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Dissertation

A LOCAL PROJECTION APPROACH TO THE IMPACT OF CLIMATE SHOCKS: EVIDENCE FROM A PORTUGUESE PANEL OF MUNICIPALITIES

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Carried Out Under the Supervision Of:

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A LOCAL PROJECTION APPROACH TO THE IMPACT OF CLIMATE SHOCKS: EVIDENCE FROM A PORTUGUESE PANEL OF MUNICIPALITIES

By Dhruv Akshay Pandit

Abstract

We investigate the impact of climate shocks on key macroeconomic variables, focusing on a Portuguese panel of municipalities. We combine a local projection approach with big data. Utilizing quarterly data from 2007 to 2021, we analyze how deviations from historical averages, and variability in weather variables - specifically temperature, precipitation, and surface pressure affect inflation, unemployment, disposable income, and housing prices. The results indicate that temperature shocks are associated with transient inflation spikes, whereas precipitation variability leads to more pronounced and immediate economic disruptions. Our findings suggest that localized climate shocks pose substantial challenges to monetary policy, particularly within the constraints of the Eurozone's centralized interest rate policy. The study highlights the necessity for integrating climate-related variables into the ECB's policy framework and adopting regional strategies to mitigate the economic consequences of climate variability. As the first paper of its kind for Southern Europe, this research provides critical insights into the dynamic relationship between climate shocks and economic stability in Portugal, offering a framework for future policy considerations.

Keywords: Panel VAR, Local Projections, Climate Change, Portuguese Municipalities

JEL: C33, C53, E31

Resumo

Esta dissertação investiga o impacto de choques climáticos em variáveis macroeconómicas chave, focando-se num painel de municípios portugueses. Neste trabalho combina-se uma abordagem de projeções locais com big data. Utilizando dados trimestrais de 2007 a 2021, analisa-se como é que desvios das médias históricas e variabilidade nas variáveis meteorológicas - especificamente temperatura, precipitação e pressão à superfície - afetam a inflação, o desemprego, o rendimento disponível e o preço da habitação. Os resultados indicam que os choques de temperatura estão associados a picos transitórios de inflação, enquanto a variabilidade na precipitação leva a perturbações económicas mais pronunciadas e imediatas. As conclusões sugerem que os choques climáticos localizados colocam desafios importantes à política monetária, particularmente dentro das restrições da política de taxa de juro centralizada da Zona Euro. O estudo destaca a necessidade de integrar variáveis relacionadas com o clima no quadro de políticas do BCE e de adotar estratégias regionais para mitigar as consequências económicas da variabilidade climática. Sendo o primeiro estudo deste género para o sul da Europa, esta investigação fornece resultados importantes sobre a relação dinâmica entre choques climáticos e estabilidade económica em Portugal, oferecendo um quadro para futuras considerações políticas.

Palavras-chave: VAR em Painel, Projeções Locais, Alterações Climáticas, Municípios Portugueses

JEL: C33, C53, E31

Declaration of Authorship

I hereby certify that this dissertation has been composed by me and is based on my own work, unless stated otherwise. No other person's work has been used without due acknowledgement in this dissertation. All references and verbatim extracts have been quoted, and all sources of information, including graphs and data sets, have been specifically acknowledged.

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Contents

List of Keywords

By Order of Appearance:

- EU: European Union
- VAR: Vector Autoregressive
- PVAR: Panel Vector Autoregressive
- SAARC: South Asian Association for Regional Cooperation
- VARX: Vector Autoregressive With Exogenous Regressors
- BVAR: Bayesian Vector Autoregressive
- ENSO: El Niño–Southern Oscillation
- SVAR: Structural Vector Autoregressive
- ECB: European Central Bank
- GDP: Gross Domestic Product
- LP: Local Projections
- IRF: Impulse Response Function
- HICP: Harmonised Index of Consumer Prices
- YoY: Year On Year
- ERA5: Global Reanalysis Climate Dataset
- t2m: 2-Metre Temperature
- tp: Total Precipitation
- stl2: Soil Temperature Layer 2
- sp: Surface Pressure

1. Introduction

Climate change, brought on by human activities, has led to significantly adverse impacts on both natural and human systems globally, often exceeding their capacity to adapt (Pörtner et al., 2022). This phenomenon, marked by the increased frequency and intensity of extreme weather events, has manifested in various forms, including unprecedented wildfires, changing precipitation patterns, and escalating sea levels, contributing to a landscape where both ecosystems and human populations face heightened vulnerabilities. Particularly affected are those regions and communities at the intersection of socio-economic development challenges, unsustainable land and ocean use, and systemic inequities, all of which exacerbate the susceptibility to climate-induced adversities (Pörtner et al., 2022).

Europe has not been immune to these developments, as it is now projected to warm faster than the global average (Bednar-Friedl et al., 2022). The continent has witnessed a series of high-cost climate catastrophes, such as the 2017 wildfires that ravaged over a million hectares across the European Union (EU), around half of which was located within Portugal, and the July 2021 floods across Germany, Belgium, and the Netherlands, incurring economic damages amounting to 44 billion euros (European Environment Agency, 2024). These incidents serve to highlight the evolving nature of climate risks to macroeconomic stability, fiscal health, and financial markets within the region. While Europe has, to date, averted a major sovereign financial crisis directly attributed to climate-related events, the increasing economic losses from such extremes pose substantial threats to public finances, the viability of insurance markets, and the broader economy (European Environment Agency, 2024). This situation is further aggravated in Southern Europe, where projections indicate a continuing rise in temperatures, amplifying critical risks such as agricultural production losses, water scarcity, and the inadequacy of current adaptation measures to mitigate these impending challenges (Bednar-Friedl et al., 2022).

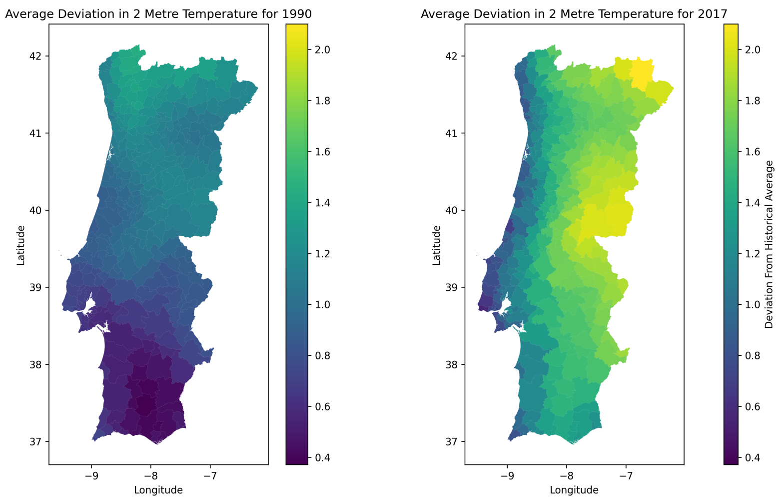
Portugal is situated at the westernmost edge of the Iberian Peninsula, and includes the Atlantic islands of the Azores and Madeira[1]. Its geographic and climatic profile places it in the hot-summer Mediterranean climate zone, known for its susceptibility to climate-induced challenges such as droughts and wildfires (Cerejeira et al., 2023). Despite Portugal's small size, its mainland displays a diverse climate, ranging from subtropical oceanic conditions in the north, marked by wet winters and warm summers, to a more continental climate inland. A distinct climatic gradient also exists from the wetter north to the drier south, and from the cooler, mountainous regions to the warmer

[1]A detailed exploration of Portugal's climate and geography exceeds the scope of this study. Interested readers may refer to Fragoso (2008) and de Lima et al. (2013)

coastal areas, leading to a noted variability in local weather conditions across the country.

Moreover, the temporal standard deviation of the average annual temperature in Portugal is notably higher than the global average (Antunes et al., 2022). Despite this, literature focusing on the impacts of climate change on Portugal's economy is sparse; though existing studies highlight the tangible negative effects. Pintassilgo et al. (2016) predict a reduction in tourist arrivals between 2.5% and 5.2% due to rising temperatures, potentially reducing Portugal's GDP between 0.19% and 0.40%. Cerejeira et al. (2023) document the immediate negative effects of wildfires on local tourism and delayed spillover effects in adjacent areas. Furthermore, Füssel et al. (2017) reported that from 1980 to 2013, Portugal faced economic losses of 6.783 billion EUR due to climate-related hazards. Finally, Vrontisi et al. (2022) investigate the impact of climate change on southern European islands. They find Madeira to be part of the group of islands with higher impacts to the Blue Economy sectors, and Azores to be part of the group with moderate impacts. Interestingly, they observe positive GDP impacts in Azores under the RCP2.6 scenario[2]. The scarcity of existing literature, combined with Portugal's unique climatic challenges, emphasizes the importance of further research into the climate-macroeconomy interface within this specific context.

Figure 1: **Long Term Trend in Deviations from Historical Averages**



Note: The historical baseline considered for the average is from 1940 - 1980. Observe the shifting patterns, from a north-south divide to an east-west divide.

[2]The RCP 2.6 scenario refers to a Representative Concentration Pathway that aims to limit global warming to below 2°C above pre-industrial levels by the end of the century, primarily through significant reductions in greenhouse gas emissions.

The primary objective of this study is to explore the impacts of weather shocks on Portugal's macroeconomy, emphasizing the direct consequences on variables crucial to individuals and households: unemployment rate, disposable income, inflation, and housing price index. Distinguished from the long-term changes commonly associated with climate, short-run weather fluctuations are examined for their immediate economic impacts. We prioritize the analysis of short-term responses to recognize the immediate concern of households facing unexpected weather events, and their effects on employment, spending power, living costs, and housing stability. By centering on these aspects, we seek to address a notable void in the current literature, which often bypasses the immediate economic fallout of weather shocks on such indicators. Accordingly, the research questions we set out to answer are as follows: 1) What is the extent to which weather shocks influence crucial macroeconomic variables within Portugal? 2) What is the role of weather variability in shaping these economic dynamics?

Our study leverages a panel vector autoregressive (PVAR) framework with exogenous regressors (X) to analyze the interactions between weather variations and key macroeconomic indicators within Portugal. We further utilise local projections for the construction of impulse response functions to weather shocks. The study spans from 2007 to 2021, analysed at a quarterly frequency [3]. We consider four weather variables to represent the climate in Portugal, specifically, air temperature, soil temperature, precipitation, and surface pressure. Data for the aforementioned weather variables is sourced from the ERA5 reanalysis dataset via the Copernicus Climate Data Store.

This study contributes to the literature on climate economics, focusing on the effects of weather shocks on the Portuguese economy—a domain where empirical evidence remains sparse. First, by examining the macroeconomic repercussions of weather variability and shocks with an emphasis on Portugal, it fills a gap in the understanding of climate impacts, particularly contributing to the literature on the Southern European economy. Second, our approach diverges from conventional studies by dissecting the heterogeneous weather impacts at a municipal level, employing a panel VAR analysis. Third, it extends the scope of analysis beyond the commonly examined temperature and precipitation variables to include soil temperature, air temperature, and surface pressure, providing a holistic view of the climate's influence on economic indicators. The findings of this study are expected to inform policy formulation, offering insights into the short-term economic adjustments needed by sudden climate-induced changes. It serves as a reference for similar regional studies within Europe, advocating for localized climate impact assessments to tailor policy interventions effectively. Moreover, by highlighting the importance of considering a wide range of

[3] The shorter time period is based on the availability of macroeconomic data at the municipal level, provided by the Instituto Nacional de Estatistica (INE) and Confidencial Imobiliario.

climate variables and their variability, we hope to encourage future studies into understanding the comprehensive impact of weather shocks on the macroeconomy.

This dissertation is structured as follows: Section 2 reviews related literature, focusing on panel VAR models, the economic impacts of temperature and precipitation, and the effect of climate change on inflation. Section 3 outlines the model specification, providing a rationale for the chosen methodology. Section 4 provides a description of the data and explicates the methodology employed. Section 5 presents the empirical results. Section 6 discusses the implications of these findings for policy formulation and adaptation strategies. The dissertation concludes with Section 7, summarizing the key insights and contributions. For further information on the methods, data, and more, a comprehensive appendix is available at the end of the document (see Appendix A).

2. Literature Review

The climate-economy literature has witnessed significant growth over the last decade. Studies in this realm have focused on a range of outcomes, from economic growth to labor productivity; however, the diversity of methods and geographic focus across studies has led to contrasting results, making it challenging to draw broad conclusions. To this extent, readers interested in the development of the field are directed to survey reviews and meta-analyses that synthesize findings across studies; we specifically highlight the seminal works of Dell et al. (2014) and Tol (2009, 2014, 2018, 2024), which offer an overview of the current state of knowledge on the economic impacts of climate and weather variations.

VAR models serve as a key tool in climate econometrics research; as such, various models have been applied across a range of studies. For instance, Uddin and Wadud (2014) utilize a VAR model to probe CO2 emissions' influence on GDP in countries within the South Asian Association for Regional Cooperation (SAARC), paralleling Gallic and Vermandel (2020)'s investigation into New Zealand's economic sensitivity to weather shocks. Skrinjaric (2023) extends this to the Croatian economy, examining extreme weather's inflationary pressures through a VAR model. Ahmadi et al. (2022) employ a Bayesian Structural Global VAR with Exogenous Regressors (BSGVAR-X) model to discern the heterogeneous impacts on global economies, whereas Kim et al. (2022) leverage a nonlinear VAR model to detail the multifaceted effects of severe weather conditions on the US economy over six decades. Romero et al. (2023) utilize a Bayesian VAR-X model to assess El Niño–Southern Oscillation (ENSO) related weather shocks in Colombia, focusing on the agricultural sector and inflation. Lucidi et al. (2024) and Beirne et al. (2021) adopt a Bayesian SVAR model and a SVAR model respectively, to analyze temperature shocks and disaster events' effects on the euro area economies, emphasizing the necessity for the ECB to consider climate shocks. Ciccarelli et al. (2023)'s application of a seasonal dependent BVAR further explores the seasonal impact of temperature shocks on inflation within the euro area, highlighting significant variations across countries and seasons.

In recent years, the adoption of panel VAR (PVAR) models has surged, attributed to their ability to combine the strengths of standard VAR models with panel data techniques, effectively addressing endogeneity issues and facilitating endogenous interactions among model variables (Habib, 2022)[4]. Mukherjee and Ouattara (2021) investigate temperature shocks' influence on inflation in a study spanning 1961–2014, highlighting long-lasting inflationary pressures across developed and

[4]See Canova and Ciccarelli (2013) for an overview of PVAR models used in macroeconomic and financial literature.

developing countries. Alessandri and Mumtaz (2021) examine climate volatility's effects on GDP growth and volatility across 133 countries from 1960 to 2019, identifying the negative consequences of temperature variability. Habib (2022) focuses on North African countries, revealing the dual impact of climate variability on GDP reduction and the stabilizing role of remittances. Aslan et al. (2024) analyze temperature anomalies' impact on EU countries' economic growth and technological indicators, noting a particular increase in patent applications. Huber et al. (2023) use a Bayesian PVAR to assess climate shocks on agricultural markets and macroeconomic indicators in high-income economies, finding significant global reactions. Lastly, Ciccarelli and Marotta (2024) apply a PVAR model to estimate climate change effects on the economy from 1990 to 2019, emphasizing the effectiveness of counteracting climate risks in the medium term.

Furthermore, fixed effects panel regression has been widely employed to analyze the economic impacts of climate variables, with studies by Kalkuhl and Wenz (2020) exploring temperature and precipitation's effects on global economic production, Kotz et al. (2023) on inflation, and Li et al. (2023) on inflation across 26 countries. Additionally, Deryugina and Hsiang (2014) focus on temperature variations and income in the U.S. Complementing these are broader inquiries into temperature and economic growth (Burke et al., 2015; Dell et al., 2009; Diffenbaugh and Burke, 2019), labor productivity (Deryugina and Hsiang, 2014), energy demand (Auffhammer and Schlenker, 2014; Wenz et al., 2017) , and crop yields (Chen et al., 2016; Schlenker and Roberts, 2008), as detailed by Dell et al. (2014) and Kolstad and Moore (2020). This body of work, controlling for time-invariant heterogeneity, sheds light on the economic ramifications of climate change, predicting potentially higher losses than earlier models suggested.

Finally, recent literature employing local projections has provided insights into the impacts of climate and financial shocks on economic variables. Local projections, initially proposed by Jorda (2005), have gained popularity in the past decade as an alternative method to estimate impulse response functions per Adämmer (2019). Natoli (2022) used such an approach to analyze the effect of temperature surprise shocks on the U.S. economy, highlighting changes in consumption, investment, and price variability, and noting central bank responses. **?** explored the short-term effects of financial crises on climate change resilience, showing a decrease in resilience, especially in developing economies

Across numerous studies, the impact of temperature on the economy has been extensively documented, illustrating a complex array of effects across different regions and economic variables. Kalkuhl and Wenz (2020) alongside Dell et al. (2012) , Burke et al. (2015), and Diffenbaugh and Burke (2019), identify significant negative impacts of temperature on global economic production and per-capita GDP, pointing to a persistent sensitivity of economies to temperature changes.

Mukherjee and Ouattara (2021), Kotz et al. (2023, 2021), and Ciccarelli et al. (2023) extend this narrative, revealing how temperature shocks precipitate significant inflationary pressures, affecting both developed and developing nations, and suggest potential complications for maintaining inflation and price stability over prolonged periods. Gallup et al. (1999) and Nordhaus (2006) point to a significant reduction in economic growth in developing countries, further affirmed by Burke et al. (2015); meanwhile, Jones and Olken (2010) and Lucidi et al. (2024) suggest that temperature shocks affect exports and electricity prices differently across economies. Temperature's economic impacts are increasingly highlighted through the variability effects on GDP growth and volatility, as shown by Alessandri and Mumtaz (2021) and the implications on sector-specific outputs like agriculture, as indicated by Natoli (2022). This relationship between temperature and economic outcomes further extends to consumption, investment, and labor productivity, with research indicating that average summer temperature increases could significantly decelerate U.S. economic growth (Colacito et al., 2019). Thus, the extant literature on the nexus between temperature and economic outcomes collectively illustrates that both developed and developing countries face substantial economic risks from temperature fluctuations, with potential long-term macroeconomic effects that could slow investment, impact labor productivity, and influence consumption growth.

While the impact of temperature on the economy has been extensively studied, the effects of precipitation on economic outcomes, although significant, have received less attention. Investigations by Kalkuhl and Wenz (2020) and Kotz et al. (2022) into the relationship between precipitation and global economic production reveal the sensitivity of economies to rainfall variations, alongside temperature changes. Kotz et al. (2022) highlight that increased wet days and extreme rainfall events lead to declines in economic growth rates, affecting high-income nations and sectors such as services and manufacturing notably. Habib (2022) further explore climate volatility's impact, including precipitation, on GDP growth and stability, emphasizing that fluctuations in rainfall contribute to unpredictable climate conditions, thereby reducing GDP growth and increasing GDP volatility.

Further studies have extended the focus beyond temperature and precipitation to explore how a variety of climate variables influence economic performance. The comprehensive analyses by Dell et al. (2009, 2014) and Burke et al. (2015) illustrate the relationship between different weather outcomes—including temperature variability and extreme weather events—and economic indicators like productivity, output, and growth, uncovering the non-linear impacts of climate variables on macroeconomic production. They forecast considerable welfare losses due to anticipated climate changes. Skrinjaric (2023) investigates extreme weather effects on Croatia's economy, identifying significant inflationary pressures from droughts. Furthermore, evidence from Dell et al. (2012), Kalkuhl and Wenz (2020), and Pörtner et al. (2022) highlight the disproportionately severe economic impacts on low-income countries and the poorest global regions. Dasgupta et al. (2021) contribute to this narrative by demonstrating climate change's adverse effects on labor productivity in tropical countries.

The literature investigating the relationship between climate variability and inflation remains limited, with only a select few studies addressing the direct impact of climate-related variables and natural disasters on inflation. Heinen et al. (2019) and Parker (2018) identify that floods, hurricanes, and other natural disasters can lead to inflation, with impacts varying based on disaster type and inflation measure composition. Similarly, case studies by Laframboise and Loko (2012) and Abe et al. (2014) provide mixed evidence, suggesting that while some countries experience an increase in inflation following disasters, others, like Japan after the 2011 earthquake, see minimal inflationary effects. More recent analyses, such as those by Faccia et al. (2021), Mukherjee and Ouattara (2021), and Ciccarelli et al. (2023), expand on these findings by examining the effects of temperature changes and variability, revealing the varied impact of temperature on inflation, with more pronounced effects in warmer regions during summer months and instances of increased temperature variability contributing to inflation rises.

3. Panel VARX

3.1. Model Description

We employ a panel vector autoregressive (PVAR) framework with exogenous regressors (X) to model the interactions between the weather and key macroeconomic variables for Portugal, an extension of VAR models, which have become a foundational methodology in empirical macroeconomic analysis since the pioneering work of Sims (1980). Our model includes weather variables as exogenous factors, enabling us to treat shocks to these variables as external to the model and isolate their impacts on macroeconomic outcomes. This strategy aligns with the practices in contemporary research, acknowledging the long-run, slow-moving nature of anthropogenic climate effects compared to the short- to medium-term horizons relevant to our study (Alessandri and Mumtaz, 2021; Ciccarelli and Marotta, 2024; Kim et al., 2022).

In our analysis we estimate a panel VARX with fixed effects using the R package `panelvar` (Sigmund and Ferstl, 2021)[5], i.e,

[5] See Appendix A.

$$\boldsymbol{y_{i,t}} = \boldsymbol{\mu_i} + \sum_{l=1}^{p=4} A_l \boldsymbol{y_{i,t-l}} + B\boldsymbol{w_{i,t}} + \sum_{j=1}^{q=4} C_j \boldsymbol{w_{i,t-j}} + \boldsymbol{\epsilon_{i,t}} \tag{1}$$

where $\boldsymbol{y_{i,t}}$ is an $m \times 1$ vector of endogenous variables for the ith cross-sectional unit (municipality) at time t, and $\boldsymbol{\mu_i}$ is a vector that captures time invariant fixed effects. We let $\boldsymbol{y_{i,t-l}}$ be an $m \times 1$ vector of lagged endogenous variables, and A_l the $m \times m$ companion matrices for the coefficients corresponding to the vector of lagged endogenous variables $\boldsymbol{y_{i,t-l}}$. $\boldsymbol{w_{i,t}}$ is an $n \times 1$ vector of n strictly exogenous variables that are independent of $\boldsymbol{\epsilon_{i,t}}$ and $\boldsymbol{\epsilon_{i,t-s}}$ for $s = 1, \ldots, T$. $\boldsymbol{w_{i,t-j}}$ is a $n \times 1$ vector of lagged exogenous variables, and B and C_j the $m \times n$ companion matrices for the coefficients associated with the weather variables.

Furthermore, we assume that the error terms $\boldsymbol{\epsilon_{i,t}}$ are independently and identically distributed (i.i.d.) for all i and t with $E[\boldsymbol{\epsilon_{i,t}}] = 0$ and $Var[\boldsymbol{\epsilon_{i,t}}] = \Sigma_\epsilon$, where Σ_ϵ is a positive semidefinite matrix. The cross sectional units i and the time section t for our model are defined as follows: $i = 1, 2, ..., 278$ (island municipalities are excluded), and $t = 1, 2, ..., 60$ (15 years of quarterly data). The associated subscripts are accordingly: $m = 4$, $n = 12$, and $p = q = 4$, and we assume that the parameters A_l $(m \times m)$, B $(m \times n)$, and C_j $(m \times n)$ are homogeneous across all i. The vector of variables are defined as follows:

$$\begin{aligned}
\boldsymbol{y_{i,t}} &= \left[\text{hicp_yoy_pct}_{i,t}, \text{ur_L1}_{i,t}, \text{disp_inc_conc_l_L1}_{i,t}, \text{hpi_l_L1}_{i,t}\right]^\intercal, \\
\boldsymbol{w_{i,t}} &= \left[w_{i,t}^{\text{t2m_hd}}, w_{i,t}^{\text{tp_hd}}, w_{i,t}^{\text{t2m_std}}, w_{i,t}^{\text{tp_std}}, w_{i,t}^{\text{sp_hd}}, w_{i,t}^{\text{sp_std}}, w_{i,t}^{\text{stl2_hd}}, w_{i,t}^{\text{stl2_std}}, w_{i,t}^{\text{tp_hd}^2}, w_{i,t}^{\text{tp_hd}^3}, w_{i,t}^{\text{t2m_hd}^2}, w_{i,t}^{\text{t2m_hd}^3}\right]^\intercal.
\end{aligned} \tag{2}$$

In our PVARX model, we specify the ordering of the variables based on their assumed exogeneity and potential to influence each other within the same quarter. By positioning *hicp_yoy_pct* first, we assume that inflation rates are the most exogenous variable, impacting all subsequent variables — the unemployment rate (*ur_L1*), household disposable income (*disp_inc_conc_l_L1*), and house price index (*hpi_l_L1*) — without being contemporaneously affected by them. As such, fluctuations in inflation could drive changes in the labor market, income levels, and housing markets, with each subsequent variable influenced by those preceding it but not exerting instantaneous influence in return.

The decision to focus on subnational, high-resolution data for Portugal is driven by the recognition that national averages of climate variables can obscure significant regional variations and localized impacts of climate change (Rodrigues et al., 2024). Analyzing data at a more granular level enhances statistical power, and mitigates the dilution of climate and economic signals that often accompanies spatial aggregation (Burke and Tanutama, 2019; Harari and Ferrara, 2018; Huber et al., 2023). This approach not only offers more nuanced insights into the aggregate effects of extreme events but also supports the development of tailored adaptation policies informed by local conditions and vulnerabilities (Skrinjaric, 2023; Vrontisi et al., 2022). The PVARX framework is particularly suited to our analysis due to its ability to integrate the benefits of VAR models with the strengths of panel data techniques. It allows for the control of unobserved heterogeneity across units, and the examination of dynamic responses via impulse response functions and variance decomposition, thereby enhancing the inference of causality in our findings (Habib, 2022). Furthermore, the use of subnational data enables the inclusion of region-specific fixed effects, which helps to avoid omitted variable bias—a common limitation in cross-sectional analyses of the climate-economy relationship[6]. This methodology distinguishes between the short-term shocks and long-term changes in climate conditions, acknowledging that while societies may adapt to long-term trends, short-term shocks and extreme events present distinct challenges (Kalkuhl and Wenz, 2020; Kotz et al., 2021).

3.2. Local Projections of Weather Shocks

We explore the impact of weather shocks on Portuguese macroeconomic variables through the use of local projections (LP) to estimate the impulse response functions of macroeconomic variables under consideration. Local projections eschew the extrapolation of parameters across distant horizons in favor of sequentially estimating parameters at each desired point. This methodology boasts several advantages over the structural vector autoregressive (SVAR) approach. Firstly, LPs are simpler to estimate, relying on straightforward linear regressions. Secondly, they facilitate easier pointwise or joint inference. Thirdly, impulse responses derived from LPs tend to be more robust against misspecifications in (linear) VAR models (Adämmer, 2019; Jorda, 2005). Further, Plagborg-Møller and Wolf (2021) demonstrated that when lag structures are unrestricted, LPs and VAR models yield identical impulse responses, suggesting that empirical impulse responses from LPs and SVARs align closely at short horizons but may diverge at longer ones. This versatility extends to panel data analysis, allowing for nuanced examination of the effects of weather shocks on economic outcomes. We implement this framework using the R package lpirfs `adammer2019lpirfs`, constructing linear impulse responses for each endogenous variable to explore the effects of specified weather variable shocks. The impulse response functions (IRFs) are developed using the entirety of the sample set, with each IRF setup individually, focusing on the cumulative multipliers to assess the overall impact [7]. We adopt a fixed effects approach, to maintain fidelity to our panel VARX estimation. To construct our IRF plots, we estimate a regression model for each response variable $y^r_{i,t}$ in $\boldsymbol{y_{i,t}}$, similar to Jorda et al. (2015), where the general equation used for each regression is defined as

[6] We assumes that the regional characteristics controlled for by fixed effects are time invariant. If this assumption is violated, the model may not fully account for all variations, potentially leaving residual biases unaddressed.

[7] Cumulative responses are estimated through $y_{t+h} - y_{t-1}$ where $h = 0, ..., H - 1$.

follows:

$$y^r_{i,t+h} = \alpha^h_i + w^k_{i,t}\beta^h + X_{i,t}\Gamma^h + \sum_{l=1}^{q=4} S_{i,t-l}\Phi^h_l + \epsilon_{i,t+h}; h = 0, 1, ..., H - 1 \tag{3}$$

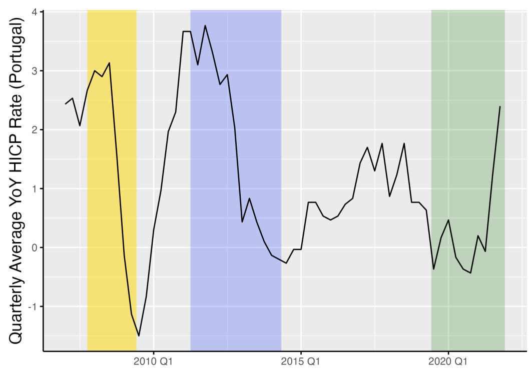
where $y^r_{i,t+h}$ is the rth target of interest, the subscript i denotes the municipality, and α^h_i denotes the (cross-sectional) fixed effect for each municipality within our panel. Let $w^k_{i,t}$ denote the weather variable representing the identified shock from the vector of weather variables $\boldsymbol{w_{i,t}}$ we are interested in. Then $X_{i,t}$ is a vector that includes all the variables in our system (contemporaneous and predetermined), both response and weather, observed at time t for municipality i except for the rth target of interest (y^r) and the weather variable w^k. Furthermore, the vector $S_{i,t-l}$ contains the lags of all the elements in $X_{i,t}$ as well as the lags of the rth target of interest (y^r) and the weather variable w^k. The model incorporates four lags of the regressors; confidence intervals are set at 95%, analyzed over 12 horizons—equating to three years of quarterly data. The endogenous variables are expressed in the same manner as they are in the panel VARX model.

4. Data

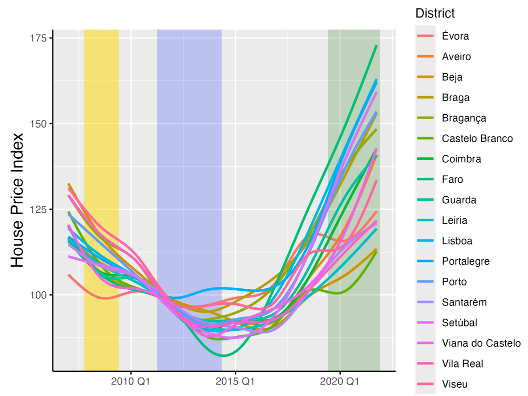
4.1. Economic Data

For our analysis, we utilize quarterly data spanning from 2007Q1 to 2021Q4, covering 278 municipalities (*concelhos*) in mainland Portugal, excluding the island regions of Azores and Madeira. This balanced panel features a block of four endogenous macroeconomic variables in vector $\boldsymbol{y_{i,t}}$: Year-on-Year (YoY) inflation rate represented by the harmonized index of consumer prices (*hicp*) (*hicp_yoy_pct*), house price index (*hpi*), disposable income of households (*disp_inc_conc*), and the unemployment rate (*ur*) (see Figure 2). The house price index, disposable income, and unemployment rate are available at the subnational level for each municipality. For the *hicp*, we employ national-level data for all municipalities, under the assumption of uniform economic conditions across regions. Following Fomby et al. (2013), we apply a log transformation to the *hpi* and *disp_inc_conc*.

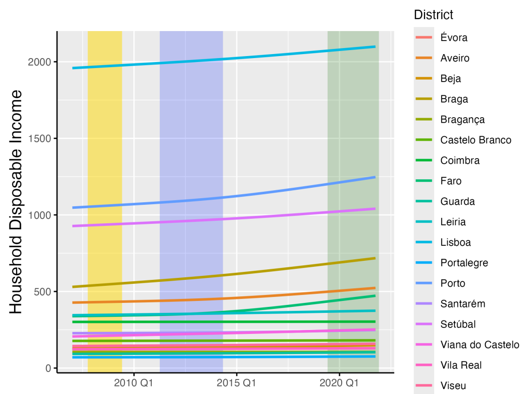
Figure 2: **Plots of Macroeconomic Variables Considered**



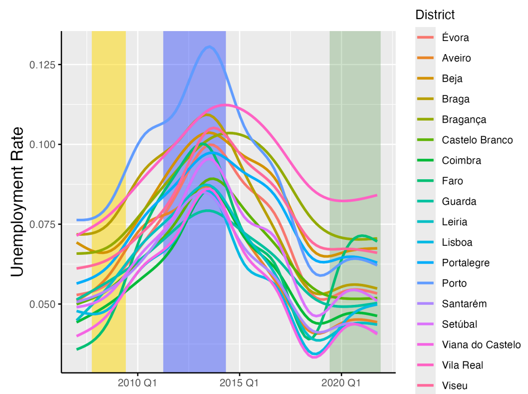
(a) **hicp_yoy_pct**



(b) **hpi**



(c) **disp_inc_conc**



(d) **ur**

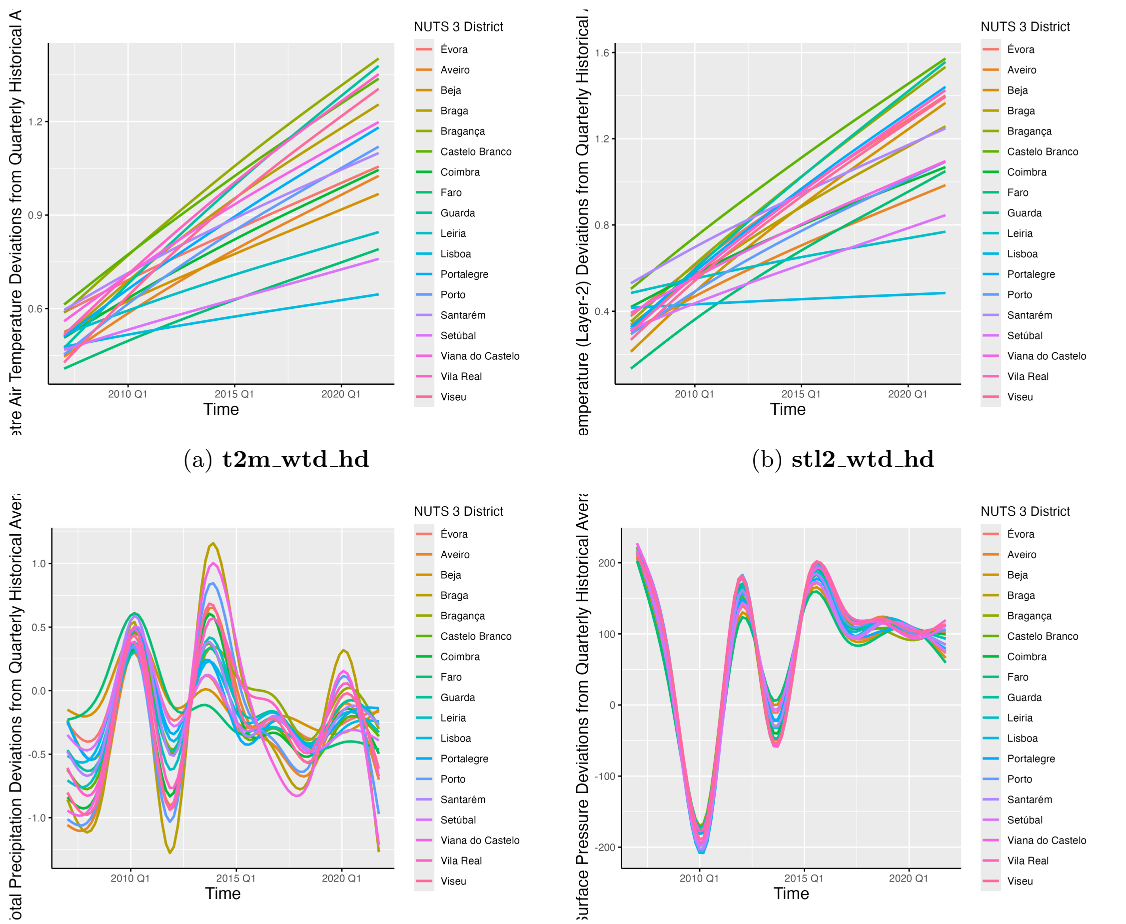
Note: We display the smoothed conditional means for all variables except for the **hicp_yoy_pct** to enable a more parsimonious representation of the trends present in the series. The highlighted regions correspond to the following events: Great Recession (*yellow*), Sovereign Debt Crisis (*blue*) and the Real Estate Boom (*green*).

4.2. Climate Data

Climate data is sourced from the ERA5 reanalysis, detailed by Hersbach et al. (2018, 2020), which integrates model simulations with globally observed meteorological data into a singular dataset, made available through the Copernicus Climate Change Service. This reanalysis data combines information from various sources, such as ground stations and satellites with a climate model, estimating weather variables across a detailed grid structure. It is provided at a high spatial and temporal resolution, specifcally 0.25° × 0.25° grid intervals on an hourly basis, extending back to the mid-20th century. To accurately aggregate climate data at the municipal level across

Portugal, we employ a spatial aggregation method that calculates the area-weighted mean of the ERA5 reanalysis grid cells overlapping, at least partially, with municipal boundaries. This process, adhering to the methodology outlined by Kotz et al. (2021), involves using an algorithm to estimate the proportion of each grid cell within the administrative boundaries, as obtained from the *Agência para a Modernização Administrativa*, which enables a precise depiction of the climate experienced by each municipality, facilitating a more accurate assessment of weather impacts on the local economy (see Appendix A for more details).

Figure 3: **Deviations of Weather Variables from Historical Averages, Aggregated at a District Level**



(a) **t2m_wtd_hd**

(b) **stl2_wtd_hd**

(c) **tp_1000_wtd_hd**

(d) **sp_wtd_hd**

Note: We display the smoothed conditional means for all variables to enable a more parsimonious representation of the trends present in the series. Note the distinct rise in deviations for the air and soil temperatures across all districts, representing a broader pattern of global warming.

Our study focuses on four primary climate variables: 2-metre temperature (*t2m*), total precipitation (*tp*), surface pressure (*sp*), and soil temperature at level 2 (*stl2*)(see Figure 3). This selection is guided by the necessity to examine the multifaceted impacts of climate change, as highlighted by Auffhammer et al. (2013). We transform the total precipiation by multiplying it by a factor of 1000 to convert it from (m) to $(mmday^{-1})$[8]. We also transform the surface pressure by multiplying it by a factor of 100 to convert it from Pa to hPa[9]. Our analysis incorporates both changes in weather means and weather volatility as exogenous variables ($\boldsymbol{w_{i,t}}$), addressing the literature's emphasis on temperature changes and the economic implications of weather extremes. Following Moberg et al. (2000), day-to-day variability for each weather variable is captured through the intra-monthly standard deviation of daily values, averaged quarterly for similar periodicity as the macroeconomic data as implemented by Kotz et al. (2021)[10]. Furthermore, to account for the presence of non-linear dependencies, we include the squared and cubed transformations of the historical deviations for the 2-metre temperature (*t2m_2_wtd_hd, t2m_3_wtd_hd*), and total precipitation (*tp_2_wtd_hd, tp_3_wtd_hd*) as exogenous regressors.

5. Results

5.1. Unit Root

We begin with presenting the unit root test results to assess the stationarity of our balanced panel dataset, addressing the necessity for unit root tests that account for cross-dependence among panel units. Given the plausible influence of common factors on *ur*, *hicp_yoy_pct*, *hpi*, and *disp_inc_conc* across different regions, we employ the tests outlined in Demetrescu et al. (2006) and Costantini and Lupi (2013) [11]. These tests are specifically chosen to mitigate the risk of over-rejection by the Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS) tests due to cross-section dependence (Kleiber and Lupi, 2011). We further we incorporate the Simes test for multiple hypothesis testing at three significance levels, following the approach suggested by Hanck (2013) based on Simes (1986) method. This test is particularly apt for our dataset as it remains robust under conditions of positive dependency among test statistics, effectively testing the unit root null hypothesis across the panel (Kleiber and Lupi, 2011).

The results indicate that *hicp_yoy_pct* is stationary at significance levels of 0.01, 0.05, and 0.10. The *ur* displays non-stationarity in its series but is stationarity once differenced, across all tested

[8] We refer to the ERA5 data documentation herein: "*Most hydrological parameters are in units of 'm of water per day', so these should be multiplied by 1000 to convert to kgm^{-2} day^{-1} or mmday^{-1}*"

[9] We refer to the ERA5 data documentation herein: "*The units of this parameter are Pascals (Pa). Surface pressure is often measured in hPa and sometimes is presented in the old units of millibars, mb (1 hPa = 1 mb= 100 Pa).*"

[10] See Appendix A for a detailed overview.

[11] See Appendix A for further details.

significance levels. The log of *hpi* (*hpi_l*) is non-stationary, but is stationary upon differencing. Similarly, the log of *disp_inc_conc* (*disp_inc_conc_l*) is non-stationary, but is stationary once it undergoes differencing at all levels of significance. These findings inform our subsequent analysis, leading to the inclusion of *hicp_yoy_pct* in the panel VARX in an untransformed form, with the remaining variables entering after appropriate transformations (see Table III).

Additionally, we examine the stability properties of our panel VARX. Lütkepohl (2005) and Hamilton (1994) have demonstrated that a VAR is stable if the eigenvalues of the VAR reside within the unit circle, implying moduli strictly less than one. As shown in Figure 4, all the eigenvalues are indeed located within the unit circle, thus fulfilling the stability condition. This allows us to proceed with the presentation of the model estimation results.

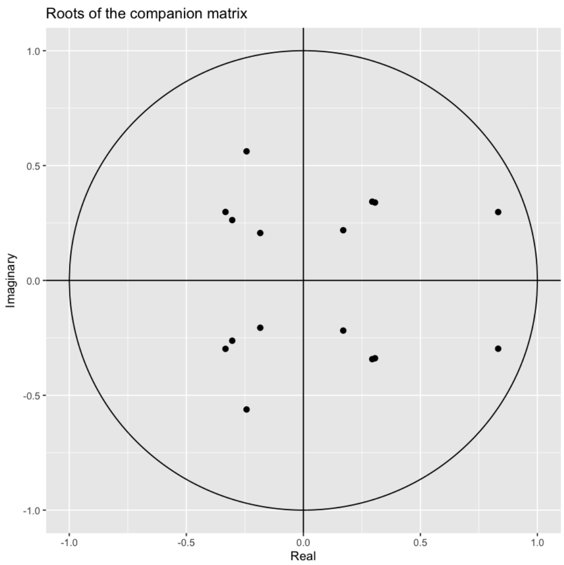


Figure 4: **Stability of PVARX model**

5.2. PVARX Results

The complete results from the PVARX fixed effects estimation are outlined in Table IV. The variables placed in the first row horizontally are considered as the dependant variables, while the regressors can be found in the first column vertically. The coefficients corresponding to each regressor can be found in the rows of the table, with the standard errors provided in brackets, and the associated significance indicated by the asterisk(s). We begin with presenting the results related to the year-on-year inflation rate, covering the contemporaneous effects of weather variables first, and following with the lagged effects. Temperature, both air (*t2m*) and soil (*stl2*), alongside total precipitation (*tp*), emerge as significant drivers of inflation. Specifically, a one degree increase in the deviation from the historical average for the 2-metre temperature leads to a **0.1014** percentage point increase in the year-on-year inflation observed, while a one standard deviation increase in the variability of the soil temperature corresponds to a **0.5042** percentage point increase in the inflation rate (with a p-value of < 0.001). Deviations from the historical average for the 2-metre temperature further exhibit a non-linear relationship with inflation, with the squared term decreasing inflation (**-0.0342**) and the cubed term increasing it (**0.0018**). However, the largest effects are observed for the total precipitation; a one standard deviation increase in the variability of precipitation results in a **2.6049** percentage point increase in the inflation rate. Thus, changes in rainfall patterns lead to immediate inflationary pressure. This contrasts with the results that indicate increases in deviations for the historical average for precipitation coincide with a decrease in the year-on-year inflation. The results further demonstrate a [statistically] significant non-linear relationship associated with precipitation and inflation. Finally, surface pressure displays an impact of **0.0003** for deviations from historical averages, and a nil coefficient for variability, suggesting a limited role in driving inflationary outcomes in Portugal.

Lagged effects further articulate the temporal dimension of weather impacts. Deviations from the historical average for the 2-metre temperature persistently affect inflation up to the fourth lag, with a peak increase observed at the second lag (**0.1910**). Soil temperature's lagged variability, particularly at the first (**0.6309**) and third lags (**0.8038**), also amplify inflation, possibly indicating a delayed response to temperature shifts. Conversely, the lagged variability in the 2-metre temperature appears to decrease inflation at the first (**-0.4661**) and the fourth lags (**-0.1744**); additionally, changes in the lagged deviations for the soil temperature minimally decrease the inflation rate until the fourth lag. The effect that variability in precipitation has on inflation is corroborated by the lagged analysis, wherein an increase in variability at the second lag increases inflation by **1.0535** percentage points, whereas the fourth lag reverses this trend, reducing inflation by **-1.4899** percentage points. Interestingly, while the weather variables highlighted above are [statistically] significant in influencing inflation, their impact on the unemployment rate, disposable income, and housing price index is less pronounced. None of the climate variables considered appear to impact the unemployment rate, suggesting that the channels of impact are more complex than the model investigated herein depicts. Temperature further exhibits a varied relationship with disposable income, an increase in the variability of the 2-metre temperature and the soil temperature at the first lag corresponds to a **0.86%** increase and a **1.92%** decrease accordingly, while minimal increases are observed with the lagged squared terms of precipitation deviations. Finally, no [significant] impacts are observed on the housing price index for Portugal from changes in the climate variables examined herein.

The findings of this section align with prior research, namely Burke et al. (2015), Kotz et al.

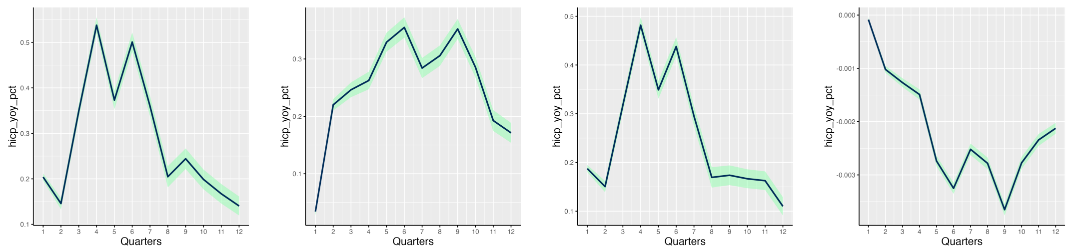
(2023), and Li et al. (2023), which document a nonlinear relationship between temperature and inflation. Similarly, the observed inflationary pressures linked to temperature variability corroborate with the findings of Mukherjee and Ouattara (2021) and Ciccarelli et al. (2023). Furthermore, we extend the work of Kotz et al. (2022) on the effects of rainfall on economic output, to cover inflation, as well as put forth evidence to support a non-linear relationship between precipitation and inflation.

5.3. Impulse Response Analysis

In this section, we present results for the impulse response functions generated from the local projections, beginning with shocks in the deviations from the historical averages for each weather variable considered, followed by the shocks in the variability of each weather variable. Impulse response functions from one standard deviation shock are highlighted, where each period represents one quarter of the year, and are displayed with the associated 95% confidence bands. Before proceeding with the results, it is crucial to elucidate the distinction between the two types of shocks analyzed and their implications, not just for the climate but for the economy as well. A shock in the deviation from historical averages occurs when the observed value of a weather variable significantly strays from its long-term historical norm. This type of shock signifies an anomalous weather event relative to what has historically been expected, such as an unusually hot summer compared to the average conditions over several decades. This directly impacts economic sectors such as agriculture, energy, and consumer behaviors by altering the conditions they typically operate under, and reflect the economy's short-term capacity to adapt to sudden and unexpected changes in weather patterns. On the other hand, a shock in the variability of weather variables indicates a change in the range of fluctuations around the average weather conditions. This includes more frequent or intense swings between extremes, such as periods of drought followed by heavy rainfall. Unlike the immediate impact of deviations from historical averages, shocks in variability represent a broader systemic challenge, highlighting the increased uncertainty that climate volatility introduces into economic planning and decision-making processes.

5.3.1. Shocks in the Deviations From Historical Averages

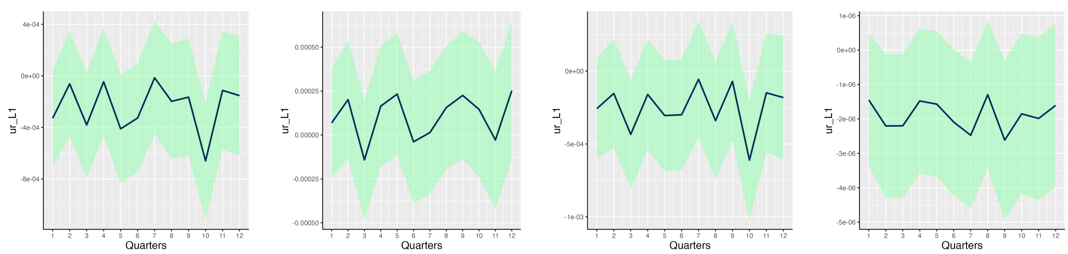
For 2-metre temperatures, a shock in the deviations (*t2m_wtd_hd*) corresponds to initial increases in the YoY-inflation, peaking at a **0.5377** percentage point increase in the fourth quarter before gradually decreasing to **0.1404** percentage points by the twelfth quarter (see Figure 5). Similarly, shocks in the deviations for total precipitation (*tp_1000_wtd_hd*) show an increasing impact on inflation, starting with a **0.0341** percentage point increase in the first quarter and peaking at a **0.3549** percentage point increase by the sixth quarter, with effects stabilizing in the following quarters. Shocks in soil temperature deviations (*stl2_wtd_hd*) demonstrate a response mirroring the pattern observed with 2-metre temperature deviations, indicating a pronounced but transient effect on inflation. A **0.4817** percentage point increase is observed by the fourth quarter, with a decline starting in the seventh quarter and slowing down at the end of the three year period observed. In contrast, shocks in the surface pressure (*sp_wtd_hd*) exhibit a consistent, minimal negative impact on inflation across all quarters.



(a) **t2m_wtd_hd** (b) **tp_1000_wtd_hd** (c) **stl2_wtd_hd** (d) **sp_wtd_hd**

Figure 5: **Impulse Responses For Shocks in Deviations From Historical Averages - YoY HICP**

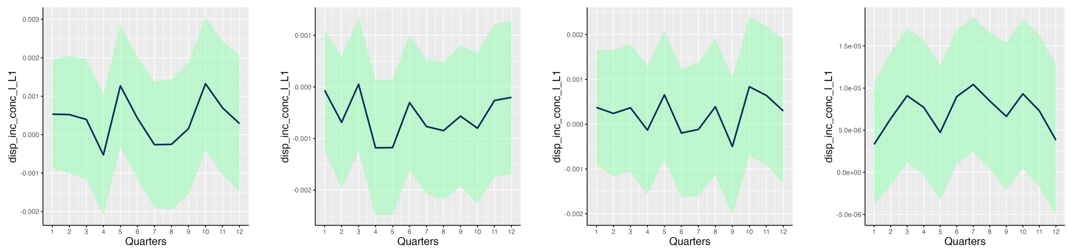
Examining the responses of the unemployment rate, shocks in the 2-metre temperature generally exhibit a slight but consistently negative impact on the unemployment rate (see Figure 6). Shocks in the total precipitation display variable impacts over quarters, with an increase in the twelfth quarter. Soil temperature deviations follow a similar trend to air temperature, with a substantial negative effect on the unemployment rate in the tenth quarter. Finally, surface pressure deviations have a minimal and mostly negative influence across all periods. Notably, we observe a wider confidence band on the impulse responses projected across all variables for the unemployment rate.



(a) **t2m_wtd_hd** (b) **tp_1000_wtd_hd** (c) **stl2_wtd_hd** (d) **sp_wtd_hd**

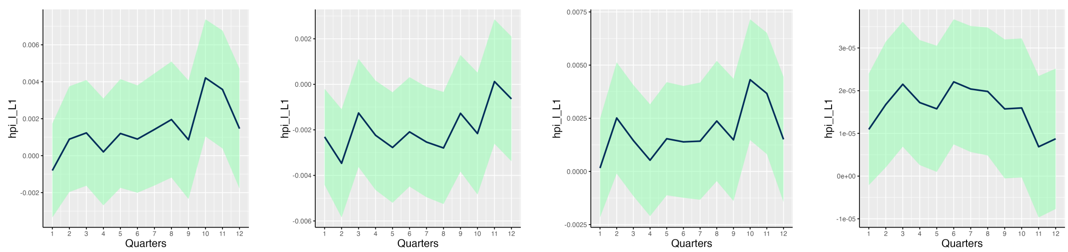
Figure 6: **Impulse Responses For Shocks in Deviations From Historical Averages - UR**

Shocks in the 2-metre air temperature lead to a notable fluctuation in disposable income concentration, with a peak increase of **0.13**% by the tenth quarter (see Figure 7). Conversely, shocks in total precipitation from historical averages precipitate a decrease in disposable income concentration, with a maximum downturn of **0.12**% by the fifth quarter. For the house price index, a shock in the 2-metre air temperature from its historical average induces a peak increase of **0.42**% by the tenth quarter, while a similar shock in the total precipitation results in a peak reduction of **0.35**% by the second quarter (see Figure 8). Additionally, a one standard deviation increase in the soil temperature manifests in a peak increase of **0.43**% by the tenth quarter. Surface pressure deviations continue to exert a minimal impact, indicating the predominant role of temperature and precipitation variables in shaping economic outcomes related to disposable income and house prices, although this effect is far less significant than observed in the impacts to the YoY inflation.



(a) **t2m_wtd_hd** (b) **tp_1000_wtd_hd** (c) **stl2_wtd_hd** (d) **sp_wtd_hd**

Figure 7: **Impulse Responses For Shocks in Deviations From Historical Averages - Disposable Income**

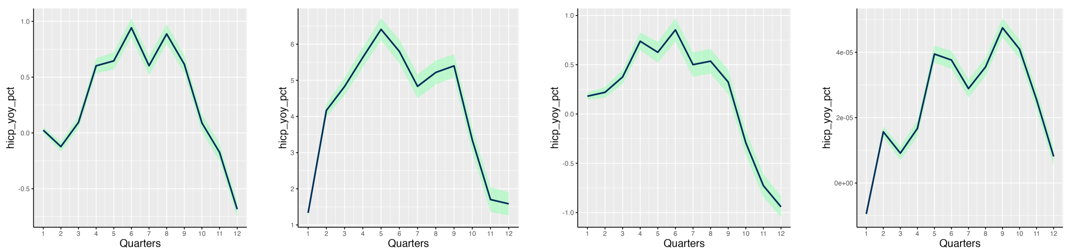


(a) **t2m_wtd_hd** (b) **tp_1000_wtd_hd** (c) **stl2_wtd_hd** (d) **sp_wtd_hd**

Figure 8: **Impulse Responses For Shocks in Deviations From Historical Averages - HPI**

5.3.2. Shocks in the Variability Of Weather Values

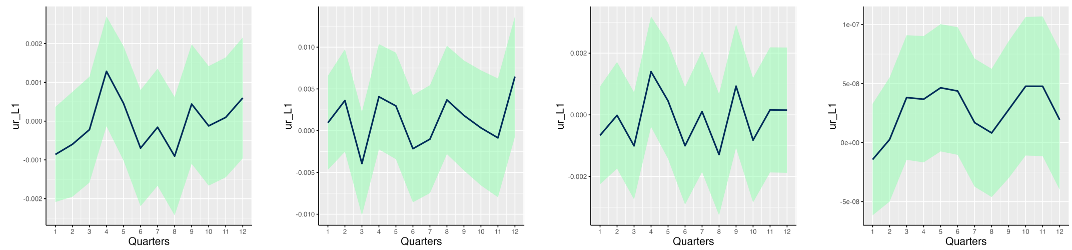
Shocks in the variability reveal distinctly different effects to those observed from shocks in the deviations from historical averages (see Figure 9). For a shock in the 2-meter temperature variability (*t2m_wtd_std*), an initial positive impact on inflation is observed, with a peak increase of **0.6015** percentage points in the fourth quarter, before witnessing a reversal to a negative impact, culminating at **-0.6837** percentage points by the twelfth quarter. The response displayed demonstrate a more pronounced and immediate effect compared to the gradual and less volatile response observed with historical deviations, suggesting that the variability in temperature, reflecting sudden changes within a quarter, exerts a more direct influence on inflation, potentially due to the immediate adjustments required in consumption and production patterns. Similarly, the variability in total precipitation (*tp_1000__wtd_std*) exerts an escalating effect on inflation, starting from an increase of **1.3337** percentage points in the first quarter and peaking at **6.4097** percentage points in the fifth quarter, before slightly receding. Such an impact of precipitation variability on inflation is markedly stronger and more sustained than that of historical deviations, possibly due to the heightened costs of adaptation to extreme weather conditions such as floods or droughts, affecting both supply chains and consumer prices more acutely than longer-term historical trends.



(a) **t2m_wtd_std** (b) **tp_1000_wtd_std** (c) **stl2_wtd_std** (d) **sp_wtd_std**

Figure 9: **Impulse Responses For Shocks in Variability- YoY HICP**

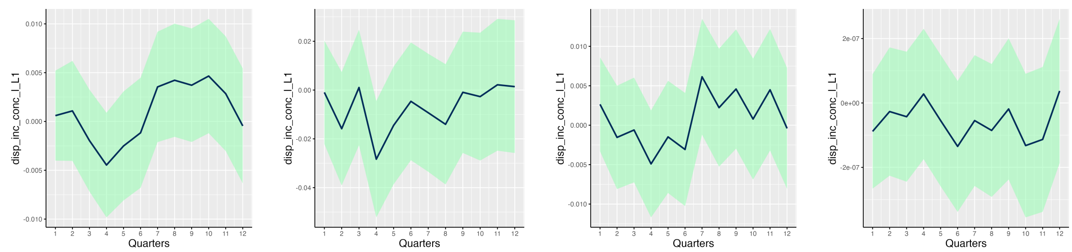
A shock in the variability of soil temperature (*stl2_wtd_std*) shows a peak positive effect on inflation of **0.8534** percentage points in the sixth quarter, followed by a gradual decline, in contrast to the relatively steady influence observed with historical deviations. Conversely, the variability in surface pressure (*sp_wtd_std*) shows negligible effects on inflation, with the impacts remaining close to zero throughout the quarters. This indicates that surface pressure variability has a minimal direct influence on inflation within the observed period. Thus, variability shocks, capturing short-term fluctuations, reveal immediate and often more volatile impacts on inflation, highlighting the economic system's sensitivity to sudden weather changes. In comparison, historical deviations reflect the economy's adaptation to long-term climate trends, with generally milder and more predictable effects on inflation.



(a) **t2m_wtd_std** (b) **tp_1000_wtd_std** (c) **stl2_wtd_std** (d) **sp_wtd_std**

Figure 10: **Impulse Responses For Shocks in Variability - UR**

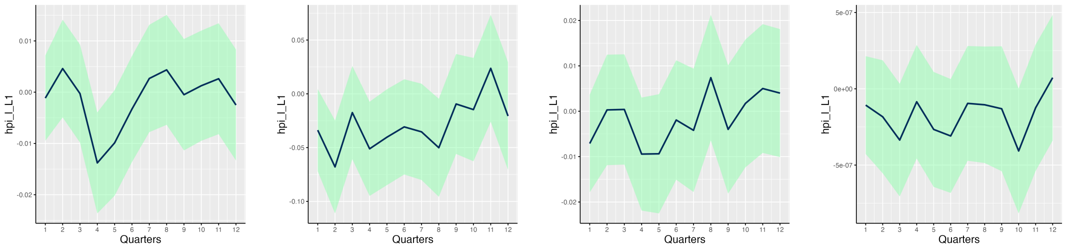
For the unemployment rate, shocks to the variability of 2-meter air temperature initially lead to a minor reduction, with a **0.0008** percentage point decrease in the first quarter (see Figure 10). However, this is followed by a gradual stabilization and a slight positive shift in the unemployment rate by the fourth quarter. For precipitation variability, the response of the unemployment rate reveals a more volatile pattern, swinging from a modest initial increase of **0.0010** percentage points in the first quarter to an increase of **0.0065** percentage points by the twelfth quarter. This suggests that fluctuations in precipitation levels can induce more pronounced shifts in employment conditions over time, possibly due to the varied impact on different sectors of the economy. The variability in soil temperature and surface pressure, similarly, show an initial decrease in the unemployment rate, followed by an oscillating trend that indicates a delayed response of the labor market to these environmental variables. The observed dynamics illustrate that while immediate effects might be minimal, the cumulative impact over quarters can lead to noticeable although less significant changes in employment rates, when contrasted with the significance of the responses observed for the inflation rate.



(a) **t2m_wtd_std** (b) **tp_1000_wtd_std** (c) **stl2_wtd_std** (d) **sp_wtd_std**

Figure 11: **Impulse Responses For Shocks in Variability - Disposable Income**

Initially, a one standard deviation shock in the variability of 2-meter air temperature leads to a marginal increase in disposable income by approximately **0.06**% in the first quarter (see Figure 11). This is followed by a fluctuation that culminates in a decrease of around **0.45**% by the fourth quarter that somewhat stabilizes towards the end of the observed period, showcasing the potential for short-term economic stress following temperature variability increases. Precipitation variability introduces a more apparent dynamic, initially leading to a **0.10**% decrease in disposable income in the first quarter, with the effects intensifying to a reduction of approximately **2.83**% by the fourth quarter. Soil temperature variability's shock displays a mixed effect on disposable income, beginning with a slight improvement before witnessing a decline. In comparison, the responses from shocks in historical deviations show a less pronounced and more stable impact on disposable income, although both responses are equally insignificant with wider confidence bands present.



(a) **t2m_wtd_std** (b) **tp_1000_wtd_std** (c) **stl2_wtd_std** (d) **sp_wtd_std**

Figure 12: **Impulse Responses For Shocks in Variability - HPI**

Finally, for temperature variability, the immediate response indicates a slight decrease in house price index by approximately **0.12**% in the first quarter, which contrasts sharply with a subsequent increase, peaking at about **0.46**% in the second quarter (see Figure 12). The impact of precipitation variability on house prices is markedly more severe, with an initial sharp decline of **3.38**% in the first quarter. This decline continues to be pronounced across the year, providing insights into the sensitivity of housing prices to precipitation variability and the potential for significant market disruptions. Soil temperature variability shows a mixed impact on HPI, with minor fluctuations indicating the less apparent effect of soil temperature changes on housing prices compared to air temperature and precipitation variability. Surface pressure variability has negligible effects on house price index, with changes being minimal and indicating a lack of significant direct impact on housing prices.

6. Implications For Portuguese Economic Policy

The results highlight distinct implications for Portuguese policy making due to weather shocks. Specifically, historical deviations from average weather conditions primarily lead to transient effects on key economic variables, whereas shocks due to variability invoke more immediate and severe impacts. For example, a notable spike in inflation follows temperature shocks, which demonstrates an initial upsurge before gradually tapering off over subsequent quarters. Similarly, variability in precipitation significantly escalates inflation rates, highlighting the acute sensitivity of Portugal's economy to sudden climatic fluctuations. This initial response to weather variability suggests a critical need for dynamic and responsive economic policies to mitigate the immediate impacts of such climatic anomalies on Portugal's macroeconomic stability. Given the magnitude and significance of the inflationary responses observed, we wish to primarily focus on the policy implications arising from the management of inflation due to weather shocks in Portugal, in contrast to the uncertainty and fluctuating nature of impacts on other economic variables.

Mukherjee and Ouattara (2021) provide an insight into on how central banks might respond to temperature shocks, which is pertinent in understanding monetary policy implications in Portugal. They demonstrate that temperature shocks typically generate sustained inflationary pressures, a phenomenon observed in both developed and developing countries. As central banks globally strive to maintain price stability and low inflation, essential for fostering high economic growth, the persistence of inflationary pressures induced by temperature shocks poses significant challenges to achieving these objectives.

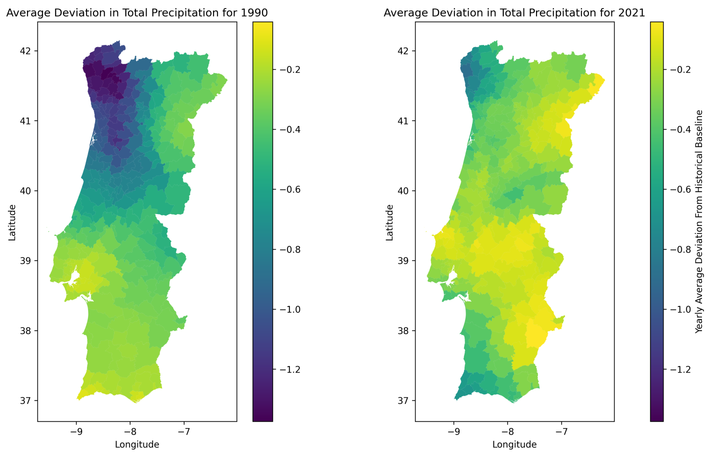
As a guideline for setting interest rates based on economic conditions, consider the Taylor Rule,

$$i_t = \pi_t + r_t^* + \alpha_\pi(\pi_t - \pi_t^*) + \alpha_y(y_t - \bar{y}_t) \tag{4}$$

where i_t is the nominal interest rate, π_t represents the current inflation rate, often gauged by the GDP deflator or consumer price index, the variable r_t^* denotes the assumed natural or equilibrium interest rate, which reflects the rate at which the economy neither overheats nor underperforms when inflation is stable. The coefficients α_π and α_y measure the responsiveness of the policy rate to deviations in inflation $(\pi_t - \pi_t^*)$ from the target inflation rate π_t^*, and the output gap $(y_t - \bar{y}_t)$, respectively, where y_t is the logarithm of actual GDP and $\bar{y}_t$ is the logarithm of potential GDP.

Within this monetary policy framework, a central bank's policy rate should adjust in response to deviations in both inflation and output from their target levels. Specifically, the rule suggests that the interest rate should increase when inflation is above its target or when GDP exceeds its potential, and decrease in the opposite scenarios, a principle supported by several studies (Bullard and Mitra, 2002; Galí, 2015; Woodford, 2001). In the context of Portugal, where our findings indicate marked inflation increases following precipitation and temperature shocks, ECB, along with the Bank of Portugal, may need to consider altering interest rates to align with its inflation targets. This adjustment process, however, is complicated by the persistent nature of climate-induced inflation, which stands in contrast to other inflationary pressures, as it may necessitate

Figure 13: **Long Term Trend in Deviations from Historical Averages**

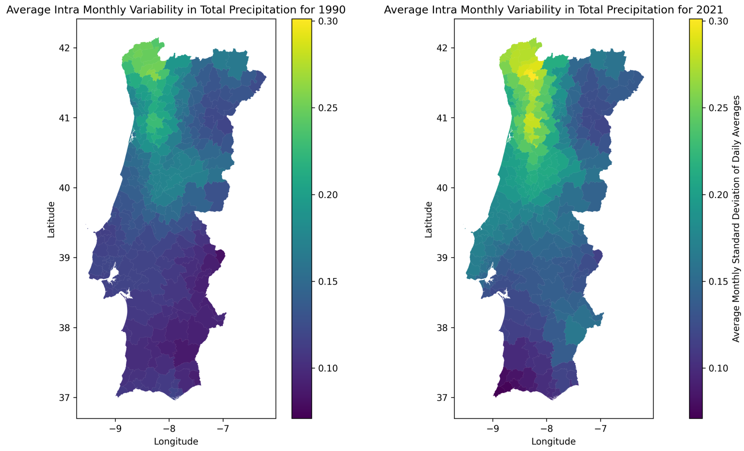


Note: The historical baseline considered for the average is from 1940 - 1980.

prolonged periods of elevated interest rates. Persistently high interest rates can have wide-ranging economic repercussions. They increase borrowing costs, potentially stifling investment and increasing the debt burden for existing borrowers. Moreover, as interest rates rise, so might other prices and wages, further stoking inflation in a feedback loop that complicates monetary policy implementation. Additionally, higher interest rates may attract capital inflows, leading to currency appreciation, which could impact export competitiveness (Mukherjee and Ouattara, 2021). Another significant challenge arises from the nature of temperature shocks as supply shocks. Unlike demand shocks, supply shocks require central banks to navigate a delicate balance between curbing inflation and supporting economic output (Mukherjee and Ouattara, 2021). Given the evidence that temperature shocks tend to reduce output, the ECB faces the complex task of formulating a response that mitigates inflation without exacerbating economic contraction (Mukherjee and Ouattara, 2021).

Managing inflation in Portugal is made more challenging due to the ECB's control over interest rates for the Eurozone. This centralized control complicates the Bank of Portugal's ability to address inflation spikes directly influenced by localized climate shocks. Ciccarelli et al. (2023) highlight the asymmetric impacts from climate shocks across the Eurozone, varying not only in magnitude but also in their temporal occurrence. Such heterogeneity means that the timing and intensity of inflationary pressures from climate shocks can differ significantly across member states, making a tailored monetary response more difficult to coordinate within the constraints set by overarching Eurozone policies. Furthermore, the regional disparities in climate impacts can be

Figure 14: **Long Term Trend in Precipitation Variability**



observed within Portugal as well. Let us consider the yearly total precipitation Portugal receives, comparing the data observed for 1990 and 2021. The data indicates that while the country has experienced reduced rainfall compared to historical averages, the deviation from these averages has lessened in recent years, especially in the north (see Figure 13). Yet, this apparent trend toward normalization masks increasing variability, especially in northern and coastal urban areas such as Lisbon and Porto, suggesting heightened unpredictability and extremes in weather patterns (see Figure 14). Such regional variability poses significant risks to local economies where tourism heavily influences economic activity and environmental sustainability, such as in the Algarve region (OECD, 2022; Pörtner et al., 2022).

To effectively mitigate these risks, it is imperative to implement regional policy measures focused on enhancing resilience to climate extremes through sustainable planning and infrastructure adaptation. This approach should include integrating climate risk assessments into investment decisions and urban planning, especially in regions like the Algarve, where tourism's impact on sustainability has been critically assessed as non-sustainable (Pimentel de Oliveira and Pitarch-Garrido, 2023). In response to the broader economic challenges posed by climate shocks, the study advocates for the integration of climate-related variables into the ECB's monetary policy framework. By acknowledging weather shocks as persistent supply-side disturbances, more nuanced monetary strategies can be devised. Following Mukherjee and Ouattara (2021), it is recommended that central banks adopt green monetary policies, such as differentiated reserve requirements and green quantitative easing, to promote environmentally sustainable practices within the financial sector. Ultimately, these recommendations emphasize the necessity for central banks, including the

ECB, to incorporate climate considerations into their policy frameworks to adeptly manage the economic ramifications of climate variability. Proactive engagement in environmentally focused monetary policy can enhance economic stability, maintain policy effectiveness, and uphold the credibility of monetary authorities in an era of escalating climate challenges.

7. Conclusion

This study examines the immediate impacts of weather shocks on Portugal's macroeconomy, focusing on key variables that affect individual and household economics: unemployment rate, disposable income, inflation, and housing price index. The study utilizes a panel vector autoregressive (PVARX) framework and local projections to compute impulse response functions to explore how these transient weather events influence employment, spending power, living costs, and housing stability from 2007 to 2021, using quarterly data.

Our analysis identifies temperature (both air and soil) and total precipitation as key drivers influencing inflation in Portugal. Specific findings reveal that deviations from historical averages in 2-meter air temperature and precipitation exhibit a non-linear relationship with inflation. Precipitation variability triggers immediate and significant inflationary pressures, highlighting its critical role in short-term economic fluctuations. In contrast, surface pressure has a negligible influence on inflationary trends, with coefficients indicating limited impact on the studied macroeconomic variables. While these climate variables significantly affect inflation, their influence on unemployment rates, disposable income, and housing prices appears less pronounced, indicating that the channels of impact might be more complex than those captured by our study.

Furthermore, we find that shocks in temperature and precipitation have persistent inflationary impacts over the study period. Temperature shocks lead to an initial upsurge in inflation, which peaks by the fourth quarter before gradually diminishing, while shocks from precipitation variability generate sustained inflationary pressures that peak in the fifth quarter. This persistence suggests that weather shocks have a lasting influence on inflation, rather than just immediate or transient effects. Additionally, these climate shocks also affect other economic variables, though the effects are less pronounced. Temperature fluctuations moderately influence disposable income and housing prices, highlighting their broad but varying impact on the economy.

This study substantiates the findings from Mukherjee and Ouattara (2021), Kalkuhl and Wenz (2020), and Kotz et al. (2022), highlighting the persistent and non-linear effects of temperature and precipitation shocks on inflation and economic output. Furthermore, it aligns with the work of Natoli (2022), who utilize local projections to elucidate the dynamic responses of the U.S. economy to unexpected temperature variations, and complements the broader insights from Burke et al. (2015) and Diffenbaugh and Burke (2019) regarding the sensitivity of global economic production to temperature changes.

Additionally, our findings validate the observations by Kotz et al. (2022) and others that increased variability in rainfall negatively impacts economic growth, particularly in high-income regions and key sectors like services and manufacturing. This aligns with the broader literature on the economic consequences of climate variability, including the detailed analyses by Faccia et al. (2021) and Ciccarelli et al. (2023), which discuss the significant impact of temperature variability on inflation, especially in warmer regions during summer months.

It is important to note that our study encounters certain limitations. First, our use of quarterly data, rather than monthly, potentially obscures finer temporal dynamics critical for assessing short-term weather fluctuations. Moreover, the unavailability of inflation data at the municipal level precludes a more detailed spatial analysis of price variations, while our timeframe, limited to 2007-2021, may also omit relevant economic cycles and longer-term trends. Furthermore, we did not consider the effects of non-Portuguese weather shocks or the potential spillover effects of weather shocks within the Eurozone, nor did we account for the possible changing response to shocks amid evolving climatic conditions or interactions with other economic shocks. The omission of wind data, particularly relevant for Portugal, from the weather variables might have overlooked the identification of other significant relationships. In recognizing these gaps, we suggest that future research could address them by incorporating a more diverse set of data, and extending the framework to enhance the robustness and applicability of the findings.

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A. Appendix

Literature Review Selection Criteria

To obtain a set of papers relevant for the literature review, we adopt the snowball approach put forth by Wohlin (2014), illustrated in Figure 15. This iterative method begins with a core set of research papers and expands by identifying additional relevant works cited within these papers, thus effectively capturing a wide spectrum of related literature.

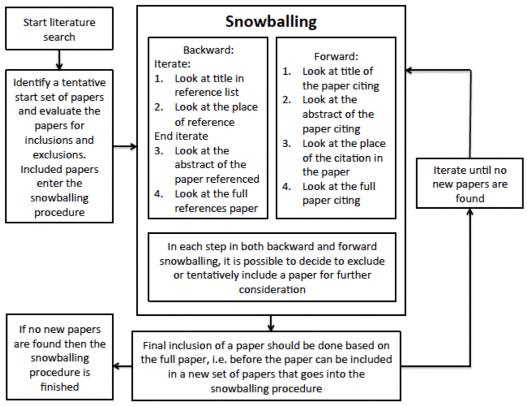


Figure 15: Snowball method as outlined in Wohlin (2014)

The initial set of papers was sourced from the *EconPapers* database using two distinct search queries designed to encompass a broad range of topics within the scope of this study. The first search term used was `(portugal OR portuguese) AND (economy OR macroeconomy OR macroeconomic) AND ("climate change" OR "climate shocks" OR 'weather shocks')`. The second search term was `(panel var) OR (panel vector autoregressive) OR (panel vector autoregression) AND municipalities AND climate`. A guide to the papers is presented in Table I, along with the climate variables investigated and model used therein, as well a summary of the key results.

Methodology

Historical Deviation

In section 4.2, we construct a variable to capture deviations from historical weather patterns, specifically focusing on the period from 1940 to 1980. This period serves as our historical baseline against which current weather data are compared. Utilizing the ERA5 monthly averaged data on single levels, which spans from 1940 to the present, we first calculate a historical average for each weather variable by averaging its values over the 1940-1980 period. Subsequently, for each month in our dataset, we subtract this historical average from the observed value to obtain a monthly deviation. These deviations are then averaged over each quarter to generate a quarterly average deviation from the historical average for each weather variable. The mathematical expression for calculating the quarterly average deviation from the historical average is given by:

$$\zeta_t = \frac{1}{3}\sum_{i=1}^{3}(\omega_{i,t} - \lambda) \tag{5}$$

where ζ_t represents the deviation for the quarter t, while $\omega_{i,t}$ refers to the value of the weather variable for month i within the quarter t, and λ is the mean value of that variable over the baseline period of 1940-1980. ζ_t is calculated for each point in the grid cell for which the ERA5 dataset is recorded.

Quarterly Average Intra-Monthly Standard Deviation

In section 4.2, we utilize the variability within our weather data in conjunction with deviations fromm historical averages. This is captured through the quarterly average intra-monthly standard deviations. This metric serves as a proxy for the fluctuation within each month, reflecting short-term variability in weather conditions. Utilizing the ERA5 reanalysis dataset, which provides hourly weather data from 1940 to the present, we first consolidate this hourly data into daily averages for each weather variable. Subsequently, we compute the standard deviation of these daily averages for each month, yielding the intra-monthly standard deviation. The final step involves averaging these monthly standard deviations over each quarter to derive the variable for quarterly average intra-monthly standard deviation.

The mathematical representation of this process is given by:

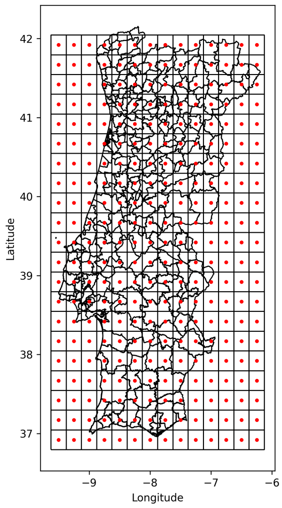
$$\psi_t = \frac{1}{3}\sum_{i=1}^{3}\sqrt{\frac{1}{N_i - 1}\sum_{j=1}^{N_i}(\upsilon_{ij,t} - \bar{\upsilon}_{i,t})^2} \tag{6}$$

where ψ_t represents the quarterly average intra-monthly standard deviation, $\upsilon_{ij,t}$ denotes the daily average value of the weather variable on day j within month i of quarter t, $\bar{\upsilon}_{i,t}$ is the average of these daily values within the month i, and N_i represents the total number of days in month i.

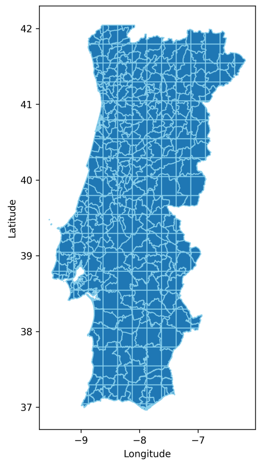
Spatial Aggregation Technique

In section 4.2, we briefly touch on the spatial aggregation process used for the climate data processing. To accurately attribute ERA5 climate data to specific municipalities, we initiated a spatial aggregation process that involves constructing polygons for each 0.25° × 0.25° ERA5 grid cell. There are two generally methods used for the spatial weighting of climate data, one is by population and the other is by area (Dell et al., 2014). Population based weighting is preferred for large geographic areas, especially those large swathes of land where few people are present, such as the United States of America. However, given the smaller geographic extent of Portugal, we opt for an area-weighted procedure for climate data aggregation.

Figure 16



(a) ERA5 Spatial Resolution



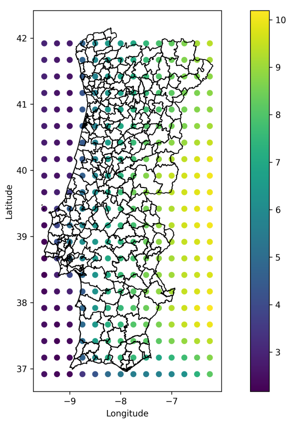
(b) Municipalities Overlaid with Intersecting Grids

Note: The points in red are the points in space at which the ERA5 data is recorded. The surrounding grids are the polygons we construct (*left*). The municipalities are overlaid with the intersecting grids, leaving only those grids present within the boundary of Portugal (*right*).

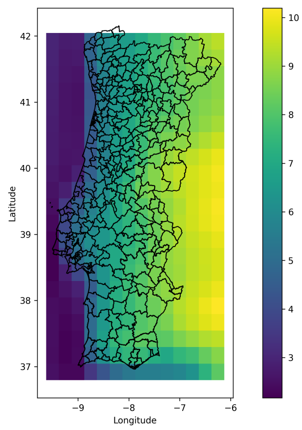
For each grid cell, a polygon is created by identifying the geographic coordinates of its corners based on the grid's latitude and longitude resolution. This polygon effectively represents the spatial extent of the grid cell, allowing for an area-weighted aggregation of climate variables. By delineating these polygons, we ensure a precise and geographically relevant application of ERA5 data in our analysis, enabling a detailed investigation of climate impacts at the municipal level.

Following the creation of polygons for ERA5 grid cells, the next step in our spatial aggregation process involves performing a spatial overlay to identify the intersecting areas between these ERA5 polygons and municipal boundaries. This overlay allows us to determine the specific area contributions of each ERA5 grid cell to the municipalities, ensuring a precise geographical allocation of climate data. Subsequently, we execute a spatial join (`sjoin`) to consolidate this information, which

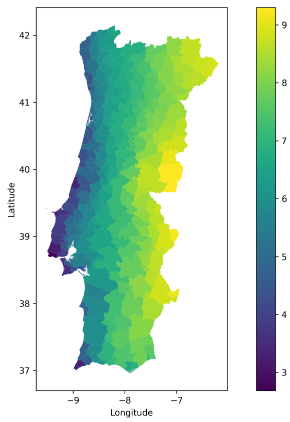
Figure 17: 2-Metre Air Temperature Deviations from Historical Average for 2017Q3



(a) ERA5 Point Values



(b) Constructed Grid Values



(c) Area-Weighted Values

Note: The above figure(s) depict the process of spatial aggregation of ERA5 climate data, using the example of 2-meter air temperature deviations from the historical average in the third quarter of 2017. Panel 17a illustrates the point data for each 0.25° × 0.25° ERA5 grid cell across Portugal. Panel 17b shows the constructed polygons based on these grid cells, delineating the geographic boundaries used for area-weighted aggregation. Finally, panel 17c presents the area-weighted average temperatures for each municipality.

lays the groundwork for calculating area-weighted climate variable values for each municipality.

To compute these area-weighted averages, we first calculate the area of each intersecting polygon, representing the portion of the ERA5 grid cell contributing to a municipality. The sum of these areas for each municipality is then determined, facilitating the computation of weighted averages. For each climate variable, its value is multiplied by the ratio of the intersecting polygon's area to the total area of the municipality. This process is repeated for all relevant climate variables, such as temperature, sea-level pressure, and precipitation, yielding a set of area-weighted climate variables that accurately reflect the climatic conditions experienced within each municipal boundary. This methodological rigor ensures our analysis captures the nuanced impact of climate variability across different regions of Portugal.

Panel Unit Root Testing

In section 5.1, we utilized panel unit root tests developed by Demetrescu and Costantini and Lupi. The implementation of these tests was intended through a package by Kleiber and Lupi (2011) within the R programming environment. Due to compatibility issues with the package and the latest stable R release (version 4.3.3 used in our analysis), we could not directly apply these tests. To address this, we extracted the source code for the tests from `https://rdrr.io/rforge/punitroots/f/` and executed it locally, which allowed us to conduct the necessary panel unit root tests.

Panel VARX Estimation

We note that estimation of our model is feasible in STATA using the `pvar` command, although it lacks the capability for fixed effects estimation, a limitation not present within the R package (Abrigo and Love, 2016). Despite this, the STATA implementation offers the advantage of constructing dynamic multipliers for both exogenous and endogenous variables, a feature not currently present in the `panelvar` package in R. For a comprehensive overview of the estimation methods implemented, readers are referred to the pertinent literature Sigmund and Ferstl (2021).

B. Tables

Table I: Selected Papers from Snowball Search for Literature Review

Author	**Method Used**	**Climate Variables**	**Summary**
Burke et al. (2015)	-	temperature	
Dell et al. (2014)	literature review	-	
Dell et al. (2012)	panel regression	temperature precipitation	
Diffenbaugh and Burke (2019)	fixed effects panel regression (bootstrap)	temperature precipitation	
Tol (2018)	literature review	-	
Dell et al. (2009)	fixed effects panel regression	temperature precipitation	
Hsiang (2016)	literature review	-	
Deryugina and Hsiang (2014)	panel regression	temperature	Deryugina and Hsiang (2014) employ panel regression to analyze how daily temperature variations affect annual income in U.S. counties. Their findings reveal a productivity decrease of about 1.7% for every 1°C rise in temperature beyond 15°C, highlighting the enduring economic impact of environmental conditions despite progress in adaptation measures.
Kalkuhl and Wenz (2020)	fixed effects panel regression	precipitation, temperature	Kalkuhl and Wenz (2020) utilize fixed effects panel regression to explore the relationship between climate conditions—specifically temperature and precipitation—and economic production globally. Their analysis reveals that, despite the absence of long-term growth effects, significant negative impacts of temperature on per-capita Gross Regional Product (GRP) persist, indicating economies remain sensitive to temperature changes without diminished influence from technological advancements.

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Colacito et al. (2019)	panel regression	temperature, precipitation, snowfall	Colacito, Hoffmann, and Phan (2019) analyze the U.S. economy's sensitivity to temperature, precipitation, and snowfall using panel regression. They find that a 1°F increase in average summer temperature could decrease state-level output's annual growth rate by 0.15 to 0.25 percentage points, potentially reducing U.S. economic growth by up to one-third over the next century.
Acevedo et al. (2020)	local_projections	temperature, precipitation	Acevedo Mejia et al. (2018) utilize local projections to examine the impact of temperature and precipitation shocks on economic activity, pinpointing reduced investment, lower labor productivity, deteriorating human health, and decreased agricultural and industrial output as key transmission channels. Their findings highlight that hot, low-income countries face the severest economic repercussions, with an average annual temperature rise of 1 degree potentially reducing aggregate output by about 2% and investment by around 10% after seven years, indicating economic development plays a crucial role in mitigating the effects of temperature shocks.
Kotz et al. (2022)	fixed effects panel regression	temperature precipitation	Kotz, Levermann, and Wenz (2022) apply fixed effects panel regression to assess how variations in rainfall impact economic production, drawing on a global dataset of subnational economic output across 1,554 regions over four decades. They discover that economic growth rates decrease with more wet days and extreme daily rainfall events, particularly affecting high-income nations and the services and manufacturing sectors, thereby highlighting the complex ways in which daily rainfall variability can influence the economy.

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Kotz et al. (2021)	fixed effects panel regression	temperature	Kotz et al. (2021) utilize fixed effects panel regression to explore how day-to-day temperature variability affects economic growth, beyond the influence of annual average temperature changes. Analyzing temperature fluctuations and economic data from 1,537 regions over 40 years, they reveal that increased temperature variability can significantly hinder regional economic growth rates by an average of five percentage points, with the most pronounced effects in low-latitude, low-income regions.
Parker (2018)	panel regression	disasters	Parker (2018) employs panel regression to investigate the relationship between disasters and consumer price inflation, uncovering marked differences between advanced and developing economies. The study finds that while the inflation impact is negligible in advanced economies, it can persist for several years in developing ones. Additionally, the type of disaster plays a role, with storms briefly elevating food price inflation and earthquakes reducing CPI inflation excluding food, housing, and energy.
Mukherjee and Ouattara (2021)	panel var	temperature	Mukherjee and Ouattara (2021) apply panel VAR analysis to examine how temperature shocks influence inflation in both developed and developing countries over the period 1961–2014. Their research reveals that climate change triggers inflationary pressures, with the effects on inflation remaining significant for several years following the initial shock. This presents a considerable challenge for central banks striving to maintain inflation and price stability, highlighting the importance of considering temperature shocks in monetary policy decisions and forecasting.

Table I continued from previous page

Author	Method Used	Climate Variables	Summary
Gallic and Vermandel (2020)	svar	-	Gallic and Vermandel (2020) bridge the gap between theoretical and empirical analyses of weather shocks' economic impacts by employing a Vector Auto-Regressive model on New Zealand data and constructing a general equilibrium model focused on a weather-dependent agricultural sector. Their study reveals that weather shocks account for approximately 35% of GDP and agricultural output fluctuations in New Zealand, with a notable welfare cost that could intensify under more severe climate change scenarios.
Uddin and Wadud (2014)	var	co2 emissions	Uddin and Wadud (2014) conduct a VAR analysis on the causal relationship between CO_2 emissions and economic growth in SAARC countries from 1972 to 2012, revealing a positive, significant long-term impact of emissions on GDP, and highlighting the importance of integrating environmental considerations into macroeconomic policy for environmental management.
Alessandri and Mumtaz (2021)	panel var	temperature precipitation	Alessandri and Mumtaz (2021) examine the effects of climate volatility on economic growth using panel VAR analysis on data from 133 countries between 1960 and 2019. Their findings indicate that increasing volatility in annual temperatures, independent of temperature changes, contributes to less predictable climate conditions, resulting in an average decline of 0.3% in GDP growth and a 0.7% increase in GDP volatility, impacting both developed and developing nations.
Tol (2024)	literature review	-	-
Fernando et al. (2021)	G-Cubed model	temperature, precipitation, droughts , wildfires, extreme temperature events , storms, floods	
Vrontisi et al. (2022)	general equilibrium model	-	

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Kotz et al. (2023)	fixed-effects panel regression	precipitation, temperature, Standardised Precipitation Evapotranspiration Indices	Kotz et al. (2023) explore the relationship between global warming and inflation using fixed-effects panel regression on a global dataset of monthly consumer price indices. Their analysis reveals that rising average temperatures exert non-linear upward pressures on inflation, persisting over 12 months across both higher- and lower-income countries.
Ciccarelli et al. (2023)	seasonal dependent BVAR	temperature, precipitation	Ciccarelli, Kuik, and Martínez Hernández (2023) analyze weather shocks' inflationary effects in the euro area using seasonal dependent Bayesian Vector Autoregressions (BVAR). They uncover significant seasonal variations in inflation responses to temperature shocks, particularly through food, energy, and service prices, with pronounced effects in warmer countries during summer and autumn. Their findings highlight the complex, nonlinear nature of weather impacts on inflation, suggesting greater inflationary pressures with increased temperature variability, especially in southern European nations.
Natoli (2022)	panel local_projections	temperature	Natoli (2022) employs panel analysis and local projections with daily county-level data from the United States since 1970 to examine the impact of temperature surprise shocks, distinguishing the unexpected effects of heat and cold events each season. The study reveals that, contrary to popular belief, the mix of heat and cold surprises has been balanced in the era of global warming, showing a reduction in size over time. The findings indicate that these shocks negatively affect the US economy through consumption and investment at the business cycle frequency, with a variable impact on prices. Additionally, it's noted that the central bank adjusts its economic projections and interest rate policies in response to these temperature shocks, influencing the yield curve.
Creti et al. (2021)	literature review	-	

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Habib (2022)	panel var	temperature , precipitation	Habib (2022) analyzes the impact of climate variability on North African countries' GDP using panel VAR, revealing that while weather changes slightly reduce GDP, remittances significantly contribute to economic stability by offsetting these effects.
Huber et al. (2023)	panel var	Global Standardized Precipitation Evapotranspiration Index	Huber, Krisztin, and Pfarrhofer (2023) employ a Bayesian panel VAR approach to explore climate shocks' effects on agricultural commodity markets and macroeconomic indicators in high-income economies, revealing significant global reactions and strong interconnections between regional shocks and global markets.
Liu et al. (2023)	fixed-effect panel regression	temperature , precipitation, ENSO	Liu et al. (2023) utilize a fixed-effect panel regression with a smooth nonlinear climate-economy model to assess the economic impacts of El Niño under climate change, finding that El Niño events lead to significant economic losses, with effects intensifying for three years post-event and predicting increased economic damage with heightened ENSO variability.
Skrinjaric (2023)	var	extreme variables	Škrinjarić (2023) explores the short- to medium-term economic impacts of extreme weather on Croatia using VAR models with data from 1999 to 2022, finding significant weather-induced inflationary pressures, particularly from droughts, highlighting the need for monetary policy and the insurance industry to adapt to increasing weather extremes.
Accetturo and Alpino (2023)	panel regression	precipitation, temperature	Accetturo and Alpino (2023) analyze the impact of weather shocks on key agricultural yields in Italy through panel regression, utilizing province-level panel data. They uncover significant non-linearities in temperature effects, notably finding grapevines less temperature-sensitive than cereals. Their projections indicate varying impacts of climate change on crop yields by 2030, with corn at higher risk of yield reduction.

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Jalles (2024)	local projections	ND-GAIN index	Jalles (2023) employs the local projection method to investigate the impact of financial crises on climate change resilience, analyzing data from 178 countries between 1995–2019. The study finds that while resilience to climate shocks has generally increased, financial crises, especially systemic banking ones, cause a short-term decline in resilience, particularly affecting developing economies.
Ahmadi et al. (2022)	bayesian svar	temperature precipitation	Ahmadi et al. (2022) use a Bayesian Structural Global VARX model to explore how temperature and precipitation shocks affect economic growth in various countries, noting significant heterogeneity in impacts. Contrary to the common belief that hot, poor countries suffer the most, their findings reveal that rich, cold countries also face severe economic challenges due to climate shocks, with trade interdependence playing a crucial role in mediating these effects.
Zappalà (2023)	panel regression	temperature, precipitation, dryness conditions ,wind speed, Tropical cyclones	Zappalà (2023) uses panel regression to assess the impact of climate variables like temperature, precipitation, dryness, wind speed, and tropical cyclones on sectoral production. The study reveals that agriculture suffers the most from these weather shocks, with notable cross-sectoral economic losses due to heat shocks.
Kim et al. (2022)	nonlinear var	High temperatures Low temperatures Heavy precipitation Drought High wind Sea level	Kim, Matthes, and Phan (2022) employ a nonlinear VAR model to analyze the effects of severe weather shocks, including high and low temperatures, heavy precipitation, drought, high wind, and sea level changes, on the US economy over sixty years. They document increasing significant impacts over time, showing reduced industrial production and consumption growth, along with higher unemployment and inflation, indicating minimal adaptation at the macroeconomic level.

Table I continued from previous page

Author	**Method Used**	**Climate Variables**	**Summary**
Li et al. (2023)	panel two-way fixed effects model	temperature	Li, Zhang, and He (2023) utilize a panel two-way fixed effects model to investigate the impact of temperature fluctuations, as proxies for climate shocks, on inflation in 26 countries from 1995 to 2021. Their analysis reveals a positive link between temperature changes and inflation, with energy demand highlighted as a key channel influencing this relationship. Furthermore, the study identifies a nonlinear relationship between temperature change and inflation, moderated by GDP per capita.
Zouabi (2021)	general equilibrium model	temperature, precipitation	Zouabi (2021) uses a dynamic general equilibrium model to analyze how temperature and precipitation changes impact Tunisia's agriculture and macroeconomics through 2050, finding declines in citrus, cereal, and olive production, alongside negative shifts in consumption, investment, and unemployment rates.
Sugiarto et al. (2023)	fixed effects panel regression	-	demonstrated that climate-related disasters, especially floods, significantly impact the banking sector in Indonesia, notably reducing credit availability and increasing non-performing loans (NPLs) between 2011 and 2021, indicating an urgent need for policy and regulatory adaptations.
Aslan et al. (2024)	panel var	annual global land temperature anomalies	Aslan, Altinoz, and Polat (2023) employ a panel VAR approach to explore how temperature anomalies impact economic and technological indicators in EU countries from 1996 to 2018, revealing negative effects on economic growth, investment, and labor productivity, while notably increasing patent applications by 0.4% in the long term.
Romero et al. (2023)	B var-x	El Niño Southern Oscillation (ENSO) fluctuations	Romero, Naranjo-Saldarriaga, and Muñoz (2023) use a BVAR-X model to examine the effects of ENSO-related weather shocks on Colombia's economy, focusing on agricultural output and inflation. Their study confirms that such adverse weather events reduce agricultural production and spur inflation, while overall GDP growth remains largely unaffected, paving the way for a New Keynesian model that accounts for these dynamics through price channels.

Table II: Data Description

Variable	Variable Name	Frequency Available	Units	Source
t2m	2-Metre Temperature	Hourly	Kelvin	ERA5
tp	Total Precipiation	Hourly	m	ERA5
sp	Surface Pressure	Hourly	Pa	ERA5
stl2	Soil Temperature Level 2	Hourly	Kelvin	ERA5
hicp_yoy_pct	Year on Year Harmonised Index of Consumer Prices Percentage	Monthly	Percentage	INE, Banco De Portugal
ur	Unemployment Rate	Quarterly	Percentage	INE, Banco De Portugal
disp_inc_conc	Household Disposable Income	Quartlerly	Euros	INE, Banco De Portugal
hpi	House Price Index	Quartlerly	Points	Confidencial Imobiliario, Banco De Portugal

Results

Panel Unit Root Test Results

Table III: Panel Unit Root Test Results for Demetrescu et al. (2006)

Variable	Test Statistic	p-value
hicp_yoy_pct	-2.619	0.004
ur	-0.159	0.437
ur_L1	-34.642	0.000
disp_inc_conc	7.193	1
disp_inc_conc_l	2.323	0.990
disp_inc_conc_l_L1	-34.553	0.000
hpi	18.402	1
hpi_l	3.296	0.999
hpi_l_L1	-35.195	0.000

Panel VARX Estimation Set-Up and Results

Transformation: demean

Group variable: CCA_2

Time variable: time

Number of observations = 16680

Number of groups = 278

Obs per group: min = 60, avg = 60, max = 60

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

Table IV: Panel VARX Estimation Results

	demeaned_hicp_yoy_pct	demeaned_ur_L1	demeaned_disp_inc_conc_l_L1	demeaned_hpi_l_L1
demeaned_lag1_hicp_yoy_pct	1.2239 *** (0.0073)	-0.0005 (0.0004)	0.0015 (0.0015)	0.0006 (0.0028)
demeaned_lag1_ur_L1	-0.0738 (0.1841)	-0.0423 *** (0.0101)	0.0096 (0.0385)	-0.0332 (0.0710)
demeaned_lag1_disp_inc_conc_l_L1	0.0460 (0.0493)	0.0011 (0.0027)	-0.0316 ** (0.0103)	-0.0099 (0.0190)
demeaned_lag1_hpi_l_L1	-0.0116 (0.0285)	-0.0030 (0.0016)	0.0019 (0.0060)	-0.0276 * (0.0110)
demeaned_lag2_hicp_yoy_pct	-0.4761 *** (0.0107)	0.0004 (0.0006)	-0.0024 (0.0022)	0.0020 (0.0041)
demeaned_lag2_ur_L1	0.2863 (0.1834)	-0.0116 (0.0101)	0.0040 (0.0383)	0.0360 (0.0708)
demeaned_lag2_disp_inc_conc_l_L1	0.0163 (0.0493)	-0.0031 (0.0027)	-0.0024 (0.0103)	0.0109 (0.0190)
demeaned_lag2_hpi_l_L1	-0.0060 (0.0285)	0.0024 (0.0016)	-0.0077 (0.0060)	-0.0221 * (0.0110)
demeaned_lag3_hicp_yoy_pct	0.2647 *** (0.0108)	-0.0001 (0.0006)	0.0003 (0.0022)	-0.0060 (0.0041)
demeaned_lag3_ur_L1	0.2975 (0.1833)	-0.0242 * (0.0101)	0.0521 (0.0383)	0.1469 * (0.0707)
demeaned_lag3_disp_inc_conc_l_L1	-0.0657 (0.0493)	0.0033 (0.0027)	-0.0294 ** (0.0103)	-0.0066 (0.0190)
demeaned_lag3_hpi_l_L1	0.0052 (0.0285)	-0.0045 ** (0.0016)	0.0065 (0.0060)	0.0119 (0.0110)
demeaned_lag4_hicp_yoy_pct	-0.2835 *** (0.0069)	0.0003 (0.0004)	-0.0009 (0.0015)	0.0019 (0.0027)
demeaned_lag4_ur_L1	0.1345 (0.1835)	-0.0327 ** (0.0101)	-0.0251 (0.0383)	-0.0969 (0.0708)

Table IV continued from previous page

	demeaned_hicp_yoy_pct	demeaned_ur_L1	demeaned_disp_inc_conc_l_L1	demeaned_hpi_l_L1
demeaned_lag4_disp_inc_conc_l_L1	-0.0016 (0.0494)	-0.0015 (0.0027)	-0.0320 ** (0.0103)	0.0062 (0.0190)
demeaned_lag4_hpi_l_L1	0.0144 (0.0286)	-0.0021 (0.0016)	0.0050 (0.0060)	-0.0150 (0.0110)
demeaned_t2m_wtd_hd	0.1014 *** (0.0170)	0.0002 (0.0009)	0.0020 (0.0036)	-0.0067 (0.0066)
demeaned_tp_1000_wtd_hd	-0.0538 *** (0.0095)	-0.0001 (0.0005)	0.0000 (0.0020)	-0.0037 (0.0036)
demeaned_t2m_wtd_std	0.1075 *** (0.0212)	-0.0016 (0.0012)	0.0035 (0.0044)	0.0076 (0.0082)
demeaned_tp_1000_wtd_std	2.6049 *** (0.1202)	0.0032 (0.0066)	0.0091 (0.0251)	0.0359 (0.0464)
demeaned_sp_wtd_hd	0.0003 *** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
demeaned_sp_wtd_std	-0.0000 *** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
demeaned_stl2_wtd_hd	-0.0478 ** (0.0157)	0.0002 (0.0009)	-0.0037 (0.0033)	0.0026 (0.0060)
demeaned_stl2_wtd_std	0.5042 *** (0.0309)	0.0015 (0.0017)	0.0008 (0.0065)	-0.0077 (0.0119)
demeaned_t2m_wtd_L1_hd	0.1381 *** (0.0157)	0.0014 (0.0009)	0.0023 (0.0033)	-0.0093 (0.0061)
demeaned_t2m_wtd_L2_hd	0.1910 *** (0.0164)	0.0002 (0.0009)	0.0014 (0.0034)	0.0005 (0.0063)
demeaned_stl2_wtd_L1_hd	-0.1071 *** (0.0139)	-0.0013 (0.0008)	-0.0019 (0.0029)	0.0073 (0.0054)
demeaned_stl2_wtd_L2_hd	-0.0970 *** (0.0147)	-0.0000 (0.0008)	-0.0030 (0.0031)	-0.0035 (0.0057)
demeaned_sp_wtd_L1_hd	0.0006 *** (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
demeaned_sp_wtd_L2_hd	-0.0003 *** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
demeaned_tp_1000_wtd_L1_hd	0.1160 *** (0.0097)	-0.0003 (0.0005)	0.0019 (0.0020)	0.0018 (0.0037)
demeaned_tp_1000_wtd_L2_hd	-0.1037 *** (0.0097)	-0.0001 (0.0005)	-0.0033 (0.0020)	0.0011 (0.0037)
demeaned_t2m_wtd_L3_hd	0.0636 *** (0.0156)	0.0015 (0.0009)	-0.0060 (0.0033)	-0.0076 (0.0060)
demeaned_t2m_wtd_L4_hd	0.0539 *** (0.0156)	-0.0003 (0.0009)	0.0018 (0.0033)	0.0040 (0.0060)

Table IV continued from previous page

	demeaned_hicp_yoy_pct	demeaned_ur_L1	demeaned_disp_inc_conc_l_L1	demeaned_hpi_l_L1
demeaned_stl2_wtd_L3_hd	-0.1059 *** (0.0140)	-0.0010 (0.0008)	0.0047 (0.0029)	0.0042 (0.0054)
demeaned_stl2_wtd_L4_hd	-0.0354 * (0.0144)	0.0005 (0.0008)	-0.0020 (0.0030)	-0.0061 (0.0056)
demeaned_sp_wtd_L3_hd	0.0007 *** (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
demeaned_sp_wtd_L4_hd	-0.0007 *** (0.0000)	0.0000 * (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
demeaned_tp_1000_wtd_L3_hd	0.0223 * (0.0096)	0.0004 (0.0005)	-0.0022 (0.0020)	0.0019 (0.0037)
demeaned_tp_1000_wtd_L4_hd	0.1273 *** (0.0090)	0.0004 (0.0005)	-0.0015 (0.0019)	-0.0041 (0.0035)
demeaned_t2m_wtd_L1_std	-0.4661 *** (0.0210)	-0.0013 (0.0012)	0.0086 * (0.0044)	0.0112 (0.0081)
demeaned_t2m_wtd_L2_std	-0.0832 *** (0.0212)	0.0005 (0.0012)	-0.0019 (0.0044)	-0.0022 (0.0082)
demeaned_stl2_wtd_L1_std	0.6309 *** (0.0291)	0.0020 (0.0016)	-0.0192 ** (0.0061)	-0.0092 (0.0112)
demeaned_stl2_wtd_L2_std	0.5114 *** (0.0299)	-0.0010 (0.0016)	0.0003 (0.0063)	0.0018 (0.0115)
demeaned_sp_wtd_L1_std	0.0000 *** (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
demeaned_sp_wtd_L2_std	0.0000 *** (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
demeaned_tp_1000_wtd_L1_std	-1.2688 *** (0.1319)	0.0091 (0.0072)	-0.0307 (0.0276)	-0.0793 (0.0509)
demeaned_tp_1000_wtd_L2_std	1.0535 *** (0.1306)	-0.0065 (0.0072)	0.0422 (0.0273)	0.0326 (0.0504)
demeaned_t2m_wtd_L3_std	-0.1744 *** (0.0219)	0.0005 (0.0012)	-0.0059 (0.0046)	-0.0106 (0.0085)
demeaned_t2m_wtd_L4_std	0.0693 ** (0.0229)	0.0023 (0.0013)	-0.0067 (0.0048)	-0.0171 (0.0088)
demeaned_stl2_wtd_L3_std	0.8038 *** (0.0317)	-0.0010 (0.0017)	0.0084 (0.0066)	0.0191 (0.0122)
demeaned_stl2_wtd_L4_std	0.0076 (0.0320)	-0.0018 (0.0018)	0.0051 (0.0067)	0.0091 (0.0124)
demeaned_sp_wtd_L3_std	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
demeaned_sp_wtd_L4_std	-0.0000 *** (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)

Table IV continued from previous page

	demeaned_hicp_yoy_pct	demeaned_ur_L1	demeaned_disp_inc_conc_l_L1	demeaned_hpi_l_L1
demeaned_tp_1000_wtd_L3_std	0.9402 *** (0.1306)	-0.0001 (0.0072)	-0.0133 (0.0273)	-0.0514 (0.0504)
demeaned_tp_1000_wtd_L4_std	-1.4899 *** (0.1254)	0.0010 (0.0069)	0.0052 (0.0262)	0.0248 (0.0484)
demeaned_tp_2_wtd_hd	0.0259 *** (0.0015)	0.0000 (0.0001)	-0.0004 (0.0003)	0.0002 (0.0006)
demeaned_tp_2_wtd_hd_L1	0.0333 *** (0.0015)	0.0001 (0.0001)	-0.0003 (0.0003)	0.0002 (0.0006)
demeaned_tp_2_wtd_hd_L2	0.0128 *** (0.0014)	0.0000 (0.0001)	0.0007 * (0.0003)	0.0001 (0.0006)
demeaned_tp_2_wtd_hd_L3	-0.0019 (0.0015)	-0.0000 (0.0001)	0.0006 * (0.0003)	0.0010 (0.0006)
demeaned_tp_2_wtd_hd_L4	-0.0206 *** (0.0015)	0.0001 (0.0001)	0.0004 (0.0003)	-0.0002 (0.0006)
demeaned_tp_3_wtd_hd	-0.0042 *** (0.0003)	0.0000 (0.0000)	0.0000 (0.0001)	-0.0000 (0.0001)
demeaned_tp_3_wtd_hd_L1	-0.0051 *** (0.0003)	-0.0000 (0.0000)	-0.0000 (0.0001)	0.0000 (0.0001)
demeaned_tp_3_wtd_hd_L2	-0.0012 *** (0.0003)	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0000 (0.0001)
demeaned_tp_3_wtd_hd_L3	-0.0008 ** (0.0003)	-0.0000 (0.0000)	-0.0000 (0.0001)	-0.0001 (0.0001)
demeaned_tp_3_wtd_hd_L4	-0.0012 *** (0.0003)	-0.0000 (0.0000)	-0.0000 (0.0001)	0.0001 (0.0001)
demeaned_t2m_2_wtd_hd	-0.0342 *** (0.0007)	0.0001 (0.0000)	0.0001 (0.0002)	-0.0003 (0.0003)
demeaned_t2m_2_wtd_hd_L1	-0.0064 *** (0.0008)	0.0000 (0.0000)	0.0002 (0.0002)	-0.0001 (0.0003)
demeaned_t2m_2_wtd_hd_L2	0.0066 *** (0.0008)	0.0000 (0.0000)	-0.0001 (0.0002)	0.0004 (0.0003)
demeaned_t2m_2_wtd_hd_L3	-0.0061 *** (0.0008)	0.0001 (0.0000)	-0.0005 ** (0.0002)	-0.0006 (0.0003)
demeaned_t2m_2_wtd_hd_L4	0.0256 *** (0.0009)	-0.0000 (0.0000)	0.0001 (0.0002)	-0.0001 (0.0003)
demeaned_t2m_3_wtd_hd	0.0018 *** (0.0001)	-0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
demeaned_t2m_3_wtd_hd_L1	0.0000 (0.0001)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
demeaned_t2m_3_wtd_hd_L2	-0.0018 *** (0.0001)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)

Table IV continued from previous page

	demeaned_hicp_yoy_pct	demeaned_ur_L1	demeaned_disp_inc_conc_l_L1	demeaned_hpi_l_L1
demeaned_t2m_3_wtd_hd_L3	-0.0000 (0.0001)	-0.0000 * (0.0000)	0.0000 ** (0.0000)	0.0001 ** (0.0000)
demeaned_t2m_3_wtd_hd_L4	-0.0031 *** (0.0001)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)