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CLIMATE CHANGE AND ITS REGIONAL EFFECTS ON LABOUR PRODUCTIVITY: EVIDENCE FROM PORTUGAL

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Abstract: This study investigates the impacts of temperature and precipitation deviations and variability on labour productivity across Portugal's NUTS III regions using fixed-effects panel regression with annual data from 2008 to 2022. Two approaches are applied: one considers productivity at current prices and inflation as a control variable, while the other uses a constant-price productivity proxy. Results indicate that precipitation variability and deviations significantly influence productivity nationally and in northern regions, while temperature variability lacks statistical significance. These findings underscore the need for improved data granularity to inform targeted climate adaptation policies that reduce dependence on precipitation.

Keywords: Climate Economics, Labour Productivity, Fixed-Effects Panel Regression,

Regional Disparities

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1 Introduction

Climate change stands as one of this century's greatest challenges to humankind. The year 2023 was marked by extreme heat waves, droughts, and wildfires that severely impacted southern Europe and made it the warmest year on record, globally. Average global temperatures exceeded pre-industrial levels by 1.48°C, approaching the critical 1.5°C threshold established by the Paris Agreement as a limit for the end of the century (World Meteorological Organization, 2024).

Europe, the fastest-warming continent according to the European Environment Agency (2024), has borne substantial economic and social consequences in recent years. Coastal cities are grappling with rising sea levels, while southern Europe faces an accelerated march toward desertification. These effects are not confined to southern regions, as droughts have extended their reach to traditionally less-affected areas such as Luxembourg and Poland (Shah et al., 2024).

Extreme weather events, including heatwaves, storms, and heavy rainfall, are becoming increasingly frequent, contributing to immense economic losses. Between 2021 and 2023, damages in the European Union caused by extreme weather events totalled €162 billion, according to the European Environment Agency (2024). For example, in May 2023 in Italy, precipitation ratios surged to nearly eight times the historical average (Shah et al., 2024), and in October 2024, flash floods in Spain tragically claimed over 200 lives. These events highlight the escalating risk to both human lives and economic stability as climate variability intensifies. The economic toll is particularly pronounced in the southern Mediterranean. Galeotti (2020) highlights the disproportionate burden borne by this region, where the combined effects of reduced labour productivity, agricultural failures, and coastal damage could lead to considerable GDP losses under high-warming scenarios. These findings emphasise the vulnerability of southern Europe and the critical need for targeted mitigation and adaptation strategies to address these escalating risks effectively.

While studies on this topic are not abundant for Portugal, a few authors describe important findings on the economic impact of climate change in the country. Adão et al. (2022) highlight the economic consequences of climate change in this southern European country, which according to Carvalho et al. (2013) are exacerbated due to Portugal's Mediterranean climate, marked by increasing temperatures, declining precipitation, and intensifying extreme weather events.

The study by Adão et al. (2022) highlights significant challenges in Portuguese southern regions like Alentejo, where water scarcity and heat stress reduce productivity in key crops like olives and grapes. Simultaneously, reduced precipitation raises the risk of wildfires, a factor that has contributed to Portugal ranking first among European countries in the area burned by wildfires between 2006 and 2023 (Statista, 2024).

Finally, while irregular rainfall results in urban flooding, rising temperatures hinder the transition to renewable energy by increasing the energy demand for cooling (Adão et al., 2022). These findings underscore the economic risks climate change poses to Portugal's key sectors, emphasising the urgency of sector-specific strategies to bolster resilience and mitigate long-term economic losses.

This research focuses on exploring the effects of temperature and precipitation shocks on labor productivity in Portuguese regions. Specifically, it addresses the following research question: How do temperature and precipitation historical deviations and variability affect labor productivity in Portugal's different regions?

A fixed-effects panel regression is employed to address this question, using annual data from Portugal's NUTS III regions for the period 2008–2022. Two distinct approaches are used: one considers labour productivity at current prices controlling for the effects of inflation, while the other considers a proxy for labour productivity at constant prices. The model also accounts for regional fixed effects to isolate time-invariant regional characteristics and ensure robust estimation. The study focuses on annual data and provides insights into how climate variability interacts with regional productivity.

The structure of the paper is outlined as follows. Section 2 reviews existing literature on the economic impacts of climate change, focusing on productivity, as well as on the methodologies employed in prior studies. Section 3 outlines the data processing techniques and describes the fixed-effects regression model, including the rationale for its two distinct approaches. Section 4 presents and discusses the results, while Section 5 identifies the study's limitations and explores paths for future research. Finally, Section 6 concludes by summarizing the key findings. An appendix provides supplementary information to support the analysis.

2 Literature Review

The previous research on the economic effects of climate change offers the analytical framework and techniques required to investigate how economic systems are impacted by changes in climate patterns. These studies establishe the importance of using rigorous econometric techniques to examine temperature, precipitation, and extreme weather, providing important insights into the mechanisms linking climate and economy. Thanks to their contributions, the field is able to adress important questions about productivity, sectoral dynamics, and growth trajectories over time and across regions.

Dell et al. (2014) emphasise the broad spectrum of economic outcomes affected by climate change, ranging from agriculture to labour productivity and energy systems. Chang et al. (2023) offer a methodological framework to examine temperature impacts on GDP, focusing on growth and level effects while advancing econometric approaches essential for accurate modelling. The sectoral and global ramifications are further explored in the works of Adão et al. (2022) and Burke et al. (2015), which underline the systemic difficulties presented by climate change. Collectively, these studies provide a theoretical and methodological framework for comprehending and measuring the economic effects of climatic variability.

There has been an abundance of scholarly research on the economic implications of climate change, with a substantial amount of literature analysing how it affects macroeconomic factors like GDP and inflation. The financial consequences of climate change, in particular the performance and profitability of firms, have also been object of great interest. This dual emphasis illustrates the extensive and complex effects of weather fluctuations in the macro and microeconomic spheres. Iliyasu et al. (2023) examine the connection between inflation and climate change by looking at how climate variability affects GDP and inflation in the biggest economies in Africa. The study focuses on how temperature anomalies and other climatic disruptions lead to food price inflation, which in turn fuels inflation in consumer prices as a whole. In a similar vein, Jones and Olken (2010) examine how temperature rises affect export performance, highlighting how climate shocks impede trade flows, especially in developing nations and industries dependent on agriculture. At the firm level, climate variability presents mixed outcomes. With an emphasis on how local climate data impacts firms operating in temperature-sensitive regions, Hugon and Law (2023) investigate the economic impact of temperature anomalies on firm profitability in the United States. They find that climate disruptions, such as historical deviations in temperature, have a negative effect on earnings, particularly for firms reliant on stable weather conditions. Anton (2021), on the other hand, examines how rising temperatures affect the profitability of European gas and energy corporations by examining data from 147 companies in 21 nations, including Portugal. His findings reveal that increases in temperature correlate positively with profitability, especially for highly profitable firms, underlining the diverse impacts of climate change across industries and regions.

The implementation of fixed-effects panel regressions has emerged as an essential part of research on the climate economy, offering reliable instruments for isolating the impacts of climate variability on economic outcomes. By accounting for unobserved heterogeneity across regions and time, these models allow for the possibility of capturing causal relationships between climate variables and economic indicators, often focussing specifically on productivity. Dell et al. (2009) employ fixed-effects models to study the short- and long-term link between temperature variations and income, using both country-level and subnational data from the Americas. Similarly, Burke et al. (2015) use country-level fixed effects and quadratic time trends to examine the non-linear effects of temperature on global economic production, identifying a threshold temperature of 13°C at which productivity peaks. Kotz et al. (2021) employ fixed-effects panel regression to investigate how short-term temperature fluctuations affect macroeconomic growth, over 40 years. The study finds that variability increases uncertainty for economic agents, complicating investment and planning decisions, with more severe effects during seasons with reduced adaptive capacity while disproportionately harming low-latitude and low-income regions. Henseler and Schumacher (2019) and Dell et al. (2008) employ fixed-effects regressions to examine the effects of temperature and precipitation on GDP growth. Henseler and Schumacher (2019) emphasize the vulnerability of total factor productivity (TFP) to high temperatures. Precipitation variability is also shown to influence employment levels in poorer countries, with deviations from normal precipitation leading to significant economic disruptions. Both findings demonstrate how fixed-effects models successfully capture global differences in climate impacts by highlighting the disproportionate vulnerabilities of poorer nations to climate anomalies.

Although fixed-effects models predominate in the literature, other approaches have also gained prominence. Chang et al. (2023) discuss the emergence of hybrid models combining linear and non-linear approaches to better address long-term climate trends and thresholds. Similarly, Acevedo et al. (2020) adopt the Local Projection Method (Jordà, 2005) to capture dynamic responses to weather shocks, offering insights into investment and productivity losses over time. These complementing methods offer insightful viewpoints, especially when examining systemic economic responses to climate variability and longer-term adaptation.

Labour productivity is among the most critical economic variables affected by climate change, with both temperature and precipitation playing significant roles in shaping productivity dynamics. The literature consistently emphasises the nonlinear link between productivity and climate variables, highlighting the differences in their impact depending on the economic activity and region. Dell et al. (2014) document the vulnerability of labour-intensive sectors to rising temperatures, particularly in low-income countries. Their research highlights how productivity losses in these areas are exacerbated by a lack of access to mitigating equipment, such as air conditioning. Wealthier nations and industries less reliant on physical labour, on the other hand, are better equipped to handle the effects of climate change. However, even in high-income countries, the protective effect of wealth is not absolute. Burke et al. (2015) also came to this result, showing that economic resilience is not immune to the consequences of climate variability. Bijnens et al. (2023) delve deeper into these dynamics within the European Union, offering insights into the nature and mechanisms of climate impacts on productivity. They find that temperature rises have different impacts throughout Europe with moderate warming potentially benefiting colder regions, while on the other hand temperatures beyond 25°C lead to substantial productivity losses in both manual and cognitive tasks. The study states that physical exertion becomes severely limited above a humidity-inclusive temperature of 35°C – a phenomenon increasingly common in Portugal during the summer – and that workers in climate-exposed industries may lose up to an hour of working time on days when temperatures exceed 29°C. Precipitation patterns also show up as important productivity drivers even if water availability and agricultural output are disrupted by erratic rainfall and increased drought risks, particularly in Southern Europe. While cooling systems and protective infrastructure like sea walls are examples of how economies are reacting to climate concerns, Bijnens et al. (2023) alert to the fact that these investments are non-productive, and may potentially divert resources from innovation and long-term productivity growth.

Bijnens et al. (2023) and Dell et al. (2014) clearly identify the broader implications of extreme weather events, such as floods and wildfires, which destroy infrastructure and capital, increasing costs and reducing economic efficiency. In fact, while small-scale disasters may occasionally foster creative destruction, whereby countries take the opportunity to upgrade capital and achieve higher growth rates, this positive effect is entirely absent in the context of large-scale disasters (Bijnens et al., 2023). Furthermore, the research provides substantial evidence of sustained outward migration from areas severely affected by extreme weather events, which exacerbates regional economic disparities and accelerates the relative economic decline of these regions. At the firm level, Hugon and Law (2023) investigate the disproportionate effect of extreme weather occurrences on financial performance, especially in industries that rely significantly on stable weather conditions. Their study incorporates an extreme weather index, which captures the cumulative effects of temperature extremes, droughts, and precipitation events, revealing how these factors amplify operational challenges and reduce profitability. While extreme weather events, such as hurricanes, floods, droughts, and windstorms, are widely acknowledged for their devastating impacts, the academic literature quantifying these effects remains less abundant compared to broader studies on gradual climate change. Nonetheless, the existing research provides valuable insights into both the immediate and long-term economic consequences of such phenomena.

3 Methodology

3.1 Climate Data

The climate data for this study is sourced from the Copernicus Climate Data Store (2024a), a large database containing information dating back to 1940. The data is derived from a combination of satellite observations, weather station measurements and numerical weather prediction models and is available on a high spatial resolution 0.25º x 0.25º grid for every atmospheric variable on hourly (Copernicus Climate Data Store, 2024b) and monthly averaged data (Copernicus Climate Data Store, 2024c).

The research focuses on two key variables: temperature of the air, 2 meters above the surface, (*t2m*) and total precipitation (*tp*) which measures the accumulated liquid and frozen water that falls to the Earth's surface in an hour and in a day for hourly data and monthly averaged data, respectively. To ensure consistency and clarity in the analysis, temperature values are converted from Kelvin (K) to degrees Celsius (°C). Similarly, precipitation values are standardised to mm.day^{-1} (millimeters per day) for ease of interpretation and comparability. For monthly averaged data, the original values in m.day^{-1} (meters per day) are multiplied by 1000. For hourly data, the original values in m.hour^{-1} (meters per hour) are multiplied by 1000 x 24 to account for the daily aggregation of hourly data. All data points located south of 36º latitude or west of -10º longitude were excluded to eliminate observations corresponding to the Azores and Madeira archipelagos. This exclusion was necessary because the climatic conditions in these regions differ significantly from those on the mainland, which could potentially distort the results and reduce the robustness of the analysis.

To assess the effects of deviations from historical averages and the volatility of weather patterns, climate data is considered for two distinctive periods. Monthly averaged data for the 1940-1980 period is used to calculate yearly averages for temperature and precipitation. Following the methodology adopted by a substantial portion of the literature, these values are used to establish the baseline historical mean, representing the climatological norms for this period. They then serve as a reference point when analyzing data for subsequent periods. Hourly data is used to capture day-to-day variability for the 2008-2022 period, which after Moberg et al. (2000) is determined by the intra-monthly standard deviation of daily values. Finally, the intra-monthly standard deviation is averaged yearly to obtain the variability of temperature and precipitation for each year, *t2m_std* and *tp_std*, respectively. Climate data for this period is additionally used to calculate annual averages, that are employed to determine deviations from the established historical means for each year, *t2m_hd* and *tp_hd*. A summary of the variables used is available in Appendix A1

Following Kotz et al. (2021), the processed climate data for each grid point is then spatially aggregated by determining the area-weighted contribution of each grid cell that is located inside the administrative borders of the NUTS III regions in mainland Portugal, ensuring that climate variables are properly represented at the regional level while considering the dataset's spatial heterogeneity and consequently its regional effects. This method is described in detail by Pandit (2024, 38–41).

3.2 Economic Data

Information on labour productivity is obtained via Instituto Nacional de Estatística (2023). Specifically, it provides yearly data on the apparent labour productivity of businesses, *ALP*, expressed in euros and broken down per region, more precisely NUTS III, and by economic activity, ranging from 2008 to 2022. For the purposes of this study, the breakdown per economic activity is not considered. Instituto Nacional de Estatística (INE) defines apparent labour productivity as the gross value added (GVA), at current prices, generated per unit of personnel employed (see Appendix A2).

To obtain labour productivity values that reflect GVA at constant prices, the *ALP* is adjusted using a deflator, resulting in the calculation of ALP_{real}. The deflator is derived from two time series provided by INE at a national level: one for GVA at current prices (Instituto Nacional de Estatística, 2024b) and another for GVA at constant 2021 prices (Instituto Nacional de Estatística, 2024a), covering the analysis period. The deflator is computed by dividing the GVA series at current prices by the corresponding series at constant prices, yielding a time series that is used to adjust *ALP* for inflationary effects. All regions are deflated by the same time series due to lack of subnational data.

The consumer price index, *CPI*, serving as a measure of inflation, is used as a control variable. The data, spanning the period from 2008 to 2022, is disaggregated at the NUTS II regional level and sourced from Instituto Nacional de Estatística (2024c). Since this study focuses on NUTS III regions, it is assumed that each NUTS III region shares the same inflation level as the NUTS II region to which it belongs.

To include education level as a control variable in this analysis, the percentage of employees with higher education qualifications, *educ*, is considered. This is defined as holding at least a bachelor's degree or an equivalent or higher qualification (see Appendix A3 for more details). This information is broken down at the NUTS II regional level and can be found in the "Quadros de Pessoal" annual reports of the Gabinete de Estratégia e Planeamento (GEP) (2023), which have been available for the last two decades. In line with the approach taken for *CPI*, it is assumed that each NUTS III region shares the same education level as its corresponding NUTS II region. Data on self-employed individuals is not considered.

3.3 Model

This study employs a fixed-effects panel regression to estimate the relationship between weather variability and labour productivity by analysing dynamic patterns across multiple regions and years. The fixed-effects panel model is particularly appropriate for this analysis as it considers the effect of unobserved, time-invariant regional factors, such as geographic and structural characteristics, that could bias the results. By focusing on changes within regions over time, the model isolates the effects of weather variability while accounting for other unobservable factors that remain constant.

Two distinct approaches are considered for this analysis. For the first approach, labour productivity at current prices is used as the dependent variable, with inflation included as a control variable to account for its effects on this measure of productivity. The second approach focuses on a proxy for labour productivity at constant prices, which is calculated by deflating the values at current prices considered in the first approach.

Approach 1: Labour Productivity at Current Prices Controlled for Inflation

For this approach, the dependent variable is the natural logarithm of labour productivity at current prices. The natural logarithm is applied to simplify the analysis, allowing variability changes to be interpreted as percentage changes rather than absolute differences. To account for the effect of inflation, which naturally increases the value of GVA and, consequently, *ALP*, we include *inflation* as a control variable, ensuring that the impact of the other independent variables on productivity is not overestimated. Furthermore, the education level is also considered by including *educ* as a control variable. The model can be described as follows:

$$\begin{aligned} \ln(\text{ALP})_{it} = \alpha_i + \beta_1\, t2m\_hd_{it} + \beta_2\, tp\_hd_{it} + \beta_3\, \ln(t2m\_std_{it}) \\ +\beta_4\, \ln(tp\_std_{it}) + \beta_5\, educ_{it} + \beta_6\, CPI_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

where $i = 1, 2, \ldots, 23$ (regions of mainland Portugal) and $t = 1, 2, \ldots, 15$ (years of yearly data). α_i captures unobserved time-invariant region-specific effects and ϵ_{it} is the error term.

Approach 2: Labour Productivity at Constant Prices Proxy

For this approach, the dependent variable is the natural logarithm of labour productivity at constant prices. As for the previous approach, the natural logarithm is applied to simplify the analysis. While we once again consider the education level by including *educ*, inflation is taken into account exclusively through the dependent variable, as explained in the Economic Data section. The model is specified as follows:

$$\ln(\text{ALP}_{\text{real}})_{it} = \alpha_i + \beta_1\, t2m\_hd_{it} + \beta_2\, tp\_hd_{it} + \beta_3\, \ln(t2m\_std_{it}) + \beta_4\, \ln(tp\_std_{it}) + \beta_5\, educ_{it} + \epsilon_{it} \tag{2}$$

where, as before, i and t represent region and time, respectively, α_i captures unobserved time-invariant region-specific effects and ϵ_{it} is the error term.

The two fixed-effects panel regressions employed in this study operate under several key assumptions. First, the error terms ϵ_{it} are assumed to have a mean of zero and to be uncorrelated with the independent variables, which ensures their exogeneity and allows for unbiased and consistent parameter estimates. To account for potential heteroskedasticity and autocorrelation within regions over time, while maintaining the assumption of independence across regions, robust standard errors clustered by region are employed. This approach ensures the model remains robust to violations of homoskedasticity and serial independence. Finally, it is assumed that all variables are stationary, as non-stationary data could lead to spurious regression results. This assumption will be tested and discussed in the Results section below.

It is also important to carefully assess the possibility of introducing year-fixed effects. While year-fixed effects are usually beneficial for addressing time-specific influences, their introduction in this scenario would likely be counterproductive. Given the relatively short time frame of analysis and the large number of regions under study, the incorporation of year-fixed effects would lead to a loss of degrees of freedom. Moreover, year-fixed effects absorb shocks common to all regions, including those directly related to the independent variables. Therefore, a climate shock imposed on the whole country, which could have a meaningful impact on productivity, would actually be disregarded by the model.

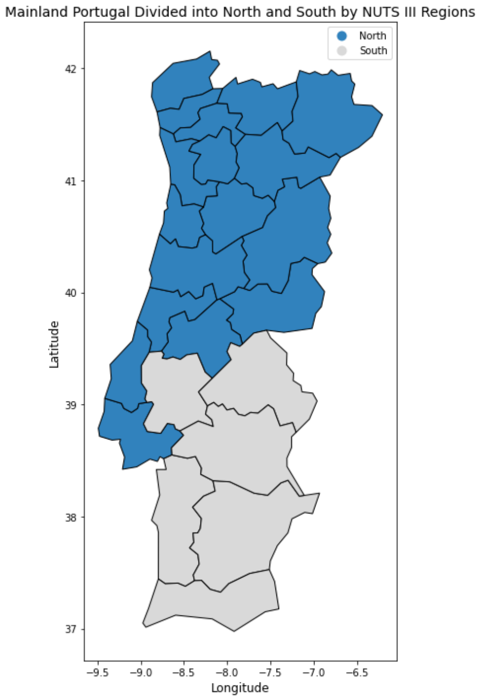

Figure 1: Portugal NUTS III regions grouped by North and South

To evaluate the varied impacts of climate change on labour productivity across the country, the analysis is conducted not only at the national level, encompassing the entire panel, but also by disaggregating the 23 regions of mainland Portugal into two distinct groups (see Appendix A4): North and South, as shown in Figure 1. This approach aims to explore potential regional heterogeneities in the effects of climatic variables, investigating whether these variables exert differential impacts on labor productivity across two distinct regions of the country, characterised by markedly different socio-economic profiles. Such regional differentiation is critical for understanding localised vulnerabilities and informing targeted policy interventions. The Lisbon Metropolitan Area (”Área Metropolitana de Lisboa (PT170)”) is classified as part of the northern region due to reasons described in the end of the Discussion section.

4 Results

4.1 Stationarity

To ensure reliable and robust results, all independent and dependent variables are tested for stationarity. To address the potential over-rejection bias often associated with conventional tests like Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS) — which may arise due to cross-sectional dependence among the data — the advanced methodology proposed by Demetrescu et al. (2006) is employed. This method combines the significance levels of correlated test statistics to improve reliability and minimise the risk of drawing wrong conclusions regarding stationarity, guaranteeing that dependencies across panel units have little impact on the results of this test.

The results presented in Table 1 reveal that all eight variables exhibit combined Z-scores exceeding the critical values across all tested confidence intervals. This holds true both for the full panel and for the subsamples representing the Northern and Southern regions. These findings provide robust evidence in favour of stationarity across the panel.

Table 1: Combined Z-Scores for Panel Stationarity Tests

Variable	**Full Panel**	**North**	**South**
ln_ALP	-31.07	-30.19	-10.67
ln_ALP_real	-10.75	-14.67	2.70
t2m_hd	7.14	5.49	4.64
tp_hd	38.37	40.89	7.73
ln_t2m_std	21.40	17.70	12.04
ln_tp_std	32.69	31.82	11.16
educ	-6.04	-15.93	13.14
CPI	-33.96	-29.05	-17.65

Note: We reject the H_0 of existence of unit root if $|\text{Z-score}| > \text{CV}$. CV = 2.576 (99%); 1.960 (95%); 1.645 (90%).

4.2 Approach 1: Labour Productivity at Current Prices Controlled for Inflation

The regression is first run across the panel following the methodology outlined above. Complete outputs are available in section A5 of the Appendix. From the initial results, it is evident that temperature variability (*ln_t2m_std*) does not have a significant impact on labour productivity (**p-value: 0.832**). To improve the clarity of the analysis and ensure that only statistically meaningful predictors are considered, this variable is excluded from the subsequent regression.

ln_ALP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0306088	.0109228	2.80	0.010	.0079562	.0532614
tp_hd	.0301183	.010889	2.77	0.011	.0075359	.0527008
ln_tp_std	-.1195874	.0665235	-1.80	0.086	-.2575487	.018374
educ	.0103887	.0075553	1.38	0.183	-.0052801	.0260576
CPI	.0104254	.0025252	4.13	0.000	.0051884	.0156624
_cons	8.800785	.2411877	36.49	0.000	8.300592	9.300978

Figure 2: Adjusted Regression Output: Full Panel

In the adjusted regression, both temperature and precipitation historical deviations emerge as statistically significant predictors. Specifically, a 0.1°C increase in temperature is associated with a **0.306%** increase in labour productivity, while a 0.1 mm.day^{-1} increase in precipitation is linked to a **0.301%** increase in productivity. Additionally, a **1%** increase in precipitation variability (*ln_tp_std*) is estimated to reduce labour productivity by **0.12%**. However, this result is statistically significant only at the 90% confidence level. The results also highlight the significant role of inflation (*CPI*) as a driver of labour productivity measured at current prices (**p-value: 0.000**). In contrast, the education level (**p-value: 0.183**) is not statistically significant at any conventional confidence level.

The same methodology is applied to the analysis of the northern and southern regions. In the case of the northern regions, temperature variables — both historical deviations (**p-value: 0.272**) and variability (**p-value: 0.467**) — are excluded from the regression due to their lack of statistical significance.

ln_ALP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
tp_hd	.0432684	.0143735	3.01	0.008	.0127979	.0737389
ln_tp_std	-.2164054	.0872272	-2.48	0.025	-.4013188	-.0314919
educ	.0164203	.0083329	1.97	0.066	-.0012447	.0340853
CPI	.007983	.0030106	2.65	0.017	.0016007	.0143652
_cons	9.136745	.3340817	27.35	0.000	8.428523	9.844966

Figure 3: Adjusted Regression Output: Northern Regions

For the adjusted regression, the results suggest that a 0.1 $mm.day^{-1}$ increase in the historical deviation of precipitation is associated with a **0.433%** increase in labour productivity. Conversely, a 1% increase in precipitation variability corresponds to a **0.22%** decrease in labour productivity. Inflation remains statistically significant, while education emerges as statistically significant at the 90% confidence level, contrasting with its relatively limited importance in the national-level analysis.

In the southern regions of the country, precipitation variables, including both historical deviations (**p-value: 0.318**) and variability (**p-value: 0.968**), are found to lack statistical significance and are therefore excluded from the regression.

ln_ALP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0825673	.0175912	4.69	0.005	.0373478	.1277869
ln_t2m_std	-.1843204	.1044419	-1.76	0.138	-.4527967	.0841559
educ	.0069794	.0149203	0.47	0.660	-.0313745	.0453334
CPI	.010984	.005392	2.04	0.097	-.0028764	.0248445
_cons	8.758085	.3788628	23.12	0.000	7.784187	9.731983

Figure 4: Adjusted Regression Output: Southern Regions

Among the variables retained in the model, temperature historical deviations emerge as the most significant determinant of labour productivity. The findings indicate that a 0.1ºC increase in the average annual temperature would explain a **0.826%** rise in labour productivity. Inflation continues to exhibit statistical significance but only at the 90% confidance level, while education does not appear to play a significant role (**p-value: 0.660**). Additionally, no evidence supports the significance of temperature variability (**p-value: 0.138**) within any confidence interval, even when education is excluded from the model.

4.3 Approach 2: Labour Productivity at Constant Prices Proxy

In this approach, the regression is conducted across the panel, now using a proxy to apparent labour productivity converted to constant prices. Unlike the first approach, inflation is no longer included as a control variable. Consistent with the findings of the first approach, temperature variability is not statistically significant (**p-value: 0.919**) at any confidence interval and is therefore excluded from the model.

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0135452	.0090543	1.50	0.149	-.0052323	.0323227
tp_hd	.0250331	.0082995	3.02	0.006	.007821	.0422452
ln_tp_std	-.123981	.0511347	-2.42	0.024	-.230028	-.0179341
educ	.0102174	.0042908	2.38	0.026	.0013188	.019116
_cons	9.958275	.1338688	74.39	0.000	9.680648	10.2359

Figure 5: Adjusted Regression Output: Full Panel

For the national-level analysis, precipitation emerges as a strongly significant variable, with a 0.1 mm.day^{-1} increase in average precipitation associated with a **0.250%** increase in labour productivity. Conversely, precipitation variability has a detrimental effect, as a 1% increase in variability leads to a **0.12%** reduction in productivity. Notably, education exhibits a marked improvement in significance compared to the first approach, being statistically significant at the 95% confidence level and contributing positively to labour productivity. In contrast to what is observed using the first approach, temperature deviations are not statistically significant at any confidence level.

In the northern regions of the country, as observed in the previous approach, temperature deviations (**p-value: 0.955**) and variability (**p-value: 0.450**) do not demonstrate statistical significance and are therefore excluded from the analysis.

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
tp_hd	.0325628	.0106918	3.05	0.008	.0098972	.0552284
ln_tp_std	-.1829179	.0641084	-2.85	0.012	-.3188216	-.0470143
educ	.0102455	.0052294	1.96	0.068	-.0008403	.0213313
_cons	10.07051	.1735615	58.02	0.000	9.702578	10.43845

Figure 6: Adjusted Regression Output: Northern Regions

For precipitation, the findings suggest that a 0.1 mm.day^{-1} increase in average precipitation leads to a **0.326%** increase in labour productivity while a 1% rise in precipitation variability results in a **0.18%** reduction in productivity. Additionally, education continues to exhibit statistical significance in this regional analysis, contributing positively to labour productivity in the northern regions, but only at the 90% significance level.

In the southern regions, precipitation variability (**p-value: 0.611**) and historical deviations (**p-value: 0.203**) are excluded from the model, confirming the findings observed in the first approach.

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.051209	.0093733	5.46	0.003	.027114	.0753039
ln_t2m_std	-.1486882	.0991976	-1.50	0.194	-.4036839	.1063075
educ	.0125298	.0037211	3.37	0.020	.0029645	.0220952
_cons	9.871098	.1263572	78.12	0.000	9.546286	10.19591

Figure 7: Adjusted Regression Output: Southern Regions

For the adjusted regression, the results indicate that education is statistically significant at the 95% confidence level, contrasting with the results for Approach 1. As in any other previous scenario, there is no evidence that temperature variability is statistically significant. On the other hand, a 0.1ºC increase in temperature historical deviations is associated with a **0.512%** increase in labour productivity in the southern regions.

4.4 Discussion

Figure 8 illustrates the p-values associated with the climate variables across different regions and approaches. The bars represent the statistical significance of each variable, with confidence thresholds highlighted by horizontal lines.

A comparison of the two approaches reveals consistent evidence that temperature variability does not impact labour productivity, as it lacks statistical significance at both the national and regional levels in both models. However, temperature historical deviations exhibit a positive effect on productivity in the southern regions of Portugal, with increases of **0.51–0.83%** associated with a 0.1°C rise in average annual temperature. For the northern regions, there is no evidence to suggest that temperature historical deviations influence productivity. At the national level, the findings are less conclusive, with statistical significance observed in one approach but absent in the other.

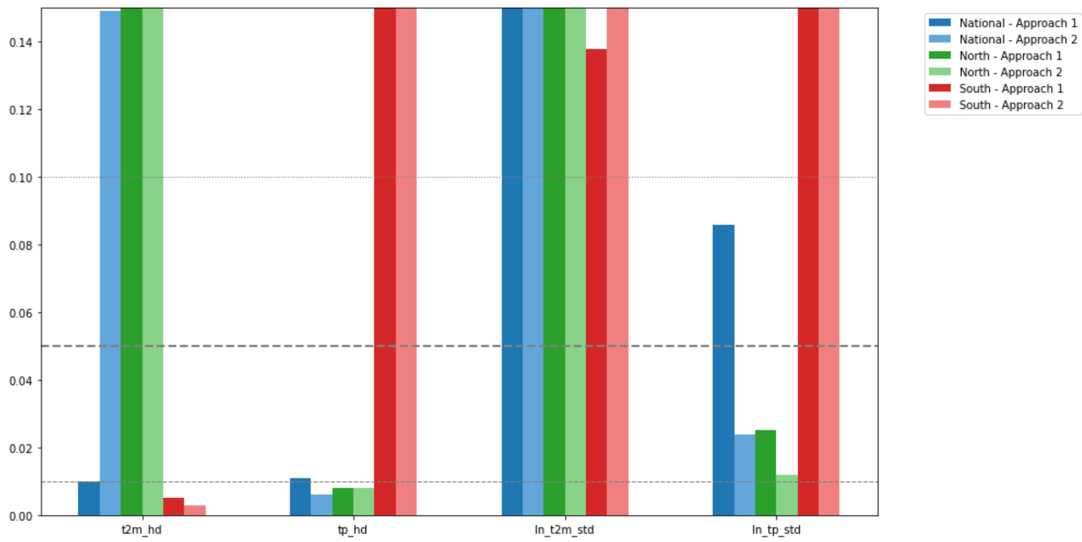

Figure 8: P-Values for Climate Variables Across Regions and Approaches

These findings stand in contrast to the prevailing literature on the subject, which typically identifies rising temperatures as detrimental to economic outcomes. For instance, studies such as Adão et al. (2022) and Dell et al. (2008) consistently document declines in GDP growth associated with higher temperatures. While existing research emphasises the non-linear effects of temperature on productivity and economic performance, with studies like Burke et al. (2015) and Bijnens et al. (2023) identifying specific thresholds until which productivity benefits from increasing temperatures, the average temperatures in southern Portugal already exceed this optimal point, suggesting that the positive relationship between temperature and productivity may actually be a consequence of the nature of the dependent variable. Moreover, the absence of non-linear temperature terms in the model could have misattributed the observed productivity increases to linear temperature effects. Finally, it is also important to note that this result is limited to the interior regions of southern Portugal. In fact, a thorough analysis of data by region reveals that no statistical evidence is found to support that positive deviations in temperature lead to increased productivity in the two coastal regions of the south.

Nonetheless, the inconclusive findings at the national level and the lack of statistical significance in the northern regions are supported by Bijnens et al. (2023), who observe that the impact of temperature deviations and variability, while generally negative for southern European countries, does not achieve statistical significance in their analysis.

With respect to precipitation, both models yield consistent results. Positive deviations of 0.1 mm.day^{-1} from historical precipitation averages are associated with productivity increases of approximately **0.25–0.30%** at the national level, with this effect amplifying to **0.33–0.43%** in the northern regions. Precipitation variability demonstrates a negative impact on productivity, with a 1% increase in variability reducing productivity by **0.18–0.22%** in the northern regions and by **0.12%** at the national level, though the evidence is less robust in the latter case. Notably, neither approach identifies a statistically significant relationship between precipitation deviations or variability and productivity in the southern regions of the country.

Given the linear structure of the model, it can be inferred that the trend of decreasing precipitation levels exerts a negative impact on productivity, as evidenced in both the full panel and northern region analyses. On the other hand, increased precipitation volatility also leads to a decrease in productivity in these regions. These results align with the prevailing literature, particularly regarding precipitation variability. Specifically, Adão et al. (2022) argue that shifts in precipitation patterns significantly affect water-intensive industries, agriculture, and urban infrastructure, a point also highlighted by Dell et al. (2014). Furthermore, reduced precipitation levels, coupled with rising temperatures, intensify drought conditions, compounding their adverse effects. Henseler and Schumacher (2019) corroborate these observations, attributing the detrimental impact to the uncertainty introduced by irregular precipitation patterns.

The results also suggest that the southern regions of Portugal are statistically unaffected by precipitation-related variables. The existing literature supports this finding, noting that the northern interior is a pocket of significant precipitation reduction in the 1950–2020 period (Adão et al., 2022) and that the north is more vulnerable to precipitation variability compared to the rest of the country, a pattern corroborated by the data (see Figure 9). Furthermore, the south's semi-arid climate, characterized by historically lower and more erratic rainfall, has probably incentivised the adoption of agricultural practices less dependent on precipitation. For example, Vicente (2019) highlights that while the North and Center regions remain reliant on precipitation, Alentejo, and the Algarve rely predominantly on irrigation systems, which are less susceptible to fluctuations in precipitation patterns. Finally, the South's reliance on tourism provides additional context for the apparent lack of sensitivity to precipitation-related variables in this region.

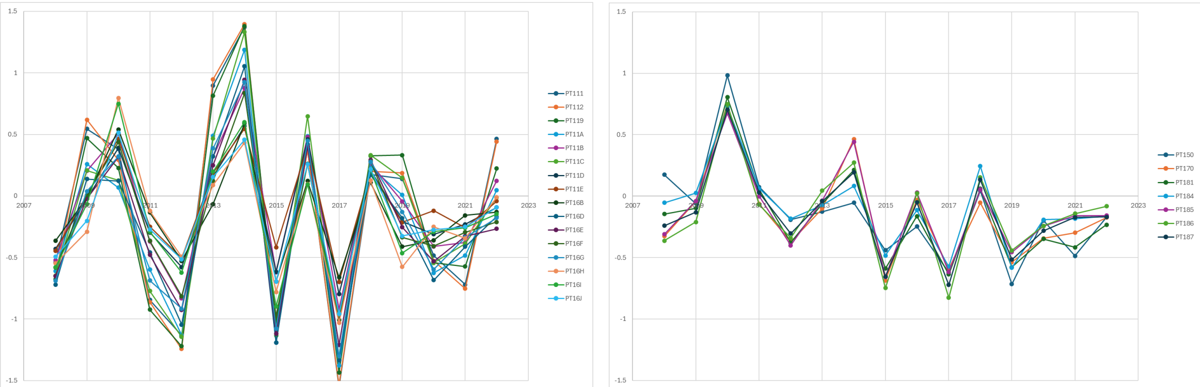

Figure 9: Average Annual Precipitation Variability in mm.day^{-1} for Northern Regions (left) and Southern Regions (right)

Both approaches show that the education level of the workforce emerges as a statistically significant driver of productivity in the northern regions, although with p-values slightly above the 0.05 threshold, underscoring the importance of controlling for this variable. For the southern regions and at the national level, education is strongly significant in Approach 2 but falls short of significance in Approach 1, providing some indication of its relevance in the overall analysis.

In this study, the Lisbon Metropolitan Area ("Área Metropolitana de Lisboa (PT170)") is classified as part of the northern region due to the comparable sensitivity of labour productivity to climate variables, which aligns more closely with northern regions than with southern ones. However, when this region is grouped with the south, the overall results remain consistent, although with reduced statistical significance.

5 Limitations & Further Research

This study sets a foundation for future analyses on the impact of climate change on labour productivity in Portugal, an area of growing importance. However, several limitations, primarily related to data availability, have constrained the depth of the analysis. The most significant limitation is the restricted availability of labour productivity data — or other economic proxies — at the subnational level, which is only accessible on a yearly basis. This limitation poses major challenges for capturing the nuanced impacts of extreme events and seasonal phenomena on productivity. One critical consequence of relying on yearly data is the loss of detailed information on short-term climatic events, such as heatwaves or floods, that are likely to hinder productivity during specific months or quarters. Aggregating climate data to annual averages smooths out these extreme variations, significantly reducing their dimension. Consequently, the inability to capture these events in their temporal context reduces the model's ability to reflect the real-world effects of climate variability on labour productivity.

This limitation also precludes the inclusion of non-linear terms in the model. In fact when using yearly data in this model, the use of squared or cubed terms for the historical deviations variables leads to a lack of statistical significance for these terms rather than enhancing the model's ability to detect non-linear relationships. In these circumstances these higher-order terms lack theoretical justification and may introduce noise instead of improving explanatory power.

Access to quarterly data would resolve many of these challenges. It would enable researchers to test the impact of extreme weather events, which the literature consistently identifies as highly detrimental to economic activity and productivity.

Moreover, the use of quarterly data would reduce the susceptibility of the model to uncontrolled variables, such as region-specific changes, which could cause moderate and progressive shifts in productivity over time. These influences are more likely to distort yearly data and would tend to be less impactful at the quarterly level.

The challenges previously outlined are further exacerbated by the limited number of observations, primarily resulting from the availability of productivity data only for the past 15 years.

Expanding the temporal scope of the data, ideally starting in the late 20th century, would address this limitation in several ways. A longer time frame would not only increase the number of observations, but would also enable the model to capture long-term trends, such as sustained increases in warming and decreases in precipitation. By including data from earlier decades, the analysis could better reflect the gradual evolution of climate patterns over time, rather than being confined to a relatively short period characterized by high deviations from the historical 1940–1980 climate standards but limited variation within the period under of observation. This extended perspective would provide a more robust basis for understanding how gradual climatic changes interact with economic productivity, offering insights into both long-term trends and the short-term impacts of extreme deviations.

Accounting for the effects of inflation is critical, as demonstrated by the results of the model. Failing to address this issue and relying solely on productivity on current prices would artificially inflate the impact and statistical significance of climate change on productivity, as previously discussed. However, addressing inflation at the subnational level poses significant challenges due to the unavailability of productivity data at constant prices. To address this limitation, one potential solution is to control for inflation effects using the consumer price index. While this approach provides some degree of adjustment, it is not entirely accurate, as consumer inflation does not perfectly reflect the rate of change of prices at the production level. An alternative approach is to deflate productivity at current prices. However, as described in the methodology, the deflator is only available at the national level. While this method ensures a more accurate adjustment for inflation, it diminishes the model's ability to detect regional differences, as regional variations in inflation are not accounted for. Both approaches involve trade-offs in the pursuit of accurately capturing the true relationship between climate change and productivity, highlighting the need for more granular economic data at the regional level.

A similar issue emerges when attempting to control for education, as data on educational attainment is only available at the NUTS II level, which encompasses just five regions — far fewer than the 23 regions analysed in this study.

Future research should address the limitations of this study by improving data resolution and scope, including access to quarterly or monthly productivity data, extending the temporal range to capture long-term climate trends, developing region-specific inflation adjustments, and incorporating finer educational data. It should also explore the non-linear and interactive effects of climate variables to better understand regional vulnerabilities and control for the effects of external variables like tourist inflows, contributing to more accurate results. Beyond these technical improvements, future research should also examine the role of adaptation and mitigation policies in shaping the relationship between climate change and productivity. Comparing regions with differing policy measures could offer valuable insights into strategies that effectively reduce climate vulnerability and enhance resilience, providing actionable recommendations for policymakers to address the economic challenges posed by climate change.

6 Conclusion

This study aimed to assess the short-term effects of temperature and precipitation deviations and variability on labour productivity in Portugal's NUTS III regions. By employing a fixed-effects panel regression with annual data spanning from 2008 to 2022 and measuring labour productivity using GVA, two distinct methodological approaches were implemented: one using labour productivity at current prices and inflation as a control variable and the other employing a proxy for labour productivity at constant prices. The research question guiding this analysis focused on whether deviations from historical climatic norms, as well as intra-monthly variability, significantly influence regional productivity. The model incorporated region-specific fixed effects to account for unobservable heterogeneity, ensuring robust estimates of climate's impact on productivity.

A comparison of both approaches reveals that precipitation historical deviations and variability are statistically significant at the national level and within the Portuguese northern regions. Lower precipitation levels and greater variability negatively impact labour productivity which is consistent with the findings of Adão et al. (2022) and Dell et al. (2014). In contrast, temperature variability shows no statistically significant relationship with labour productivity. Aligning with the findings of Bijnens et al. (2023), temperature historical deviations are not statistically significant in the northern regions while at the national level there are contradicting signs regarding its significance. However, in the southern regions, increasing temperature deviations exhibit a positive effect on productivity, which contrasts with the majority of the literature eventually as a consequence of the nature of the dependent variable. These findings are limited to the interior regions of southern Portugal since when the two coastal regions of the south are considered individually, no statistical evidence is found to support a causal relationship between temperature and labour productivity.

The limitations encountered in this study highlight the need for more granular and comprehensive data to enhance the understanding of climate change's impacts on labour productivity. The reliance on yearly data constrained the ability to capture the effects of short-term climatic events, such as heatwaves or floods, which likely have significant but transient impacts on productivity. Additionally, being regional productivity data only available at current prices, adjustments for inflation had to be made, eventually leading to approximation errors given the absence of regional price indices. Furthermore, the relatively short time frame of the dataset limited the ability to identify long-term trends or cumulative effects of climate change. Future research should focus on addressing these limitations by leveraging higher-frequency data, such as quarterly productivity and climate statistics. Expanding the temporal scope of analyses to include earlier decades would also provide valuable insights into the evolution of climate impacts over time, enabling more robust and actionable conclusions to guide policy interventions.

The findings of this study underscore significant policy implications. Governments must prioritise strategic investments in technology and infrastructure to enhance the economy's and population's resilience to declining precipitation levels and increasing variability. Such initiatives are essential to mitigate the adverse effects of these climatic trends on productivity and economic stability. Furthermore, regional governments are encouraged to undertake similar research to better comprehend the localised impacts of climate change. This deeper understanding will enable the formulation of targeted adaptation strategies and the development of effective pathways to address the specific challenges posed by climate change to regional economies and communities.

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A Appendix

A.1 Variables Used

Table 2: Summary of Variables Used and their Description

Climate Variables	
t2m_hd	Yearly average deviation from temperature historical means (ºC)
tp_hd	Yearly average deviation from precipitation historical means (mm.day^{-1})
t2m_std	Yearly average day-to-day variability of temperature (ºC)
tp_std	Yearly average day-to-day variability of precipitation (mm.day^{-1})
Economic Variables	
ALP	Apparent labour productivity at current prices (euros)
ALP_real	Proxy for apparent labour productivity at constant prices (euros)
educ	Percentage of employees with higher education qualifications
CPI	Consumer price index

A.2 Apparent Labour Productivity as defined by INE

$$\text{Apparent Labour Productivity} = \frac{\text{Gross Value Added at Factor Costs}}{\text{Number of Employees}} \tag{3}$$

A.3 Education Level

Table 3: Employees by region (NUTS II) of mainland Portugal, broken down by education level (2008)

Niv. Habil.	Total	Bacharel.	Licenc.	Mest.	Dout.	Desconh.
Norte	1038303	18190	90888	5533	1603	2028
Centro	599126	12420	51244	2641	566	4260
Lisboa	937083	26185	148110	8869	1754	10902
Alentejo	175709	2962	12385	699	120	1715
Algarve	144144	2647	10390	591	126	3761

Higher education qualifications is defined as holding at least a bachelor's degree or an equivalent or higher qualification. To calculate percentage of employees with higher education qualifications, *educ*, for each region we use the following method.

$$educ = \frac{\text{Bacharelato} + \text{Licenciatura} + \text{Mestrado} + \text{Doutoramento}}{\text{Total} - \text{Desconhecido}} \tag{4}$$

where, "Licenciatura", "Mestrado" and "Doutoramento" stand for Bachelor's degree, Master´s degree and PhD, respectively. "Bacharelato" is a former academic degree, no longer awarded, and equivalent to the current Bachelor's degree.

A.4 Northern and Southern Regions of Portugal

Table 4: NUTS III Portuguese Regions Grouped by North and South

Northern Regions	**Southern Regions**
Alto Minho (PT111)	Lezíria do Tejo (PT185)
Cávado (PT112)	Alentejo Litoral (PT181)
Ave (PT119)	Baixo Alentejo (PT184)
Área Metropolitana do Porto (PT11A)	Alto Alentejo (PT186)
Alto Tâmega (PT11B)	Alentejo Central (PT187)
Tâmega e Sousa (PT11C)	Algarve (PT150)
Douro (PT11D)	
Terras de Trás-os-Montes (PT11E)	
Região de Aveiro (PT16D)	
Região de Coimbra (PT16E)	
Região de Leiria (PT16F)	
Viseu Dão Lafões (PT16G)	
Beira Baixa (PT16H)	
Beiras e Serra da Estrela (PT16J)	
Oeste (PT16B)	
Médio Tejo (PT16I)	
Área Metropolitana de Lisboa (PT170)	

A.5 Model Outputs

Approach 1: Regression Complete Output - Full Panel

```
Fixed-effects (within) regression               Number of obs     =        345
Group variable: NUTS_ID_num                     Number of groups  =         23

R-squared:                                      Obs per group:
     Within  = 0.5049                                         min =         15
     Between = 0.0684                                         avg =       15.0
     Overall = 0.2015                                         max =         15

                                                F(6, 22)          =     116.34
corr(u_i, Xb) = 0.0075                          Prob > F          =     0.0000

                               (Std. err. adjusted for 23 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
      ln_ALP | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |   .0311071   .0126574     2.46   0.022     .0048574    .0573569
       tp_hd |   .0301931   .0107544     2.81   0.010     .0078899    .0524963
  ln_t2m_std |  -.0125772    .058693    -0.21   0.832     -.134299    .1091446
   ln_tp_std |  -.1197024   .0664546    -1.80   0.085    -.2575209    .0181161
        educ |   .0103521    .007505     1.38   0.182    -.0052123    .0259165
         CPI |    .010348   .0025757     4.02   0.001     .0050063    .0156897
       _cons |   8.819635   .2291831    38.48   0.000     8.344339    9.294932
-------------+----------------------------------------------------------------
     sigma_u |  .18370712
     sigma_e |  .09068594
         rho |  .80406244   (fraction of variance due to u_i)
```

Figure 10

```
Fixed-effects (within) regression               Number of obs     =        345
Group variable: NUTS_ID_num                     Number of groups  =         23

R-squared:                                      Obs per group:
     Within  = 0.5048                                         min =         15
     Between = 0.0620                                         avg =       15.0
     Overall = 0.1971                                         max =         15

                                                F(5, 22)          =     130.21
corr(u_i, Xb) = 0.0027                          Prob > F          =     0.0000

                              (Std. err. adjusted for 23 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
      ln_ALP | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |   .0306088   .0109228     2.80   0.010     .0079562    .0532614
       tp_hd |   .0301183    .010889     2.77   0.011     .0075359    .0527008
   ln_tp_std |  -.1195874   .0665235    -1.80   0.086    -.2575487     .018374
        educ |   .0103887   .0075553     1.38   0.183    -.0052801    .0260576
         CPI |   .0104254   .0025252     4.13   0.000     .0051884    .0156624
       _cons |   8.800785   .2411877    36.49   0.000     8.300592    9.300978
-------------+----------------------------------------------------------------
     sigma_u |  .18431486
     sigma_e |  .09054893
         rho |  .80557505   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Figure 11

Approach 1: Regression Complete Output - Northern Regions

```
Fixed-effects (within) regression               Number of obs     =        255
Group variable: NUTS_ID_num                     Number of groups  =         17

R-squared:                                      Obs per group:
     Within  = 0.5282                                         min =         15
     Between = 0.0600                                         avg =       15.0
     Overall = 0.1756                                         max =         15

                                                F(6, 16)          =      66.98
corr(u_i, Xb) = -0.1335                         Prob > F          =     0.0000

                              (Std. err. adjusted for 17 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
      ln_ALP | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |   .0144668    .012724     1.14   0.272    -.0125068    .0414404
       tp_hd |   .0435009   .0146127     2.98   0.009     .0125233    .0744784
  ln_t2m_std |   .0475547   .0638526     0.74   0.467    -.0878068    .1829161
   ln_tp_std |   -.214897   .0881494    -2.44   0.027    -.4017655   -.0280286
        educ |   .0163857   .0081287     2.02   0.061    -.0008464    .0336178
         CPI |   .0075848   .0030399     2.50   0.024     .0011405     .014029
       _cons |   9.119609   .3015341    30.24   0.000     8.480385    9.758833
-------------+----------------------------------------------------------------
     sigma_u |  .20153223
     sigma_e |  .08792356
         rho |  .84009874   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Figure 12

```
Fixed-effects (within) regression               Number of obs     =        255
Group variable: NUTS_ID_num                     Number of groups  =         17

R-squared:                                      Obs per group:
     Within  = 0.5247                                         min =         15
     Between = 0.0863                                         avg =       15.0
     Overall = 0.1981                                         max =         15

                                                F(4, 16)          =      82.89
corr(u_i, Xb) = -0.1166                         Prob > F          =     0.0000

                                 (Std. err. adjusted for 17 clusters in NUTS_ID)
```

ln_ALP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
tp_hd	.0432684	.0143735	3.01	0.008	.0127979	.0737389
ln_tp_std	-.2164054	.0872272	-2.48	0.025	-.4013188	-.0314919
educ	.0164203	.0083329	1.97	0.066	-.0012447	.0340853
CPI	.007983	.0030106	2.65	0.017	.0016007	.0143652
_cons	9.136745	.3340817	27.35	0.000	8.428523	9.844966
sigma_u	.19767742					
sigma_e	.08786906					
rho	.83501257	(fraction of variance due to u_i)				

Figure 13

Approach 1: Regression Complete Output - Southern Regions

```
Fixed-effects (within) regression               Number of obs     =         90
Group variable: NUTS_ID_num                     Number of groups  =          6

R-squared:                                      Obs per group:
     Within  = 0.5307                                         min =         15
     Between = 0.0131                                         avg =       15.0
     Overall = 0.2327                                         max =         15

                                                F(5, 5)           =          .
corr(u_i, Xb) = 0.0035                          Prob > F          =          .

                                  (Std. err. adjusted for 6 clusters in NUTS_ID)
```

ln_ALP	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0893213	.0149453	5.98	0.002	.050903	.1277395
tp_hd	.0490423	.0441839	1.11	0.318	-.0645361	.1626208
ln_t2m_std	-.2293338	.1148923	-2.00	0.102	-.524674	.0660063
ln_tp_std	-.0052382	.1237887	-0.04	0.968	-.3234473	.3129709
educ	.0119801	.0152983	0.78	0.469	-.0273455	.0513057
CPI	.0102185	.0056571	1.81	0.131	-.0043235	.0247604
_cons	8.815183	.5207013	16.93	0.000	7.476678	10.15369
sigma_u	.16061835					
sigma_e	.0933205					
rho	.74762445	(fraction of variance due to u_i)				

Figure 14

```
Fixed-effects (within) regression               Number of obs     =         90
Group variable: NUTS_ID_num                     Number of groups  =          6

R-squared:                                      Obs per group:
     Within  = 0.5172                                         min =         15
     Between = 0.0105                                         avg =       15.0
     Overall = 0.2249                                         max =         15

                                                F(4, 5)           =      71.22
corr(u_i, Xb) = 0.0040                          Prob > F          =     0.0001

                                   (Std. err. adjusted for 6 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
      ln_ALP | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |   .0825673   .0175912     4.69   0.005     .0373478    .1277869
  ln_t2m_std |  -.1843204   .1044419    -1.76   0.138    -.4527967    .0841559
        educ |   .0069794   .0149203     0.47   0.660    -.0313745    .0453334
         CPI |    .010984    .005392     2.04   0.097    -.0028764    .0248445
       _cons |   8.758085   .3788628    23.12   0.000     7.784187    9.731983
-------------+----------------------------------------------------------------
     sigma_u |  .16090482
     sigma_e |  .09346949
         rho |  .74769489   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Figure 15

Approach 2: Adjusted Regression Complete Output - Full Panel

```
Fixed-effects (within) regression               Number of obs     =        345
Group variable: NUTS_ID_num                     Number of groups  =         23

R-squared:                                      Obs per group:
     Within  = 0.1538                                         min =         15
     Between = 0.0691                                         avg =       15.0
     Overall = 0.0829                                         max =         15

                                                F(5, 22)          =      12.51
corr(u_i, Xb) = 0.0127                          Prob > F          =     0.0000

                                  (Std. err. adjusted for 23 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
 ln_ALP_real | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |   .0137295   .0102971     1.33   0.196    -.0076253    .0350843
       tp_hd |   .0250325   .0083188     3.01   0.006     .0077805    .0422846
  ln_t2m_std |  -.0054509   .0532693    -0.10   0.919    -.1159247    .1050229
   ln_tp_std |  -.1238457   .0520005    -2.38   0.026    -.2316881   -.0160033
        educ |   .0101409   .0040084     2.53   0.019      .001828    .0184539
       _cons |   9.963765   .1128254    88.31   0.000     9.729779    10.19775
-------------+----------------------------------------------------------------
     sigma_u |  .18362933
     sigma_e |  .07873444
         rho |  .84470713   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Figure 16

```
Fixed-effects (within) regression               Number of obs     =        345
Group variable: NUTS_ID_num                     Number of groups  =         23

R-squared:                                      Obs per group:
     Within  = 0.1538                                         min =         15
     Between = 0.0668                                         avg =       15.0
     Overall = 0.0809                                         max =         15

                                                F(4, 22)          =      14.70
corr(u_i, Xb) = 0.0094                          Prob > F          =     0.0000

                                 (Std. err. adjusted for 23 clusters in NUTS_ID)
```

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0135452	.0090543	1.50	0.149	-.0052323	.0323227
tp_hd	.0250331	.0082995	3.02	0.006	.007821	.0422452
ln_tp_std	-.123981	.0511347	-2.42	0.024	-.230028	-.0179341
educ	.0102174	.0042908	2.38	0.026	.0013188	.019116
_cons	9.958275	.1338688	74.39	0.000	9.680648	10.2359
sigma_u	.18385275					
sigma_e	.0786119					
rho	.84543337	(fraction of variance due to u_i)				

Figure 17

Approach 2: Adjusted Regression Complete Output - Northern Regions

```
Fixed-effects (within) regression               Number of obs     =        255
Group variable: NUTS_ID_num                     Number of groups  =         17

R-squared:                                      Obs per group:
     Within  = 0.1751                                         min =         15
     Between = 0.0428                                         avg =       15.0
     Overall = 0.0586                                         max =         15

                                                F(5, 16)          =      10.77
corr(u_i, Xb) = -0.1197                         Prob > F          =     0.0001

                                 (Std. err. adjusted for 17 clusters in NUTS_ID)
```

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0006552	.011557	0.06	0.955	-.0238444	.0251549
tp_hd	.0326891	.0108954	3.00	0.008	.0095919	.0557864
ln_t2m_std	.0464361	.0599246	0.77	0.450	-.0805983	.1734705
ln_tp_std	-.1831922	.0659058	-2.78	0.013	-.3229062	-.0434782
educ	.0107025	.0045247	2.37	0.031	.0011105	.0202945
_cons	10.02281	.1356862	73.87	0.000	9.735172	10.31046
sigma_u	.20139968					
sigma_e	.07655165					
rho	.87376338	(fraction of variance due to u_i)				

Figure 18

```
Fixed-effects (within) regression               Number of obs     =        255
Group variable: NUTS_ID_num                     Number of groups  =         17

R-squared:                                      Obs per group:
     Within  = 0.1728                                         min =         15
     Between = 0.0613                                         avg =       15.0
     Overall = 0.0755                                         max =         15

                                                F(3, 16)          =      16.38
corr(u_i, Xb) = -0.0905                         Prob > F          =     0.0000

                             (Std. err. adjusted for 17 clusters in NUTS_ID)
```

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
tp_hd	.0325628	.0106918	3.05	0.008	.0098972	.0552284
ln_tp_std	-.1829179	.0641084	-2.85	0.012	-.3188216	-.0470143
educ	.0102455	.0052294	1.96	0.068	-.0008403	.0213313
_cons	10.07051	.1735615	58.02	0.000	9.702578	10.43845
sigma_u	.19866333					
sigma_e	.07633231					
rho	.87135924	(fraction of variance due to u_i)				

Figure 19

Approach 2: Adjusted Regression Complete Output - Southern Regions

```
Fixed-effects (within) regression               Number of obs     =         90
Group variable: NUTS_ID_num                     Number of groups  =          6

R-squared:                                      Obs per group:
     Within  = 0.2138                                         min =         15
     Between = 0.0093                                         avg =       15.0
     Overall = 0.0613                                         max =         15

                                                F(5, 5)           =     491.03
corr(u_i, Xb) = 0.0003                          Prob > F          =     0.0000

                              (Std. err. adjusted for 6 clusters in NUTS_ID)
```

ln_ALP_real	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
t2m_hd	.0534266	.007804	6.85	0.001	.0333657	.0734874
tp_hd	.0515565	.0351831	1.47	0.203	-.0388844	.1419975
ln_t2m_std	-.1788905	.1052607	-1.70	0.150	-.4494718	.0916908
ln_tp_std	-.0511782	.0943817	-0.54	0.611	-.2937942	.1914377
educ	.0146664	.0039822	3.68	0.014	.0044297	.0249031
_cons	9.929044	.2390369	41.54	0.000	9.31458	10.54351
sigma_u	.16087828					
sigma_e	.08147609					
rho	.79586968	(fraction of variance due to u_i)				

Figure 20

```
Fixed-effects (within) regression               Number of obs     =         90
Group variable: NUTS_ID_num                     Number of groups  =          6

R-squared:                                      Obs per group:
     Within  = 0.1987                                         min =         15
     Between = 0.0009                                         avg =       15.0
     Overall = 0.0502                                         max =         15

                                                F(3, 5)           =      21.55
corr(u_i, Xb) = -0.0091                         Prob > F          =     0.0027

                               (Std. err. adjusted for 6 clusters in NUTS_ID)
------------------------------------------------------------------------------
             |               Robust
 ln_ALP_real | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      t2m_hd |    .051209   .0093733     5.46   0.003      .027114    .0753039
  ln_t2m_std |  -.1486882   .0991976    -1.50   0.194    -.4036839    .1063075
        educ |   .0125298   .0037211     3.37   0.020     .0029645    .0220952
       _cons |   9.871098   .1263572    78.12   0.000     9.546286    10.19591
-------------+----------------------------------------------------------------
     sigma_u |  .16167428
     sigma_e |  .08123208
         rho |  .79843585   (fraction of variance due to u_i)
```

Figure 21