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THE ROLE of CLIMATE VARIABLES in ITALIAN ECONOMIC FLUCTUATIONS:
Evidence from Macro-Regional Analysis

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Abstract

This work project explores the economic repercussions of climate variability on Italy's macroeconomic stability, focusing on inflation, unemployment, disposable income, and housing expenditure. Using a Panel Vector Autoregressive model with exogenous regressors (PVARX), it examines the differential impacts of temperature and precipitation shocks across Italy's macro-regions. Findings reveal significant climate-driven inflationary pressures and labour market shifts, with marked regional heterogeneity, while housing expenditure remains unaffected. By addressing critical gaps in the literature, this study provides valuable insights into climate-economy dynamics, offering evidence-based recommendations for adaptive policy measures to support economic resilience against evolving climate challenges.

Keywords: Economy, Climate, Italy, Panel Data, Regions, Inflation, Unemployment, Income, Temperature, Precipitation

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1. Introduction

Climate change, predominantly caused by human actions, is transforming both environmental and economic conditions globally. Europe, especially, is experiencing warming at a rate that surpasses the global average, and this increase has resulted in a growing variety of intense climate occurrences (Intergovernmental Panel on Climate Change 2023). In recent decades, there have been record-breaking heatwaves, increased drought frequency, alterations in precipitation patterns, and a rise in extreme weather events. For example, Central and Northern Europe have faced devastating floods and heavy rainfall events, putting pressure on infrastructure and leading to significant economic damages. In contrast, extended droughts and extreme summer heat have challenged agriculture in Southern Europe, diminished water resources, and increased risks of wildfires. These extremes pose risks to ecosystems and affect multiple economic sectors, financial markets, and public finances throughout the continent (European Environment Agency 2024).

Due to rising temperatures exceeding global averages and a rise in destructive weather incidents threatening markets, infrastructure, and public finances, Italy holds a uniquely important and delicate position within the wider European context. In the North, the melting of glaciers, shifts in precipitation patterns, and modified hydrological cycles could impact energy provision and winter tourism, whereas, in the South, escalating heatwaves, unpredictable rainfall, and increased agricultural pressure endanger food security, labour output, and water supplies. The central regions, characterised by their diverse microclimates and varied economies, encounter complex challenges as changes in temperature and rainfall impact areas such as tourism, energy, and manufacturing.

Although Italy experiences short-term climate variations that could impact essential elements of economic life, research examining these direct macroeconomic effects is still scarce. Current studies frequently emphasise long-term climate change scenarios, neglecting the immediate, short-term impacts of sudden weather variations on economic factors. This gap is crucial since unexpected weather events can directly impact living costs, job opportunities, purchasing ability, and housing choices, thus influencing households' everyday lives and welfare.

The primary goal of this work project is to fill this gap by examining how short-term fluctuations in temperature and precipitation affect Italy's macroeconomic indicators throughout its diverse macro-regions. Focusing on factors directly related to household incomes and analysing these impacts quarterly, this research recognises the urgent, immediate issues that policymakers and communities confront. Grasping these short-term effects is crucial for creating flexible and localised strategies that reduce negative results, leverage beneficial impacts, and strengthen overall resilience. To do this, we utilise a Panel Vector Autoregressive (PVAR) model enhanced with exogenous variables (PVARX) and apply local projections to create impulse response functions (IRFs). This methodological strategy allows for adaptable and strong estimation of dynamic reactions to climate shocks without enforcing excessively limiting structural assumptions.

Utilising quarterly regional data over several years, our study considers spatial diversity and temporal changes, offering a detailed insight into how various regions of Italy endure and react to climatic disruptions. In doing so, this work contributes to the broader discourse in climate economics and European climate policy. First, by focusing on Italy, a nation with pronounced regional differences, it offers insights relevant to other Southern European countries that face similar vulnerabilities. Second, the emphasis on weather-induced shocks, rather than extended climate trajectories, highlights immediate economic stakes and household-level consequences. Third, by examining both temperature and precipitation shocks and by simultaneously assessing multiple macroeconomic variables, the work project presents a comprehensive and integrated view of how climate variability propagates through the economic system.

The work project is structured as follows: Section 2 reviews relevant literature on climate shocks, particularly in Europe and Italy, advocating for short-term analyses. Section 3 discusses PVARX and local projection methods for assessing localised climate variability impacts. Section 4 presents data sources, including climate and economic indicators. Section 5 analyses findings related to temperature and precipitation shocks on inflation, unemployment, income, and housing in Italy's regions. Section 6 discusses policy implications for enhancing regional resilience and the conclusions.

2. Literature Review

The relationship between climate variability and economic results has become an important field of research in recent years, highlighting the urgent requirement to understand how climate change affects significant macroeconomic factors like inflation, unemployment, income, and investment. This collection of literature has examined different methodological approaches, geographical settings, and climate factors, yielding varied results that highlight the intricate, regionally specific, and nonlinear characteristics of climate-economy connections.

Temperature and precipitation are some of the most frequently studied climate factors because of their direct and indirect effects on economic systems. Temperature variations are consistently associated with inflationary pressures, declines in productivity, and volatility in GDP (Dell et al. 2014; Burke et al. 2015). In their study, Kalkuhl and Wenz (2020) emphasise that fluctuations in temperature greatly diminish economic productivity, particularly in countries reliant on agriculture.

Precipitation, while not as thoroughly researched, also shows significant economic impacts. Kotz et al. (2022) illustrate how shifts in rainfall patterns affect global economic output, revealing that severe rainfall occurrences hinder growth in affluent countries by interrupting services and manufacturing processes. Habib (2022) further examines the dual function of precipitation, indicating that while increased rainfall secures agricultural output, erratic precipitation trends heighten economic instability.

Field-specific research further demonstrates the diverse effects of climate variability. Burke et al. (2015) and Dell et al. (2014) recognise agriculture as one of the most at-risk sectors, where temperature and precipitation change crop production and escalating food costs. Similarly, Chen et al. (2016) and Schlenker and Roberts (2008) highlight the nonlinear connection between climate factors and agricultural output, pointing out that extreme weather occurrences have a greater impact on low-income communities dependent on subsistence farming. Aside from agriculture, energy requirements represent another vital field of investigation. Auffhammer and Schlenker (2014), along with Wenz et al. (2017) illustrate how temperature extremes boost energy use for heating or cooling, putting pressure on power grids and raising household costs. These results are especially pertinent for Italy, where seasonal temperature changes can lead to considerable energy needs, influencing inflation and available income.

Regional diversity is a common topic in climate-economy literature, highlighting areas' varying vulnerabilities and adaptive abilities in response to climate change. For example, Ciccarelli et al. (2023) investigate the seasonal effects of temperature shocks in the Eurozone, revealing that inflationary pressures differ markedly among countries and seasons.

In Italy, the industrial foundation of the North, the administrative and service-driven economy of the Centre, and the agricultural reliance of the South generate varied avenues by which climate variability impacts regional economic results. This work project expands upon these insights by examining Italy’s macro-regions individually, allowing for a detailed comprehension of how climate shocks spread through regional economies.

Despite significant advances, key gaps remain in the climate-economy literature. Most existing studies focus on long-term climatic trends, overlooking the immediate economic disruptions caused by short-term weather shocks.

In the context of Italy, existing research remains sparse despite the country's susceptibility to climatic changes. Studies have largely focused on specific sectors or the supra-national or regional level, neglecting comprehensive assessments of how climate variability influences macroeconomic indicators. This work project aims to fill this gap by examining Italy's macro-regions through a panel VARX (PVARX) framework (Dhruv et al. 2024), offering insights into the dynamic interactions between climate shocks and economic performance.

The growing intricacy of climate-economy interactions has required the implementation of advanced econometric methods. VAR models, along with their panel variations (PVAR), have been crucial in understanding the dynamic relationships between climatic and economic factors. Alessandri and Mumtaz (2021) utilise a PVAR framework to examine the impact of temperature fluctuations on GDP in 133 countries, showing notable growth declines in areas with considerable climatic variability. Likewise, Ciccarelli and Marotta (2024) employ a PVAR model to assess the medium-term effects of climate change on Eurozone economies, highlighting the efficacy of regional policies in mitigating climate risks. The local projections (LP) approach, introduced by Jordà (2005), has also become popular as a reliable option for calculating impulse response functions. Its adaptability and robustness to model inaccuracies make it especially well-suited for examining short-term climate disturbances. Adämmer (2019) emphasises that LPs yield strong estimates regarding the direct impacts of temperature and precipitation shocks on economic metrics, whereas Natoli (2022) utilises this approach to evaluate how temperature fluctuations influence consumption and investment in the U.S.

This work project addresses these gaps by integrating PVARX and LP methodologies to analyse the short-term impacts of climate shocks on Italy's macro-regions, emphasising regional diversity and sectoral specificity. This study's results add to the increasing literature on climate economics by highlighting the varied effects of temperature and rainfall on inflation, unemployment, disposable income, and housing costs, showcasing the benefits of integrating econometric approaches for an in-depth examination of climate-economy connections and providing policy-relevant insights for formulating region-specific adaptation strategies to strengthen Italy's economic resilience against climate variability.

3. Panel VARX

3.1 Model Description

In this work, we utilised a Panel Vector autoregressive model with exogenous variables (PVARX) to investigate the dynamic relationships between climate variables and key macroeconomic factors within Italy's 20 regions and its macro areas.

Sims (1980) first introduced the VAR model to capture the interdependencies among multiple time series variables. The Panel VAR extension builds on this by enabling the inclusion of exogenous variables and panel data, which controls for unobserved heterogeneity across regions and exploits both cross-sectional and time-series dimensions of the data.

Adding climate variables as part of the exogenous component (X) allows us to treat changes in these variables as external shocks, separating their effects on macroeconomic outcomes. This methodology aligns with contemporary research practices that recognise the gradual and enduring impact of anthropogenic climate change, contrasting with the shorter-term focus typical of economic studies (Alessandri & Mumtaz 2019; Kalkuhl & Wenz 2020; Kotz et al. 2021). The PVARX framework offers several advantages. It captures dynamic responses to shocks through impulse response functions (IRFs) and variance decomposition, controls for unobserved regional traits, and differentiates between short-term weather shocks and long-term climate effects. This is particularly relevant for our study, which utilises detailed subnational data to explore the nuanced impacts of climate variables on regional economies. By focusing on Italy's regions, this analysis captures variations that would be overlooked by national averages, as highlighted by Burke and Tanutama (2019).

To estimate the PVARX model, we utilised the *panelvar* package in R (Sigmund & Ferstl 2021). We employed Fixed Effects Ordinary Least Squares (OLS) estimation, which is appropriate given the number of regions and periods in our dataset. Additionally, robust standard errors were calculated to adjust for potential heteroskedasticity and serial correlation. The PVARX model is specified as follows:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p} A_l y_{i,t-l} + \sum_{j=0}^{q} C_j x_{i,t-j} + \epsilon_{i,t}$$

where $y_{i,t}$ represents a $m \times 1$ vector of endogenous economic variables for region i at time t, while region-specific fixed effects are captured by μ_i. A_l is a $m \times m$ coefficient matrix for the lagged endogenous variables $y_{i,t-l}$, and $x_{i,t-j}$ is a $n \times 1$ vector of exogenous climate variables for region i at time $t - j$. For the exogenous variables, we also have C_j that is a $m \times n$ coefficient matrix for these variables and, ultimately $\epsilon_{i,t}$, the error term, which we assume to be independently and identically distributed (i.i.d.) with mean zero and covariance matrix Σ_ϵ. The parameters p and q denote the number of lags for the endogenous and exogenous variables, respectively.

The endogenous variables ($y_{i,t}$) in the model are: Inflation Rate (*HICP*), measured by the Harmonized Index of Consumer Prices; Unemployment Rate (*Unemployment rate),* calculated based on the proportion of the workforce that is without a job; Disposable Income Growth (*Diff_Log_Disposable Income)* and Housing Expenditure Grow (*Diff_Log_Housing Expenditure*). Regarding these last two variables, we performed a log-transformation to stabilise variance and measure the growth rate (Gujarati & Porter 2009 and Wooldridge 2020) and, after unit root testing, we applied first differences to make the two variables stationary.

For the same reasons, we also treated the exogenous climate variables ($x_{i,t}$) with the same methodology: the 2-metre temperature (*Diff_Log_t2m_kelvin)* and total precipitation *(Diff_Log_precipitation)* have both been log-transformed and differenced to capture the percentage change in the climate variables. Also, all variables are demeaned to account for individual fixed effects, emphasising changes within regions over time.

To account for seasonality and recurring patterns in economic and climate data, we included the first three seasonal dummies of the year: *QuarterQ1, QuarterQ2* and *QuarterQ3*, using the fourth quarter as the baseline category; this is fundamental since it ensures that the estimated relationships are not biased by seasonally driven fluctuations.

The specific parameters of the model include 20 regions, a quarterly dataset spanning approximately 76 observations per region, and four lags ($p = 4$) for the endogenous variables to capture dynamic relationships over one year. The climate factors are considered strictly exogenous, indicating they are not affected by the economic variables being studied.

Furthermore, the coefficients A_l (endogenous lag terms) and C_j (exogenous variables) are assumed to be uniform across all regions in Italy, indicating that the economic relationships remain constant across the country. Through the incorporation of fixed effects specific to each region, the model accounts for unobserved, constant traits of each region, mitigating possible bias from omitted variables. This guarantees that the predicted connections between climate variables and macroeconomic results are not skewed by factors like regional infrastructure, historical climate conditions, or other structural disparities.

In our PVARX model, the endogenous variables are ordered based on their presumed exogeneity and ability to influence one another within the same quarter. This ordering is critical for identifying structural shocks and understanding the dynamic relationships among the variables. Inflation Rate (*HICP*) is ranked first, reflecting its role as the most exogenous variable in the system. Inflation can immediately affect other economic variables but is not influenced by them contemporaneously within the same timeframe. The Unemployment Rate is ranked second, as it is directly affected by inflation; fluctuations in inflation can alter unemployment levels through wage adjustments and labour market dynamics. Disposable

Income growth is positioned third, as higher unemployment rates typically reduce disposable income due to job losses and lower wages. Finally, Housing Expenditure growth is ranked last, as housing market adjustments are slower and primarily determined by disposable income and the overall state of the economy. This variable ordering establishes a causal hierarchy where each variable can influence those ranked lower but not those ranked higher within the same period. This sequence aligns with economic theory, ensuring that the model effectively captures the directional relationships between the variables while facilitating the identification of structural shocks.

The analysis focuses on the entire Italian territory and its subnational data, acknowledging that national averages of climate factors may overlook important differences between regions and localised effects. This method captures subtle connections and strengthens statistical significance by utilising detailed regional data.

3.2 Local Projections of Climate Shocks

We employ local projections (LPs) to investigate how climate shocks, measured by changes in temperature and rainfall, affect important Italian economic indicators. Local Projections are appropriate for our needs as they provide a flexible and precise method to estimate impulse response functions without the need to rely on the extrapolation of parameters across various time frames. Since they depend on linear regressions, they are also easier to implement than SVAR models. This method also has the advantage of being resistant to model misspecification, as inaccuracies influence less the Impulse Responses produced by Local Projections in the VAR model (Adämmer 2019), making LPs well-suited for panel data analysis and enabling the exploration of varied impacts across various regions or groups.

We use the LP framework to investigate how weather shocks, indicated by changes in precipitation and temperature variables, impact macroeconomic results in Italian macro-regions.

To construct the linear impulse response functions for every endogenous variable, we utilise the R package *lpirfs* by Adämmer (2019) to build the linear impulse response functions for every endogenous variable. The structure for the general regression model we used follows the one outlined by Jordà (2005) and Dhruv et al. (2024):

$$y_{i,t+h}^{r} = \alpha_i^h + w_{i,t}^k \beta^h + X_{i,t}\Gamma^h + \sum_{l=1}^{q=4} S_{i,t-l}\Phi_l^h + \epsilon_{i,t+h}\,; \quad h = 0,1,\ldots.,H-1$$

We can decompose the equation stating that $y_{i,t+h}^{r}$ represents the r target economic variable depending on the situation, α_i^h denotes the region-specific fixed effect; $w_{i,t}^k$ is the climate variable of interest (total precipitation or 2-metre temperature); $X_{i,t}$ describes the vector of variables that are either contemporaneous or predetermined in the system (excluding y^r and w^k); $S_{i,t-l}$ the lags of all variables in $X_{i,t}$, along with lags of y^r and w^k. As for the PVARX model, the number of lags included is $q = 4$ and $\epsilon_{i,t+h}$ the error term. The model was estimated with four lags of regressors, and the IRFs examined a period of 12 quarters (three years). Confidence intervals of 95% give a thorough understanding of the uncertainty linked to the estimated data.

Following the analysis of the entire Italian territory, we extended our investigation to examine the heterogeneity in climate shock effects across the three Italian macro-regions: North, Centre, and South. This regional focus allowed us to account for territorial and cultural differences, offering a more granular understanding of the impact of climate variability on economic outcomes.

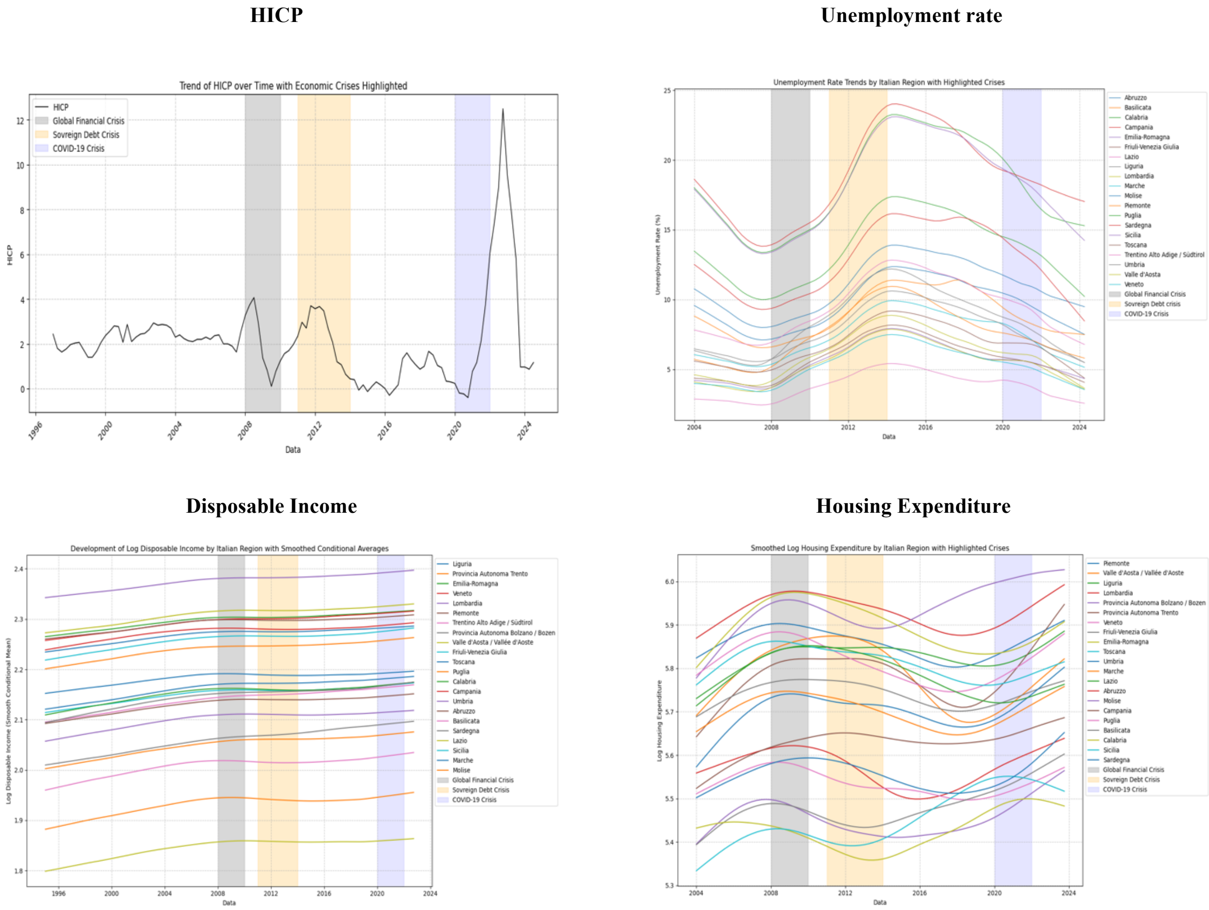
4. Data

4.1 Economic Data

For our analysis, we utilised quarterly data spanning from 2004Q1 to 2022Q4, examining the 20 Italian regions. This panel contains a block of four endogenous macroeconomic variables:

the Harmonised Index of Consumer Prices (*HICP*), which measures the evolution over time of the inflation rate in the Italian peninsula, the Unemployment Rate (*Unemployment rate*), the Disposable Income of Italians' families (*Diff_Log_Disposable Income*), and the Consumption Expenditure in the households (*Diff_Log_Housing Expenditure*); see Figure 1.

Figure 1: **Plot of the Macroeconomic Variables Considered**



Note: For the variables *Unemployment rate*, *Disposable Income* and *Housing Expenditure,* we show the smoothed conditional means to provide a more concise depiction of the patterns in the series. The highlighted periods indicate the Global Financial Crisis (grey), Sovereign Debt Crisis (yellow) and COVID-19 crisis (blue).

The Unemployment Rate, Disposable Income and Housing Expenditure are subnational variables gathered for every specific region from the ISTAT[1] database. At the same time, for

[1] To know more about the database, consult: http://dati.istat.it/Index.aspx.

the HICP, the national-level data gathered from Eurostat[2] is used for all regions, assuming that economic conditions are equal in all areas.

4.2 Climate Data

The climate data has been gathered from the "ERA5 monthly averaged data on single levels from 1940 to present" dataset[3], which is the fifth-generation ECMWF (European Centre for Medium-Range Weather Forecasts) reanalysis for the global climate and weather, accessible through the Copernicus Climate Change Service (ECMWF 2024). This evaluation combines model simulations with worldwide observed meteorological data into one dataset; it integrates data from different sources like ground stations and satellites with a climate model to estimate weather variables over a detailed grid structure. Data is provided hourly, estimated for a large number of atmospheric, ocean-wave and land-surface quantities and, with a grid resolution of 0.25° x 0.25° in both time and space.

To successfully aggregate the climate variables in the administrative regions of Italy, we utilised, as a reference for spacial aggregations, a shapefile containing the boundaries of Italian regions obtained from the Istituto Nazionale di Statistica (ISTAT). To ensure the spatial compatibility between the climate variables and the shapefile, both datasets were reprojected into a Common Reference System (CRS). The climate data points were assigned to Italian regions based on their geographic location. This was achieved using a spatial join methodology, where each climate data point was overlaid onto the geospatial boundaries and points falling within a specific region were associated with that region's identifier (see Figure 2). Once the points were assigned to their respective regions, the climate variables were aggregated to generate region-level metrics. For climate data sets that include a time-series element, the information was combined and summarised for distinct time frames. Aggregation was

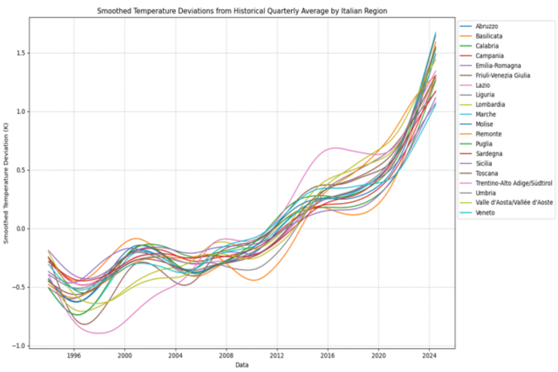
[2] To know more about the dataset, consult: https://shorturl.at/FFX61

[3] To consult the database visit: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=overview

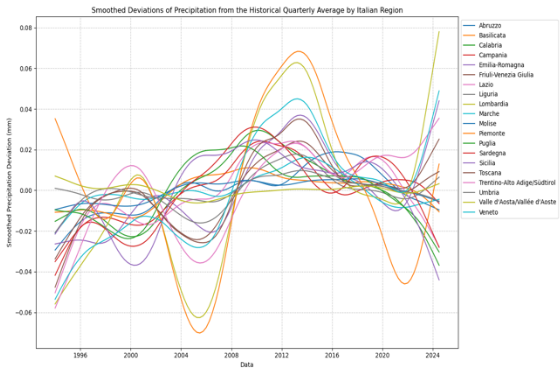
conducted every quarter to synchronise with economic data utilised in the later analysis. This aggregation methodology aligns with the approach described by Kotz, Wenz, Stechemesser, Kalkuhl & Levermann (2021), where climate variables have been aggregated from grid cells to administrative regions.

Figure 3: **Deviations of Weather variables from Historical Averages, divided by Region**

t2m_kelvin deviation



precipitation deviation



Note: Here, we represent the smoothed conditional means for the climate variables to implement a more concise portrayal of the trends in the series.

The study focuses on two main climate indicator variables: 2-metre temperature (*t2m_kelvin*) and total precipitation (*precipitation*) (see Figure 3). We chose those two variables because both have a direct economic impact on sectors like agriculture, energy, transportation, and tourism. In addition, they depict changes in weather patterns within different areas, clarifying variations in economic productivity within regions. 2-metre temperature is maintained in the Kelvin unit of measurement in order not to have problems with negative or zero values with the log transformation and is the air temperature at the height of 2 meters above the land, sea, or inland waters' surface. Precipitation is the combination of extensive precipitation, measured in meters, containing liquid and frozen water, such as rain and snow. (ECMWF 2024). A logarithmic transformation was employed to enhance the statistical characteristics of the climate variables.

This change assists in standardising the information, stabilising variability, and correcting asymmetry (Tabachnick & Fidell 2013).

5. Empirical Results

5.1 The PVARX Estimates

The entire findings from the PVARX fixed effects analysis for the Italian territory (see Table 1) and its macro-regions (see Tables 2, 3 and 4) are concisely presented in the relevant tables. Every table displays the coefficients derived from the estimation, facilitating a comparative analysis among the regions and variables of interest. The columns in each chart showcase the dependent variables of interest, which consist of *HICP*, *Unemployment rate*, *Diff_Log_Disposable Income* and *Diff_Log_Housing Expenditure*. The rows display regressors, including lagged dependent variables, climate variables, and seasonal dummies, representing continuity, time-related dependencies, weather disturbance impacts, and quarterly economic performance fluctuations. Every coefficient is presented alongside its standard error in parentheses, with statistical significance denoted by: *, ** and ***, indicating statistical significance at 5%, 1% and 0,1%, respectively.

To initiate the examination of our findings, we begin by analysing one economic variable individually and explore how these effects vary based on the geographic focus we emphasise. The first variable we are going to discuss is the **HICP**; the estimation findings for this variable in the **complete PVARX model** illustrate the impact of climate variables on inflation throughout Italy's regions. The analysis highlights a significant positive relationship between **temperature** changes and inflation. In the aggregate model, a 1% increase in temperature is associated with a **9.73-unit** rise in the HICP ($p < 0.001$), suggesting that higher temperatures may drive inflation through reduced agricultural productivity, increased energy demand, and supply chain disruptions. Conversely, **precipitation** changes have no statistically significant impact on inflation. Additionally, the first lag of HICP is highly substantial, indicating strong inflation persistence, while QuarterQ3 exhibits a significant negative effect.

For the three macro-regions, we find that for all of the three models, precipitation is not a significant climate variable while, in the **North,** a 1% increase in temperature is linked to a **15.30-unit** rise in the HICP ($p < 0.001$), for the **Centre**, temperature fluctuations significantly influence inflation, with a 1% increase leading to an approximate **11.10-unit** rise ($p < 0.05$), and in the **South**, it is also not significant.

Building on the earlier analysis of inflation, we shift focus to the impact of climate variables on the **Unemployment Rate**, beginning with the Total PVARX model. **Temperature** fluctuations exhibit a significant positive impact, where a 1% rise in temperature corresponds to an approximate **9.86-unit** increase ($p < 0.05$). This relationship likely stems from extreme heat impairing productivity, causing health issues, and disrupting agriculture, leading to layoffs, absenteeism, and crop damage. Conversely, **precipitation** shows a significant negative effect, with a 1% increase linked to a **0.1080-unit** reduction in unemployment ($p < 0.05$). This suggests that greater precipitation supports agricultural productivity, increases labour demand, and benefits industries such as hydroelectric energy and manufacturing, aiding in job retention. The analysis also highlights the persistence of unemployment and inflation, as evidenced by the significant effects of lagged HICP and the unemployment rate. Seasonal dummies indicate lower unemployment rates during the second and third quarters, potentially reflecting seasonality in labour-intensive sectors.

In the regional models, climate variables show minimal influence on unemployment in the **North** and **Centre**. However, in the **South**, precipitation has a significant inverse relationship with unemployment; a 1% increase in precipitation is associated with a **0.2441-unit** decrease in the unemployment rate ($p < 0.05$). This is likely due to the South’s reliance on agriculture and water-dependent industries such as farming, fishing, and hydropower, where increased precipitation supports job retention and growth.

The analysis of **Disposable Income** begins as before with the Total PVARX model, where a minor but statistically significant positive relationship is observed between **precipitation** and disposable income growth. A 1% increase in precipitation corresponds to a **0.0014%** rise in disposable income growth, likely driven by improved agricultural productivity and related sectors. **Temperature** changes, however, show no significant effect. Growth in disposable income is also influenced by previous values, rising unemployment, inflation, and seasonal factors, reflecting broader economic adjustments such as government policies, salary changes, and sector-specific hiring. In the **North** macro-region, temperature remains insignificant, but precipitation shows a stronger impact. A 1% rise in precipitation results in a **0.0032%** increase in disposable income growth ($p < 0.01$). In contrast, climate variables in both the **Central** and **Southern** regions do not significantly affect household disposable income.

In analysing **Housing Expenditure**, neither **total precipitation** nor **2-metre temperature** significantly impacts housing expenditure across any of the models. However, other variables consistently exhibit significant effects. Specifically, the fourth lag of housing expenditure growth shows a notable negative impact across all models, highlighting cyclical trends in housing markets. Seasonal dummy variables for the first three quarters consistently demonstrate positive and significant effects, suggesting increased housing expenditure during these periods. In some models, particularly for the **Centre** macro-region, the lagged unemployment rate (e.g., the third lag) shows a significant negative relationship, indicating the influence of labour market conditions on housing investment decisions. Overall, the findings suggest that while climate variables do not directly influence housing expenditure growth, other factors, including past expenditure values, labour market dynamics, and seasonal trends, play a critical role. These results reinforce the broader pattern observed across the PVARX models: climate variables significantly impact inflation and unemployment, while their effects on disposable income growth and housing expenditure are more nuanced or insignificant.

The research emphasizes the importance of including climate elements in economic modelling and policy development to strengthen economic resilience amid persistent climate change, thereby supporting economic growth.

5.2 Stability Tests

Following the estimation of the PVARX models, we proceed to assess the stability of our panel dataset. Stability is a crucial requirement for using Panel VARX models, as unstable models may result in unreliable impulse response functions and incorrect conclusions about the dynamic connections between variables. Considering the possible influence of shared elements on our economic indicators (HICP, Unemployment Rate, Disposable Income, and Housing Expenditure) across different Italian regions, it is essential to guarantee the stability of our models. To assess the stability of the PVARX models, we conducted eigenvalue decomposition on the companion matrix obtained from each model. This approach is a recognised method for evaluating the stability of VAR systems (Hamilton 1994). The companion matrix provides a thorough representation of the dynamic relationships between all variables and their lags within the VAR structure. To apply this method, we derive the companion matrix from the estimated parameters of the PVARX model. The eigenvalues of this matrix are subsequently computed and represented on the complex plane, where the unit circle acts as the stability threshold. This illustration supports both numerical validation and an intuitive grasp of the model's dynamic characteristics.

First, we tested the complete PVARX Model (*Total PVARX model),* which includes the observations for all Italian regions (see Table 5). These values are then plotted on the complex plane, showing the real components on the x-axis and the imaginary ones on the y-axis. The plot features the unit circle, which denotes the stability boundary.

The analysis shows that all eigenvalues are strictly inside the unit circle, confirming that the PVARX model meets the stability condition (see Figure 4). This discovery is vital for confirming the estimated relationships among climate factors.

In addition, stability tests were conducted separately for the North, Centre, and South macro-regions to ensure robustness and stationarity within each subset of the dataset. The methodology follows the approach applied to the total PVARX model, utilising eigenvalue analysis to determine whether the companion matrix remains within the unit circle for each regional model (see Table 6). The stability findings show that every eigenvalue for the PVARX models corresponding to the North, Centre, and South areas lies within the unit circle, verifying the stability of these regional models. The visual proof in Figure 5 justifies the numerical stability results, confirming the strength and dependability of the PVARX models throughout the three macro-regions. This stability is essential for correctly interpreting impulse response functions and ensuring the validity of the following analysis of climate shocks on regional economic results.

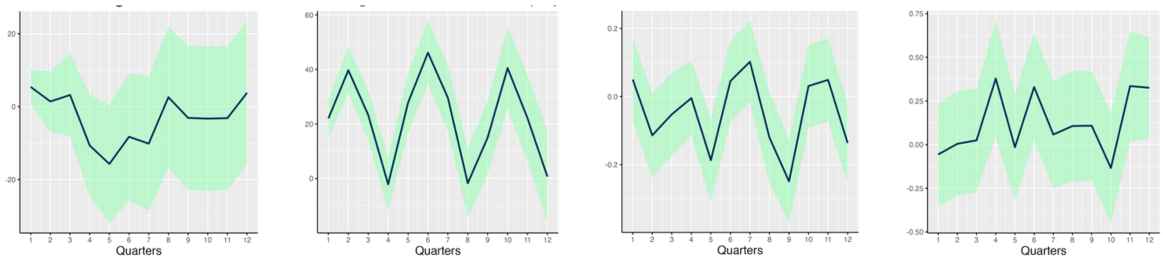
5.3. Impulse Response Analysis

In this part, we examine the results of the Impulse Response Functions generated from the Local Projections (LPs). This enables us to estimate the dynamic impacts of climate shocks (temperature and precipitation) on the Italian economic variables. The discussion centres on economic metrics (HICP, Unemployment Rate, Disposable Income, and Housing Expenditure), offering insights into the scale, direction, and duration of climate shocks across different regions.

Regional examinations reveal spatial diversity in reactions, influenced by the economic, cultural, and geographical traits of the North, Centre, and South. The approach covers 12 quarters (three years), encompassing both the short-term and delayed impacts of climate disturbances. Utilising regional panel data and applying a fixed-effects model, this study addresses unobserved variations and highlights the regional distinctions in economic reactions to climate fluctuations.

We are going to start by analysing the Impulse Responses of the Total model, first with a focus on the temperature effects (see Figure 6) and later on the total precipitation ones (see Figure 7). The Impulse Response Function shows an initial suppression followed by recovery. In the first few quarters, inflation (**HICP**) declines due to **temperature** shocks, possibly due to lower demand for weather-sensitive goods or services. But, over time, inflation stabilises and shows signs of recovery and a positive effect. By the end of the horizon, the response is closer to zero, suggesting the initial suppressive effect may dissipate.

Figure 6: **Impulse Responses for Temperature Shocks of Total Model**

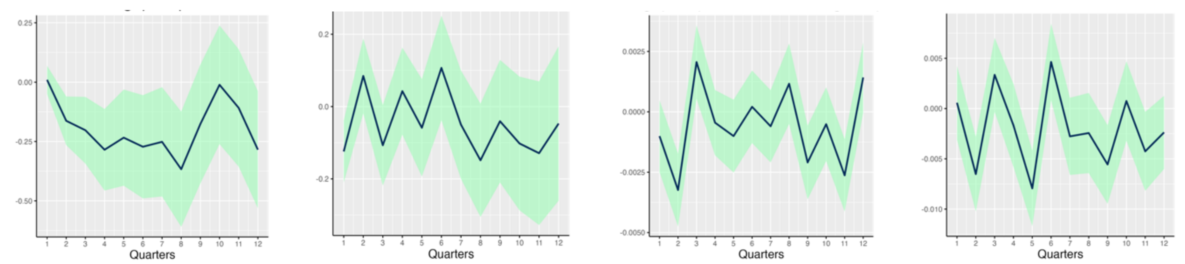


HICP | Unemployment rate | Diff_Log_Disposable Income | Diff_Log_Housing Expenditure

The **Unemployment rate** exhibits strong oscillations over the 12-quarter horizon, with significant increases in the second and sixth quarters. These oscillations suggest temporary labour market disruptions, especially in climate-sensitive industries like agriculture and construction. Extreme temperatures could increase unemployment in outdoor industries while creating job opportunities in energy or disaster management sectors. The IRF for **Disposable Income** indicates varying impacts of temperature changes throughout 12 quarters. Peaks near the fifth and ninth quarters imply possible income growth, yet drops point to an unreliable connection. This behaviour suggests an absence of a statistically significant impact of temperature on the economic variable, which could indicate susceptibility in areas such as agriculture and tourism to temperature-related disturbances. The analysis of temperature variations on **Housing expenditure** over 12 quarters reveals no statistically significant effects. The broad confidence intervals overlapping with zero suggest that observed variations are likely due to noise rather than a meaningful relationship.

For the **total precipitation** shocks (see Figure 7), we see that these variations affect inflation (**HICP**), exhibiting a declining trend in the initial quarters and a possible deflationary influence in the third quarter. This could be caused by diminished consumer demand or decreased agricultural prices as a result of heavy rainfall. For the **Unemployment rate**, we can see that for the first periods, there is no clear trend in the behaviour of the variable in response to the precipitation shock, with many oscillations between positive and negative values, however, after the 6th period, we have a declining negative effect for the unemployment rate. For the **Disposable Income** variable, the precipitation has a positive effect from the very first stages and later has very moderate fluctuations and a modest upward trend toward the end of the horizon. The analysis of precipitation's effect on **Housing expenditure** over 12 quarters shows minor fluctuations, including a small initial decrease, variable impacts, and a peak in the fifth quarter. However, these effects remain statistically insignificant, indicating that rainfall fluctuations have minimal influence on the economic variable.

Figure 7: **Impulse Responses for Precipitation Shocks of Total Model**



HICP | Unemployment rate | Diff_Log_Disposable Income | Diff_Log_Housing Expenditure

By analysing the effects of climate variables for the aggregated Northern regions, we were unable to obtain satisfactory results from IRFs for both temperature and total precipitation, resulting in graphs with fluctuations in the economic variables that were not statistically significant as instead found for certain variables in the PVARX model (temperature was significant at 0,1% level for HICP; total precipitation was also significant for Disposable Income at 1%) (see Figure 8). For the Centre and South IRFs, we also encountered the same issue; the figures correctly highlighted that there were no significant effects on most economic variables from climate ones but failed to depict the significance of temperature to HICP (a significant positive effect at the 5% level) in the Centre (see Figure 9), and the effect of precipitation on the Unemployment rate in the South (a significative effect at 5% level)(see Figure 10).

The IRFs show regionally varied and often modest impacts of climate shocks on Italy's economy, with some variables responding significantly but briefly, while others remain unaffected. This underscores the need for region-specific policies and further research to strengthen economic resilience to climate challenges.

6. Implications for Italian Economic Policy and Conclusion

This research has emphasised the complex connection between Italy's climate fluctuations and essential macroeconomic indicators. By examining the immediate impacts of temperature and precipitation shocks in various macro-regions, it offers practical recommendations for policymakers looking to alleviate and actively tackle the negative effects of climate change on the Italian economy.

The results highlight the importance of localised policies to deal with the vulnerabilities and strengths of Italy's macro-regions. In the North, the inflationary pressures resulting from temperature shocks necessitate focused actions. Policymakers should concentrate on improving energy efficiency, addressing supply chain disruptions, and funding adaptive agricultural technologies. For instance, supporting climate-resistant crop types or enhancing storage and transportation systems could mitigate the inflationary impacts of climate fluctuations.

In the Centre, where temperature variations likewise influence inflation, regional strategies must emphasize promoting sustainable tourism and energy-efficient facilities. Considering the economic dependence on service sectors and city areas, investing in sustainable urban design and low-emission transport systems can enhance resilience to climate disruptions.

The South, known for its farming and water-reliant sectors, shows notable job growth due to higher rainfall. To maximize this beneficial effect, policymakers ought to prioritize the modernization of irrigation systems, the promotion of sustainable agricultural practices, and the enhancement of water management infrastructure. These efforts not only increase agricultural output but also generate employment and strengthen local economies.

At the national level, it is crucial to incorporate climate factors into monetary and fiscal policies. The identified connection between temperature and inflation highlights the necessity for a climate-conscious monetary policy structure at the European Central Bank (ECB). Although the ECB's centralized strategy restricts Italy's autonomy, the Bank of Italy can push for inflation adjustments tailored to regions or suggest methods to mitigate localized climate impacts. Financial strategies, including climate-oriented subsidies or tax breaks for eco-friendly technologies, could enhance monetary initiatives by tackling sector-specific weaknesses.

Integrating climate risks into Italy's long-term economic strategies is just as essential. Due to the ongoing nature of specific macroeconomic impacts, including inflation and unemployment, investments in flexible infrastructure and education initiatives to improve workers' skills can strengthen the resilience of the labour market. For example, training programs focused on renewable energy or disaster management could mitigate climate-related job losses and promote sustainable development.

This study also highlights the significance of tackling systemic inequalities in climate resilience. Areas with restricted adaptive abilities, like the agricultural South, need further assistance to achieve fair economic results nationwide. Improving cooperation among regional authorities, national bodies, and international entities can promote the exchange of knowledge and distribution of resources for better climate adaptation.

Additionally, we uncover deficiencies in comprehending the impact of short-term climate disturbances on economic results. Future studies might build upon these results by investigating the indirect impacts of climate variability, including its effects on consumer behaviour, investment choices, or health results. Furthermore, including a wider range of climate factors, such as extreme weather occurrences, could offer a deeper insight into Italy’s economic weaknesses.

In conclusion, this work project adds to the wider conversation on climate economics by emphasising the importance of localised, short-term assessments in comprehending and tackling the economic effects of climate fluctuation. Our study shows that climate variability significantly affects Italy's macroeconomic indicators, although the impacts vary by region. Utilising sophisticated econometric methods, the research offers an in-depth examination of how temperature and rainfall disturbances affect the economy. These insights highlight the critical need to incorporate climate factors into Italy’s economic policy framework to strengthen resilience, reduce risks, and encourage sustainable growth.

Tackling climate-related economic issues necessitates a comprehensive strategy that integrates monetary, fiscal, and regional methods. Policymakers should focus on investing in adaptive infrastructure, sustainable technologies, and workforce development while promoting increased flexibility in the ECB's monetary system. By coordinating these initiatives with the unique requirements of Italy’s various regions, the nation can enhance its economic resilience and guarantee sustainable growth amid changing climate circumstances.

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8. Appendix

Figure 2: Map of Italy with aggregation points

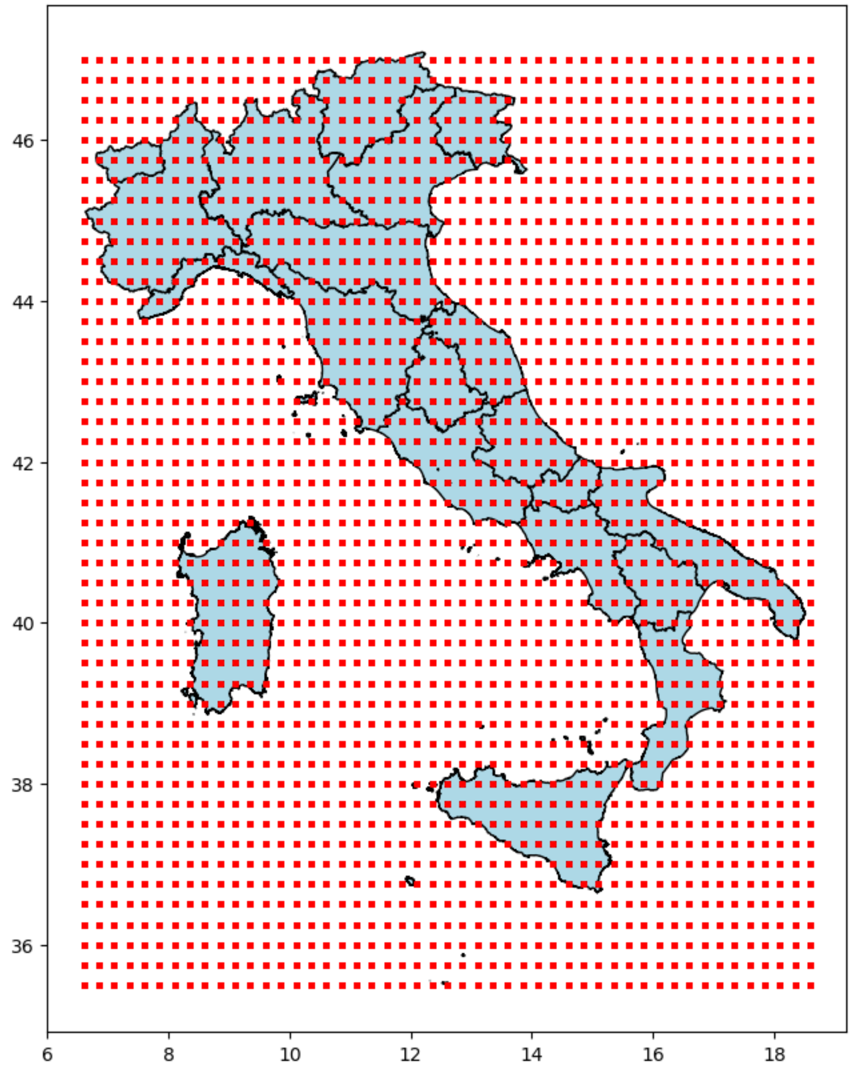

Table 1: Panel VARX (Total) Estimation results

Fixed Effects OLS Panel VAR estimation

Transformation: demean
Group variable: Region
Time variable: Time
Number of observations = 1519
Number of groups = 20
Obs per group: min = 75
avg = 75.95
max = 76

	demeaned_HICP	demeaned_Unemployment_rate	demeaned_Diff_Log_Disposable_Income	demeaned_Diff_Log_Housing_Expenditure
demeaned_lag1_HICP	1.2477 ***	-0.0817	-0.0063 ***	-0.0023
	(0.0301)	(0.0591)	(0.0008)	(0.0019)
demeaned_lag1_Unemployment_rate	0.0182	0.6546 ***	0.0004	-0.0011
	(0.0141)	(0.0278)	(0.0004)	(0.0009)
demeaned_lag1_Diff_Log_Disposable_Income	0.8103	2.2240	0.3256 ***	0.0271
	(0.9703)	(1.9078)	(0.0263)	(0.0624)
demeaned_lag1_Diff_Log_Housing_Expenditure	0.4826	0.0033	-0.0229 *	-0.0056
	(0.4110)	(0.8081)	(0.0112)	(0.0264)
demeaned_lag2_HICP	-0.1418 **	0.3275 ***	0.0077 ***	0.0049
	(0.0464)	(0.0912)	(0.0013)	(0.0030)
demeaned_lag2_Unemployment_rate	0.0364 *	0.0511	0.0026 ***	0.0016
	(0.0166)	(0.0325)	(0.0004)	(0.0011)
demeaned_lag2_Diff_Log_Disposable_Income	-1.6550	-7.9403 ***	0.2618 ***	0.0084
	(0.9985)	(1.9632)	(0.0271)	(0.0642)
demeaned_lag2_Diff_Log_Housing_Expenditure	1.7350 ***	-0.7048	-0.0209	-0.0019
	(0.4108)	(0.8077)	(0.0112)	(0.0264)
demeaned_lag3_HICP	-0.3231 ***	-0.4576 ***	-0.0049 ***	-0.0026
	(0.0474)	(0.0932)	(0.0013)	(0.0030)
demeaned_lag3_Unemployment_rate	-0.1071 ***	0.1956 ***	-0.0029 ***	-0.0009
	(0.0172)	(0.0338)	(0.0005)	(0.0011)
demeaned_lag3_Diff_Log_Disposable_Income	0.7922	3.5352 *	0.2804 ***	0.0418
	(0.9124)	(1.7940)	(0.0248)	(0.0587)
demeaned_lag3_Diff_Log_Housing_Expenditure	0.0370	-1.7355 *	-0.0172	-0.0033
	(0.4136)	(0.8133)	(0.0112)	(0.0266)
demeaned_lag4_HICP	-0.0115	0.4139 ***	0.0014	0.0001
	(0.0314)	(0.0617)	(0.0009)	(0.0020)
demeaned_lag4_Unemployment_rate	-0.0103	0.0857 **	-0.0007	-0.0004
	(0.0151)	(0.0297)	(0.0004)	(0.0010)
demeaned_lag4_Diff_Log_Disposable_Income	-0.0021	0.1154	0.0006	-0.0040
	(0.0852)	(0.1674)	(0.0023)	(0.0055)
demeaned_lag4_Diff_Log_Housing_Expenditure	-0.6305	-1.0774	-0.0424 ***	-0.2712 ***
	(0.3351)	(0.6590)	(0.0091)	(0.0215)
demeaned_Diff_Log_precipitation	-0.0285	-0.1080 *	0.0014 *	0.0018
	(0.0236)	(0.0465)	(0.0006)	(0.0015)
demeaned_Diff_Log_t2m_kelvin	9.7293 ***	9.8560 *	0.0998	-0.0789
	(2.2135)	(4.3522)	(0.0601)	(0.1423)
demeaned_QuarterQ1	-0.1309	-1.1210	-0.0235	0.3228 ***
	(0.6124)	(1.2041)	(0.0166)	(0.0394)
demeaned_QuarterQ2	-0.9043	-5.6247 ***	0.5232 ***	0.3864 ***
	(0.7393)	(1.4536)	(0.0201)	(0.0475)
demeaned_QuarterQ3	-1.3258 **	-5.7082 ***	0.4535 ***	0.3190 ***
	(0.4919)	(0.9671)	(0.0134)	(0.0316)

*** p < 0.001; ** p < 0.01; * p < 0.05

Table 2: Panel VARX (North) Estimation results

Fixed Effects OLS Panel VAR estimation

Transformation: demean
Group variable: Region
Time variable: Time
Number of observations = 607
Number of groups = 8
Obs per group: min = 75
avg = 75.875
max = 76

	demeaned_HICP	demeaned_Unemployment_rate	demeaned_Diff_Log_Disposable_Income	demeaned_Diff_Log_Housing_Expenditure
demeaned_lag1_HICP	1.2774 ***	-0.0203	-0.0057 ***	-0.0034
	(0.0478)	(0.0618)	(0.0013)	(0.0028)
demeaned_lag1_Unemployment_rate	0.0016	0.6588 ***	0.0008	-0.0012
	(0.0338)	(0.0436)	(0.0010)	(0.0020)
demeaned_lag1_Diff_Log_Disposable_Income	-0.2065	-2.9157	0.2824 ***	0.0166
	(1.4731)	(1.9016)	(0.0415)	(0.0870)
demeaned_lag1_Diff_Log_Housing_Expenditure	1.0685	-0.0853	-0.0264	-0.0353
	(0.7461)	(0.9631)	(0.0210)	(0.0441)
demeaned_lag2_HICP	-0.1660 *	0.1416	0.0064 **	0.0072
	(0.0747)	(0.0964)	(0.0021)	(0.0044)
demeaned_lag2_Unemployment_rate	0.0822 *	-0.0266	0.0049 ***	0.0039
	(0.0400)	(0.0517)	(0.0011)	(0.0024)
demeaned_lag2_Diff_Log_Disposable_Income	-0.8494	-2.8662	0.2892 ***	0.0109
	(1.4950)	(1.9298)	(0.0422)	(0.0883)
demeaned_lag2_Diff_Log_Housing_Expenditure	1.7625 *	-2.0786 *	-0.0258	-0.0197
	(0.7458)	(0.9627)	(0.0210)	(0.0440)
demeaned_lag3_HICP	-0.3262 ***	-0.3081 **	-0.0047 *	-0.0030
	(0.0751)	(0.0969)	(0.0021)	(0.0044)
demeaned_lag3_Unemployment_rate	-0.1084 **	0.2590 ***	-0.0031 **	-0.0004
	(0.0413)	(0.0533)	(0.0012)	(0.0024)
demeaned_lag3_Diff_Log_Disposable_Income	1.0679	4.7649 **	0.3080 ***	0.0289
	(1.4007)	(1.8082)	(0.0395)	(0.0827)
demeaned_lag3_Diff_Log_Housing_Expenditure	0.0900	-3.3365 ***	-0.0307	-0.0255
	(0.7508)	(0.9692)	(0.0212)	(0.0443)
demeaned_lag4_HICP	-0.0048	0.4040 ***	0.0014	-0.0004
	(0.0503)	(0.0649)	(0.0014)	(0.0030)
demeaned_lag4_Unemployment_rate	-0.0457	0.0937 *	-0.0035 ***	-0.0048 *
	(0.0362)	(0.0467)	(0.0010)	(0.0021)
demeaned_lag4_Diff_Log_Disposable_Income	0.0346	0.0950	0.0054	-0.0007
	(0.1199)	(0.1548)	(0.0034)	(0.0071)
demeaned_lag4_Diff_Log_Housing_Expenditure	-1.0695	-1.4329	-0.0768 ***	-0.1691 ***
	(0.6494)	(0.8383)	(0.0183)	(0.0383)
demeaned_Diff_Log_precipitation	-0.0360	0.0077	0.0032 **	0.0020
	(0.0407)	(0.0525)	(0.0011)	(0.0024)
demeaned_Diff_Log_t2m_kelvin	15.3032 ***	3.0897	0.2049	-0.1061
	(3.7295)	(4.8142)	(0.1052)	(0.2202)
demeaned_QuarterQ1	-0.5085	-3.2216 **	-0.0458	0.2927 ***
	(0.9520)	(1.2289)	(0.0268)	(0.0562)
demeaned_QuarterQ2	-1.5060	-5.6555 ***	0.4991 ***	0.3495 ***
	(1.1528)	(1.4881)	(0.0325)	(0.0681)
demeaned_QuarterQ3	-1.2513	-3.0399 **	0.4597 ***	0.2865 ***
	(0.7515)	(0.9701)	(0.0212)	(0.0444)

*** p < 0.001; ** p < 0.01; * p < 0.05

Table 3: Panel VARX (Centre) Estimation results

Fixed Effects OLS Panel VAR estimation

Transformation: demean
Group variable: Region
Time variable: Time
Number of observations = 380
Number of groups = 5
Obs per group: min = 76
avg = 76
max = 76

	demeaned_HICP	demeaned_Unemployment_rate	demeaned_Diff_Log_Disposable_Income	demeaned_Diff_Log_Housing_Expenditure
demeaned_lag1_HICP	1.2211 ***	-0.2819 *	-0.0070 ***	-0.0058
	(0.0618)	(0.1212)	(0.0018)	(0.0043)
demeaned_lag1_Unemployment_rate	0.0301	0.5701 ***	0.0009	-0.0012
	(0.0288)	(0.0564)	(0.0008)	(0.0020)
demeaned_lag1_Diff_Log_Disposable_Income	1.6081	10.9627 **	0.3573 ***	0.1434
	(1.9536)	(3.8332)	(0.0562)	(0.1349)
demeaned_lag1_Diff_Log_Housing_Expenditure	-0.1365	0.3425	-0.0314	-0.0071
	(0.7618)	(1.4948)	(0.0219)	(0.0526)
demeaned_lag2_HICP	-0.1208	0.6490 ***	0.0081 **	0.0078
	(0.0962)	(0.1887)	(0.0028)	(0.0066)
demeaned_lag2_Unemployment_rate	0.0148	0.1613 *	0.0029 **	0.0043
	(0.0337)	(0.0661)	(0.0010)	(0.0023)
demeaned_lag2_Diff_Log_Disposable_Income	-4.0211 *	-10.7480 **	0.2841 ***	0.0480
	(2.0149)	(3.9535)	(0.0580)	(0.1391)
demeaned_lag2_Diff_Log_Housing_Expenditure	3.4528 ***	-0.4880	-0.0354	-0.0139
	(0.7566)	(1.4846)	(0.0218)	(0.0522)
demeaned_lag3_HICP	-0.3369 ***	-0.5199 **	-0.0049	0.0012
	(0.0993)	(0.1948)	(0.0029)	(0.0069)
demeaned_lag3_Unemployment_rate	-0.1129 ***	0.0615	-0.0044 ***	-0.0071 **
	(0.0333)	(0.0654)	(0.0010)	(0.0023)
demeaned_lag3_Diff_Log_Disposable_Income	1.1959	-1.7287	0.2504 ***	-0.0829
	(1.8050)	(3.5416)	(0.0520)	(0.1246)
demeaned_lag3_Diff_Log_Housing_Expenditure	0.1577	-0.5877	-0.0161	0.0018
	(0.7812)	(1.5327)	(0.0225)	(0.0539)
demeaned_lag4_HICP	-0.0134	0.3045 *	0.0013	-0.0035
	(0.0644)	(0.1265)	(0.0019)	(0.0044)
demeaned_lag4_Unemployment_rate	-0.0161	0.1783 **	-0.0002	0.0019
	(0.0309)	(0.0606)	(0.0009)	(0.0021)
demeaned_lag4_Diff_Log_Disposable_Income	-0.0701	0.0244	-0.0074	-0.0078
	(0.1517)	(0.2976)	(0.0044)	(0.0105)
demeaned_lag4_Diff_Log_Housing_Expenditure	-0.2852	-0.3048	-0.0157	-0.3447 ***
	(0.6754)	(1.3252)	(0.0194)	(0.0466)
demeaned_Diff_Log_precipitation	0.0393	-0.0196	0.0026	0.0044
	(0.0543)	(0.1065)	(0.0016)	(0.0037)
demeaned_Diff_Log_t2m_kelvin	11.0952 *	5.3241	0.2220	-0.0508
	(5.6535)	(11.0927)	(0.1627)	(0.3903)
demeaned_QuarterQ1	-0.2879	4.1607	-0.0130	0.4338 ***
	(1.2098)	(2.3738)	(0.0348)	(0.0835)
demeaned_QuarterQ2	-1.2508	-1.0072	0.5396 ***	0.5111 ***
	(1.4651)	(2.8746)	(0.0422)	(0.1011)
demeaned_QuarterQ3	-2.3702 *	-6.5077 ***	0.4535 ***	0.3537 ***
	(0.9826)	(1.9279)	(0.0283)	(0.0678)

*** p < 0.001; ** p < 0.01; * p < 0.05

Table 4: Panel VARX (South) Estimation results

Fixed Effects OLS Panel VAR estimation

Transformation: demean
Group variable: Region
Time variable: Time
Number of observations = 532
Number of groups = 7
Obs per group: min = 76
avg = 76
max = 76

	demeaned_HICP	demeaned_Unemployment_rate	demeaned_Diff_Log_Disposable_Income	demeaned_Diff_Log_Housing_Expenditure
demeaned_lag1_HICP	1.2111 ***	-0.0614	-0.0066 ***	-0.0010
	(0.0519)	(0.1259)	(0.0012)	(0.0034)
demeaned_lag1_Unemployment_rate	0.0162	0.6991 ***	0.0000	-0.0007
	(0.0194)	(0.0471)	(0.0005)	(0.0013)
demeaned_lag1_Diff_Log_Disposable_Income	1.7891	0.8836	0.3140 ***	-0.0421
	(1.8636)	(4.5208)	(0.0445)	(0.1213)
demeaned_lag1_Diff_Log_Housing_Expenditure	0.3032	0.2908	-0.0115	0.0035
	(0.6724)	(1.6312)	(0.0161)	(0.0438)
demeaned_lag2_HICP	-0.1222	0.2989	0.0081 ***	0.0017
	(0.0787)	(0.1908)	(0.0019)	(0.0051)
demeaned_lag2_Unemployment_rate	0.0430	0.1063	0.0021 ***	-0.0005
	(0.0235)	(0.0569)	(0.0006)	(0.0015)
demeaned_lag2_Diff_Log_Disposable_Income	-0.7340	-11.1150 *	0.2342 ***	0.0238
	(1.9390)	(4.7037)	(0.0463)	(0.1262)
demeaned_lag2_Diff_Log_Housing_Expenditure	0.2579	0.1849	-0.0095	0.0017
	(0.6674)	(1.6190)	(0.0159)	(0.0434)
demeaned_lag3_HICP	-0.3038 ***	-0.4824 *	-0.0039 *	-0.0033
	(0.0824)	(0.1998)	(0.0020)	(0.0054)
demeaned_lag3_Unemployment_rate	-0.1081 ***	0.2043 ***	-0.0022 ***	0.0020
	(0.0240)	(0.0583)	(0.0006)	(0.0016)
demeaned_lag3_Diff_Log_Disposable_Income	0.5551	4.6803	0.2517 ***	0.1221
	(1.7134)	(4.1565)	(0.0409)	(0.1115)
demeaned_lag3_Diff_Log_Housing_Expenditure	-0.3395	-0.7970	-0.0090	-0.0068
	(0.6658)	(1.6151)	(0.0159)	(0.0433)
demeaned_lag4_HICP	-0.0399	0.4343 **	0.0001	0.0001
	(0.0549)	(0.1332)	(0.0013)	(0.0036)
demeaned_lag4_Unemployment_rate	-0.0107	-0.0239	-0.0003	-0.0011
	(0.0216)	(0.0524)	(0.0005)	(0.0014)
demeaned_lag4_Diff_Log_Disposable_Income	0.0167	0.2426	0.0011	-0.0044
	(0.2230)	(0.5409)	(0.0053)	(0.0145)
demeaned_lag4_Diff_Log_Housing_Expenditure	-0.6706	-1.1336	-0.0345 **	-0.2922 ***
	(0.5058)	(1.2271)	(0.0121)	(0.0329)
demeaned_Diff_Log_precipitation	-0.0217	-0.2441 *	0.0001	0.0005
	(0.0419)	(0.1016)	(0.0010)	(0.0027)
demeaned_Diff_Log_t2m_kelvin	9.9693	16.0157	0.2025	0.1970
	(5.3300)	(12.9295)	(0.1273)	(0.3469)
demeaned_QuarterQ1	0.3183	-2.0359	-0.0150	0.2689 ***
	(1.1397)	(2.7648)	(0.0272)	(0.0742)
demeaned_QuarterQ2	-0.4731	-8.5074 *	0.5155 ***	0.3300 ***
	(1.4002)	(3.3967)	(0.0334)	(0.0911)
demeaned_QuarterQ3	-1.1317	-7.7992 ***	0.4380 ***	0.3182 ***
	(0.9546)	(2.3158)	(0.0228)	(0.0621)

*** p < 0.001; ** p < 0.01; * p < 0.05

Table 5: Eigenvalues for Stability test of Total PVARX model

Eigenvalues Total PVARX
0.948299059+0.0000000i
0.922545788+0.0000000i
0.813011871+0.3221869i
0.813011871-0.3221869i
-0.509754482+0.5104830i
-0.509754482-0.5104830i
0.507450293+0.5107877i
0.507450293-0.5107877i
-0.340559884+0.4601817i
-0.340559884-0.4601817i
-0.075790145+0.5231032i
-0.075790145-0.5231032i
-0.504667324+0.0000000i
0.151834544+0.0000000i
-0.089010713+0.0000000i
0.004533641+0.0000000i

Table 6: Eigenvalues of North, Centre and South PVARX models

North Eigenvalues	Centre Eigenvalues	South Eigenvalues
0.9434398+0i	0.948258004+0.0000000i	0.94320248+0.0000000i
0.9332516+0i	0.928102556+0.0000000i	0.87964311+0.0000000i
0.8090561+0.3020809i	0.812756870+0.3311535i	0.80023942+0.3507326i
0.8090561-0.3020809i	0.812756870-0.3311535i	0.80023942-0.3507326i
0.4784887+0.4768612i	0.538812709+0.5639192i	-0.51953655+0.5234872i
0.4784887-0.4768612i	0.538812709-0.5639192i	-0.51953655-0.5234872i
-0.4459424+0.4503182i	-0.542654413+0.5513358i	0.51674900+0.5103516i
-0.4459424-0.4503182i	-0.542654413-0.5513358i	0.51674900-0.5103516i
-0.0521633+0.6114533i	-0.575078810+0.0000000i	-0.35453457+0.4671884i
-0.0521633-0.6114533i	-0.357056098+0.4453962i	-0.35453457-0.4671884i
-0.3713757+0.4493527i	-0.357056098-0.4453962i	-0.17353145+0.5004133i
-0.3713757-0.4493527i	0.049193829+0.5076127i	-0.17353145-0.5004133i
-0.4869492+0i	0.049193829-0.5076127i	-0.46146656+0.0000000i
-0.1609214+0i	-0.253100754+0.0000000i	0.41410544+0.0000000i
0.1199018+0i	0.086166201+0.0000000i	-0.08313769+0.0000000i
-0.001518741+0i	0.004916288+0.0000000i	-0.00339900+0.0000000i

Figure 4: Stability of Total PVARX model

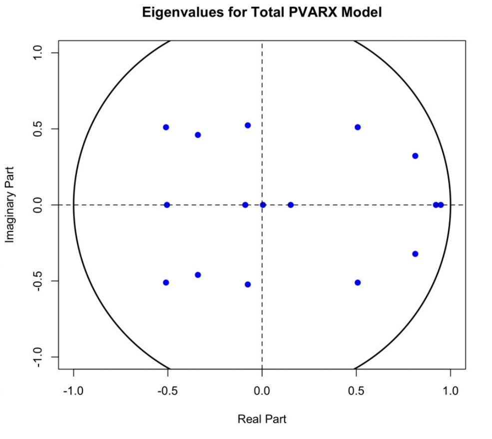

Figure 5: Stability of North, Centre and South PVARX models

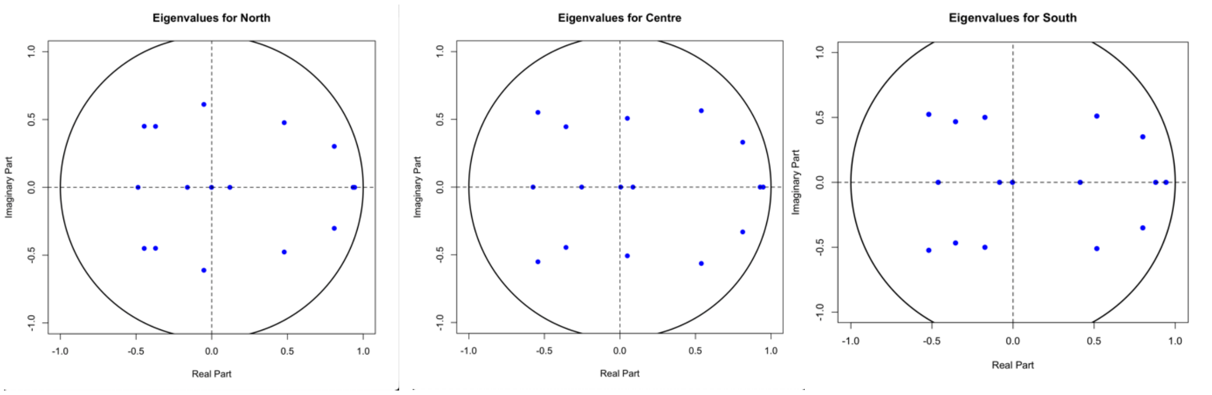

Figure 8: Impulse Responses for North Model

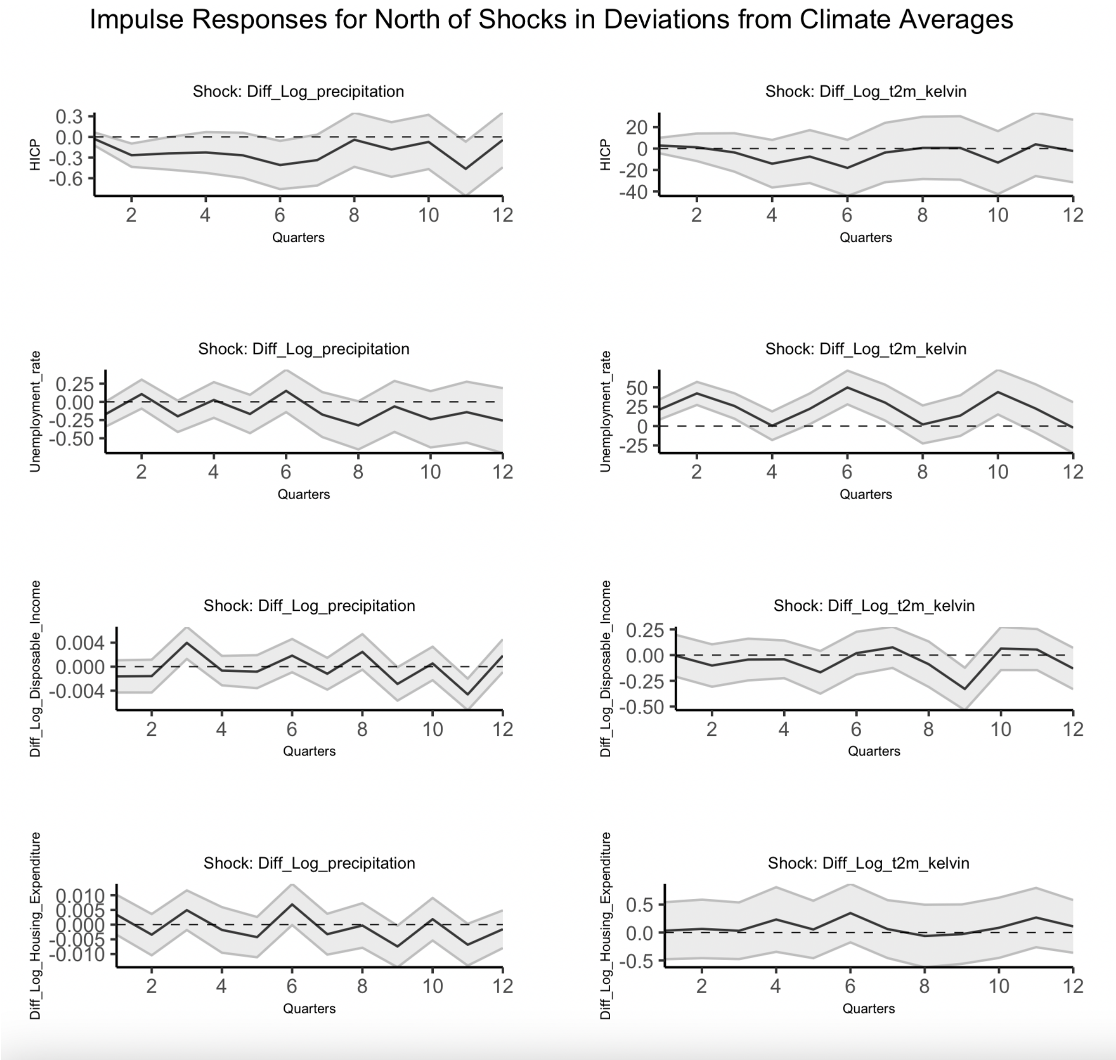

Figure 9: Impulse Responses for Centre Model

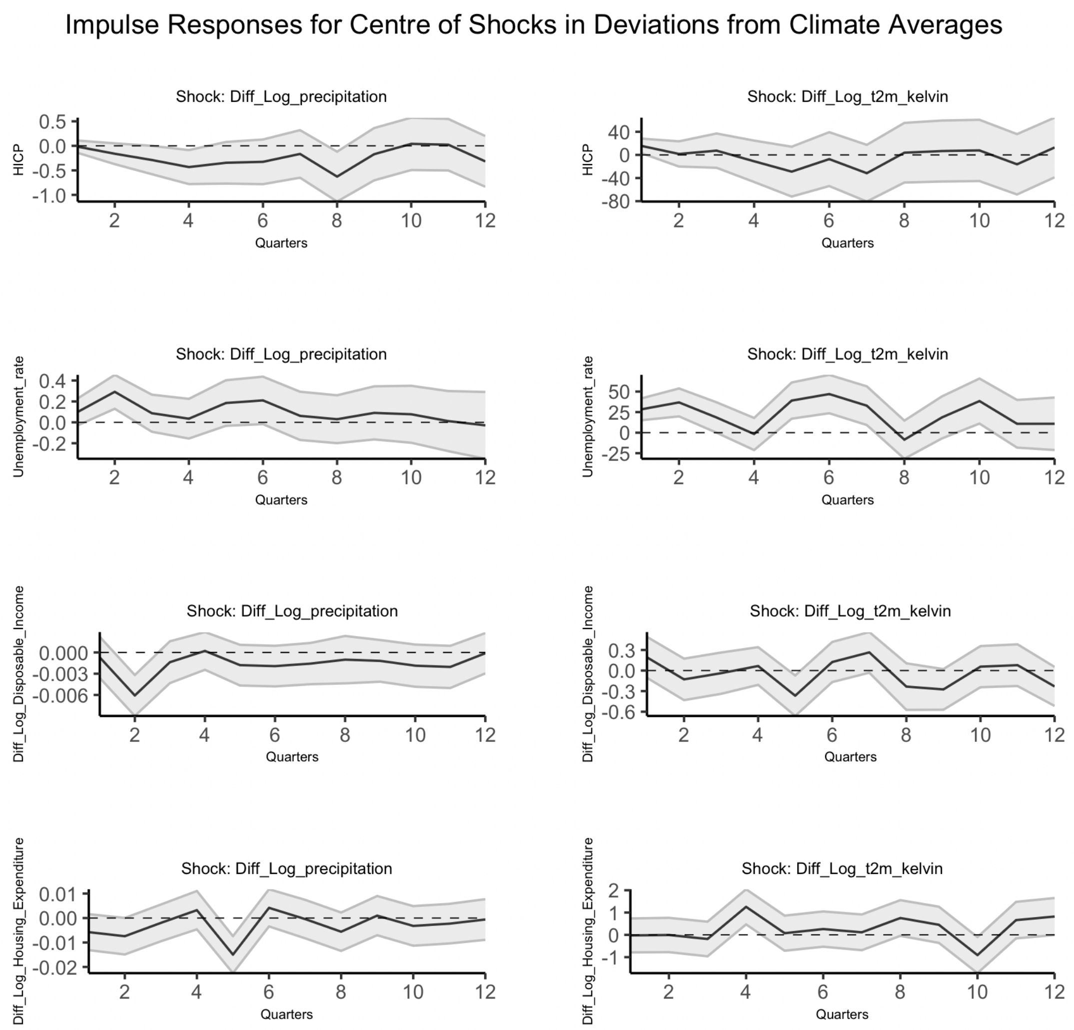

Figure 10: Impulse Responses for South Model