogeneity across provinces when analyzing the effects of climate change.

5 Conclusion

This paper provides a comprehensive analysis of the macroeconomic impacts of climate shocks for output and inflation in Thailand. We find that overall, the physical risks that stem from climate change causes real output growth to contract at both short and medium run horizons, albeit with less pronounced effects on inflation. However, the dynamic impact of climate shocks in Thailand heavily depends on the sector of production and disaggregated component of inflation. For example, the agricultural sector is particularly vulnerable to climate shocks as well as vegetable prices. Also, we find that the effect of climate shocks are both asymmetric and non-linear as the impact becomes increasingly severe as the shock becomes more persistent and extreme, and the effect of the shock for various sectors depend crucially on the direction of the climate shock. The effects of climate change also varies across provinces, with poorer provinces and provinces that are more reliant on agricultural activities disproportionately affected.

Against the backdrop of a warmer climate trend, and greater occurrences of more severe and persistent climate shocks for Thailand, some implications from our results for policymakers are as follows. First, a slowdown in output growth can be expected. Key sectors that Thailand are heavily reliant upon namely agriculture and tourism are at the greatest risk, alongside poor provinces that are most vulnerable and may face challenges adjusting. In other words, it implies that the impact of climate change will

[18] Note that while we would also like to consider the impact of extreme climate conditions on regional output, given that the panel regression utilizes annual data, our sample size limitations does not allow for this possibility.

be unevenly distributed across economic sectors, posing further challenges to monetary policy in promoting inclusive and sustainable growth.

Second, while we find that the impact of climate change on inflation is rather muted, climate shocks can be inflationary for some components of inflation, particularly raw food. Given that a large portion of Thailand's CPI consumption basket is tied to raw food, greater occurrences of climate shocks can induce heightened inflation risks to Thailand. Moreover, it is possible that more persistent and extreme climate shocks can lead to a changing inflation process as relative price shocks may become more volatile, persistent and broad-based. Should this occur, policymakers need be particularly wary to the possibility that relative price shocks, particularly in the food sector, may trigger second-round effects or de-anchor inflation expectations. Thus, a credible monetary policy regime is key towards dealing with the possible price stability risks of climate change.

Finally, policymakers need to be acutely aware of important asymmetries and nonlinearities in the impact of climate change on output and prices. Indeed, these characteristics complicate the policymakers' task of understanding as well as mitigating the impact of climate change on the macroeconomy, as non-linearity implies that probability distributions of risks in historical data may be a poor gauge of what the future holds. As such, empirical work related to the impacts of climate change that can account for such features are highly encouraged. Furthermore, while we acknowledge the important impact of climate shocks on the macroeconomy, we do not account for the endogenous feedback loop between the macroeconomy to climate conditions, which will only become all the more important over future years. Future research work in this area will be critical and highly welcomed.

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