Università
Ca'Foscari
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in Economics, Finance and Sustainability

Final Thesis

A Panel Data Approach to Estimating the Impact of Climate Adaptation on the Temperature-Labor Productivity Relationship

Supervisors:
Ch. Prof. Enrica De Cian
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Abstract

As climate change is expected to intensify in the coming years, understanding and quantifying the relationship between climate, weather, and economic outcomes is becoming increasingly essential. This thesis employs a high-dimensional fixed effects (HDFE) model to estimate the impact of temperature on sector-specific labor productivity and quantifies the role of adaptation strategies in mitigating these adverse effects. The findings reveal that countries with a high per capita air conditioning stock can effectively mitigate the negative impacts of rising temperatures across many economic sectors. In contrast, countries with limited access to such technologies experience more significant declines in labor productivity due to temperature shocks. Furthermore, the diminishing returns of per capita air conditioning stock on the attenuation of the temperature effect on labor productivity suggest a saturation effect.

Keywords: Adaptation; Damage Function; Labor Productivity; Temperature

Introduction

This thesis estimates the role of climate adaptation in moderating the relationship between temperature and sector-specific labor productivity, aiming to bridge the gap between micro- and macro-level evidence. The structure comprises five chapters. Chapter One provides the theoretical motivations behind the analysis by introducing Integrated Assessment Models (IAMs) and highlighting their importance for optimal policy decisions. It also presents the main methods and discusses related issues in estimating the impact of climate and weather on economic outputs, offering a comprehensive review of the latest findings regarding the effect of temperature on labor productivity at both micro and macro levels. Chapter Two proposes a theoretical model and an associated empirical strategy based on a high-dimensional fixed effects (HDFE) model to estimate the impact of temperature on sector-level labor productivity. This approach explicitly integrates external adaptation strategies as a moderating factor, aiming to reconcile the divergent empirical results across the two scales of analysis. Chapter Three describes and provides context for the main variables used in the empirical model. These variables include proxies for sector-level labor productivity, temperature exposure, and the level of adaptation strategies implemented by each country. Specifically, labor productivity is measured as value added per worker, temperature exposure is quantified using Cooling Degree Days (CDDs), and the proxy for adaptation strategies is constructed as a country-level discounted cumulative sum of the value of imported air conditioning machines over the previous fifteen years. The final section of the chapter outlines the preferred specification of the empirical model implemented in the statistical analysis. Chapter Four presents the main results of the statistical models, addressing the variability in estimated temperature impacts caused by differences in adaptation capacities and sector-level dynamics. Utilizing climate model predictions based on an intermediate scenario, the final section applies these findings to estimate the hypothetical effect on current global labor productivity if the projected 2050 climate conditions were realized today, considering present regional and national adaptation capacities. Chapter Five discusses the results, confirming the essential role of adaptation as a moderating factor in the relationship between temperature and sector-level labor productivity. The concluding section emphasizes the thesis's contribution to bridging the gap between micro and macro-level evidence in the literature, offering promising applications for Integrated Assessment Models (IAMs).

Chapter 1

Literature Review

This Chapter provides the theoretical motivations behind the analysis and is divided into five sections. Section One introduces the Chapter. Section Two describes Integrated Assessment Models (IAMs), highlighting their importance for optimal policy decisions. Section Three presents the Climate Damage Function implemented in these models, discussing the main issues related to its calibration. Section Four analyzes the primary econometric approaches used in the literature to estimate the influence of climate on economic outcomes. Section Five reviews the most relevant evidence concerning the effect of temperature on labor productivity at both micro and macro levels.

1.1 Motivation

The idea that climate can affect our lives is deeply rooted in human history. As reported by Dell, Jones, and Olken (2012), historical evidence of this can be traced back to the writings of the Ancient Greeks and continues through to the Enlightenment where Montesquieu, in his work "The Spirit of Laws" (1748), observed that an *excess of heat* could render people *slothful and dispirited.* This causal relationship has gained particular attention in the literature of the last decades due to the increasing awareness of the possible negative consequences of climate change. Dell, Jones, and Olken (2014) reports that literature on climate and weather economics has concentrated on the impact on various key outcomes, including aggregate economic output, agricultural output, labor productivity, energy demand, health, conflicts, and economic growth, among others. Estimating these causal relationships—referred to as *ex-post analysis*—provides the foundation for *ex-ante modeling*, which seeks to derive future policy implications from established causal or associative relationships. Specifically, Integrated Assessment Models (IAMs) have been the workhorse to guide climate policy design. As the temperature is bound to increase over the next decades, while we must reduce emissions in order to prevent an even more rapid rise in the global average temperature, at the same time we need to cope with a changed climate. IAMs are one of the few economic tools capable of integrating economic decisions related to adaptation and mitigation with the physical and biophysical dynamics of our planet and climate. The next section provides a short description of this tool, explaining how this thesis provides an important contribution to that literature as well.

1.2 Integrated Assessment Models (IAMs)

The climate literature refers to Integrated Assessment Models (IAMs) as the broad class of models that integrates economic and geophysical information. These models are primarily used to predict climate change evolution and assess its consequences. Usually, the IAMs are built with four main components or *blocks*: a model predicting

the future path of GHG emissions, a model to predict how this GHG path will change the climate, a damage function to quantify the costs of climate change and an aggregated welfare function for aggregating damages over time and across space (Dell, Jones, and Olken 2014).
The pioneer IAM has been the DICE model (W. D. Nordhaus 1991; W. D. Nordhaus 1993), developed by the 2018 Nobel Prize William Nordhaus. More recent examples of DICE/RICE models include (W. D. Nordhaus and Z. Yang 1996; W. D. Nordhaus and Boyer 2003). Other relevant IAMs are the PAGE model (Hope, Anderson, and Wenman 1993; Hope 2006) and the FUND model (R. S. Tol 1999; R. S. Tol 2013). One of the main goals of these models is to obtain the optimal Social Cost of Carbon (SCC), which is the discounted present value of the damages caused by the emission of one additional ton of CO2 equivalent (GHG) at a specific point in time.[1] The SCC is a valuable tool for evaluating the optimal allocation of resources over time, particularly in guiding policy decisions related to climate change mitigation and adaptation strategies. However, it is important to note that this estimate relies on a range of model assumptions that involve significant uncertainty. The main ones in the two geophysical *blocks* involve: the relationship between greenhouse gas (GHG) emissions (flows) and GHG concentrations (stocks), the rate of heat transfer into the deep ocean, and the feedback loops between warming and atmospheric GHG levels (Hegerl et al. 2006; Weitzman 2013). The main uncertainties of the other two economic *blocks* involve: the choice of the discount rate, since the damages have to be inter-temporally allocated; the time horizon; the changes to risks and the reflection of uncertainties (Auffhammer 2018; Rose 2012); the shape of the utility function, since the concavity choice involves re-distributive issues between generation and between rich versus poor countries; the damage function, which has to translate the climate information into economic damages. The choice of the concavity has been commonly addressed with the imposition of the Negishi principle, fixing the current distribution of income over time (Negishi 1972). The debate around the discount rate is instead more controversial since the choice largely affects the amount of the

[1]Note that as the SCC is derived from a dynamic optimization process, and greenhouse gas (GHG) concentrations in the atmosphere are expected to rise over time, the SCC will increase as well (Auffhammer 2018)

SCC. Stern (2007) argues that the choice of the discount rate should be approached as a normative question, subject to ethical debate within society. In contrast, others believe that the discount rate should be determined based on empirical estimates, as discussed by Litterman (2013)) and Weitzman (2013). However, even within this empirical debate, there is disagreement on which specific market discount rate is the most appropriate. Dell, Jones, and Olken (2014) compared different outcomes across some of the most relevant Integrated Assessment Models (IAMs) analysis, demonstrating significant variations in the Social Cost of Carbon (SCC) based on the discount rate used. For instance, W. Nordhaus (2008) estimates the SCC to be $20 when applying a 5.5% discount rate. With a discount rate of 7%, the SCC estimated by Weitzman (2013) would be $1, $21 with a 3% discount rate and $266 with a 1% discount rate. Stern (2007) shows that with a 1.4% discount rate, the SCC is approximately $200.

1.3 The Climate-Damage Function

The other key element of the economic component of Integrated Assessment Models (IAMs) is the climate damage function. This function estimates how fluctuations in climate, particularly temperature changes, impact economic outcomes at specific times. Given its crucial role in the dynamic optimization process underlying the Social Cost of Carbon (SCC), precise calibration based on empirical evidence is essential.

In the DICE model, the production function follows a Cobb-Douglas form, with capital (K) and labor (L) as inputs. The formula also includes an external factor, Total Factor Productivity (TFP), which grows endogenously at a constant rate. This formula represents the economic output, typically measured as GDP, in a world without climate change (Dell, Jones, and Olken 2014). To introduce the climate-damage feedback, the output is reduced using a D(T) factor

$$D(T) = \frac{1}{1 + \pi_1 T + \pi_2 T^2} \tag{1.1}$$

where T represent the period temperature anomalies and π are parameters that must be calibrated. Output is then modeled as

$$Y_t = D(T_t)A_tF(K_t, L_t) \tag{1.2}$$

where $D(T_t) = 1$ denotes the outcome in a world without climate change.[2]
Parameters can be selected in various ways. Historically, calibrating IAMs using empirical estimates has always been challenging, as noted by Dell, Jones, and Olken (2014). For example, the DICE model of W. Nordhaus and Sztorc (2013) has been calibrated using R. S. J. Tol (2009) cross-sectional estimates increased by 25% to account for non-monetized damages like biodiversity, ecosystem services, and potentially catastrophic scenarios. While DICE implements the same damage function for all the world, the PAGE model has been calibrated considering regional-specific parameters (Hope 2006). In the FUND, climate damages are instead calculated at the regional-by-sector level and then aggregated.(R. S. J. Tol 2009). Pindyck (2013) strongly argued that without a precise calibration based on the empirical evidence, Integrated Assessment Models (IAMs) cannot effectively inform us about catastrophic events, which the author identifies as the main drivers of the SCC. In light of these considerations, Dell, Jones, and Olken (2014) highlights a significant opportunity to improve climate damage functions by rigorously incorporating panel data evidence. The discussion on the advantages and disadvantages between different empirical approaches, including cross-sectional and panel data, will be presented in Section 1.4.

Given that the objective of the Integrated Assessment Models (IAMs) is to predict both the short-term and long-term impacts of climate change, a crucial element to keep in mind during the choice of the damage function is that it is involved in a dynamic process. In fact, there are two main drivers that can influence the relationship between temperature and economic outcome over time. The first factor is the functional form of the damage function. It is crucial to determine if the dam-

[2]Abatement costs are omitted to improve the clarity of the exposition.

age function affects the levels of the economic outcomes or its growth rates, and in which way temperature affects the objective outcome. The second relevant factor is the adaptation process, which can gradually smooth the impact of the climate on economic outcomes.

1.3.1 The Functional Form

As Dell, Jones, and Olken (2012) and many other contributions shown, the modeler choice regarding the functional form of the damage function is a crucial aspect of estimating the long-run effect of climate change.[3] The main Integrated Assessment Models (IAMs) assume that climate impacts only the level of economic outcomes, as illustrated in Equation 1.2, with the growth rate of Total Factor Productivity (A) remaining exogenous.

To present the main differences between the two main functional forms, we consider the empirical framework proposed by Dell, Jones, and Olken (2012).[4] In this context, the effects of temperature in a basic economy can be represented as

$$Y_{it} = e^{\beta T_{it}} A_{it} L_{it} \tag{1.3}$$

$$\frac{\Delta A_{it}}{A_{it}} = g_i + \gamma T_{it} \tag{1.4}$$

where Y is aggregate output, L measures population, A measures labor productivity, and T measures weather. Equation 1.3 captures the level effect of weather on production, e.g., the effect of current temperature on agricultural production. Equation 1.4 captures the growth effect of weather, e.g., the effect of temperature on features such as institutions that influence productivity growth. Clearly, both effects can be present in real-world dynamics.

Although in a given year the difference between the two types of effects may ap-

[3] See for example (Dell, Jones, and Olken 2014; S. Hsiang 2016; Heal and J. Park 2016)

[4] The authors report that it is derived from the one proposed by Bond, Leblebicioğlu, and Schiantarelli (2010).

pear not so relevant, their impact on the evolution of the data-generation process is substantial. Dell, Jones, and Olken (2014) shows the consequences of this dynamic assuming that a permanent increase in temperature has the effect of reducing current GDP by 1 percent in a given year. If the function is modeled following a level approach, with an exogenous growth rate, the GDP after 100 years would be reduced by 1 percent. Using a model based on growth impacts, reducing the growth rate by 1 percentage point each year would result in GDP being approximately 63 percent lower.

As remarked by Newell, Prest, and S. E. Sexton (2021), there is no definitive theoretical framework that prescribes a specific, estimable structural relationship between climate variables and economic outcomes. As a consequence, empirical models differ from the choice of the economic relationship (GDP level effects, growth effects, and lag effects) and the temperature functional form. For instance, Dell, Jones, and Olken (2012) employed a log-linear function of temperature and precipitation to estimate the impact on per capita growth, controlling for country-specific and time-related trends. Their findings suggest that aggregate per capita level and growth are both affected by climate variables, but only in poorer countries. Conversely, Burke, S. M. Hsiang, and Miguel (2015b) hypothesized a quadratic relationship between temperature and per capita GDP growth, showing how both rich and poor countries are impacted by climate change. Other studies like (S. Hsiang 2010; Deryugina and S. M. Hsiang 2014; Deryugina and S. Hsiang 2017) postulate a non-linear relationship between daily temperature and income levels, instead of GDP growth. In particular, S. Hsiang (2010) implemented a piece-wise linear production function, showing that losses occur only on days with mean temperature above 27-29°C.

The choice of whether temperature affects the level or the growth of the economic outcomes is not trivial, since, as previously shown, it involves very different predictions in the scale of the long-run damages of climate change. The existing microeconomics literature, like Cachon, Gallino, and Olivares (2012), appears to suggest that the temperature affects the level of the economic outcome, even if the presence of persistent effects does not allow to rule out the possibility of growth rate impacts (Heal and J. Park 2016). Some contributions, such as Dell, Jones, and

Olken (2012) and Burke, S. M. Hsiang, and Miguel (2015b), suggest that high temperatures may slow economic productivity growth by reducing cognitive capacity and diminishing investment in institutions and productive capacity. Newell, Prest, and S. E. Sexton (2021) argue that while these mechanisms are plausible, they have not gained significant attention in the growth literature and currently lack robust empirical support. The literature also disagrees regarding the interpretation of the coefficients associated with lagged temperature variables. For instance, Dell, Jones, and Olken (2012) interprets the sign reversal of the lagged effects as evidence of growth effects, whereas Newell, Prest, and S. E. Sexton (2021) interprets the results as further evidence of level effects.

Another key dimension where the climate-economy literature diverges, as highlighted by Newell, Prest, and S. E. Sexton (2021), is the specification of the function that relates temperature to economic outcomes. For instance, Dell, Jones, and Olken (2012) employs a linear function, implicitly assuming that a temperature shock affects economic outcomes uniformly, regardless of the baseline temperature level. S. Hsiang (2010) uses a piecewise linear function, which allows for asymmetric effects based on deviations from an optimal temperature. Meanwhile, Burke, S. M. Hsiang, and Miguel (2015b) propose a quadratic relationship between temperature and growth, suggesting that warming could enhance growth in colder climates while reducing it in hotter regions.

1.3.2 Adaptation and the Climate-Damage Function

The other dynamic aspect to keep in mind during the estimation of a damage function is the adaptation process. While a formal explanation of this issue will be provided in Section 1.4, the intuition behind it is relatively simple. First of all, the literature refers to *climate* as the statistical moments of the weather distribution over the past 30 years for a specific location. For example, the average temperature in Venice over the last 30 years can represent its climate—although it is essential to account for other moments and variables such as humidity, wind, and precipitation. Weather, on the other hand, can be seen as individual outcomes drawn from this underlying climate distribution. Therefore, climate change is a slow shift in certain

moments of this distribution over time (Auffhammer 2018).
To quantify the economic damage that a shift in distribution will create, it's essential to include how people will react to that shift in the weather distribution. For example, if people believe that heatwaves will be more frequent in the future, they will adapt their behavior by buying more air conditioners. As formalized by Auffhammer (2018), there are two types of responses to climate change: the *extensive margin response*, which involves actions such as installing air conditioning and sea walls, and the *intensive margin response*, which involves more frequent usage of air conditioning and an increasing in energy demand. This means that in the future, the damage of a heatwave to people's health and labor productivity can be lower because they have adapted their behavior to changes in climate distribution. This adaptation process is costly and involves a trade-off.[5] People must determine the optimal level of adaptation by balancing its costs against the expected benefits.
As Dell, Jones, and Olken (2014) report, the main IAMs integrate adaptation processes in different ways. The PAGE model allows the economy to buy units of adaptation that reduce the climate impact up to a certain degree. The FUND model incorporates a sector-specific parameter that reduces climate damage by a constant fraction each year. A major concern is that this parameter is chosen by the modeler and lacks a solid empirical foundation. Anthoff and R. S. Tol (2012) highlighted that the parameters in the FUND model documentation are primarily derived from expert judgments rather than robust data. These observations underscore the urgent need to enhance the credibility of the damage function by more closely aligning its parameters and functional form with empirical evidence.

1.4 Climate Econometrics

To obtain reliable future economic estimates from IAMs, it's fundamental to calibrate the damage function in a way that captures as best as possible the real-world relationship between the climate and the economy. Before analyzing the various research designs implemented in recent climate econometrics literature - following

[5]Someone would say that there's no such thing as a free air conditioner

the framework proposed by S. Hsiang (2016) - it is essential to provide a formal and general definition of "climate" from a statistical perspective.

For any position in space i, there exists a vector of random variables at each moment in time t characterizing the conditions of the atmosphere and ocean that are relevant to economic conditions at i. Heuristically, one could imagine these random vectors as

$$\mathbf{v}_{it} = [\text{temperature}_{it}, \text{precipitations}_{it}, \text{humidity}_{it}, \ldots] \tag{1.5}$$

For an interval in time $\tau = [\underline{t}, \overline{t})$ at i, there exists a joint probability distribution $\psi(\mathbf{C}_{i,\tau})$ from which we imagine $\mathbf{v}_{it}$ is drawn:

$$\mathbf{v}_{it} \sim \psi(\mathbf{C}_{i,\tau}) \quad \forall t \in \tau \tag{1.6}$$

$\mathbf{C}_{i\tau}$ is a vector of K relevant parameters - ideally sufficient statistics - indexed by k that characterizes distributions in the $\psi(.)$ family of distributions, such as location and shape parameters. Define $\mathbf{C}_{i\tau}$ to be the climate at i during τ, as it characterizes the distribution of possible realized states $\mathbf{v}_{it}$.

For each period τ, there is an empirical distribution $\psi(\mathbf{c}_{i,\tau})$ that characterizes the distribution of states $\mathbf{v}_{i,t\in\tau}$ that are actually realized. Note that $\mathbf{c}_{i,\tau}$ and $\mathbf{C}_{i,\tau}$ are vectors of the same length with analogous elements, but they are not the same. $\mathbf{C}_{i,\tau}$ characterizes the expected distribution of $\mathbf{v}_{it}$, whereas $\mathbf{c}_{i,\tau}$ characterizes the realized distribution of $\mathbf{v}_{i,t\in\tau}$. Thus, we describe $\mathbf{c}_{i,\tau}$ to be a description of the weather during τ. S. Hsiang (2016) provides additional examples to allow a better grasp of the theoretical framework. For instance, $\mathbf{c}_{i,\tau}$ could represent the count of observed days with an average temperature exceeding 30°C, while $\mathbf{C}_{i,\tau}$ could denote the expected number of days in this category. Another illustration involves $\mathbf{c}_{i,\tau}$ represented by the mean and standard deviation of daily rainfall during a month, whereas the corresponding $\mathbf{C}_{i,\tau}$ would encompass the true population mean and true population standard deviation of rainfall that could occur during that period.

The main questions that applied econometricians have to face involve the length of the time interval τ considered and how to summarize the joint distribution $\psi(\mathbf{C})$ for the high dimensional vector $\mathbf{v}$. Regarding the first point, historically climate was defined as an average over 30 years, even if this definition is fairly arbitrary. The second issue is more complicated to solve, because, at present, there does not exist an exhaustive list of summary statistics or dimensions of $\mathbf{v}$ which fully describe all social and economic parameters. For example, should a researcher consider only average value and variance or also multiple dimensions of $\mathbf{v}$ such as temperature and humidity simultaneously? S. Hsiang (2016) suggest that even if there is not a clear answer, as current research advances the set of considered summary statistics tends to grow.[6]

S. Hsiang (2016) also formalize how social outcomes at τ are affected by the climate in two ways. A direct one (a hot climate generates heatwaves, which can result in heat exhaustion among individuals) and an indirect one, defined by individual belief over the structure of $\mathbf{C}$, regardless of what $\mathbf{c}$ is realized (if people believe their climate is hot, some will buy air-conditioners). These actions derived by beliefs are defined by the vector $\mathbf{b}$ of length N, indexed by n. The social outcome, such as labor productivity, can thus be characterized as

$$\mathbf{Y}(\mathbf{C}) = Y[\mathbf{c}(\mathbf{C}), \mathbf{b}(\mathbf{C})] \tag{1.7}$$

with $\mathbf{c}(\mathbf{C})$ defined as a realization of weather characteristics $\mathbf{c}$ conditional on climate characteristics $\mathbf{C}$. The total marginal effect of the climate on outcome Y is characterized by the K-element vector of derivatives

$$\begin{aligned}\frac{dY(\mathbf{C})}{d\mathbf{C}} &= \nabla_c Y(\mathbf{C}) \cdot \frac{d\mathbf{c}}{d\mathbf{C}} + \nabla_{\mathbf{b}} Y(\mathbf{C}) \cdot \frac{d\mathbf{b}}{d\mathbf{C}} \\ &= \sum_{k=1}^{K} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{c}_k} \frac{d\mathbf{c}_k}{d\mathbf{C}} \quad \text{(direct effects)} \\ &+ \sum_{n=1}^{N} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{b}_n} \frac{d\mathbf{b}_n}{d\mathbf{C}} \quad \text{(belief effects)}\end{aligned}$$

[6] The empirical part of this thesis is based on "Cooling Degree Days", a summary statistic that quantifies the number and intensity of extreme heat days.

where $\nabla_{\mathbf{c}}$ and $\nabla_{\mathbf{b}}$ are defined as gradients in the subspaces of $\mathbf{c}$ and $\mathbf{b}$, respectively.[7] S. Hsiang (2016) remarks also that all partial derivatives are evaluated *locally* at the current climate $\mathbf{C}$. This point is important, as beliefs about the climate may alter $\frac{\partial Y}{\partial \mathbf{c}_k}$ if the actions individuals take based on these beliefs modify the direct effect of weather realizations $\mathbf{c}$ when they occur (for example, individuals who buy air-conditioners because they believe they are in a hot climate are less susceptible to heat exhaustion during heatwaves). The literature often refers to *adaptation* as such interactions between beliefs and direct impacts $\left(\frac{\partial^2 Y}{\partial \mathbf{b}_n \partial \mathbf{c}_k}\right)$ and belief effects themselves. Although researchers are typically interested in both pathways of influence, credibly identifying the effects of beliefs often poses a challenge due to their unobservability and because they tend to correlate with numerous other factors (S. Hsiang 2016).

Given the formalization above, the ultimate objective of climate econometrics can be understood as the identification of the climate effect on a population or economy, holding other factors fixed. Denoting the vector of observable non-climatic factors that affect the outcome Y as $\mathbf{x}$, S. Hsiang (2016) expresses the average treatment effect β for a change in climate $\Delta\mathbf{C}_{i\tau}$ as:

$$\beta = E[Y_{i\tau} \mid \mathbf{C}_{i\tau} + \Delta\mathbf{C}_{i\tau}, \mathbf{x}_{i\tau}] - E[Y_{i\tau} \mid \mathbf{C}_{i\tau}, \mathbf{x}_{i\tau}]. \tag{1.8}$$

Identifying the real value of β is challenging, as the single population i can never be exposed to both counterfactuals $\mathbf{C}$ and $\mathbf{C} + \Delta\mathbf{C}$ for the exact same interval of time τ. This issue is known by the literature as the *Fundamental Problem of Causal Inference* (Holland 1986).

In an ideal experimental context, β could be recovered assigning at two identical sample populations i and j two different climates (for example, $\mathbf{C}$ at i and $\mathbf{C} + \Delta\mathbf{C}$ at j). The effects of these two treatments on the outcome Y are able to obtain an answer to the main question. If the two populations are identical, the *unit*

[7] Observe that $\frac{d\mathbf{c}}{d\mathbf{C}}$ and $\frac{d\mathbf{b}}{d\mathbf{C}}$ are $K \times K$ and $N \times K$ Jacobians, respectively.

homogeneity assumption must hold :

$$E[Y_{i\tau} \mid \mathbf{C}, \mathbf{x}_{i\tau}] = E[Y_{j\tau} \mid \mathbf{C}, \mathbf{x}_{j\tau}], \tag{1.9}$$

The problem is that the right term is never observed, since we can assign only one $\mathbf{C}$ to a given population at time τ. It is possible to use the observations from the experiment to construct one unbiased estimator

$$\begin{aligned} \hat{\beta} &= E[Y_{j\tau} \mid \mathbf{C} + \Delta\mathbf{C}, \mathbf{x}_{j\tau}] - E[Y_{i\tau} \mid C, \mathbf{x}_{i\tau}] \\ &= E[Y_{i\tau} \mid \mathbf{C} + \Delta\mathbf{C}, \mathbf{x}_{i\tau}] - E[Y_{i\tau} \mid \mathbf{C}, \mathbf{x}_{i\tau}] = \beta. \end{aligned} \tag{1.10}$$

even if $E[Y_{i\tau} \mid \mathbf{C} + \Delta\mathbf{C}, \mathbf{x}_{i\tau}]$ is never observed. Informally, this equivalent to assume that, conditionally on the covariates and for the experimental purpose, the two population can be considered the same. So, by randomly assigning to them two different climates, it is possible to obtain the real value of β. This hypothesis holds in randomized experiments in which is possible to manually assign the climate $\Delta\mathbf{C}$. An example of one of these experiments can be measuring the difference in the score of the same logical test for two classes of randomly extracted students, assigning them to two classes with different climates. In these contexts, Equation 1.10 is sufficient for inference purposes. The main problem with this empirical strategy is that in most real-world cases it is not feasible, sometimes for practical purposes, sometimes for ethical ones, and sometimes for both.[8] In all other cases, an applied researcher requires an empirical design to approximate Equation 1.8 (S. Hsiang 2016). The primary approaches implemented in the climate econometrics literature are outlined below.[9]

1.4.1 Cross-Sectional approaches

In cross-sectional designs, following S. Hsiang (2016) notations, different populations in the same time period τ are compared to one another after conditioning

[8]For instance, randomly assigning a hurricane to different regions of a country can be challenging to implement

[9]For the readers interested in a more comprehensive and advanced explanation of causal inference methods, see Cunningham (2021)

on observable $\mathbf{x}_{i\tau}$. The key assumption of this approach is the *unit homogeneity assumption* as written in Equation 1.9. This implies that the cross-sectional design assumes that, fixed the level of covariates, if two populations have the same climate they will also have the same expected (conditional) outcome. So, all the variations in the observed conditional outcomes are attributed to differences in climate. In a linear framework, following S. Hsiang (2016), the regression equation has the form

$$Y_i = \hat{\alpha} + \mathbf{C}_i\hat{\beta}_{\text{cs}} + \mathbf{x}_i\hat{\gamma} + \hat{\epsilon}_i \tag{1.11}$$

where τ are omitted because the cross-sectional design considers observations during the same period. There, $\hat{\alpha}$ is a constant, $\hat{\gamma}$ are the effects of the observable covariates, and $\hat{\epsilon}_i$ are unexplained variations. In this context, researchers are interested in the vector of parameters $\hat{\beta}_{\text{cs}}$, which is a column vector of coefficients describing the marginal effect of terms in $\mathbf{C}_i$.[10] As described by Dell, Jones, and Olken (2014), i can represent different geographic entities like countries, region or other ones. The outcome variable can be expressed in levels or logs. The error process is typically modeled using robust standard error, often clustered at a larger spatial resolution to allow for spatial correlation in the covariance matrix.[11] The vector $\mathbf{x_i}$ should include all the variables that are correlated with $\mathbf{C}_i$ and affect the outcome of interest. In causal inference terminology, these variables are referred to as *confounders*. Examples of these variables also include exogenous geographic characteristics like elevation and ruggedness (Dell, Jones, and Olken 2014). Excluding some confounders can lead to the well-known issue of the *omitted variable bias* in the estimation of the coefficient of interest (Wooldridge 2010; Cunningham 2021). Given the complexity of accounting for all relevant variables, obtaining an accurate estimate of the true climate coefficients in this context can be extremely challenging.[12]

[10]Note that $\mathbf{C}_i$ is represented by the set of parameters chosen by the researcher to describe the probability distribution of $\mathbf{v}$ at each location i

[11]Other techniques of clustering allow the correlation to decay smoothly with distance Conley (1999)

[12]Dell, Jones, and Olken (2014) highlight the fact that in given circumstances, adding more variables as controls does not necessarily lead to a better estimate of the true coefficient. In fact, if one of these controls is caused by the climate variables and it has an effect on the outcome, this can lead to the *overcontrolling problem*, distorting the estimate of the coefficient of interest. The authors report the example of introducing institutions as a control in a hypothetical regression of

Assuming that all the relevant controls are included in equation 1.11, and without controlling for potentially intervening mechanisms, the equation will estimate the very long-run equilibrium of the relationship between climate and the outcome of interest, including by any sort of adaptation mechanism. The cross-sectional design has been the work-horse of earl empirical analysis on the effect on climate, in particular for the seminal work by Mendelsohn, W. D. Nordhaus, and Shaw (1994), who regresses farm prices in the US on increasing temperature and observable characteristics of the properties (S. Hsiang 2016). Given that the farmers who have lived in a location for a long time know very well the climate - the distribution of the weather - and have expectations about future warming, in a perfect market the prices are able to reflect the full impact of the climate, including the belief effects. The prices of the farms should in fact reflect the discounted present value of expected profits for a given parcel of land (Auffhammer 2018). Even though the ability of this approach to implicitly account for potential mechanisms of adaptation can be considered a strength, climate studies often aim to estimate the contemporaneous effects of temperature on economic activity to assess the potential impacts of forecasted temperatures over the coming decades. The cross-sectional approach may capture mechanisms that operate too slowly to accurately reflect the scale of interest in Integrated Assessment Models (IAMs), or it may include historical dynamics that are unlikely to occur in the future, such as colonialism (Dell, Jones, and Olken 2014).

1.4.2 Panel-Data approaches

Given the interest in estimating the isolated impact of climatic variables, another approach involves the use of longitudinal data- either time series or panel data- to investigate the effects of "weather shocks". The main idea behind this approach, which is the foundation of the empirical part of this thesis, is that instead of assuming that population i and population j are comparable, the same population i can be compared to itself over time and observed in different environmental conditions. The main advantage of this approach is that relies on a weaker version of

national income on temperature.

the unit homogeneity assumption, since it only assumes that a population is comparable to itself across moments in time (S. Hsiang 2016). This approach relies on *weather* variation i.e. short-run temporal variation, instead of *climate variation* i.e. long-run variation in the weather distribution. Given that weather phenomena like temperature and precipitation vary plausibly randomly over time-since they can be considered random draws from the *climate* distribution- the weather-shock approach can rely on strong identification properties (Dell, Jones, and Olken 2014). Following (S. Hsiang 2016) notation, the regression equation in this context takes the form

$$Y_{i\tau} = \hat{\alpha}_i + c_{i\tau}\hat{T}_S + x_{i\tau}\hat{+}\hat{\theta}(i)(\tau) + \hat{\epsilon}_i \tag{1.12}$$

where $\hat{\alpha}_i$ are unit-specific fixed effects that absorb the effect of all time-invariant factors that differ between units, including unobservables that could not be accounted for in the cross-sectional research design. $\theta_{(i)}(\tau)$ are trends in the outcome data, often accounted for using period fixed effects and/or linear or polynomial time trends, which may be region- or unit-specific. The inclusion of these *trend* controls helps to ensure that the relationship of interest is identified from idiosyncratic local shock (Dell, Jones, and Olken 2014). Another relevant methodological decision involves the choice of the inclusion of time-varying observables controls $x_{i\tau}$. Including these controls can help absorb residual variation and improve the estimates of the coefficient of interest. Even if the panel data approach allows to avoid the omitted variable bias caused by unobservable time-constant regressors, it remains vulnerable if there are important time-varying factors that influence the outcome and are correlated with $\mathbf{c}_{i\tau}$ or $\mathbf{x}_{i\tau}$ after conditioning on the trends $\theta_{(i)}(\tau)$ (S. Hsiang 2016). However, Dell, Jones, and Olken (2014) highlight that including regressors that are endogenous to weather variation can introduce the *over-controlling problem* reported in the cross-sectional context. Therefore, there exists a relevant trade-off regarding the inclusion of non-climatic factors $\mathbf{x}_{i\tau}$. Some authors, like Heal and J. Park (2013), added in the regression equation also controls like *human capital* and *the logarithm of the value of the stock of physical capital per capita*, in order to improve the fitting of the *control trend* for the dependent variable. Other contributions caution regarding this idea, because adding factors that are endogenous and affected by the climate can introduce new biases in the coefficients of interest. This situation is know as *bad controls* (Angrist and Pischke 2009; Dell, Jones, and Olken 2014; S. Hsiang 2016). Given the existence of this challenging debate in the literature, the empirical part of this thesis will show the consistency, and the difference, of the results under these different approaches.[13]

Another issue concerns the choice of the functional form of the independent climatic variables. In panel data setups, identification typically relies on deviations from the mean, making the use of level measurements for climate variables a common approach in the literature. Alternatively, applying logarithmic transformations to capture percentage deviations from the mean requires that temperature data be strictly positive. While this condition is satisfied when temperatures are measured on the Kelvin scale, it poses a problem when using Celsius degrees, which can include negative values. Moreover, even when data are converted to the Kelvin scale to ensure positivity, the functional form of the model is still altered. Another common approach that accounts for non-linear effects involves categorizing temperatures into different bins and analyzing the frequency with which temperatures fall into each category. For example, this method might count the number of days in a year that exceeds 33°C. Although this non-parametric technique offers significant theoretical advantages, it requires high-resolution data to be effective. Other approaches rely on climate anomalies (Dell, Jones, and Olken 2014). In general, it is best practice to follow existing research when selecting the most appropriate functional form of the temperature variables, particularly concerning the underlying biological processes. The empirical part of this thesis relies on the concept of "Cooling Degree Days", which accounts for prolonged exposure to temperatures above a specific threshold. As the following section will demonstrate, this choice is guided by the existing literature on the effects of temperature on labor productivity.

Historically, the first to propose this time series approach was likely Huntington (1922). However, it has gained prominence in modern literature after the rele-

[13] A related issue involves the inclusion of lags of the dependent variable in the regression equation. This topic is an active area of research and should be treated with caution due to the assumptions it entails. See Dell, Jones, and Olken (2014) for a more comprehensive discussion.

vant studies of Deschênes and Greenstone (2007) and Auffhammer, Ramanathan, and Vincent (2006), which examine the effects of weather shocks on agricultural outcomes. In this framework, econometric identification is achieved through within-unit, year-to-year variations in weather and economic outcomes (Auffhammer 2018; S. Hsiang 2016).

Considering that the primary goal of most empirical analyses in this field is to estimate statistical relationships that inform society about the potential implications of climate change, the panel approach is well-suited for estimating the contemporary impact of weather shocks—unlike cross-sectional analyses, which typically capture long-run effects. This focus on immediate impacts is exactly what is required for integration into Integrated Assessment Models (IAMs), which aim to estimate future damages resulting from shifts in the distribution of weather patterns. Therefore, the panel data approach offers advantages not only in terms of identification but also in aligning with the theoretical objectives of the analysis (Dell, Jones, and Olken 2014).

The main problem with this approach is that short-run responses to weather shocks are not necessarily analogous to long-run effects. Without a strong understanding of the assumptions underlying a given empirical framework, the applicability of these short-run estimates to the long-run economic impact of climate change can be problematic. Following Dell, Jones, and Olken (2014), the key issues that need to be considered are briefly outlined below.

Adaptation is likely the key challenge that standard panel data estimates can face, particularly when analyzing long-term effects. This issue arises because agents have the capacity to adjust their behavior to mitigate future damages, especially in response to environmental or economic shocks. For instance, in the case of a country experiencing a growing trend in heatwaves during the hotter seasons, it is reasonable to expect that people will adapt by purchasing air conditioners. However, this process of adaptation is gradual and is influenced by several factors, such as *technological opportunities* — which play a significant role, as air conditioners need to be invented, commercialized, and made widely accessible before they can be used as a tool for adaptation — and by the rate of *technical change*, which determines how quickly people can adopt such solutions.[14] This means that, while standard panel models may capture immediate responses, they might fail to fully account for the delayed and gradual nature of behavioral adjustments, leading to upward-biased estimates of the coefficient of interest (Dell, Jones, and Olken 2014). The empirical part of this thesis aims to adjust this bias considering these dynamics.

Intensification of climate effects. It represents a countervailing force to adaptation and may lead to downward bias in the estimate of the coefficient β of interest. This bias arises because climate change can cause significant damages that are not immediately apparent in response to small or short-term weather variations. As noted by Dell, Jones, and Olken (2014), one example is the impact of insufficient precipitation on agriculture. While a single dry year can often be managed by relying on existing water reserves, a permanent decline in rainfall can lead to severe and lasting consequences for agricultural productivity and economic activity. Such intensifying climate effects may not be fully captured by standard panel estimates, which could miss the longer-term, cumulative damage caused by persistent environmental stressors.

General Equilibrium Effects. When considering the macroeconomic effects of climate change, it becomes important to account for general equilibrium adjustments in prices and the reallocation of production factors, such as capital and labor. These adjustments can significantly influence long-term estimates of weather shocks, as the mobility of production factors is crucial in shaping the economic response to climate impacts. If both capital and labor are mobile, the long-term effects of climate change may be mitigated. However, if labor is immobile, regions facing negative climate shocks may experience capital outflows as profitability declines. This, in turn, would further reduce the marginal product of labor in those regions, exacerbating the negative economic impact (Dell, Jones, and Olken 2014).

Extrapolation beyond historical experience. The final issue arises from the uncertainty regarding whether past weather variations adequately capture the range

[14]For example, for a given type of climate, the rate of household ownership of ACs rises with economic development and incomes — very quickly in the case of the hottest and most humid countries (IEA 2018). Colelli, Wing, and Cian (2023) obtain similar results using Cooling Degree Days (CDD) constructed with a threshold of 24°C.

of future changes. This is a key limitation of panel models, which may provide incomplete estimates when projecting extreme future scenarios. For example, since yearly average temperatures rarely deviate by more than 2°C from their historical average, projecting potential damages under a hypothetical scenario of 7°C warming at the end of the century is only reliable if the relationship between variables is linear. If there are non-linearities that differ from those observed in historical data, the estimated coefficients may be biased, leading to inaccurate predictions (Dell, Jones, and Olken 2014).

These considerations highlight that, while the panel approach may accurately estimate the causal effects of weather shocks on current economic outcomes, its application to future projections—especially in catastrophic scenarios—depends on a set of highly specific assumptions. This uncertainty is amplified by the fact that it's challenging to determine which force—adaptation or intensification—will dominate in the long run. Consequently, without a clear empirical strategy, panel estimates cannot be confidently viewed as either a lower or upper bound for future impacts, as they can fail to fully capture the complex and nonlinear dynamics of long-term climate change (Dell, Jones, and Olken 2014).

1.4.3 Hybrid approaches

Motivated by concerns regarding the limitations of both cross-sectional and panel-data approaches, recent years have seen the emergence of hybrid methodologies. One prominent example is the regression strategy proposed by Burke and Emerick (2016), which aims to fully account for observable adaptation in crop yields.[15] It is known as *long-differences approach* and it can be viewed as a cross-sectional comparison of changes over time, providing a way to capture longer-term adaptation that standard methods may overlook. Following S. Hsiang (2016) notation, for two periods of observation $\{\tau_1, \tau_2\}$ the regression is

[15] Other notable contributions related to this approach include: Dell, Jones, and Olken (2012) for climate effects on economic growth, Lobell and Asner (2003) for crop yield impacts, and Burke, S. M. Hsiang, and Miguel (2015a) for climate-related conflicts, as discussed in S. Hsiang (2016).

$$Y_{i\tau_2} - Y_{i\tau_1} = \hat{\alpha} + (\mathbf{c}_{i\tau_2} - \mathbf{c}_{i\tau_1})\hat{\beta}_{LD} + (\mathbf{x}_{i\tau_2} - \mathbf{x}_{i\tau_1})\hat{\gamma} + \hat{\epsilon}_i \tag{1.13}$$

where $\hat{\alpha}$ represents the secular change in Y over time and $\hat{\beta}_{LD}$ represents the extent to which trends in climate are correlated across space with trends in Y. This approach is known as *long differences* because it is primarily used to test whether gradual changes in $\mathbf{c}$ induce gradual changes in Y, so τ_1 and τ_2 are usually chosen to be two periods far apart in time. In their estimation, Burke and Emerick (2016) analyze the differences between five-year moving averages of crop yields taken two decades apart and regress these differences on corresponding five-year moving averages of weather variables, also two decades apart, for all agricultural U.S. counties east of the 100th meridian. The underlying idea is to leverage differential time trends as a source of econometric identification, acknowledging that climate has already changed significantly over the past fifty years (Auffhammer 2018). The results showed that the coefficient calculated using the panel data approach is almost identical to the one found with the long-differences approach. This led them to conclude that gradual changes in $\mathbf{c}$ induce effects similar to more rapid changes in $\mathbf{c}$; that is, long-run adaptation has been minimal in this agricultural context (S. Hsiang 2016; Auffhammer 2018). The advantages of this approach include that it implicitly accounts for long-run adaptation dynamics in a plausibly causal way. Additionally, the distribution of observed climate trends can represent changes similar in magnitude to those expected over the next century. The main problem with this approach is its high data requirements, which can make it inapplicable in some contexts (Auffhammer 2018).

1.5 Labor Productivity

Current research has primarily examined the indirect economic consequences of climate change, such as its effects on crop production and sea levels. However, less emphasis has been placed on the direct channels impacting welfare, which can be critically important. These direct effects include harm to human health, potential decreases in human capital development, and, notably, impacts on labor productivity. All these channels can be considered fundamental drivers in the reduction of aggregate measures of welfare—like GDP—and understanding the climate dynamics that involve labor-related impacts can help improve the functional forms of damage functions in Integrated Assessment Models (Heal and J. Park 2016).

This thesis aims to advance the literature on the impact of temperature on labor productivity, including the mitigating role of adaptation technologies. Accordingly, this section provides relevant background on the current knowledge about the relationship between temperature and labor productivity at the biological, micro, and macro levels.

1.5.1 The Biology of Temperature Stress

Human beings are biological organisms with specific constraints on the environmental conditions necessary to live and function optimally. In particular, humans are easily perturbed and distracted when temperatures deviate above or below our thermal comfort zone—typically between 18°C and 22°C—commonly referred to as room temperature (Heal and J. Park 2016). The body's strategy to dissipate heat involves the production of sweat using water and salt. If exposure to heat is prolonged, many adverse health consequences can occur, such as dizziness, muscle cramps, increased blood viscosity, and cholesterol levels (Deschênes, Greenstone, and Guryan 2009), fever, cardiovascular pressure, inflammation, and many others.[16] Literature has also documented the effects of high temperatures on fetuses, infants, and brain function. Notably, when the wet-bulb temperature (WBT)[17] reaches 35°C, the human body is no longer able to dissipate metabolic heat, and prolonged periods of outdoor activity become impossible. This condition is known as hyperthermia (Lai et al. 2023; Heal and J. Park 2016).

Literature has also demonstrated that temperature can influence human behavior even in non-extreme contexts. In particular, the decline of relative performance starts from 22°C, a small deviation from the optimal zone. This phenomenon has

[16] See (Heal and J. Park 2016) and (Lai et al. 2023) for a more comprehensive list, which includes, among others, respiratory diseases and damage to the immune system.

[17] Temperature indicated by a moistened thermometer bulb exposed to air flow

been shown by numerous lab experiments, where participants were randomly assigned to hotter rooms to perform physical and mental tasks.[18] Interestingly, Seppanen, Fisk, and Lei (2006), in a meta-review, finds that the average productivity decline for temperatures above 25°C is on the order of 2% per degree Celsius, with non-linear responses as the temperature further deviates from the optimum of 20°C (Heal and J. Park 2016). These findings are summarized in Figure 1.

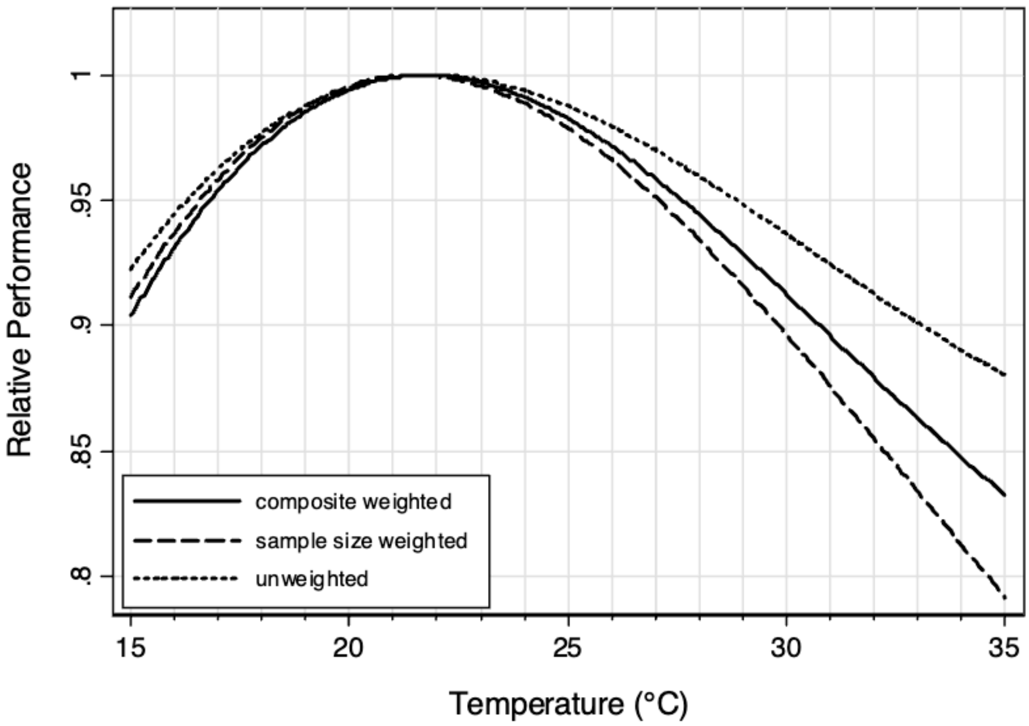


Figure 1: Temperature and normalized task productivity in laboratory setting (Seppanen, Fisk, and Lei 2006; Heal and J. Park 2016)

The results presented by Seppanen, Fisk, and Lei (2006) can be considered as the foundation of the theoretical argument behind the empirical framework of this thesis, which aims to estimate the semi-elasticity of labor productivity, considering the role of adaptation, with respect to cumulative deviations from the temperature threshold of 24°C.

[18]See, for example, Grether (1973) and Froom et al. (1993), among others.

1.5.2 Micro-Level evidence

Several studies have analyzed the relationship between temperature and labor productivity using plant-level data. For example, Cai, Lu, and J. Wang (2018) used worker-level data from a factory in Xiamen, China, spanning 2012 to 2014, and found a symmetrical inverted-U-shaped relationship between temperature and labor productivity. Their results show that an additional day with a maximum temperature above 35°C leads to an 8.5% reduction in productivity compared to a reference temperature bin centered at 25°C (Lai et al. 2023). Similarly, Stevens (2019) observed an inverted-U-shaped relationship by examining the agricultural productivity of blueberry pickers in California. They found that temperatures over 37°C lower productivity by 12% compared to a reference bin centered at 27°C (Lai et al. 2023). The results obtained by Cachon, Gallino, and Olivares (2012) suggest that using automobile assembly data, six or more days in a week above 32°C reduces labor productivity by 8%. Chen and L. Yang (2019) found that an increase in the average summer temperature of 1°C diminishes labor productivity by 3.4–4.5%. Additionally, Zhang et al. (2018) utilized annual survey data from above-scale industrial firms in China spanning 1998 to 2007 and discovered that each additional day with temperatures exceeding 32°C, relative to a reference bin centered at 13°C, decreases total factor productivity (TFP) by 0.56% and output (measured in value-added) by 0.45% (Lai et al. 2023). Somanathan et al. (2021) analyze data from various industries in India to compare the effects of temperature on labor productivity at the worker level, firm level, and subnational GDP level. They find that if the temperature increases by 1°C every day, worker output is reduced by 3%. In the same scenario, annual plant output decreases by 2.1%, showing a linear decline once the maximum daily temperature exceeds 20°C. This comparison suggests that, under a Cobb-Douglas production function, labor productivity is a key driver in this dynamic. Moreover, the results of Somanathan et al. (2021) indicate that if the average maximum temperature in a year increases by 1°C, annual district industrial output is reduced by 3.5%. The comparable magnitudes of these effects suggest that labor productivity represents a key mechanism through which temperature affects macro-level economic output (Lai et al. 2023).

Temperature affects not only the *quality* of the performance but also the *quantity*. Part of the output reduction can be explained by an increase in work absenteeism or a reduction in the hours worked. Graff Zivin and Neidell (2014) find that an additional day with a maximum temperature above 29°C, considering a baseline centered at 25°C, reduces the time allocated to work by an hour. Results by Cai, Lu, and J. Wang (2018) suggest that neither attendance decisions nor working hours are affected by temperature in a manufacturing factory in China. Lai et al. (2023) propose that this effect can be explained by the rigidity of the labor market. In contrast, Somanathan et al. (2021) observe opposite results in an industrial factory in India, where high temperatures lead to increased absenteeism, especially among workers with paid leave. This evidence suggests that the impact of temperature on overall labor productivity is complex and influenced by factors such as the extent of occupational exposure and the rigidity of the labor market.

1.5.3 Mental Productivity

The relationship between temperature and labor productivity has been studied not only from an economic perspective, but also by examining how environmental changes affect factors like learning, cognition, and decision-making. Specifically, research has explored the impact of temperature on test scores, both in surveys and student exams, across countries including the U.S., China, India, and Canada (Lai et al. 2023). The analyzed impacts involve both the current and the cumulative relationship. Understanding and quantifying in this sense is extremely important since it can direct the research on the right functional form of the IAMs' damage function.

The results on the contemporary impact of temperature converge on similar conclusions. For example, Graff Zivin, S. M. Hsiang, and Neidell (2018) shows that children's math test (but not reading) performance is affected by the temperature on that day. Specifically, each degree above 21°C results in a 0.219% decrease in math scores (Lai et al. 2023). Zivin et al. (2020) analyze data from China's National College Entrance Examination, where air conditioning is scarce, and find a 0.34%

reduction in exam scores for each additional degree Celsius. R. J. Park (2022) examine high-school exit exams in New York City and find that a 0.55°C increase in exam-time temperature decreases performance by 0.9% of a standard deviation (Lai et al. 2023).

The impact of cumulative exposure to high temperature has conclusions less homogeneous. In particular, Graff Zivin, S. M. Hsiang, and Neidell (2018) find a limited effect of climate on human capital accumulation, suggesting that while the temperature may impact immediate cognitive function, compensatory behaviors, in the long run, can mitigate these effects.[19] However, R. J. Park et al. (2020) shows that cumulative exposure to heat reduces the rate of learning in the long run. In particular, each increase of 0.55°C in the yearly maximum temperature the year before the test leads to a decrease in academic achievement by 0.2% of a standard deviation (Lai et al. 2023). Similarly, Zivin et al. (2020) reports a negative impact of extreme heat from the previous year on college entrance exam performance in China. Other studies, such as those by Cho (2017) and Garg, Jagnani, and Taraz (2020), provide comparable findings.

The cumulative effects of temperature may be influenced by the availability of mitigation technologies, such as air conditioning, which vary across regions in the study. Although the evidence is mixed, the possibility that future climate shocks could impact the accumulation of human capital cannot be ruled out (Zivin et al. 2020; R. J. Park 2022). Notably, Lai et al. (2023) note that studies linking workplace cognitive output to temperature effects are rare, with few exceptions. For instance, the findings of Heyes and Saberian (2019) demonstrate that a 5.5°C increase in temperature during work hours can adversely affect decision-making processes among U.S. immigration judges, reducing grant rates by 6.55%. Niemelä et al. (2002) show that, in a call center, each additional degree in the range 22-29°C is associated with a reduction of about 1.8% in labor productivity (Dell, Jones, and Olken 2014).

[19]For instance, if a child misses school or has reduced attention in class due to extreme heat, additional instructional time from private tutors or parents can help compensate for the resulting knowledge loss.

1.5.4 Macro Level: The GDP-Temperature relationship

In Integrated Assessment Models (IAMs), the primary economic outcome of interest is Aggregate Output. Therefore, understanding and quantifying the channels through which climate can affect it is becoming increasingly important. Although there is some ambiguity in the literature regarding the appropriate functional form (Heal and J. Park 2016; Newell, Prest, and S. E. Sexton 2021), the robust relationship between income per capita[20] and temperature has been supported by numerous empirical analyses, both cross-sectional and panel-based (Dell, Jones, and Olken 2014).

Starting with the first type, Gallup, Sachs, and Mellinger (1999) demonstrated that countries located in the tropics were 50 percent poorer per capita in 1950 and experienced annual growth rates that were 0.9 percentage points slower between 1965 and 1990. Dell, Jones, and Olken (2009) found that, in a cross-sectional analysis of the world in the year 2000, national income per capita decreased by 8.5 percent for each degree Celsius increase in temperature. Additionally, the same study revealed that within countries, municipal per capita income declined by between 1.2 and 1.9 percent for each degree Celsius rise in temperature. W. D. Nordhaus (2006) showed that, after controlling for country fixed effects, geographic variables could explain 20 percent of the income differences between Africa and the world's wealthier industrial regions (Dell, Jones, and Olken 2014).

The main issue with cross-sectional estimates is their susceptibility to omitted variable bias, as discussed in Section 1.4. To more directly isolate the contemporaneous impact of temperature, recent climate econometrics literature has increasingly focused on panel data estimates. In a global sample spanning from 1950 to 2005, Dell, Jones, and Olken (2012) analyzed the effects of annual variations in temperature and precipitation on per capita income. Their findings indicate that a 1°C increase in the yearly average temperature is associated with a 1.4 percent reduction in per capita income. Notably, this effect is observed only in poorer countries, highlighting the critical role of climate adaptation, which appears to be closely tied to income

[20]The macro-level literature has primarily focused on proxies of aggregate labor productivity, such as income per capita.

levels. The negative impact of temperature on economic growth includes both a level effect (reduction in the current level of aggregate income) and a growth effect (damage to growth drivers such as innovations and institutions), as the authors interpret lagged temperature coefficients as an indication of a persistent impact of shocks in the medium term, even in the presence of sign reversal.[21] Additionally, variations in mean precipitation were found to have no significant effect on per capita income (Lai et al. 2023). Also Burke, S. M. Hsiang, and Miguel (2015b) identified a growth effect in both the agricultural and industrial sectors using a panel of 166 countries between 1960 and 2010. The study estimates an inverted U-shape response to annual growth rate finding a globally optimal temperature of 13°C, using parametric country-specific time trends (Lai et al. 2023). It predicts that unmitigated warming could reduce average global incomes by approximately 23% by 2100, with a non-linear temperature response affecting both rich and poor countries across the agricultural and non-agricultural sectors. The analysis conducted by Deryugina and S. M. Hsiang (2014) also suggests that high temperatures reduce economic outcomes in wealthy regions. Using a sample of twenty-eight Caribbean-basin countries, (S. Hsiang 2010) found a level effect between 1970 and 2006. The estimates indicate a 2.5 percent reduction in value added per capita for each 1°C increase in temperature, but only if the increase occurs during the hottest season. Interestingly, the results show that the non-agricultural sector is affected twenty times more than the agricultural sector, with respective declines of 2.5% and 0.1%. Lai et al. (2023) suggest that this evidence implies that labor productivity losses in labor-intensive non-agricultural sectors could be a crucial mechanism behind these results.

Given the discordance in existing literature, Newell, Prest, and S. E. Sexton (2021) estimated eight hundred models, evaluating them using a range of cross-validation techniques. The authors explored different specifications of the temperature-GDP relationship, focusing on several key aspects: the functional form of the temperature relationship, the methods used to account for potentially confounding time trends, the persistence of the temperature effect (including both growth and level

[21] Newell, Prest, and S. E. Sexton (2021) strongly contests this interpretation, arguing that the sign reversal of temperature effects in their analysis indicates only a temporary impact on GDP levels.

effects), and the inclusion of lags for temperature and precipitation as covariates. The main results from Newell, Prest, and S. E. Sexton (2021) highlight the greater uncertainty in future impacts for models that specify the effects of temperature on GDP growth, due to the structural dynamic that accumulates damages over time. The 95% confidence interval, accounting for both sampling and model uncertainty across the best-performing GDP growth models, ranges from 84% GDP losses to 359% gains. Models analyzing GDP level effects show a much narrower range of GDP impacts, generally centered around 1–3% losses, aligning with the damage functions used in major IAMs. Models that incorporate lagged temperature effects suggest impacts on GDP levels rather than GDP growth. The analysis identifies statistically significant marginal effects of temperature on poor country GDP and agricultural production, but not rich country GDP, non-agricultural production, or GDP growth. These results support theories suggesting that richer countries are less vulnerable to temperature and climate shocks due to their greater capacity to adapt (Deryugina and S. M. Hsiang 2014; R. S. J. Tol 2009; W. Nordhaus 2008). Interestingly, Dell, Jones, and Olken (2014) suggest that there exists consistency between micro and macro evidence regarding the estimated loss in industrial output, with negative effects averaging around a 2 percent loss per additional 1°C when the temperature exceeds 25°C.

1.5.5 Other Sector-Level Evidence

Understanding the impacts at the sector level is crucial for identifying the main drivers of the aggregate effect, which in turn is essential for making optimal policy decisions. This short part of the review presents several empirical analyses regarding other key economic outcomes affected by weather shocks. These outcomes include Agriculture, Health, and Energy.[22]

Agriculture. Given the intrinsic relationship between the environment and agricultural production, this field has been the focus of numerous academic studies analyzing climate impacts. Interestingly, it is also the area where many significant

[22]See Dell, Jones, and Olken (2014) for a brief literature review regarding other channels in the climate-economy interface like Political Stability, Crime, Market integration, and Innovation

methodological contributions have emerged (Dell, Jones, and Olken 2014). The early debate on climate impacts in agriculture was characterized by two main approaches: the *production function* approach and the *Ricardian* approach. The *production function* approach models climate variables such as temperature and water as direct inputs in agricultural production processes.[23] This method has faced criticism because its reliance on experimental data may not accurately predict the adaptive behaviors of real-world farmers, such as switching crops in response to changing climatic conditions. The *Ricardian* approach utilizes cross-sectional regressions of land values to determine the net impact of climate on agricultural productivity (Dell, Jones, and Olken 2014). This method is predicated on the assumption that farmers, in a stationary climate, will adapt their behaviors to maximize profits. Under this assumption, land values reflect the discounted value of future profits (Auffhammer 2018). Mendelsohn, W. D. Nordhaus, and Shaw (1994) is considered the main contribution in the field and it estimated that the impacts of climate change on agricultural production not only are lower than the one estimated with the cross-sectional approach but might be even positive. This thesis has been criticized by Schlenker, Michael Hanemann, and Fisher (2005) which, after accounting irrigation, find robustly negative estimates, similar to those from earlier estimates (Dell, Jones, and Olken 2014). The main criticisms of the *Ricardian approach* include: the potential for omitted variable bias and the *causality* problems typical of cross-sectional regressions; the assumption of costless adaptation, which is unrealistic; the findings of Severen, Costello, and Deschenes (2018), which show that farmers already incorporate expectations about future climate changes, potentially leading to an underestimation of impacts (Auffhammer 2018). Interestingly, this approach has been implemented in other fields to estimate the climate impacts. Mansur, Mendelsohn, and Morrison (2008) apply it to energy consumption, where adaptation is fuel-switching. Deschênes and Greenstone (2007) motivated by the omitted variable problem, propose a panel data approach based on year-to-year within-country variation to understand if agricultural profits are reduced when the year is hotter or wetter than normal (Auffhammer 2018; Dell, Jones, and Olken 2014). They find

[23] See (Adams 1989)

no statistically significant evidence of weather impacts on U.S. agricultural profits, corn yields, or soil yields. (Fisher et al. 2012) challenged these findings, citing data errors. After corrections were made, their revised analysis identified a negative impact of climate change on U.S. agriculture, aligning with previous empirical studies. Nevertheless, the methodological contribution remains extremely important (Dell, Jones, and Olken 2014). Applying this panel data approach to developing countries typically reveals consistently negative impacts of adverse weather shocks on agricultural output.[24] Part of the literature focused also on nonlinearity in temperature effect, which can be crucial in agricultural dynamics. For example, the approach implemented by Schlenker and Roberts (2009) allows flexible estimation of nonlinear relationships, using bins, polynomials, or piece-wise splines. They find a threshold for negative output effects starting from 29-32°C. Since global change involves a right shift in the weather distribution, understanding nonlinearity can be crucial due to the intensification of extreme weather phenomena (Dell, Jones, and Olken 2014).

Health and Mortality. A great number of recent academic contributions emphasize the role of temperature on mortality, prenatal health, and human health more generally (Dell, Jones, and Olken 2014; Deschenes 2014). The panel literature highlights several ways through which temperature can affect health, both directly and indirectly. Directly, extreme temperatures are known to impact health, especially for individuals with preexisting respiratory and cardiovascular conditions. Indirectly, temperature can influence health through factors such as pollution levels and food spoilage rates. Temperature can also influence incomes through the channels outlined above, such as agriculture and labor productivity, which can in turn affect health (Dell, Jones, and Olken 2014). Deschêne and Greenstone (2011) demonstrate that in the United States, each additional day with a temperature above 32°C, relative to a moderate day with 10-15°C, increases the annual age-adjusted mortality rate by 0.11 percent. They also provide evidence of cold-related effects. A. I. Barreca (2012) obtain similar results, with an increase in mortality of 0.2 percent for each additional day of extreme heat. Notably, A. Barreca et al. (2016) revealed that the mortality effects of temperature on weather were significantly higher in the United

[24] See (Schlenker and Lobell 2010; Guiteras 2009; Welch et al. 2010; Dell, Jones, and Olken 2014)

States at the beginning of the century compared to more recent periods, with a six-fold increase in impact. The authors posit that this reduction may be attributed to the widespread adoption of residential air conditioning, highlighting an important area of research on adaptation strategies involving the effects of extreme temperatures.[25] Other contributions, like Deschênes, Greenstone, and Guryan (2009) and Kudamatsu, Persson, and Strömberg (2012), focus on the effects of weather on infant health (Dell, Jones, and Olken 2014).

Energy. Similar to agriculture, the energy sector is closely linked to the climate, particularly in the presence of adaptation responses. Understanding the relationship between energy consumption and weather variations is crucial for designing optimal electricity systems and integrating feedback loops into Integrated Assessment Models (IAMs). An example of these loops involves how adaptation responses related to energy consumption increase greenhouse gas (GHG) emissions and how, in the long term, they will influence future energy demand in relation to global warming. The response of the energy demand to weather shock is influenced by two main concepts: the occurrence of an *unusual warm day* can either increase or reduce energy consumption, depending on the location and time of year; the energy-temperature relationship depends on the available stock of heating and cooling equipment, emphasizing the significant role of the extensive margin response in the context of the study of the intensive one (Dell, Jones, and Olken 2014). In the context of panel studies, using nine temperature bins, Deschêne and Greenstone (2011) find a clear U-shape relationship between energy demand and temperature in the United States between 1968-2002, with an extra day below more or less -12 °C or above 32° raising annual energy demand by 0.3-0.4 percent. Auffhammer and Aroonruengsawat (2011), using 2003-2006 California data at the household level, confirm the U-shape relationship. As Dell, Jones, and Olken (2014) notes, using temperature bins allows to capture the convexity of the energy-temperature relationship, in which extreme temperatures provoke a much stronger energy demand increase. A well-known ap-

[25] A subset of the literature, including studies by Deschenes and Moretti (2009) and Braga, Zanobetti, and Schwartz (2001), has also explored the concept of *harvesting*, which refers to the phenomenon where an extremely hot day might precipitate the death of someone who might have otherwise died shortly thereafter, even without the high temperatures. Hajat et al. (2005) found that this effect may vary with income and potentially with access to climate control technologies.

proach in energy economics literature, as well as in this thesis, involves the use of *Cooling Degree Days* (CDDs) and *Heating Degree Days* (HDDs) as a measure of the energy required during "extreme" temperature. They are defined as the count of days below and above a threshold temperature (for example 24°C), with each day weighted by its temperature difference from the threshold.

Notably, Dell, Jones, and Olken (2014) strongly emphasize that future panel studies aiming to isolate the effect of air conditioning adoption, particularly in relation to income, will be crucial for predicting the interaction between energy demand and adaptive mechanisms. This is particularly relevant for low-middle income countries where climate control devices per capita are still low but are expected to increase (Pavanello et al. 2021; Colelli, Wing, and Cian 2023; IEA 2018). Dell, Jones, and Olken (2014) also suggest that to the extent that adaptation can influence the response to positive temperature shocks in economic outcomes - such as labor productivity, industrial output, and health - the focus should not be exclusively on increasing costs in energy demand, but rather on the more comprehensive trade-off between these costs and the adaptation benefits such energy appliances may provide. These costs should necessarily include the future damages caused by the greenhouse gas emissions related to the increase in energy demand. This thesis aims to contribute to the research that seeks to calibrate and incorporate these trade-offs in Integrated Assessment Models, particularly in the labor productivity dynamics.

1.5.6 Climate Adaptation and Labor Productivity

The literature on climate adaptation can be broadly divided into two main categories: studies that quantify the effectiveness of adaptation strategies and those that investigate the presence of these adaptive behaviors (Lai et al. 2023). The first category primarily focuses on external adaptation strategies, often involving climate control technologies such as air conditioners (Isen, Rossin-Slater, and Walker 2017; R. J. Park et al. 2020; Somanathan et al. 2021; Lai et al. 2023). The literature has also analyzed the complementary role of autogenous adaptation strategies (Cook and Heyes 2020; Qiu and Zhao 2022; S. Sexton, Z. Wang, and Mullins 2022; Lai et al. 2023). Examples of the second category involve the study of compensatory behaviors and time reallocation (Graff Zivin and Neidell 2014; Garg, Gibson, and Sun 2020; Lai et al. 2023).

Considering the studies that involve the effectiveness of external devices, Isen, Rossin-Slater, and Walker (2017) suggest that domestic air conditioning mitigated nearly all the negative effects of early-life heat exposure on adult earnings for individuals born in the U.S. between 1969 and 1977 (Lai et al. 2023). Moreover, R. J. Park et al. (2020) found that the presence of air conditioning reduces the impact of high temperatures on the performance of high school students in the years leading up to their standardized PSAT tests. Somanathan et al. (2021) show that adaptation devices eliminate performance reduction in the workplace but do not address absenteeism in India (Lai et al. 2023). Heal and J. Park (2013) demonstrates that the penetration of air conditioning can mitigate the impact of high temperature on a country's output per capita.

Part of the literature studied the phenomenon of autogenous adaptation, in particular *acclimatization*. *Acclimatization* is defined as "the beneficial physiological adaptations that occur during repeated exposure to a hot environment" (Lai et al. 2023). For example, Qiu and Zhao (2022) demonstrate that athletes trained in high-temperature regions are relatively less sensitive to the negative impacts of heat compared to athletes trained in low-temperature regions. Cook and Heyes (2020) find evidence of biological adaptation to high temperatures in the performance of foreign students. Graff Zivin and Neidell (2014) show that labor for high-risk workers is less sensitive to extreme heat in August, suggesting evidence for short-term acclimatization when heat shocks are more frequent (Lai et al. 2023).

Considering adaptive behaviors, Graff Zivin, S. M. Hsiang, and Neidell (2018) find evidence of short-term effects on math performance when temperatures exceed 26°C in a panel data fixed effects model. However, long-differences and cross-sectional estimates reveal a significantly weaker relationship between temperature and human capital, suggesting the presence of compensatory behaviors (Lai et al. 2023).

In conclusion, numerous studies demonstrate how temperature affects labor productivity at the micro-level and how climate adaptation can significantly mitigate these negative impacts. However, when considering key macro-level findings from studies such as Deryugina and S. M. Hsiang (2014), Dell, Jones, and Olken (2012), and Burke, S. M. Hsiang, and Miguel (2015a)—with the notable exception of Heal and J. Park (2013)—evidence of adaptation are very limited. Lai et al. (2023) suggest that this contrast highlights the need for further research on climate adaptation to bridge the gap between micro- and macro-level evidence.

Chapter 2

The Conceptual Framework

This chapter is organized into two sections. The first section offers an overview of the theoretical model underpinning the analysis, highlighting the role of temperature in economic production. Although the model is in partial equilibrium, it offers insights into the main channels of impact discussed in Chapter One.

The second section presents the structure of the empirical strategy adopted in this thesis, discussing the theoretical aspects of the high-dimensional fixed effects (HDFE) model utilized in the analysis.

2.1 The Theoretical Model

This thesis aims to take further steps toward reconciling the gap between micro- and macro-level evidence regarding the role of climate adaptation in the relationship between temperature and labor productivity. Before outlining the empirical strategy, the theoretical model is introduced. This framework, developed by Lai et al. (2023), is based on the model of Deryugina and S. M. Hsiang (2014).

An economy uses labor L and capital K to produce, with A_L and A_K denoting labor and capital productivity, respectively. Variables A_L and A_K respond to contemporaneous or past temperature T. In addition, the producer can spend an effort $e \in [0, 1]$ to moderate the sensitivity of labor productivity to temperature, such as by installing air conditioners. The cost of effort is $c(e)$, which is a convex function with $\frac{\partial c}{\partial e} > 0$ and $\frac{\partial^2 c}{\partial e^2} > 0$. Following the Cobb-Douglas production function, the quantity of output is written as

$$q(T) = (A_K(T)K)^{\alpha}(A_L(T, e)L)^{1-\alpha}, \tag{2.1}$$

where α and $(1 - \alpha)$ are the output elasticities of capital and labor, respectively. Denote the output price as p, the wage rate as w, and the rent rate of capital as r. The producer faces the standard profit maximization problem:

$$\max_{K,L,e} \; p \cdot (A_K(T)K)^{\alpha}(A_L(T, e)L)^{1-\alpha} - wL - rK - c(e). \tag{2.2}$$

In Equation 2.1, price variables (p, w, r) are endogenously determined by the economy in general equilibrium, and the producer is a price taker (Lai et al. 2023).

Given T and price variables, the producer chooses labor and capital inputs, as well as the effort level to maximize the profit. Denote the optimal labor and capital under the exogenous temperature T as $L^*(T)$ and $K^*(T)$. The thesis aims to investigate the total marginal effect of temperature on economic output $q(T)$ and the underlying channels, given in the following equation:

$$\begin{aligned}\frac{d\ln q(T)}{dT} &= (1-\alpha)\frac{1}{A_L(T,e^*)}\cdot\frac{dA_L(T,e^*)}{dT} + (1-\alpha)\frac{1}{L^*}\cdot\frac{dL^*(T)}{dT} \\ &\quad + \alpha\frac{1}{A_K(T)}\cdot\frac{dA_K(T)}{dT} + \alpha\frac{1}{K^*}\cdot\frac{dK^*(T)}{dT}. \end{aligned} \tag{2.3}$$

The effect of temperature on output is decomposed into four parts, even if this thesis focuses on the first two components related to labor. Given that the literature identifies an inverted U-shaped relationship between temperature and economic activities, and considering that the main variable in the empirical analysis is Cooling Degree Days (CDDs)—a measure of the persistence and intensity of high temperatures—rises in T represent a monotonic deterioration of ambient conditions (Lai et al. 2023).

The first term on the right side of Equation 2.3 reflects the effect of temperature on aggregate labor productivity. If the temperature crosses the comfortable zone, the partial effect of labor productivity is expected to be negative with $(1-\alpha)\frac{1}{A_L(T,e^*)}\cdot\frac{dA_L(T,e^*)}{dT} < 0$, as demonstrated by the literature review presented above.

The second term on the right side of Equation 2.3 presents the impact of temperature on labor demand. When the economy reaches equilibrium, the labor market is cleared, and the labor available in production is equal to the labor supply by workers. That means the impact of temperature on labor supply is implicitly reflected by $\frac{dL^*}{dT}$ (Lai et al. 2023). Given the limited literature on the impact of temperature on firms' labor demand, this thesis does not specifically address this aspect of the dynamics

Notably, the total derivative of labor productivity with respect to temperature in the first term of Equation 2.3 is a combination of two terms:

$$\frac{dA_L(T,e)}{dT} = \frac{\partial A_L(T,e)}{\partial T} + \frac{\partial A_L(T,e)}{\partial e}\cdot\frac{\partial e}{\partial T}, \tag{2.4}$$

where the first term $\frac{\partial A_L(T,e)}{\partial T}$ describes the direct effect of temperature on labor productivity, and the second term $\frac{\partial A_L(T,e)}{\partial e}\cdot\frac{\partial e}{\partial T}$ represents the effect of mitigation or adaptation efforts (Lai et al. 2023). The empirical part of this thesis aims to provide a quantitative assessment of both components of the total derivative of labor productivity, estimating the direct effect of temperature as well as the moderating role of adaptation efforts.

2.2 The Empirical Strategy

The literature has identified two main approaches to examining the effectiveness of climate adaptation strategies (Lai et al. 2023). The first approach involves the use of subsample analyses. For example, Heal and J. Park (2013) found a less concave relationship between temperature and income per capita for countries in the top third of the distribution of air conditioning penetration per capita. Other examples include Graff Zivin and Neidell (2014), Cho (2017), R. J. Park et al. (2020), and Somanathan et al. (2021). The second approach, which is adopted in the empirical part of this thesis and follows the panel methodology presented by S. Hsiang (2016) and Dell, Jones, and Olken (2014), involves incorporating an interaction term into a high-dimensional fixed effects (HDFE) regression equation. This interaction term captures the relationship between the function of temperature and the adaptation strategy used as a moderating factor. Precisely, following the notation of Lai et al. (2023), the general regression equation to estimate the impact of temperature on the labor productivity of a worker (or country) i in location c at time t is given by the high-dimensional fixed effects (HDFE) specification as follows:

$$
\begin{aligned}
Y_{ict} = \gamma f(T_{ct}) \times \text{Adapt}_{ict} + \beta f(T_{ct}) + (\rho \text{Adapt}_{ict}) \\
+ W_{ct}\lambda + X_{ict}\theta + \mu_i + \delta_c + \theta(t) + \phi(c,t) + \epsilon_{ict}
\end{aligned}
\tag{2.5}
$$

where T_{ct} represents the temperature exposure and $f(T_{ct})$ is a function of T_{ct}. Y_{ict} is a proxy for the labor productivity. β measures the direct response of labor productivity to temperature exposure and Adapt_{ct} is an indicator of the existence of external adaptation strategies (e.g., air conditioners) or a proxy for the experience of hot days in the past (e.g., a dummy for the high-temperature region, the number of hot days, or the average temperature in the past) to examine the effect of autogenous adaptation (Lai et al. 2023). The decision to include Adapt_{ct} without its interaction with $f(T_{ct})$ depends on the context of the study. The key coefficient is γ, the one which measures the moderating effect of the external adaptation strategy. W_{ct} is a vector of weather variables. X_{ict} is a vector of unit-level time-varying variables, such as gender, age, education, and others. In a national aggregate context, the vector represents elements like human capital and stock of capital per capita. Since temperature and adaptation variables may be contemporaneously correlated with W_{ict} and X_{ict}, it is essential to include these control variables in Equation 2.5 to prevent omitted variable bias. μ_i represents unit fixed effects, δ_c represents location fixed effects, and $\theta(t)$ refers to flexible time trends (Lai et al. 2023). After controlling for these fixed effects, residual shocks in temperature are plausibly random. Some studies include location-by-time fixed effects $\phi(c, t)$, which absorb location-specific temperature norms and make the temperature residual more exogenous. However, this stricter control can remove too many identifying variations and cause attenuation bias (Deryugina and S. M. Hsiang 2014). ϵ_{ict} is the error term, commonly clustered to allow spatial and serial correlation (Lai et al. 2023).

Chapter 3

Methods

This chapter is organized into two sections. The first section provides an overview of the variables and data used in the empirical analysis, with the final dataset consisting of a global unbalanced panel covering 116 countries from 1991 to 2019. The main variables include sector-level labor productivity, Cooling Degree Days (CDDs), and the stock value of the air conditioning machines per capita.

The second section introduces the preferred empirical model employed in the analysis, explaining the rationale behind the selection of its key components and examining its interpretive implications.

3.1 Data

This section presents the data regarding the main variables implied in the analysis. The list includes:

- **Labor Productivity**: A measure of output per worker, reflecting the efficiency and economic performance of a region or sector.
- **Cooling Degree Days (CDD)**: An indicator of the demand for space cooling, representing the cumulative number of degrees by which daily temperatures exceed a threshold, in this case 24°C.
- **Stock of Air-Conditioning Machines Per Capita**: An estimate of the value of air-conditioning units available per person in a given country, reflecting the capacity to meet cooling demand. It can be considered a general proxy for the level of adaptation effort adopted by a country.

3.1.1 Labor Productivity

Following the definition provided by the International Labour Organization (ILO), labor productivity represents the total volume of output (measured in terms of Gross Domestic Product, GDP) produced per unit of labor (measured in terms of the number of employed persons or hours worked) during a given reference period. This indicator allows data users to assess the levels and growth rates of GDP relative to labor input over time. It provides a broad overview of the efficiency and quality of human capital involved in the production process within a specific economic and social context, while also considering additional factors such as complementary inputs and innovations used in production.[1]

In this thesis, a proxy for the variable "Labor Productivity" is constructed as the yearly Value Added by sector divided by the number of employed persons. Data on Value Added by sector are sourced from UNData and refer to the variable *"Gross*

[1] See `http://ilostat.ilo.org/topics/labour-productivity`

Value Added by Kind of Economic Activity at current prices - US dollars".[2] Values are then converted in real terms using the *"Price level of CGDPo (PPP/XR), price level of USA GDPo in 2017=1"* from the Penn World Table (version 10.01).[3] Data regarding the number of employees across various sectors are sourced from the ILOEST database, which is maintained by the International Labour Organization (ILO).[4] The sectors included in the analysis are Aggregate (TOT), Non-Agricultural (NOAGR), Agriculture (AGR), Services (SER), Industry (IND), Manufacturing (man), Construction (con) and Mining&Utilities (minuti).

The unit of measure of the labor productivity used in this thesis is then "*Yearly Real 2017 PPP-adjusted Dollars per Employee*". The following figures and tables provide a detailed description of the labor productivity data used in the analysis. To ensure clarity in the presentation, only the statistics related to the Aggregate Sector at the regional level are presented.

Table 1: Regional Average Sectoral Shares (%) of Value Added from 1991 to 2019

Region	**% AGR**	**% minuti**	**% man**	**% con**	**% SER**
Africa	27.4	16.1	17.2	6.9	32.3
Americas	12.0	13.0	25.2	9.8	40.0
Arab States	7.8	39.9	15.0	8.0	29.3
Asia and the Pacific	16.3	8.5	27.8	8.9	38.4
Europe and Central Asia	6.7	8.9	28.2	11.2	45.0

[2] United Nations Statistics Division. "National Accounts Main Aggregates Database". *UNSD*, 2024, `https://unstats.un.org/unsd/snaama/`. Accessed 15 Jul. 2024

[3] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, DOI: 10.1257/aer.20130954, available for download at `www.ggdc.net/pwt`

[4] International Labour Organization. (2020). ILO modelled estimates database, ILOSTAT [database]. Available from `https://ilostat.ilo.org/data/`.

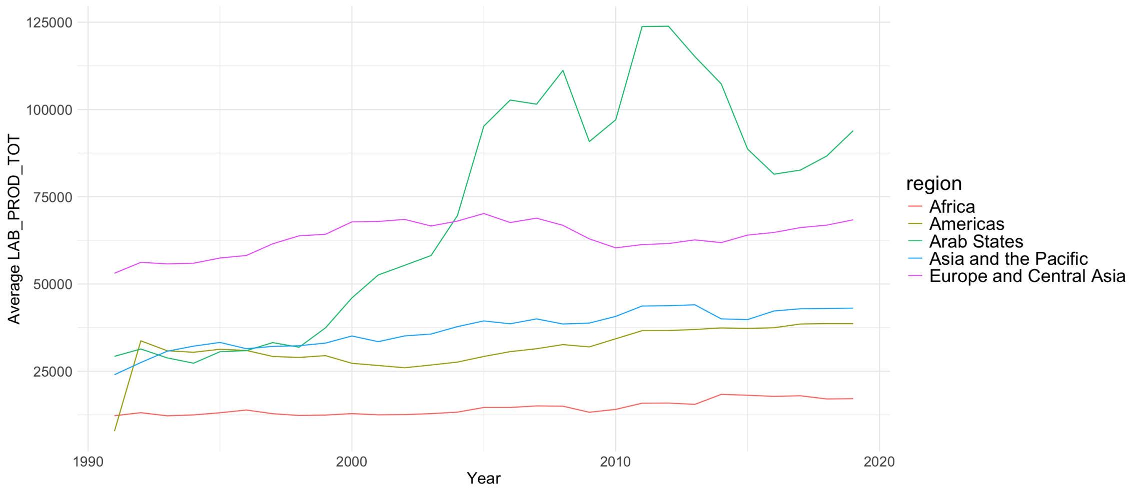


Figure 2: Yearly Average by Region of the Labor Productivity of the Aggregate sector (TOT) expressed in Real 2017 PPP-adjusted Dollars. Notably, the peak in labor productivity for the Americas in 1992 is attributable to the structure of the unbalanced panel dataset. Starting that year, the inclusion of U.S. data significantly increased the annual regional average.

Figure 3: WTI Crude Oil Prices expressed in Real 2017 PPP-adjusted Dollars. Source: *Federal Reserve Economic Data (FRED) database*

As Figure 3 shows, the labor productivity of the Arab States in Figure 2 is highly correlated with fluctuations in oil prices, highlighting the region's economic dependence on this sector. This reliance makes using "Value Added per number of Employees" as a proxy for labor productivity—understood as *worker performance*—somewhat problematic for these countries. Table 1 further confirms this dependency, illustrating that a significant portion of the regional value added is concentrated in the "Mining & Utilities" sector.

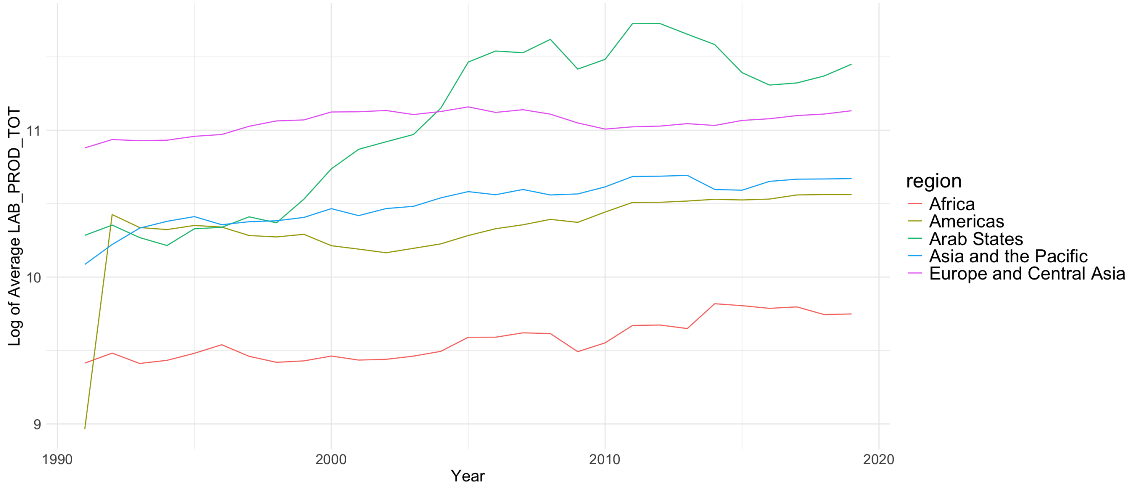


Figure 4: Logarithm of the Yearly Average by Region of the Labor Productivity of the Aggregate sector (TOT) expressed in Real 2017 PPP-adjusted Dollars

Table 2: Descriptive Statistics by Region of the Labor Productivity of the Aggregate Sector (TOT) from 1991 to 2019 expressed in Thousands of Real 2017 PPP-adjusted Dollars

Region	**Mean**	**SD**	**Min**	**Max**
Africa	14.90	14.95	1.28	71.44
Americas	32.55	26.02	5.25	125.99
Arab States	78.36	61.38	3.73	261.47
Asia and the Pacific	38.01	32.42	3.65	131.29
Europe and Central Asia	63.95	28.14	6.91	201.81

Table 3: Descriptive Statistics by Region of the Logarithm of the Average Labor Productivity of the Aggregate Sector (TOT) from 1991 to 2019 expressed in Real 2017 PPP-adjusted Dollars

Region	**Mean**	**SD**	**Min**	**Max**
Africa	9.14	0.98	7.15	11.18
Americas	10.13	0.70	8.57	11.74
Arab States	10.85	1.05	8.22	12.47
Asia and the Pacific	10.13	0.96	8.20	11.79
Europe and Central Asia	10.96	0.50	8.84	12.22

3.1.2 Cooling Degree Days (CDDs)

As reported in "The future of Cooling" by IEA[5], there are several ways of measuring the impact of the weather on the overall need for cooling. The traditional approach is by calculating CDDs, which are widely used by electricity utilities to predict load for cooling in the near future based on weather forecasts. Degree days are defined as the monthly or annual sum of the difference between a base temperature (T_b) and daily mean outdoor air temperature (T_d). The base temperature is also referred to as *threshold* temperature or *set-point* temperature, as it indicates the temperature at which the indoor cooling or heating systems do not need to operate in order to maintain human comfort levels.[6] For the purposes of this thesis, CDDs are measured in °C, with a threshold temperature of 24°C in all countries. The definition of the variable CDD used in the analysis for a given year in a specific country is

$$CDD = \sum_{i=1}^{n} (T_d - T_b)^+ \tag{3.1}$$

where n represents the number of days in the given year and T_b is set to 24°C. Normally, CDDs are calculated according to the *dry bulb temperature* (the temperature of the air measured by a thermometer freely exposed to the air, but shielded from radiation and moisture). Although the *wet-bulb temperature* provides a more accurate measure of thermal discomfort, as it does not overestimate temperature at low humidity levels (Pavanello et al. 2021), incorporating wet-bulb temperature into CDDs calculations presents challenges. Specifically, the number of days exceeding the threshold is significantly lower for wet-bulb temperature, which increases year-to-year and cross-country variability. Furthermore, accounting for factors like humidity in long-term climate predictions is highly complex, making the results less directly applicable to Integrated Assessment Models (IAMs). Given these considerations, this thesis employs CDDs based on *dry bulb temperature*. However, future improvements to the analysis should incorporate robustness checks to account for

[5] IEA (2018)

[6] See `https://www.energy-a.eu/historical-degree-days/?cn-reloaded=1`

these additional climate dimensions.

Using the same data employed in the empirical analysis, Figure 5 reports a graphical representation of the yearly average of Cooling Degree Days (CDDs) across the globe. The figure emphasizes that the demand for space cooling is predominantly concentrated in regions located within a narrow band around the equator. This band spans the tropics and subtropics, where the need for cooling is significantly higher due to consistently warm temperatures throughout the year (IEA 2018). IEA (2018) highlights also how global temperatures due to climate change will significantly increase Cooling Degree Days (CDDs) worldwide, though the impact will vary across regions. A 1°C rise in global average temperature by 2050 is projected to result in a 25% average increase in CDDs globally (using 18° base temperature). However, this rise will be uneven, with regions such as Africa, Latin America, southern and eastern Asia, and the Middle East expected to experience the largest increases, ranging from 15% to 40%. Even temperate regions like southern and northern Europe, as well as the northeastern United States, will see notable growth in CDDs, likely driving higher demand for air conditioning and increased energy consumption. For an application of climate projections to the empirical results of this thesis, see Section 4.2.

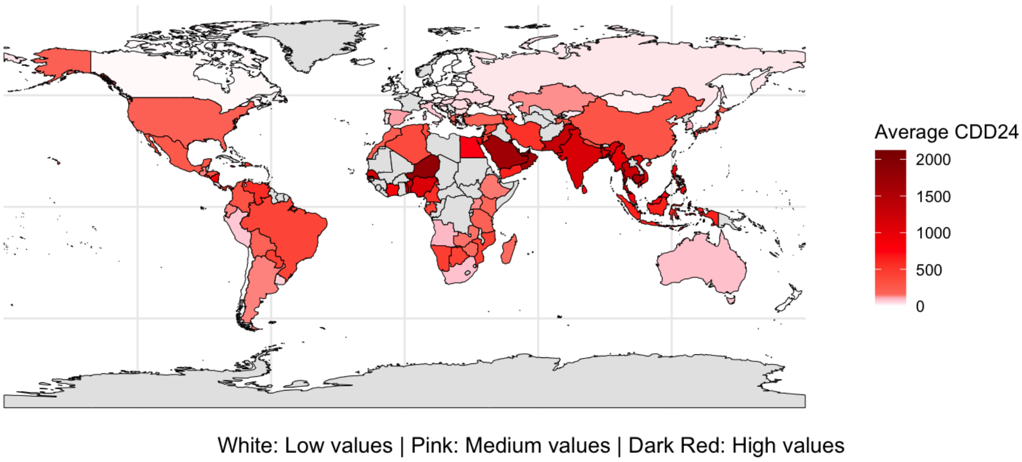


Figure 5: CDDs across the world by Country, Mean Annual Average 1991-2019 using a 24°C threshold and dry-bulb temperature.

IEA (2018) emphasizes that the primary climatic factor determining demand for space cooling is air temperature, although, as noted earlier, humidity also plays a significant role. These two factors are often correlated, as higher temperatures increase the air's capacity to hold water, though certain desert regions may experience elevated temperatures with relatively low humidity. Increased humidity levels tend to heighten the necessity for cooling to achieve a specific level of thermal comfort, and air conditioning units automatically reduce both the humidity and temperature of the air. To account for humidity's influence, a heat index, which adjusts Cooling Degree Days (CDDs) by combining air temperature and relative humidity to determine the temperature as perceived by humans, can be utilized. Relative humidity – the degree of air saturation with moisture – can impede the body's ability to perspire, thus creating a sensation of heat even when dry temperatures are not particularly high. For instance, if the dry temperature is 30°C and the relative humidity is 50%, it will feel like 31°C; however, if the relative humidity reaches 100%, it would feel like 44°C. In other words, the humidity creates a *sweltering* effect. Higher relative humidity results in a higher perceived temperature and, consequently, higher corrected CDDs. Since this thesis only considered the influence of Cooling Degree Days (CDDs) without accounting for the impact of humidity, the results may be subject to a certain degree of bias.

The following Figures and Tables provide a detailed description of the Cooling Degree Days (CDD) dataset utilized in this thesis. Population-weighted annual Cooling Degree Days (CDDs) are derived from gridded daily mean temperature data from the Global Monitoring for Environment and Security ERA5 reanalysis data (Hersbach et al. 2020) and gridded population data from SEDAC (Pages, Gallery, and Viewer 2018).

region	Mean	SD	Min	Max	Median
Africa	538.49	483.75	0.00	2033.21	358.82
Americas	309.42	266.28	0.00	1074.92	225.14
Arab States	1191.26	811.35	14.19	2310.40	1612.76
Asia and the Pacific	662.30	446.54	0.00	1765.21	679.26
Europe and Central Asia	57.14	93.49	0.00	484.62	12.30

Table 4: Descriptive Statistics of CDD24 by Region

3.1.3 Stock of Air Conditioning Machines per Capita

Building on the empirical evidence presented in Section 1.5 regarding the impact of high temperatures on labor productivity, the primary objective of this thesis is to evaluate the effectiveness of adaptation strategies in mitigating the adverse effects of temperature shocks at the macro level. Specifically, a proxy for the effort employed in these adaptation strategies has been constructed using the value of thermoregulatory capital per capita owned by each country.

Data on per capita air conditioning machine penetration is limited to a few aggregate regions and limited years. To address this gap, a proxy has been developed following the method employed by (Heal and J. Park 2013). Specifically, we constructed a proxy for *air conditioning machine penetration per capita* by calculating a discounted, moving sum of air conditioning machine imports over the past 15 years, applying a discount rate of 5%. The idea is that the volume of the imports of air conditioning equipment can be an estimate of the dimension of the internal demand for cooling.

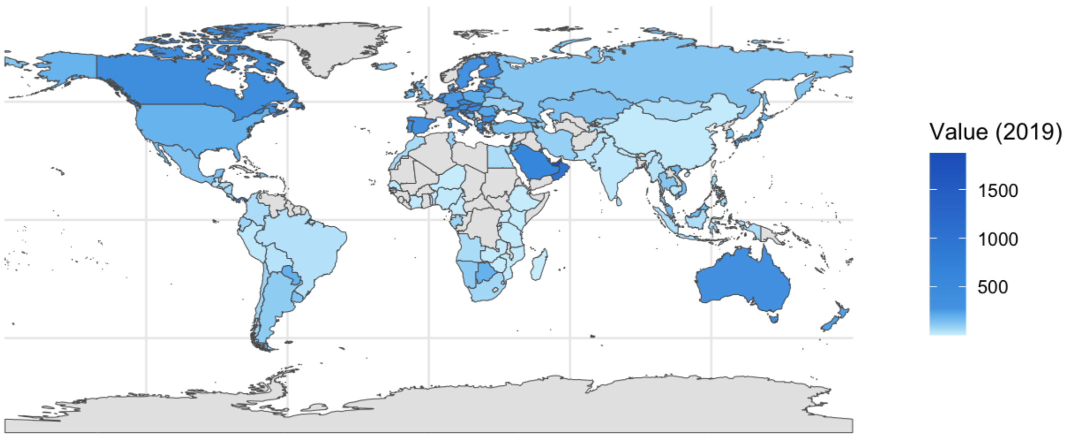


Figure 6: Value of the Stock of Air Conditioning Machines per capita in the Year 2019 by Country, expressed in Real 2017 PPP-adjusted Dollars

The trade data used in this thesis, following the approach of (Heal and J. Park 2013), is sourced from the United Nations COMTRADE database, which is a subset of the World Integrated Trade Solution dataset. Specifically, the analysis considers the value of imports classified under SITC code 7415, which in Revision 4 of the Standard International Trade Classification (SITC) refers to “Air-conditioning machines comprising a motor-driven fan and elements for changing the temperature and humidity, including those machines where the humidity cannot be separately regulated; parts thereof”. These import values have been converted to real 2017 PPP-adjusted dollars using the same index applied to labor productivity—the *"Price level of CGDPo (PPP/XR), price level of USA GDPo in 2017=1"* from the Penn World Table (version 10.01). This conversion ensures consistency in the measurement units across all variables.

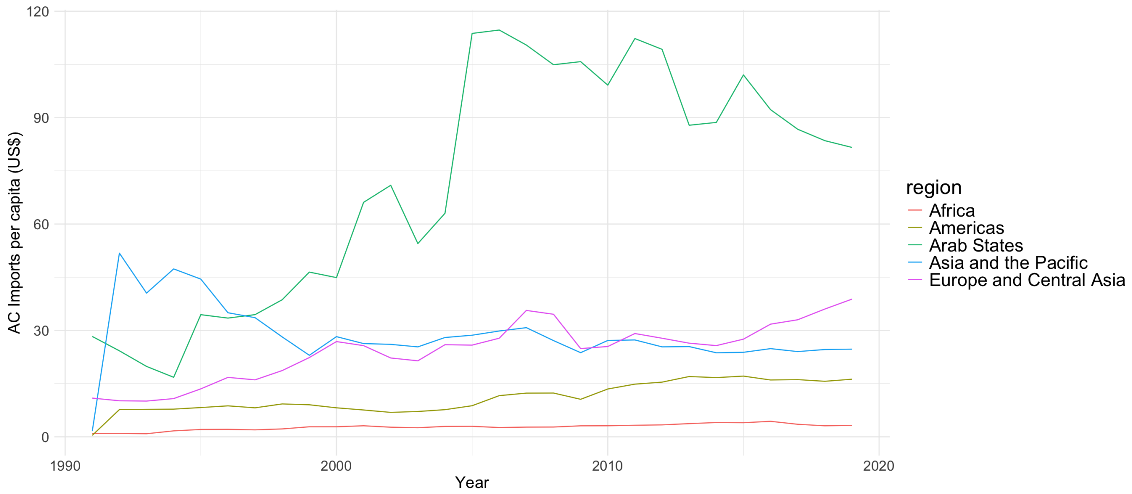
The following Figures and Tables provide a detailed description of the data utilized in this thesis. For additional country-level data, please refer to the Appendix.

Table 5: **Regional Mean of**: the Imports Flow of AC machines in US$ per Capita from 1990 to 2019 (M); the Stock of Air Conditioning Machines in US$ per Capita from 1990 to 2019 (S); the Stock of Air Conditioning Machines in US$ per Capita in 2019 (S19). The columns (lS) and (lS19) represent the logarithm of S and the logarithm of S19

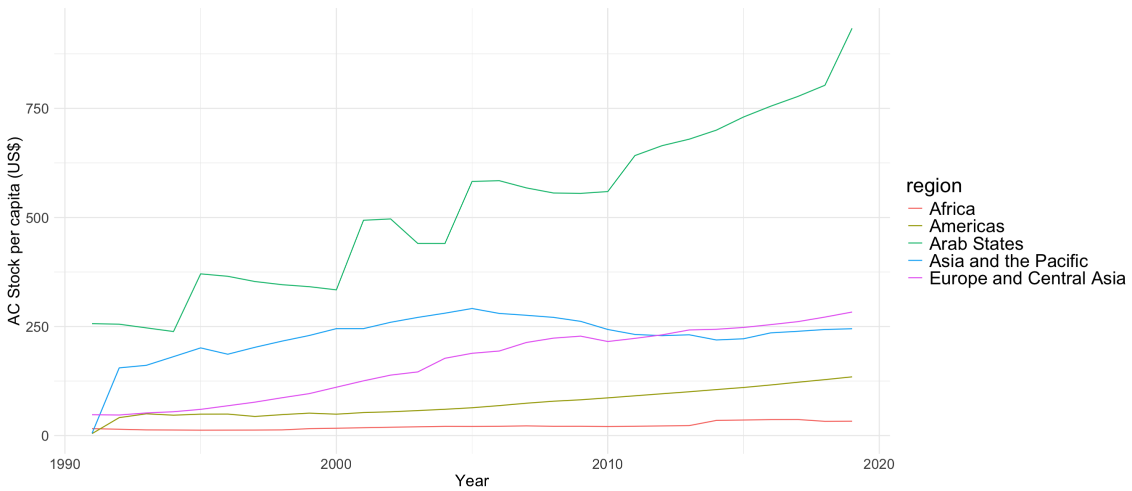
	1990-2019			2019	
Region	**M**	**S**	**lS**	**S19**	**lS19**
Africa	2.94	23.19	3.14	32.99	3.50
Americas	11.83	79.83	4.38	134.66	4.90
Arab States	79.18	555.79	6.32	933.64	6.84
Asia and the Pacific	28.27	234.41	5.46	244.94	5.50
Europe and Central Asia	26.46	193.17	5.26	283.22	5.65

Table 6: **Regional Median of**: the Imports Flow of AC machines in US$ per Capita from 1990 to 2019 (M); the Stock of Air Conditioning Machines in US$ per Capita from 1990 to 2019 (S); the Stock of Air Conditioning Machines in US$ per Capita in 2019 (S19). The columns (lS) and (lS19) represent the logarithm of S and the logarithm of S19

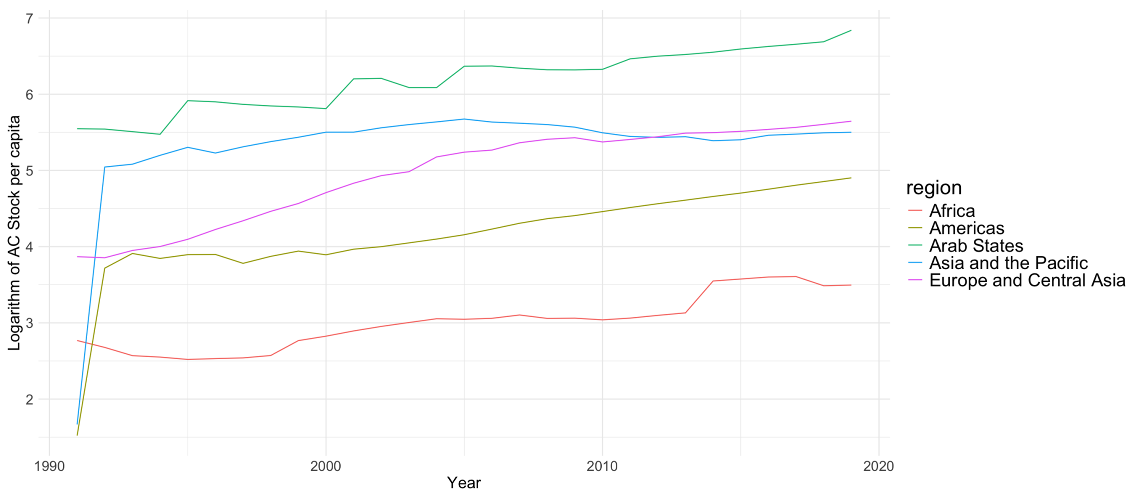
	1990-2019			2019	
Region	**M**	**S**	**lS**	**S19**	**lS19**
Africa	1.18	8.71	2.16	10.13	2.32
Americas	5.99	39.92	3.69	90.08	4.50
Arab States	37.37	360.84	5.89	987.73	6.90
Asia and the Pacific	5.07	29.21	3.37	70.31	4.25
Europe and Central Asia	21.18	142.42	4.96	256.92	5.55



(a) Yearly Average by Region of the **Flow** of Imports of Air Conditioning Machines in US$ per Capita. Similar to labor productivity, the peak observed in 1992 for *Asia and the Pacific* is due to the unbalanced panel and the inclusion of data from Hong Kong and Malaysia.



(b) Yearly Average by Region of the Value of the **Stock** of Air Conditioning Machines in US$ per Capita. This variable can be considered a proxy for *Air Conditioning Penetration*.



(c) **Logarithm** of the Yearly Average by Region of the Value of the **Stock** of Air Conditioning Machines in US$ per Capita.

Figure 7: Yearly Averages of Air Conditioning Variables.

3.2 The Empirical Model

This section presents the preferred empirical model used in the analysis. In particular, following the strategy proposed in Chapter 1, the regression equation to estimate the impact of high temperature on the labor productivity of a country i in a region r for the sector s at time t is given by the high-dimensional fixed effects (HDFE) specification as follows:

$$\begin{aligned} \log(LP_{ist}) = \beta \cdot CDD_{it} + \gamma \cdot CDD_{it} \cdot \log(ACSTOCK_{it}) \\ + X_{it}\theta + \mu_i + \delta_t + \phi(r,t) + \epsilon_{ist} \end{aligned} \tag{3.2}$$

where CDD_{it} represents the number of Cooling Degree Days for the country i at time t. $log(LP_{ist})$ is a proxy for the labor productivity of the sector s for the country i at time t. β measures the direct response of labor productivity to temperature exposure. The logarithm of $ACSTOCK_{it}$ serves as a general indicator of the level of effort a country invests in its adaptation strategies. While this proxy is based on an external adaptation measure—the penetration of air conditioners—it can also be interpreted more broadly to include all adaptive behaviors positively correlated with external adaptation efforts. Again, the key coefficient is γ, the one that measures the moderating effect of the adaptation strategies. X_{ict} is a vector of country-level time-varying variables. Following Heal and J. Park (2013), the vector includes a Human Capital Index (HC_INDEX) and the logarithm of the Value of Capital Stock per capita (log_KSpc) in real 2017 PPP- adjusted dollars of the country i at time t. The source is the Penn World Table (version 10.01).[7] These variables are recognized in the literature as the primary time-varying drivers of labor productivity (Dieppe 2021)[8]. Therefore, their inclusion aims to enhance the estimates of the other coefficients of interest. In particular, because temperature and the proxy

[7]Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, DOI: 10.1257/aer.20130954, available for download at `www.ggdc.net/pwt`

[8]As Dieppe (2021) notes, there are numerous other drivers of labor productivity. Given that unit fixed effects capture all relevant time-constant factors, the inclusion of these two variables serves as a reasonable approximation of the most significant time-varying drivers. Notably, due to data limitations, the proximity driver "Innovation" has been excluded from the analysis.

for the adaptation strategies can be contemporaneously correlated with X_{ict}, these control variables should be included in Equation 3.2 to avoid omitted variable bias. Considering the debate over whether this set of variables constitutes a *bad control*, Chapter 4 presents robustness analyses by also estimating the sector-level models without this vector (Dell, Jones, and Olken 2014; S. Hsiang 2016). μ_i represents country-fixed effects, which aim to include all the country-specific unobservable confounders that remain constant over time (such as institutions or geographic characteristics). δ_t represents time-fixed effects, a set of dummy variables that capture the variability of global shocks, such as the COVID-19 pandemic. $\phi(r, t)$ represents a flexible time trends. In our preferred specification, it is constructed as a quadratic, region-specific time trend. After controlling for these fixed effects, residual shocks in temperature are plausibly random (Lai et al. 2023). The selection of the right functional form of the time trend involved balancing the trade-off between incorporating a non-parametric trend—which requires numerous year-region dummy variables and increases standard errors—and employing a region-specific parametric trend, which may compromise the model's fit but enhance the precision of the standard errors. Observing the increasing trend in the coefficients of the year-region dummies estimated by the model, the inclusion of a quadratic time trend was deemed an effective compromise. ϵ_{ict} is the error term, clustered at the country level to allow for serial correlation (Lai et al. 2023).

Interpretation of the Marginal Effects

From an econometric point of view, fixed effects (FE) models are a very useful instrument to eliminate "unwanted variation" from the data, which Breuer and Dehaan (2024) defines as the one that is not part of the theory underlying the cause-and-effect relation of interest. One of the main characteristics of these models is that the coefficient of interest focuses on **within-group** variations. This means that the model's variability depends on deviations from each group's mean for both the independent and dependent variables. For example, in a one-way fixed effects model where each country represents a single group, and a dummy variable for each country is included in the regression equation, the estimation of the coefficient of interest

relies on within-country variation in time in X (i.e., $x_{i,t} - \bar{x}_i$) and Y (i.e., $y_{i,t} - \bar{y}_i$). Specifically, the coefficient estimates produced by this model are a linear combination (or weighted average) of the within-group estimates (Breuer and Dehaan 2024). Importantly, this means that the coefficient of interest can be obtained either by including a specific dummy for each country-thereby creating a unique intercept for each-or by regressing the group-demeaned Y on the group-demeaned X.
In a two-way fixed effects (FE) model, which incorporates both country and time dummy variables, the analysis becomes more intricate. Specifically, country-fixed effects remove the country-specific means from each variable, while time-fixed effects simultaneously eliminate the year-specific means. This means that in a two-way FE model, the double-de-meaned X only varies if a given country experiences a deviation from its mean level that is different from the average deviation of all countries in the same year.[9] As Breuer and Dehaan (2024) highlights, the process of double de-meaning is particularly complex in unbalanced panels and generally does not allow for simple closed-form solutions. Considering that our preferred empirical model includes country dummies, time dummies, and a quadratic region-specific trend, it is evident that analytically describing the mechanics of the model is a complex task.

The reliance on fixed effects (FE) models on within-country variation has significant implications for the interpretation of the estimated coefficients. Specifically, the coefficients represent the marginal effect on the dependent variable resulting from a marginal deviation of the independent variable from its group means, accounting for the influence of both time dummies and the quadratic region-specific trend included in the model. For example, considering the preferred model specification without the interaction term between CDD and $log(ACSTOCK)$, the coefficient for CDD would describe the marginal effect of an additional CDD above the country mean on the logarithm of labor productivity, accounting for the role of time fixed effects in capturing common shocks across countries and the impact of regional quadratic trends.

[9] For a detailed explanation of the functioning of fixed effects models and related econometric issues, refer to “Using and Interpreting Fixed Effects Models” (Breuer and Dehaan 2024).

Considering the preferred model specification implemented in the empirical part of this thesis, the conditional marginal effect of an additional CDD on the logarithm of the sector-level labor productivity is then expressed as

$$\frac{\partial \log(LP_{ist})}{\partial CDD_{it}} = \beta + \gamma \cdot \log(ACSTOCK_{it}) \tag{3.3}$$

Notably, the marginal effect of an additional CDD depends on the level of air conditioning stock per capita owned by a country.[10] Referring to Equation 2.4, this result represents the decomposition of the total derivative of the labor productivity with respect to temperature. The first term captures the direct effect of temperature on labor productivity, while the second term describes the mitigating effect of adaptation efforts (Lai et al. 2023). Since the dependent variable is expressed on a logarithmic scale, the total derivative represents a semi-elasticity. This indicates the percentage change in the dependent variable in response to a one-unit change in the independent variable.[11]

The conditional effect of a marginal increase in the logarithm of $ACSTOCK$ is then expressed as

$$\frac{\partial \log(LP_{ist})}{\partial \log(ACSTOCK_{it})} = \gamma \cdot CDD_{it} \tag{3.4}$$

Interestingly, the elasticity of per capita air conditioning stock with respect to temperature depends on the level of CDD experienced by the country i.

[10]Or more generally, on the efforts invested in external adaptation strategies.

[11]For example, if the estimated overall conditional marginal effect of CDD is equal to -0.01, this implies that each CDD above the yearly country average is associated with a 1% decrease in labor productivity, considering the role of time FE and regional trends.

Chapter 4

Results

This chapter is divided into two sections. The first section presents the relevant tables and figures from the analysis, taking into account the heterogeneity of the models and sectors. In particular, beyond regression results, the conditional marginal effect of CDD, $log(ACSTOCK)$ and $ACSTOCK$ are reported for all the sectors, with tables and graphical representations.

The second section extends the empirical estimates to a possible future scenario, incorporating predictions on future levels of CDD from climate models. Specifically, it aims to estimate the potential damages to yearly sector-level labor productivity resulting from a hypothetical shift in weather patterns projected for 2050 evaluated at present-day conditions, assuming no significant improvements in current adaptation strategies.

4.1 Tables and graphics

4.1.1 Aggregate Sector (TOT)

Table 7: Results for the Aggregate sector (TOT) based on the preferred specification.

Dependent Variable:	log_LAB_PROD_TOT		
Model:	(1)	(2)	(3)
Variables			
HC_INDEX	0.468251***	0.063611	0.008013
	(0.110175)	(0.099489)	(0.101920)
log_KSpc	0.590154***	0.479329***	0.450516***
	(0.077322)	(0.072216)	(0.071710)
CDD		-7.09×10^{-5}	-0.000442**
		(0.000131)	(0.000203)
CDD × log_ACSTOCK			8.74×10^{-5}***
			(2.78×10^{-5})
Fixed-effects			
iso3	Yes	Yes	Yes
time	No	Yes	Yes
Quadratic Regional Trend	No	Yes	Yes
Fit statistics			
Observations	2,469	2,469	2,469
R^2	0.97749	0.98312	0.98351
Within R^2	0.58442	0.31254	0.32817

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: **Conditional Marginal Effect of** *log_ACSTOCK* calculated at Mean and Median Regional Values of *CDD*

Region	**ME at the Mean**	**ME at the Median**
Africa	0.0468	0.0312
Americas	0.0269	0.0196
Arab States	0.1037	0.1401
Asia and the Pacific	0.0575	0.0590
Europe and Central Asia	0.0050	0.0011

Table 9: **Logarithm of the Regional Mean and Median of** $ACSTOCK$ in US$ per Capita from 1990 to 2019 (lS) and in 2019 (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	3.14	3.50	2.16	2.32
Americas	4.38	4.90	3.69	4.50
Arab States	6.32	6.84	5.89	6.90
Asia and the Pacific	5.46	5.50	3.37	4.25
Europe and Central Asia	5.26	5.65	4.96	5.55

Table 10: **Conditional Marginal Effect of** CDD calculated at the Logarithm of the Mean and the Median of $ACSTOCK$, considering the period 1991-2019 (lS) and 2019 only (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	-0.000169	-0.000137	-0.000254	-0.000240
Americas	-0.000062	-0.000016	-0.000121	-0.000050
Arab States	+0.000108	+0.000153	+0.000070	+0.000158
Asia and the Pacific	+0.000033	+0.000036	-0.000149	-0.000073
Europe and Central Asia	+0.000015	+0.000049	-0.000011	+0.000040

Figure 8: Marginal Effect of CDD Conditional on the Level of $log\_ACSTOCK$ for the Aggregate Sector (TOT). The Vertical Bars Indicate the Logarithm of the Regional Medians for 2019

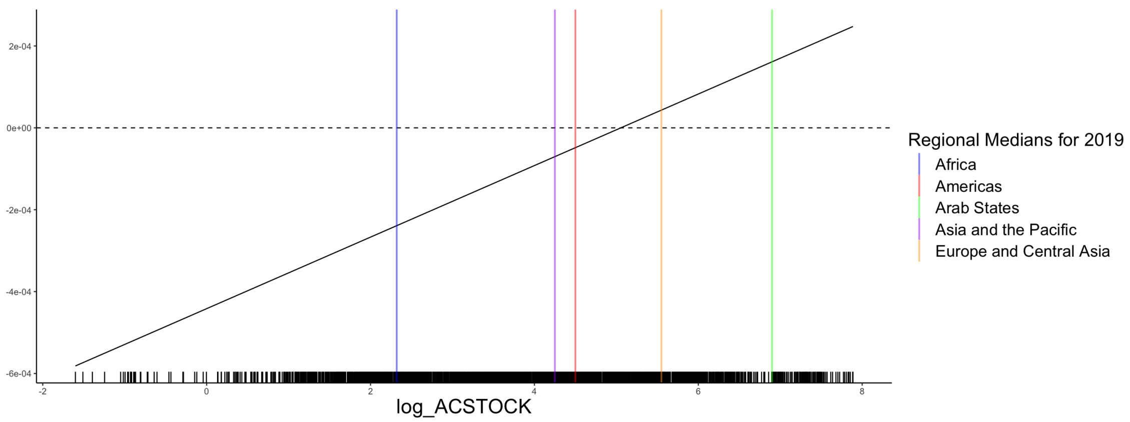


Figure 9: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Aggregate Sector (TOT). The Vertical Bars Indicate the Regional Medians for the period 1991-2019

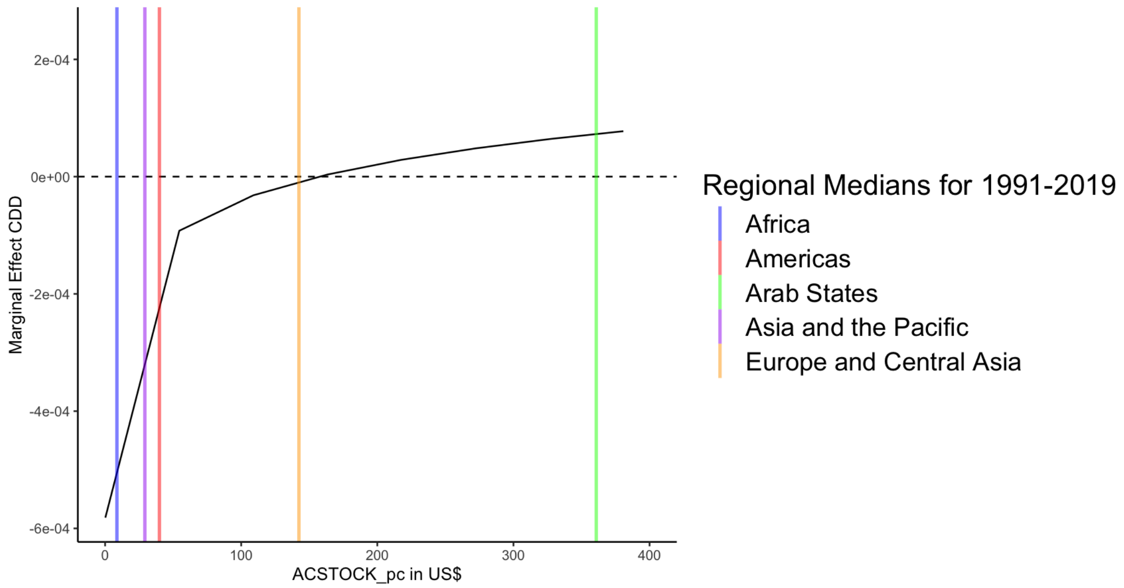
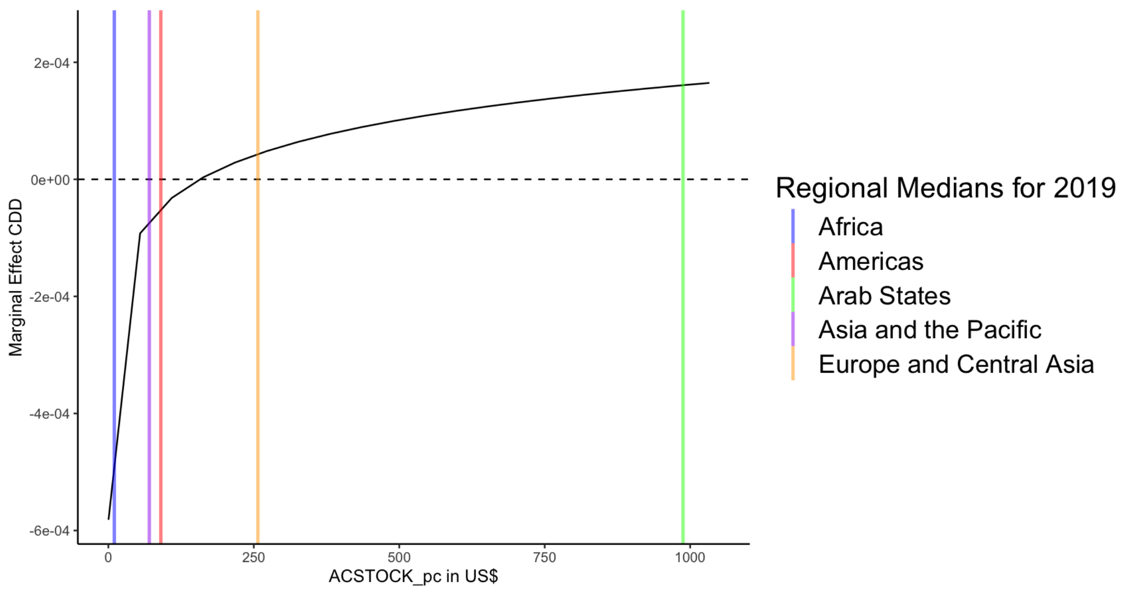


Figure 10: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Aggregate Sector (TOT). The Vertical Bars Indicate the Regional Medians for 2019



4.1.2 Non-Agricultural Sector (NOAGR)

Table 11: Results for the Non-Agricultural Sector (NOAGR) based on the preferred specification.

Dependent Variable:	log_LAB_PROD_NOAGR		
Model:	(1)	(2)	(3)
Variables			
HC_INDEX	0.392785***	0.112570	0.058460
	(0.099643)	(0.112164)	(0.114128)
log_KSpc	0.507435***	0.428362***	0.400320***
	(0.073141)	(0.087247)	(0.086833)
CDD		-0.000120	-0.000481**
		(0.000132)	(0.000217)
CDD × log_ACSTOCK			8.5×10^{-5}**
			(3.32×10^{-5})
Fixed-effects			
iso3	Yes	Yes	Yes
time	No	Yes	Yes
Quadratic Regional Trend	Yes	Yes	Yes
Fit statistics			
Observations	2,469	2,469	2,469
R^2	0.96125	0.96984	0.97040
Within R^2	0.47784	0.27573	0.28919

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: **Conditional Marginal Effect of** *log_ACSTOCK* calculated at Mean and Median Regional Values of *CDD*

Region	**ME at the Mean**	**ME at the Median**
Africa	0.0458	0.0305
Americas	0.0263	0.0191
Arab States	0.1012	0.1372
Asia and the Pacific	0.0563	0.0577
Europe and Central Asia	0.0049	0.0010

Table 13: **Logarithm of the Regional Mean and Median of** $ACSTOCK$ in US$ per Capita from 1990 to 2019 (lS) and in 2019 (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	3.14	3.50	2.16	2.32
Americas	4.38	4.90	3.69	4.50
Arab States	6.32	6.84	5.89	6.90
Asia and the Pacific	5.46	5.50	3.37	4.25
Europe and Central Asia	5.26	5.65	4.96	5.55

Table 14: **Conditional Marginal Effect of** CDD calculated at the Logarithm of the Mean and the Median of $ACSTOCK$, considering the period 1991-2019 (lS) and 2019 only (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	-0.000214	-0.000184	-0.000297	-0.000284
Americas	-0.000109	-0.000065	-0.000167	-0.000099
Arab States	+0.000056	+0.000100	+0.000020	+0.000106
Asia and the Pacific	-0.000017	-0.000014	-0.000195	-0.000120
Europe and Central Asia	-0.000035	-0.000001	-0.000059	-0.000009

Figure 11: Marginal Effect of CDD Conditional on the Level of $log\_ACSTOCK$ for the Non-Agricultural Sector. The Vertical Bars Indicate the Logarithm of the Regional Medians in 2019

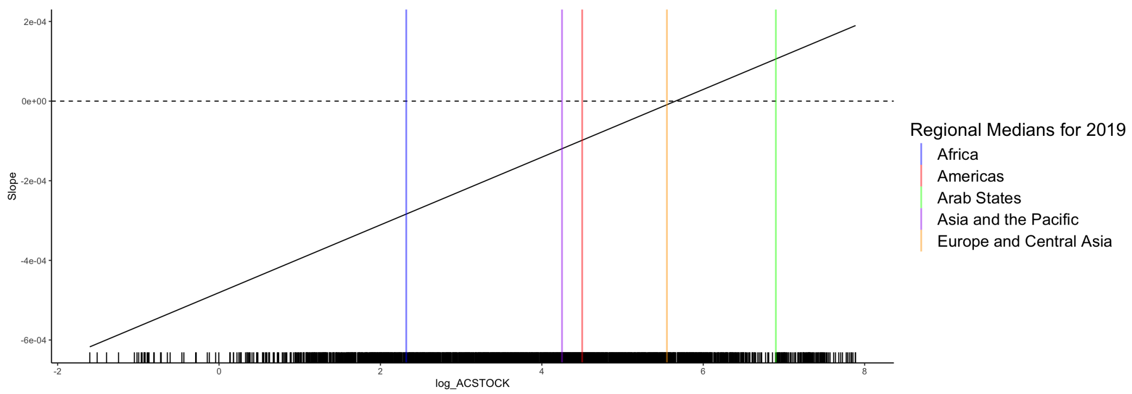


Figure 12: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Non-Agricultural Sector (NOAGR). The Vertical Bars Indicate the Regional Medians for the period 1991-2019

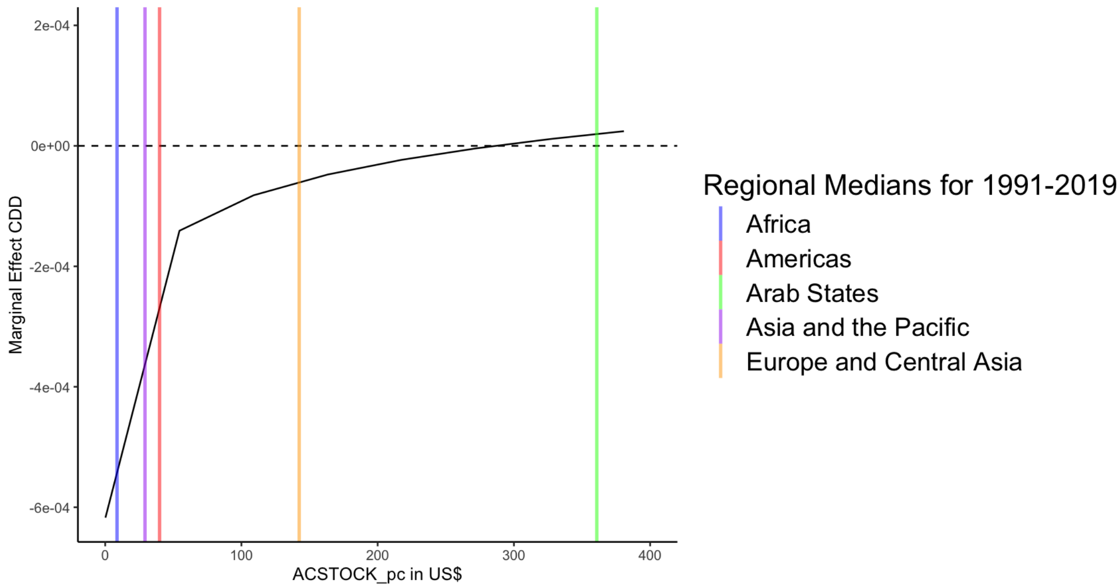
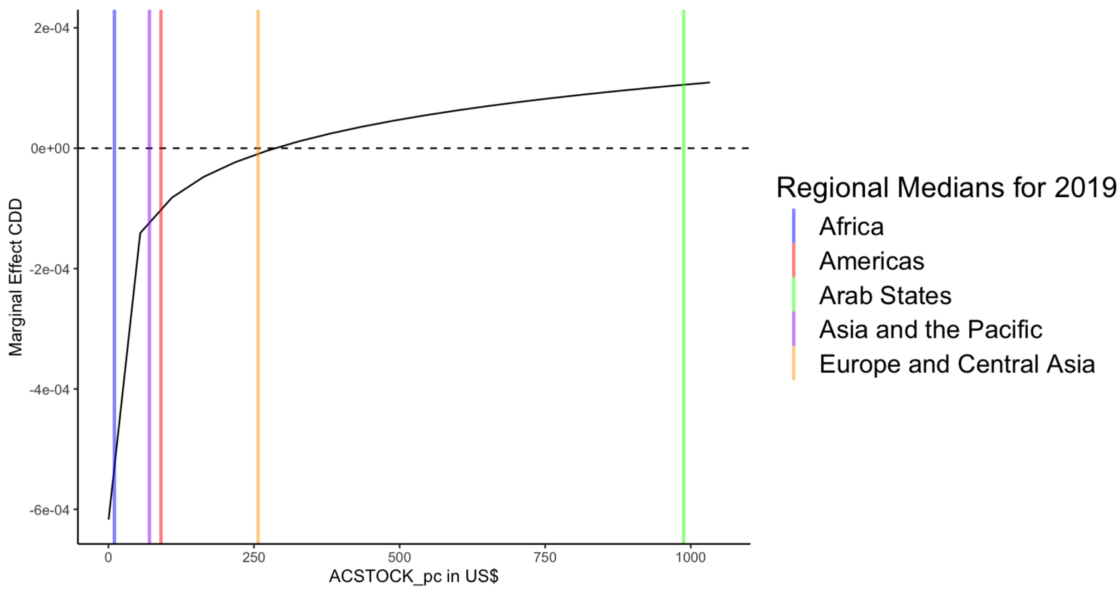


Figure 13: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Non-Agricultural Sector (NOAGR). The Vertical Bars Indicate the Regional Medians for 2019



4.1.3 Agricultural Sector (AGR)

Table 15: Results for the Agricultural Sector (AGR) based on the preferred specification.

Dependent Variable:	log_LAB_PROD_AGR		
Model:	(1)	(2)	(3)
Variables			
HC_INDEX	0.676995***	0.160361	0.093062
	(0.132153)	(0.187179)	(0.203175)
log_KSpc	0.473177***	0.216623**	0.181746*
	(0.097055)	(0.105627)	(0.106701)
CDD		-8.6×10^{-5}	-0.000535**
		(0.000153)	(0.000249)
CDD × log_ACSTOCK			0.000106**
			(4.55×10^{-5})
Fixed-effects			
iso3	Yes	Yes	Yes
time	No	Yes	Yes
Quadratic Regional Trend	No	Yes	Yes
Fit statistics			
Observations	2,469	2,469	2,469
R^2	0.96389	0.96884	0.96928
Within R^2	0.42652	0.07257	0.08568

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 16: **Conditional Marginal Effect of** $log\_ACSTOCK$ calculated at Mean and Median Regional Values of CDD

Region	**ME at the Mean**	**ME at the Median**
Africa	0.0571	0.0380
Americas	0.0328	0.0238
Arab States	0.1262	0.1708
Asia and the Pacific	0.0702	0.0720
Europe and Central Asia	0.0061	0.0013

Table 17: **Logarithm of the Regional Mean and Median of** $ACSTOCK$ in US$ per Capita from 1990 to 2019 (lS) and in 2019 (lS19)

Region	Mean lS	Mean lS19	Median lS	Median lS19
Africa	3.14	3.50	2.16	2.32
Americas	4.38	4.90	3.69	4.50
Arab States	6.32	6.84	5.89	6.90
Asia and the Pacific	5.46	5.50	3.37	4.25
Europe and Central Asia	5.26	5.65	4.96	5.55

Table 18: **Conditional Marginal Effect of** CDD calculated at the Logarithm of the Mean and the Median of $ACSTOCK$, considering the period 1991-2019 (lS) and 2019 only (lS19)

Region	Mean lS	Mean lS19	Median lS	Median lS19
Africa	-0.000201	-0.000164	-0.000306	-0.000289
Americas	-0.000071	-0.000016	-0.000144	-0.000058
Arab States	0.000135	0.000190	0.000089	0.000196
Asia and the Pacific	0.000044	0.000048	-0.000178	-0.000084
Europe and Central Asia	0.000023	0.000064	-0.000010	0.000053

Figure 14: Marginal Effect of CDD Conditional on the Level of $log\_ACSTOCK$ for the Agricultural Sector. The Vertical Bars Indicate the Logarithm of the Regional Medians in 2019

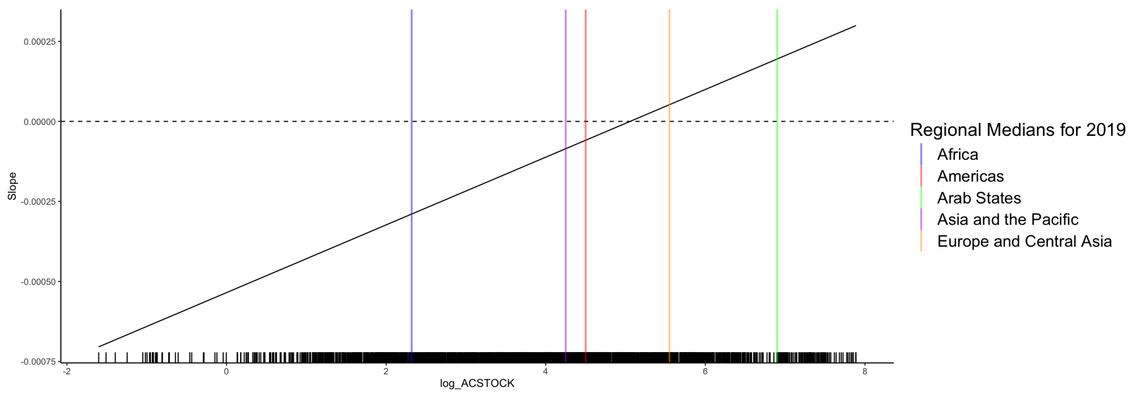


Figure 15: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Agricultural Sector (AGR). The Vertical Bars Indicate the Regional Medians for the period 1991-2019

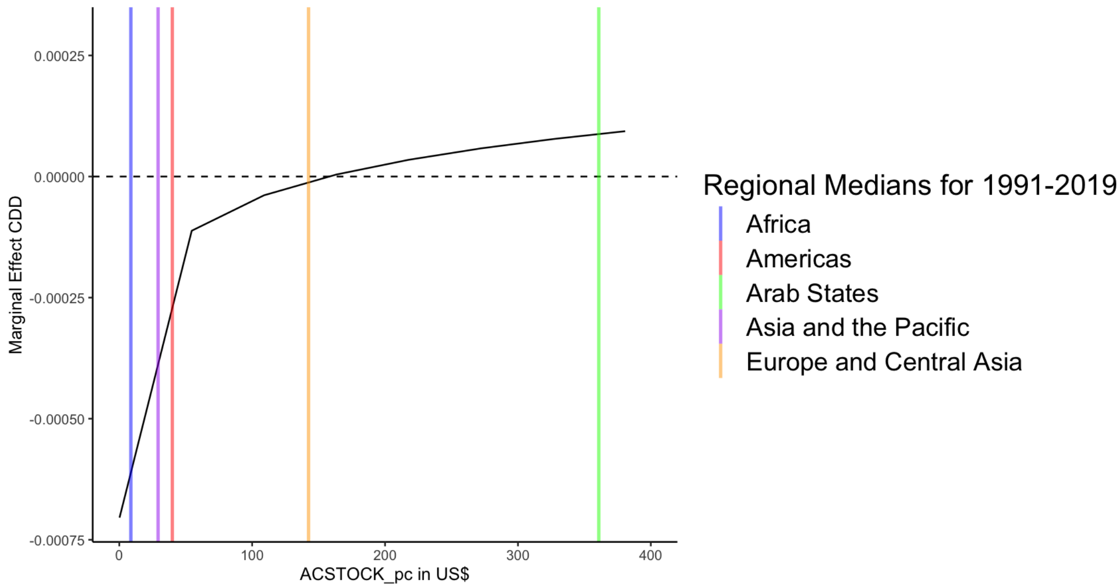
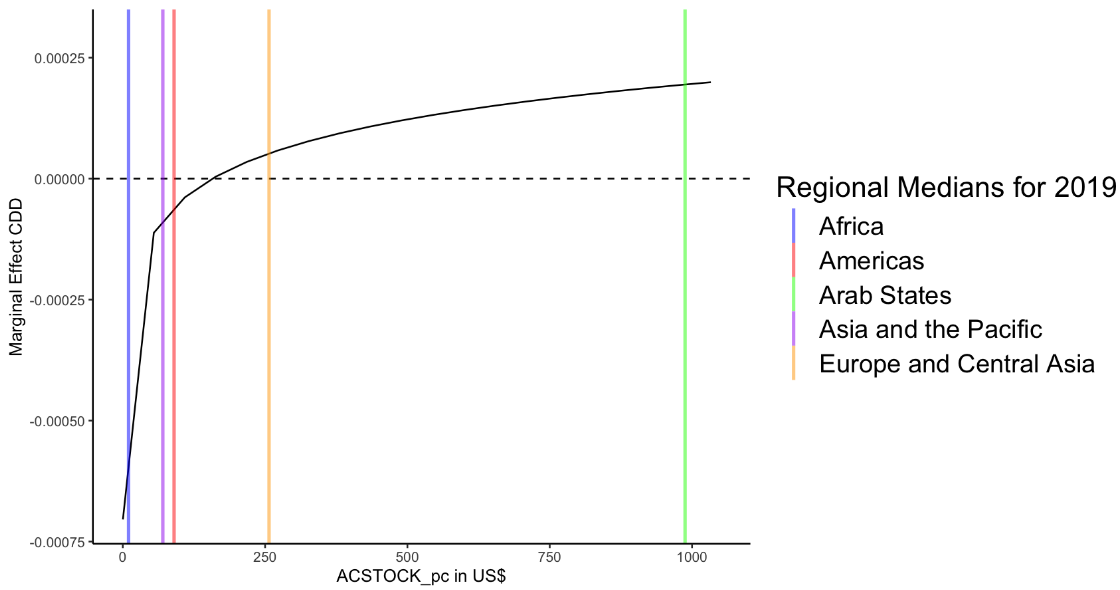


Figure 16: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Agricultural Sector (AGR). The Vertical Bars Indicate the Regional Medians for 2019



4.1.4 Services Sector (SER)

Table 19: Results for the Services Sector (SER) based on the preferred specification.

Dependent Variable:	log_LAB_PROD_SER		
Model:	(1)	(2)	(3)
Variables			
HC_INDEX	0.327119***	0.142210	0.035715
	(0.115121)	(0.127363)	(0.132101)
log_KSpc	0.464228***	0.426237***	0.371047***
	(0.089897)	(0.103411)	(0.098463)
CDD		-1.12×10^{-5}	-0.000721***
		(0.000141)	(0.000251)
CDD × log_ACSTOCK			0.000167***
			(4.18×10^{-5})
Fixed-effects			
iso3	Yes	Yes	Yes
time	No	Yes	Yes
Quadratic Regional Trend	No	Yes	Yes
Fit statistics			
Observations	2,469	2,469	2,469
R^2	0.93422	0.94337	0.94622
Within R^2	0.35744	0.21236	0.25208

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 20: **Conditional Marginal Effect of** *log_ACSTOCK* calculated at Mean and Median Regional Values of *CDD*

Region	**ME at the Mean**	**ME at the Median**
Africa	0.0899	0.0598
Americas	0.0516	0.0376
Arab States	0.1990	0.2690
Asia and the Pacific	0.1106	0.1134
Europe and Central Asia	0.0095	0.0020

Table 21: **Logarithm of the Regional Mean and Median of** $ACSTOCK$ in US$ per Capita from 1990 to 2019 (lS) and in 2019 (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	3.14	3.50	2.16	2.32
Americas	4.38	4.90	3.69	4.50
Arab States	6.32	6.84	5.89	6.90
Asia and the Pacific	5.46	5.50	3.37	4.25
Europe and Central Asia	5.26	5.65	4.96	5.55

Table 22: **Conditional Marginal Effect of** CDD calculated at the Logarithm of the Mean and the Median of $ACSTOCK$, considering the period 1991-2019 (lS) and 2019 only (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	-0.000197	-0.000137	-0.000360	-0.000334
Americas	0.000010	0.000097	-0.000105	0.000031
Arab States	0.000334	0.000420	0.000263	0.000431
Asia and the Pacific	0.000191	0.000198	-0.000158	-0.000011
Europe and Central Asia	0.000157	0.000223	0.000107	0.000206

Figure 17: Marginal Effect of CDD Conditional on the Level of $log\_ACSTOCK$ for the Services Sector. The Vertical Bars Indicate the Logarithm of the Regional Medians in 2019

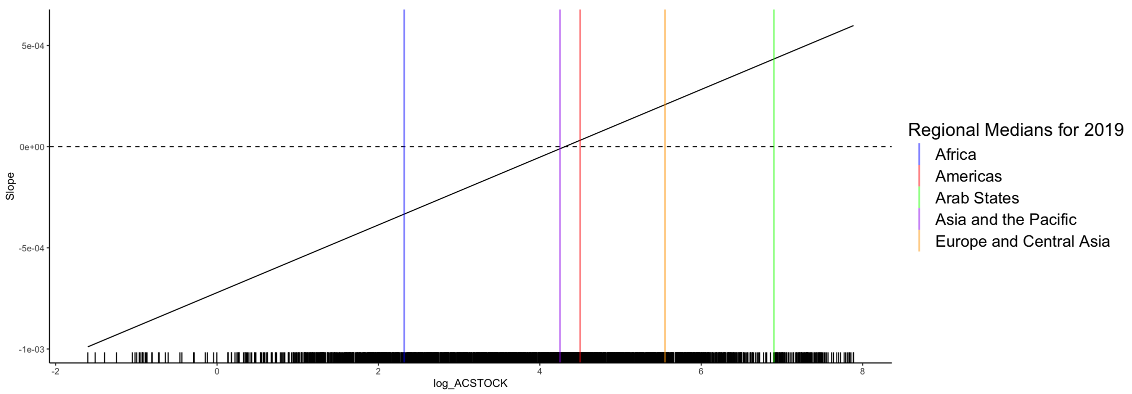


Figure 18: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Services Sector (SER). The Vertical Bars Indicate the Regional Medians for the period 1991-2019

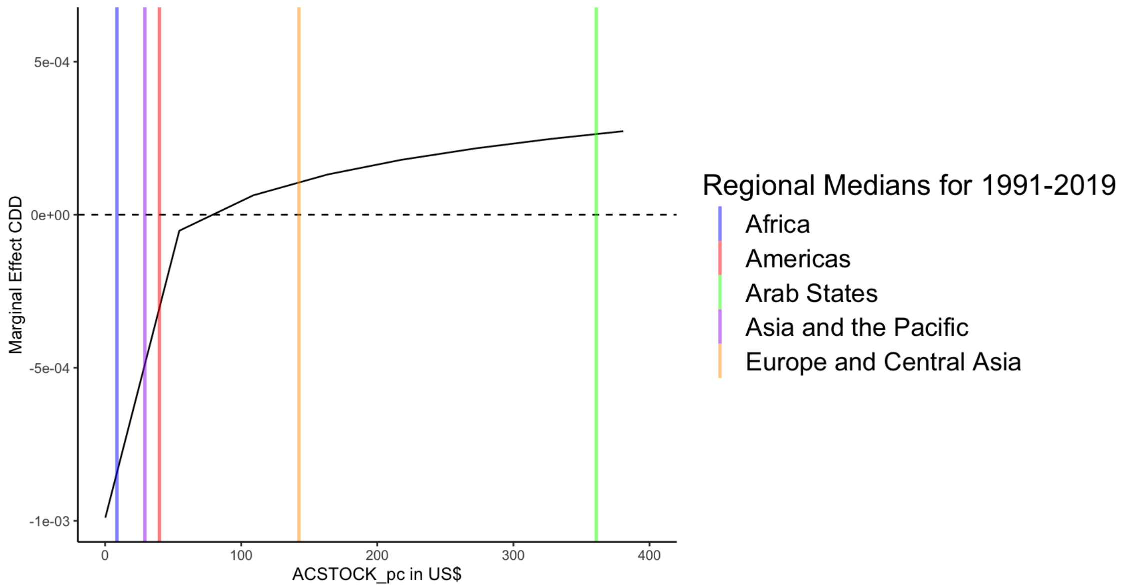
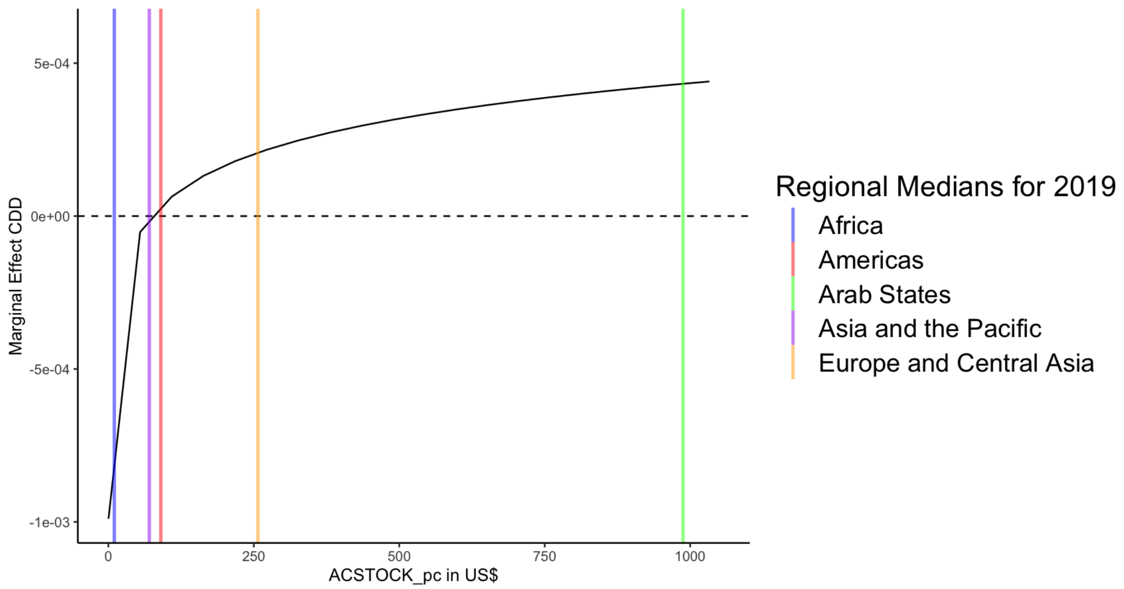


Figure 19: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Services Sector (SER). The Vertical Bars Indicate the Regional Medians for 2019



4.1.5 Industrial Sector (IND)

Table 23: Results for the Aggregate Industrial Sector (IND) and the disaggregated industrial sectors based on the preferred specification. These sub-sectors include Manufacturing (man), Construction (con), and Mining & Utilities (minuti). Together, these three sub-sectors form the Aggregate Industrial Sector (IND).

Dependent Variables:	log_LP_IND	log_LP_man	log_LP_con	log_LP_minuti
Model:	(1)	(2)	(3)	(4)
Variables				
HC_INDEX	0.151705	0.217505	-0.254875	0.376156
	(0.171087)	(0.191640)	(0.282254)	(0.284839)
log_KSpc	0.497733***	0.430085***	0.469801**	0.355039
	(0.144702)	(0.146791)	(0.196571)	(0.271954)
CDD	-0.000309	-0.000369	-0.000386	-0.001074**
	(0.000303)	(0.000338)	(0.000312)	(0.000475)
CDD × log_ACSTOCK	2.06×10^{-5}	4.44×10^{-5}	3.3×10^{-5}	0.000241***
	(4.76×10^{-5})	(5.89×10^{-5})	(5.7×10^{-5})	(7.8×10^{-5})
Fixed-effects				
iso3	Yes	Yes	Yes	Yes
time	Yes	Yes	Yes	Yes
Quadratic Regional Trend	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,469	2,466	2,469	2,466
R^2	0.96035	0.95287	0.91194	0.92084
Within R^2	0.25645	0.21459	0.09629	0.17354

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notably, the preferred specification incorporating the adaptation mediator yields statistically significant coefficients exclusively for the industrial sub-sector *Mining & Utilities (minuti)*. Consequently, the following tables and graphs focus solely on this statistical relationship involving this sub-sector. Results for “IND”, “man”, and “con” are omitted.

Mining & Utilities (minuti) Sub-Sector

Table 24: Results for the Mining & Utilities (minuti) Sub-Sector based on the preferred specification.

Dependent Variable:	log_LAB_PROD_min_uti		
Model:	(1)	(2)	(3)
Variables			
HC_INDEX	0.590805**	0.527551	0.376156
	(0.268260)	(0.325161)	(0.284839)
log_KSpc	0.280481	0.441789	0.355039
	(0.211512)	(0.277246)	(0.271954)
CDD		-5.45×10^{-5}	-0.001074**
		(0.000283)	(0.000475)
CDD × log_ACSTOCK			0.000241***
			(7.8×10^{-5})
Fixed-effects			
iso3	Yes	Yes	Yes
time	No	Yes	Yes
Quadratic Regional Trend	No	Yes	Yes
Fit statistics			
Observations	2,466	2,466	2,466
R^2	0.90077	0.91839	0.92084
Within R^2	0.13912	0.14790	0.17354

Clustered (iso3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 25: **Conditional Marginal Effect of** *log_ACSTOCK* calculated at Mean and Median Regional Values of *CDD*

Region	**ME at the Mean**	**ME at the Median**
Africa	0.1296	0.0863
Americas	0.0745	0.0542
Arab States	0.2870	0.3880
Asia and the Pacific	0.1596	0.1636
Europe and Central Asia	0.0138	0.00296

Table 26: **Logarithm of the Regional Mean and Median of** $ACSTOCK$ in US$ per Capita from 1990 to 2019 (lS) and in 2019 (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	3.14	3.50	2.16	2.32
Americas	4.38	4.90	3.69	4.50
Arab States	6.32	6.84	5.89	6.90
Asia and the Pacific	5.46	5.50	3.37	4.25
Europe and Central Asia	5.26	5.65	4.96	5.55

Table 27: **Conditional Marginal Effect of** CDD calculated at the Logarithm of the Mean and the Median of $ACSTOCK$, considering the period 1991-2019 (lS) and 2019 only (lS19)

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	−0.000317	−0.000231	−0.000554	−0.000515
Americas	−0.000018	0.000107	−0.000185	0.000011
Arab States	0.000448	0.000571	0.000346	0.000585
Asia and the Pacific	0.000240	0.000251	−0.000262	0.000169
Europe and Central Asia	0.000193	0.000287	0.000121	0.000264

Figure 20: Marginal Effect of CDD Conditional on the Level of $log\_ACSTOCK$ for the Mining & Utilities (minute) Sub-Sector. The Vertical Bars Indicate the Logarithm of the Regional Medians in 2019

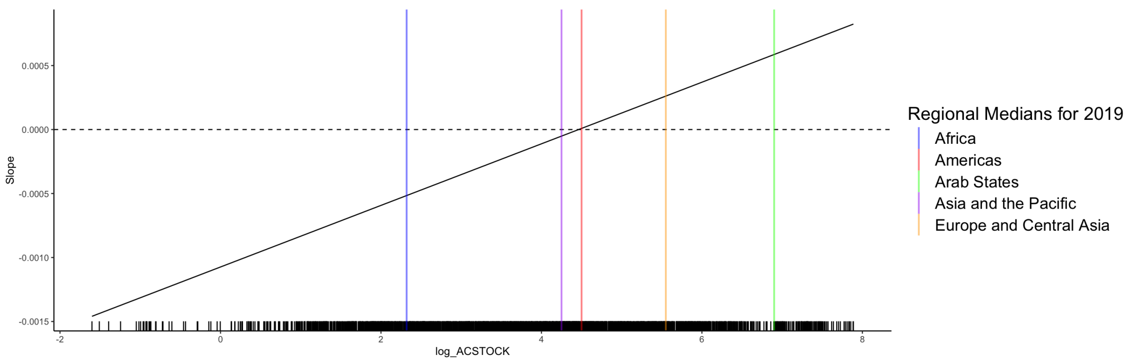


Figure 21: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Mining & Utilities (minute) Sub-Sector. The Vertical Bars Indicate the Regional Medians for the period 1991-2019

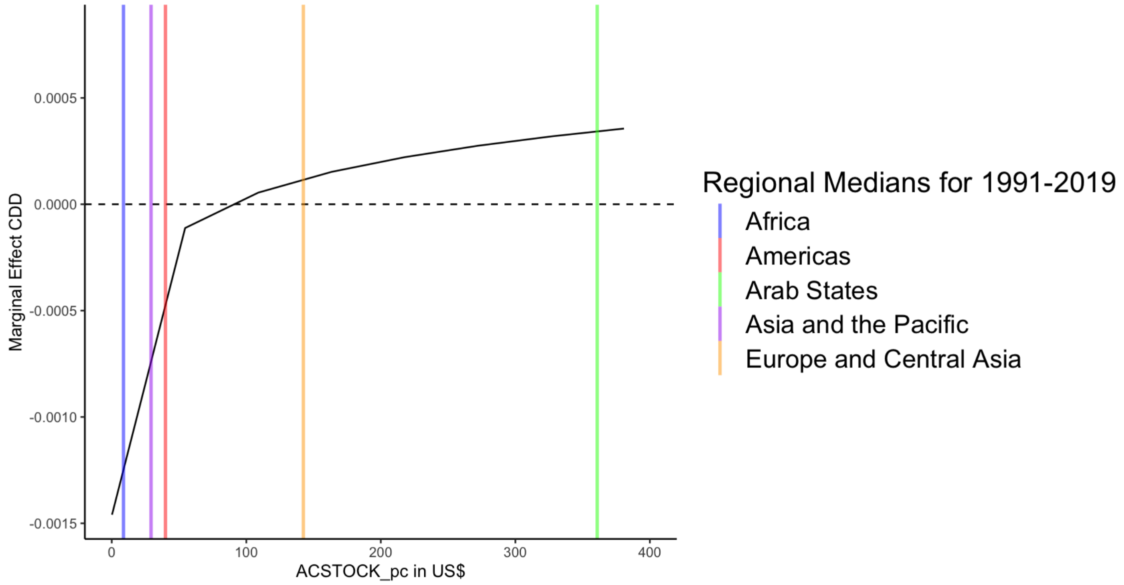
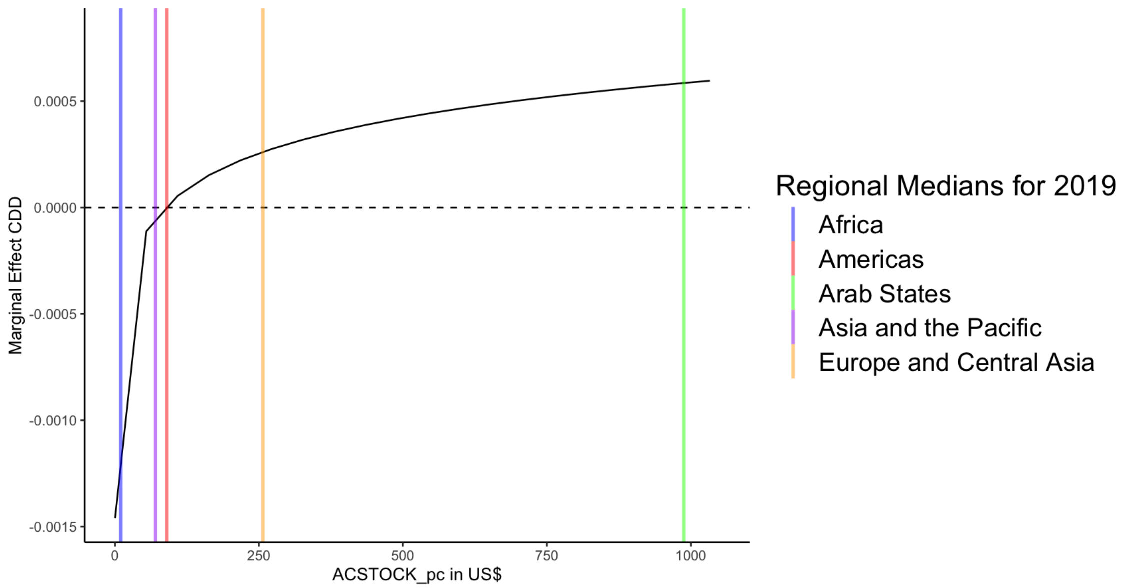


Figure 22: Marginal Effect of CDD Conditional on the Level of $ACSTOCK$ for the Mining & Utilities (minute) Sub-Sector. The Vertical Bars Indicate the Regional Medians for 2019



4.1.6 Comparison Between Different Sectors

Table 28: Comparison of the preferred model's results across various sectors

Dependent Variables:	log_LP_TOT	log_LP_NOAGR	log_LP_AGR	log_LP_SER	log_LP_minuti
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
HC_INDEX	0.008013	0.058460	0.093062	0.035715	0.376156
	(0.102345)	(0.114605)	(0.203412)	(0.132234)	(0.285188)
log_KSpc	0.450516***	0.400320***	0.181746*	0.371047***	0.355039
	(0.071538)	(0.086564)	(0.106657)	(0.098400)	(0.271674)
CDD	-0.000442**	-0.000481**	-0.000535**	-0.000721***	-0.001074**
	(0.000203)	(0.000217)	(0.000248)	(0.000251)	(0.000474)
CDD × log_ACSTOCK	8.74×10^{-5}***	8.5×10^{-5}**	0.000106**	0.000167***	0.000241***
	(2.79×10^{-5})	(3.32×10^{-5})	(4.54×10^{-5})	(4.18×10^{-5})	(7.77×10^{-5})
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
time	Yes	Yes	Yes	Yes	Yes
Quadratic Regional Trend	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,469	2,469	2,469	2,469	2,466
R^2	0.98351	0.97040	0.96928	0.94622	0.92085
Within R^2	0.32818	0.28920	0.08567	0.25208	0.17358

Clustered (iso3) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.1.7 Without the "Bad Controls"

Table 29: Comparison of the preferred model results excluding *the Human Capital Index* and *the logarithm of the capital stock per capita* as controls

Dependent Variables:	log_LP_TOT	log_LP_NOAGR	log_LP_AGR	log_LP_SER	log_LP_minuti
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
CDD	-0.000590***	-0.000616***	-0.000593***	-0.000869***	-0.001190**
	(0.000203)	(0.000225)	(0.000226)	(0.000246)	(0.000542)
CDD × log_ACSTOCK	0.000112***	0.000109***	0.000100**	0.000185***	0.000306***
	(3.55×10^{-5})	(3.95×10^{-5})	(4.51×10^{-5})	(4.62×10^{-5})	(9.29×10^{-5})
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
time	Yes	Yes	Yes	Yes	Yes
Quadratic Regional Trend	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,554	2,554	2,554	2,554	2,551
R^2	0.97948	0.96528	0.96767	0.93979	0.91769
Within R^2	0.23316	0.22858	0.09497	0.25409	0.12035

Clustered (iso3) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.2 Predictions

This section seeks to apply future climate projections to the results discussed above. Specifically, it aims to estimate the potential damages resulting from a hypothetical shift in weather patterns projected for 2050 to present-day conditions, assuming no significant improvement in current adaptation strategies. It is important to note that this is purely a theoretical exercise, as even regions with the lowest adaptive capacities are expected to enhance their efforts in response to increasing GDP per capita and overall development (IEA 2018; Colelli, Wing, and Cian 2023).

Data referring to the future global climate sourced from the *CMIP6 climate projections*[1] refers to the intermediate scenario RCP 4.5.[2] To estimate the hypothetical climate shock described above, the method involves comparing the 30-year average of Cooling Degree Days (CDDs) centered around 2050 with the historical average of annual CDDs centered around 2000. This difference represents the projected shift in climate conditions. The final simulated climate shock was constructed by averaging the projected shocks from seven different climate models. This approach provides a more robust estimate by incorporating a range of potential climate outcomes. Henceforth, this hypothetical shock will be referred to as *Delta CDDs*. For additional country-level projections, please refer to the Appendix.

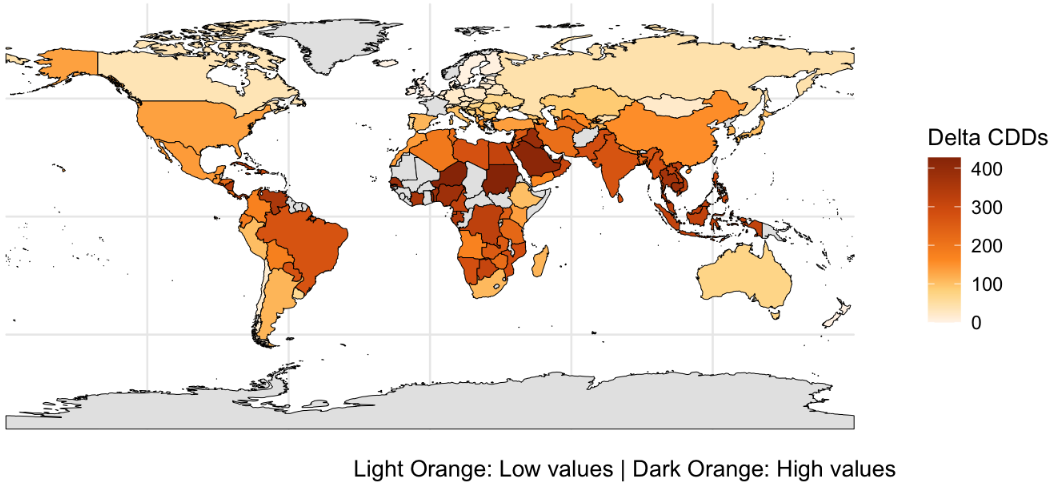
Region	**Projected Delta CDDs**
Africa	265
Americas	218
Arab States	313
Asia and the Pacific	232
Europe and Central Asia	66

Table 30: **Average Delta CDDs Projected for 2050 by Region**

[1]Copernicus Climate Change Service, Climate Data Store, (2021): CMIP6 climate projections. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). DOI: 10.24381/cds.c866074c (Accessed on 21-09-2024)

[2]Different scenarios project varying trajectories for future greenhouse gas concentrations. According to Copernicus documentation, Scenario RCP 4.5 describes a possible future where emissions begin to decline after 2050. This scenario assumes a reduction in meat consumption, stabilization of methane emissions, large-scale reforestation efforts, and the implementation of new, stringent climate policies.

Figure 23: **Average Delta CDDs Projected for 2050 by Country**



4.2.1 Predictions: Aggregate Sector (TOT)

Table 31: **Total Effect by Region of the Projected *Delta CDDs* on the Labor Productivity of the Aggregate Sector (TOT)**. The values have been calculated by multiplying the projected *Delta CDDs* by the conditional marginal effect of a CDD, calculated at the logarithm of different regional descriptive statistics of ACSTOCK.

Region	Mean lS	Mean lS19	Median lS	Median lS19
Africa	-0.045	-0.036	-0.067	-0.064
Americas	-0.014	-0.003	-0.026	-0.011
Arab States	0.034	0.048	0.022	0.050
Asia and the Pacific	0.008	0.008	-0.035	-0.017
Europe and Central Asia	0.001	0.003	-0.001	0.003

An interpretative example is proposed.[3] *Examining the last column, the estimate suggests that for Africa, considering a level of external adaptation equal to the regional median in 2019, Delta CDDs would reduce aggregate labor productivity by 6.4% compared to the current climate.* A general discussion of the results is presented in Chapter 4.

[3]The notation for the logarithm of the descriptive statistics is consistent with the format previously outlined in the thesis. In particular: **Mean lS** refers to the logarithm of the regional mean of *ACSTOCK* for the period 1991-2019 and **Mean lS19** refers to the logarithm of the regional mean of *ACSTOCK* for the year 2019. The same reasoning also applies to **Median** values.

Figure 24: Projected Impact of *Delta CDDs* for the Aggregate Sector (TOT) in 2050 by Country. The values have been calculated by multiplying the projected *Delta CDDs* by the Conditional Marginal Effect of a CDD, calculated at the logarithm of the Country Average of $ACSTOCK$

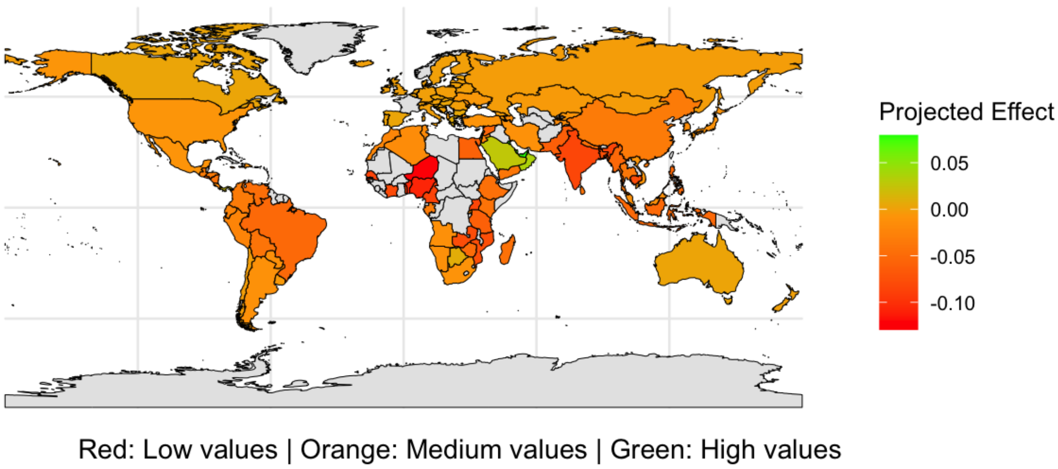
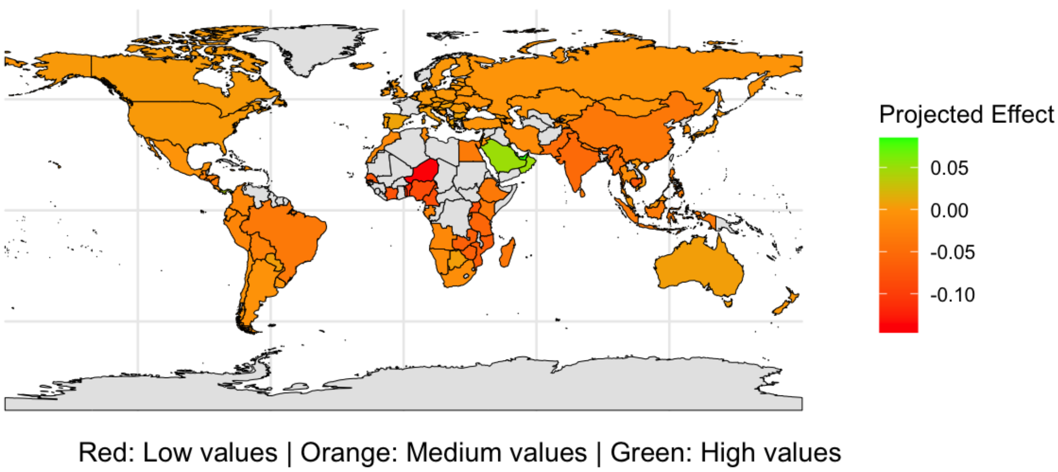


Figure 25: Projected Impact of *Delta CDDs* for the Aggregate Sector (TOT) in 2050 by Country. The values have been calculated by multiplying the projected *Delta CDDs* by the Conditional Marginal Effect of a CDD, calculated at the logarithm of the Country Value of $ACSTOCK$ for 2019



4.2.2 Predictions: Non-Agricultural Sector (NOAGR)

Table 32: **Projected Effect of *Delta CDDs* on the Labor Productivity of the Non-Agricultural Sector (NOAGR)**. The values have been calculated by multiplying the projected *Delta CDDs* by the conditional marginal effect of a CDD, calculated at the logarithm of different regional descriptive statistics of $ACSTOCK$.

Region	Mean lS	Mean lS19	Median lS	Median lS19
Africa	-0.032	-0.027	-0.067	-0.060
Americas	-0.008	-0.002	-0.028	-0.011
Arab States	0.035	0.048	0.022	0.052
Asia and the Pacific	0.007	0.008	-0.033	-0.015
Europe and Central Asia	0.001	0.003	-0.001	0.003

4.2.3 Predictions: Agricultural Sector (AGR)

Table 33: **Projected Effect of *Delta CDDs* on the Labor Productivity of the Agricultural (AGR)**. The values have been calculated by multiplying the projected *Delta CDDs* by the conditional marginal effect of a CDD, calculated at the logarithm of different regional descriptive statistics of $ACSTOCK$.

Region	Mean lS	Mean lS19	Median lS	Median lS19
Africa	-0.053	-0.043	-0.081	-0.077
Americas	-0.015	-0.003	-0.031	-0.013
Arab States	0.042	0.059	0.028	0.061
Asia and the Pacific	0.010	0.011	-0.041	-0.019
Europe and Central Asia	0.002	0.004	-0.001	0.003

4.2.4 Predictions: Services Sector (SER)

Table 34: **Projected Effect of *Delta CDDs* on the Labor Productivity of the Services Sector (SER)**. The values have been calculated by multiplying the projected *Delta CDDs* by the conditional marginal effect of a CDD, calculated at the logarithm of different regional descriptive statistics of $ACSTOCK$.

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	-0.052	-0.036	-0.095	-0.089
Americas	0.002	0.021	-0.023	0.007
Arab States	0.105	0.131	0.082	0.135
Asia and the Pacific	0.044	0.046	-0.037	-0.003
Europe and Central Asia	0.010	0.015	0.007	0.014

4.2.5 Predictions: Mining & Utilities Sub-Sector (minuti)

Table 35: **Projected Effect of *Delta CDDs* on the Labor Productivity of the Mining & Utilities Sub-Sector (minute)**. The values have been calculated by multiplying the projected *Delta CDDs* by the conditional marginal effect of a CDD, calculated at the logarithm of different regional descriptive statistics of $ACSTOCK$.

Region	**Mean lS**	**Mean lS19**	**Median lS**	**Median lS19**
Africa	-0.084	-0.061	-0.146	-0.136
Americas	-0.004	0.023	-0.040	0.002
Arab States	0.140	0.179	0.108	0.183
Asia and the Pacific	0.056	0.058	-0.061	0.039
Europe and Central Asia	0.013	0.019	0.008	0.017

Chapter 5

Discussion

This study aimed to assess the impact of high temperatures on labor productivity across different sectors, with a focus on quantifying the role of external adaptation strategies in mitigating these negative effects. Utilizing a high-dimensional fixed effects (HDFE) model based on panel data, the analysis provides valuable insights into both aspects of the research question. The findings contribute to bridging the gap between micro and macro-level empirical evidence, offering significant implications for the Integrated Assessment Models (IAMs) literature.

This chapter presents and interprets the results of the empirical models, comparing them with the existing literature. It also addresses the limitations of the analysis and provides recommendations for future research. The final section concludes the analysis, summarizing the key findings of the thesis.

5.1 Discussion

The main findings of the empirical part include that CDD, our proxy for temperature exposure, has a significant impact on the annual productivity of many economic sectors. This effect is observed in the Aggregate sector (Table 7), the Non-Agricultural sector (Table 11), the Agricultural sector (Table 15), the Services sector (Table 19), and the Mining & Utilities sub-sector (Table 24). Interestingly, the preferred specification does not produce statistically significant results for the Industrial Sector or its sub-sectors Construction and Manufacturing (Table 23). In these sectors, neither the coefficients for CDD nor the interaction terms reach statistical significance at conventional levels, despite existing evidence suggesting that temperature may have an impact (Cachon, Gallino, and Olivares 2012). One possible explanation for the Manufacturing sector's results is its rigid work organization, the climate-controlled nature of its operations, and the relatively high level of mechanization. In the Construction sector, despite its high labor intensity, the findings may suggest alternative adaptation strategies unrelated to air conditioning, such as possibly adjusting work hours to the cooler parts of the day. Another hypothesis involves the presence of compensatory behavior, given that the production structure in this sector is often characterized by long-term deadlines.

Notably, the variable CDD has a statistically significant impact on labor productivity only when even the proxy for the *adaptation strategies* is included in the regression equation, considering our preferred specifications and the selected sectors. This can be noticed by comparing Model 2 and Model 3 in each of the previously cited tables. This finding underscores the risk of obtaining misleading results if adaptation is not accounted for in panel-based regression analyses. Moreover, the results also show that the interaction coefficient between CDD and $log(ACSTOCK)$, the moderating factor, is always positive. This implies that the elasticity of labor productivity with respect to the stock of air conditioning machines is an increasing function of CDD.

The results of the total marginal effect of CDD on labor productivity, conditional on different levels of air conditioning stock for the Aggregate Sector, are presented in Figures 8, 9, 10, and Table 10.[1] These elements confirm that at low levels of air conditioning stock, the marginal effect of an additional CDD relative to the country or regional average is negative. For medium to high levels of air conditioning stock per capita—such as in the "Europe and Central Asia" case—the model predicts a marginal contribution close to zero, which varies slightly depending on the time horizon considered for the level of $ACSTOCK$. Unexpectedly, the model predicts a positive marginal effect of CDD for the "Arab States", where the level of air conditioning stock per capita is exceptionally high compared to the rest of the world. Figures 9 and 10 illustrate that the total marginal effect of CDD is a concave function of the level of air conditioning stock per capita. This concave relationship implies that the marginal contribution of air conditioning stock in mitigating adverse temperature effects decreases as the stock increases. The result provides clear evidence of a *saturation effect*, meaning that while the marginal benefit of an additional unit of air conditioning stock per capita is very high when the stock is low, it gradually diminishes as the stock increases.

Given that the per capita air conditioning stock can be considered a general proxy for a country's overall adaptation capacity, it is not surprising that air conditioning also plays a role in a typically outdoor sector like Agriculture. As previously discussed, adaptation strategies in Agriculture include measures such as improving infrastructure for water access, crop switching and protecting crops from hail, among others. Furthermore, given the labor-intensive nature of the Services sector, it is reasonable to conclude that it is highly sensitive to temperature variations and stands to gain significantly from climate adaptation strategies. The Mining & Utilities sector faces a unique trade-off, as hotter-than-average years likely boost energy demand, which can increase the sector's value-added—and, consequently, its labor productivity—even though high temperatures may reduce worker performance. This dynamic may contribute to the high sensitivity to CDD and to the level of $ACSTOCK$, making the interpretation of the estimates for this sub-sector particularly delicate.

[1] For additional country-level data, please refer to the Appendix.

Table 29 shows the results of the sector-level comparison removing from the regression equation the variables that part of the literature refers to as "bad controls", specifically *the Human Capital Index* and *the Logarithm of the Value of the Capital Stock per capita*. The rationale is that climate variables can cause these controls, so including them may absorb part of the variation that should be attributed to the climate variables. As expected, the coefficients of both CDD and its interaction with $\log(ACSTOCK)$ are larger in Table 29, likely because these variables capture more of the residual variation. However, this scenario, where adaptation is implicitly accounted for, introduces a risk of omitted variable bias if the so-called "bad controls" are removed. For instance, it is plausible that labor productivity might become less sensitive to high temperatures due to increased capital stock per capita, independent of the effect of air conditioning units. Thus, if these controls are correlated with the variables of interest, excluding them could result in biased estimates.

The section dedicated to future projections applies the results obtained for the total marginal effect of CDD to the projected climate in 2050, considering an intermediate emissions scenario and current levels of adaptive capacity. Table 30 and Figure 23 present the predicted regional and national increases in yearly CDD for 2050. Table 31 shows the predicted impact of the projected *Delta CDDs* for the Aggregate Sector at the regional level, while Figures 24 and 25 display the national-level impacts. A comparison of Figures 23 and 24 shows that countries most exposed to climate change typically have lower levels of adaptation strategies.

A notable exception to this observation is the "Arab States". In fact, in 2019, these countries displayed a regional median value of air conditioning stock per capita that was approximately four times higher than that of Europe (Table 10). For the Arab States, the projected model results predict that the climate in 2050 would lead to an increase in the yearly labor productivity of 5%, at the current level of adaptation capacity.[2] Moreover, given that the "Arab States" are characterized by a

[2]This is a strange result, that could partially be driven by the fact the economy of the Arab States highly relies on the Mining & Utilities sector, as shown in Table 1 and in the comparison between Figures 2 and 3. Furthermore, the significant volatility of Value Added in this region—largely

high variance in yearly $CDDs$ and a high level of $ACSTOCK$, data from these countries play an important role in estimating the coefficients of interest, particularly in sectors like Mining & Utilities and Services. Further analysis should more thoroughly investigate the role of climate adaptation strategies in these countries, where the climate is extremely hot and the level of adaptation strategies is very high.

Notably, directly comparing the magnitude of the results from this thesis with those in the existing literature is challenging, as none of the main reviewed studies in similar fields and at comparable scales use Cooling Degree Days (CDD) as the climate variable, and very few explicitly consider the role of adaptation. Moreover, macro-level studies often use income per capita as the dependent variable, which, although highly correlated with labor productivity, does not align precisely with its definition. Nevertheless, this thesis makes a valuable contribution to the literature by bridging the gap between micro-level evidence, which clearly demonstrates the negative impact of high temperatures on labor productivity, and macro-level evidence, which at best suggests that developed countries are less sensitive to temperature shocks but fails to explicitly quantify the role of climate adaptation in this process.

While this thesis provides valuable insights into the impact of high temperatures on sector-level labor productivity and the moderating role of adaptation strategies, it is essential to acknowledge the limitations that may influence the interpretation of the findings. Firstly, the variable used to measure labor productivity serves only as an approximation of workers' actual performance in the real world. For example, studies that utilize more precise data on output and hours worked by sector could enhance the reliability of this proxy. The same reasoning applies to the variable $ACSTOCK$, which is an import-based proxy that does not directly account for the real-world cumulative internal demand. Additionally, not controlling for other climatic factors correlated with temperature, such as humidity and wind, can lead to

driven by fluctuations in commodity markets, such as crude oil prices—suggests that using Value Added per Number of Workers as a proxy for labor productivity may not accurately capture actual worker performance in this context. Although time controls may absorb part of this effect, they probably cannot fully account for the volatility caused by commodity price swings. One potential robustness check is to develop an empirical strategy that includes oil prices as a control variable.

biased estimates. Future research should aim to incorporate these elements into the analysis, despite the challenges of defining adequate statistics at the national level for these factors. Another important area for further research involves studying the inequality aspects of temperature impacts, with a specific focus on explicitly considering adaptation capacity. For example, adaptation possibilities may vary not only between countries within a region due to differing economic characteristics but also among households within the same city and among workers within the same firm, depending on their positions within the company hierarchy. Finally, although this thesis advances the discussion on the role of adaptation in the panel-based approach context, there are still significant methodological challenges that need to be addressed. These include considering general equilibrium effects, the risks of extrapolating beyond historical experience, and the potential intensification of climate impacts.

5.2 Conclusions

This thesis aimed to estimate the impact of high temperatures on sector-level labor productivity, quantifying the contribution of adaptation strategies in mitigating the adverse effects. The empirical method involved the use of a panel data approach relying on country-level weather variations from 1991 to 2019. To assess the overall extent of external adaptation strategies implemented by a country, a proxy based on the value of imported air conditioning machines has been developed. The results highlight a significant level effect on labor productivity of both high-temperature shocks and adaptation strategies for many economic sectors. Furthermore, the diminishing returns of per capita air conditioning stock on the attenuation of the temperature effect on labor productivity suggest a saturation effect. The findings are consistent with most of the micro-level evidence, even if the results for industrial sectors underscore the need for further investigation. Additional analyses are also required to explore the underlying causes of the estimated positive effect of temperature shocks at higher levels of external adaptation strategies.

Despite the mentioned limitations, the results can be considered a first step in providing a general framework to bridge the gap between micro and macro-level evidence. In particular, the empirical estimates presented in this thesis may be relevant not only to the *ex-post analysis* literature, which aims to quantify causal relationships using historical data, but also to the *ex-ante modeling* literature, which seeks to derive future policy implications from established causal or associative relationships. The estimated results can provide a foundation for refining the climate damage functions implemented in current Integrated Assessment Models (IAMs), improving the precision of temperature damage assessments, and integrating the trade-off between labor productivity benefits and adaptation investment costs. Future research should integrate this trade-off with projections of future air conditioning penetration, evaluating the associated energy consumption and its impact on predicted emission trajectories. Incorporating these dynamics into Integrated Assessment Models (IAMs) is crucial for refining Social Cost of Carbon (SCC) estimates and guiding society toward optimal policy decisions.

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Appendix

Table 36: **Country Level Values of:** the Logarithm of the Mean of $ACSTOCK$ from 1991 to 2019 **(LM)**; the Logarithm of $ACSTOCK$ in 2019 **(L19)**; the Conditional Marginal Effect of a CDD for the Aggregate Sector (TOT) at the Logarithm of the Mean of $ACSTOCK$ **(MELM)**; the Conditional Marginal Effect of a CDD for the Aggregate Sector (TOT) at the Logarithm of $ACSTOCK$ in 2019 **(ME19)**; Country-Level Delta CDDs Projected **(DCDDs)**; the Total Predicted Impact of Delta CDDs for the Aggregate Sector (TOT) at **LM** $ACSTOCK$ Level **(PILM)**; the Total Predicted Impact of $DeltaCDDs$ for the Aggregate Sector (TOT) at **L19** $ACSTOCK$ Level **(PIL19)**

Country	Region	LM	L19	MELM	ME19	DCDDs	PILM	PIL19
AGO	Africa	4.26	3.95	-0.0070%	-0.0097%	172	-1.20%	-1.67%
ALB	Europe and Central Asia	4.71	4.99	-0.0030%	-0.0006%	115	-0.349%	-0.0641%
ARE	Arab States	7.37	7.54	0.0203%	0.0217%	393	7.95%	8.51%
ARG	Americas	3.93	4.58	-0.0099%	-0.0042%	113	-1.11%	-0.467%
ARM	Europe and Central Asia	4.31	4.60	-0.0066%	-0.0040%	71.7	-0.470%	-0.289%
AUS	Asia and the Pacific	5.43	5.88	0.0033%	0.0072%	71.6	0.236%	0.512%
AUT	Europe and Central Asia	5.39	6.10	0.0029%	0.0091%	27.6	0.0813%	0.251%
AZE	Europe and Central Asia	3.94	4.45	-0.0098%	-0.0053%	151	-1.47%	-0.806%
BEL	Europe and Central Asia	6.01	6.50	0.0083%	0.0126%	15.5	0.129%	0.196%
BEN	Africa	1.86	1.65	-0.0280%	-0.0298%	383	-10.7%	-11.4%
BGD	Asia and the Pacific	1.40	NaN	-0.0320%	NaN	233	-7.46%	NaN
BGR	Europe and Central Asia	5.74	6.19	0.0060%	0.0099%	92.1	0.553%	0.915%
BIH	Europe and Central Asia	4.96	5.02	-0.0009%	-0.0003%	63.9	-0.0565%	-0.0193%
BLR	Europe and Central Asia	4.69	4.98	-0.0032%	-0.0007%	26.4	-0.0851%	-0.0183%
BOL	Americas	2.48	3.43	-0.0226%	-0.0142%	176	-3.98%	-2.50%
BRA	Americas	2.90	3.58	-0.0189%	-0.0129%	272	-5.14%	-3.51%
BWA	Africa	5.35	5.26	0.0026%	0.0018%	309	0.802%	0.543%
CAN	Americas	6.05	5.97	0.0087%	0.0079%	35.8	0.309%	0.284%
CHE	Europe and Central Asia	4.92	5.54	-0.0012%	0.0043%	12.1	-0.0144%	0.0513%
CHL	Americas	3.89	4.34	-0.0102%	-0.0063%	15.2	-0.154%	-0.0951%
CHN	Asia and the Pacific	2.56	2.44	-0.0219%	-0.0229%	156	-3.40%	-3.56%
CIV	Africa	2.52	2.57	-0.0222%	-0.0218%	363	-8.05%	-7.89%
CMR	Africa	1.97	2.07	-0.0270%	-0.0261%	319	-8.61%	-8.34%
COL	Americas	2.83	3.89	-0.0195%	-0.0102%	174	-3.38%	-1.77%
CRI	Americas	4.04	4.30	-0.0089%	-0.0048%	221	-1.96%	-1.24%

Table 36: *(continued)*

Country	Region	LM	L19	MELM	ME19	DCDDs	PILM	PIL19
CYP	Europe and Central Asia	6.04	6.10	0.0086%	0.0091%	205	1.76%	1.86%
CZE	Europe and Central Asia	6.08	6.45	0.0090%	0.0121%	24.3	0.218%	0.295%
DEU	Europe and Central Asia	4.77	5.57	-0.0025%	0.0045%	20.5	-0.0513%	0.0912%
DNK	Europe and Central Asia	4.41	5.04	-0.0057%	-0.0002%	5.12	-0.0291%	-0.0010%
DOM	Americas	4.66	4.77	-0.0035%	-0.0025%	296	-1.03%	-0.742%
DZA	Africa	4.09	NaN	-0.0084%	NaN	192	-1.62%	NaN
ECU	Americas	3.57	4.30	-0.0130%	-0.0066%	188	-2.45%	-1.24%
EGY	Africa	2.92	3.87	-0.0186%	-0.0104%	314	-5.85%	-3.26%
ESP	Europe and Central Asia	5.36	5.85	0.0026%	0.0069%	112	0.295%	0.772%
EST	Europe and Central Asia	6.30	6.52	0.0109%	0.0128%	9.88	0.107%	0.126%
ETH	Africa	-0.0303	1.05	-0.0445%	-0.0350%	101	-4.48%	-3.52%
FIN	Europe and Central Asia	5.04	5.63	-0.0002%	0.0050%	5.62	-0.0011%	0.0281%
FRA	Europe and Central Asia	4.70	5.42	-0.0031%	0.0031%	40.1	-0.126%	0.125%
GAB	Africa	4.00	4.33	-0.0092%	-0.0064%	352	-3.24%	-2.24%
GBR	Europe and Central Asia	4.60	5.01	-0.00398%	-0.00042%	2.14	-0.00851%	-0.00089%
GEO	Europe and Central Asia	4.74	5.33	-0.0028%	0.0024%	92.7	-0.260%	0.219%
GRC	Europe and Central Asia	5.66	5.78	0.00525%	0.00635%	152	0.798%	0.966%
GTM	Americas	2.62	3.00	-0.0213%	-0.0180%	145	-3.10%	-2.61%
HKG	Asia and the Pacific	7.60	7.42	0.0222%	0.0206%	231	5.15%	4.77%
HND	Americas	3.33	3.68	-0.0151%	-0.0121%	224	-3.38%	-2.70%
HRV	Europe and Central Asia	5.77	6.00	0.0062%	0.0083%	82.7	0.512%	0.684%
HUN	Europe and Central Asia	5.72	6.16	0.00582%	0.00964%	71.5	0.416%	0.689%
IDN	Asia and the Pacific	3.20	3.85	-0.0163%	-0.0106%	317	-5.16%	-3.36%
IND	Asia and the Pacific	1.54	2.85	-0.0307%	-0.0193%	272	-8.35%	-5.24%
IRL	Europe and Central Asia	4.83	4.99	-0.0020%	-0.0006%	0.252	-0.0005%	-0.0001%
IRN	Asia and the Pacific	4.46	4.46	-0.0052%	-0.0052%	213	-1.10%	-1.11%
ISL	Europe and Central Asia	3.87	4.59	-0.0104%	-0.0041%	0	0%	0%
ISR	Europe and Central Asia	4.90	5.47	-0.0014%	0.0036%	264	-0.367%	0.950%
ITA	Europe and Central Asia	5.02	5.61	-0.0004%	0.0048%	98.0	-0.0356%	0.471%
JAM	Americas	3.80	4.50	-0.0110%	-0.0049%	298	-3.27%	-1.45%
JOR	Arab States	4.21	5.08	-0.0074%	0.0002%	267	-1.97%	0.0466%
JPN	Asia and the Pacific	4.07	5.20	-0.0086%	0.0013%	102	-0.881%	0.131%
KAZ	Europe and Central Asia	4.55	4.88	-0.0045%	-0.0015%	88.7	-0.395%	-0.134%
KEN	Africa	1.51	2.09	-0.0310%	-0.0260%	135	-4.19%	-3.52%
KGZ	Europe and Central Asia	3.04	3.61	-0.0177%	-0.0127%	37.4	-0.659%	-0.473%
KHM	Asia and the Pacific	2.75	2.90	-0.0201%	-0.0188%	389	-7.84%	-7.33%
KOR	Asia and the Pacific	3.60	4.68	-0.0127%	-0.0033%	113	-1.44%	-0.371%
KWT	Arab States	7.17	6.90	0.0185%	0.0161%	404	7.47%	6.49%
LBN	Arab States	5.59	5.36	0.00463%	0.00265%	144	0.664%	0.380%
LKA	Asia and the Pacific	3.37	3.87	-0.0148%	-0.0104%	282	-4.15%	-2.93%
LTU	Europe and Central Asia	5.24	5.84	0.0016%	0.0068%	15.7	0.0250%	0.107%
LUX	Europe and Central Asia	5.75	5.79	0.0060%	0.0064%	24.9	0.150%	0.159%
LVA	Europe and Central Asia	5.15	5.55	0.0008%	0.0043%	12.6	0.0103%	0.0542%
MAR	Africa	3.26	3.94	-0.0157%	-0.0097%	139	-2.18%	-1.35%

Table 36: *(continued)*

Country	Region	LM	L19	MELM	ME19	DCDDs	PILM	PIL19
MDA	Europe and Central Asia	4.14	4.65	-0.00798%	-0.00355%	92.6	-0.739%	-0.329%
MDG	Africa	0.672	1.21	-0.0383%	-0.0336%	113	-4.32%	-3.79%
MEX	Americas	4.41	4.86	-0.0057%	-0.0017%	141	-0.801%	-0.242%
MLT	Europe and Central Asia	6.52	6.34	0.0128%	0.0112%	45.4	0.581%	0.507%
MMR	Asia and the Pacific	2.87	3.32	-0.0191%	-0.0152%	276	-5.28%	-4.21%
MNG	Asia and the Pacific	3.50	3.93	-0.0136%	-0.0099%	20.2	-0.274%	-0.200%
MOZ	Africa	2.02	2.39	-0.0265%	-0.0233%	290	-7.68%	-6.74%
MYS	Asia and the Pacific	4.63	5.10	-0.0038%	0.0003%	326	-1.23%	0.109%
NAM	Africa	4.55	4.61	-0.0045%	-0.0039%	281	-1.26%	-1.09%
NER	Africa	1.59	1.15	-0.0303%	-0.0342%	427	-12.9%	-14.6%
NGA	Africa	1.78	2.49	-0.0286%	-0.0225%	379	-10.8%	-8.52%
NIC	Americas	3.65	4.06	-0.0123%	-0.0030%	346	-4.26%	-3.00%
NLD	Europe and Central Asia	5.21	5.81	0.00134%	0.00660%	8.04	0.0107%	0.0531%
NOR	Europe and Central Asia	5.25	5.96	0.00165%	0.00786%	1.45	0.0024%	0.0114%
NPL	Asia and the Pacific	1.72	2.38	-0.0292%	-0.0234%	156	-4.57%	-3.67%
NZL	Asia and the Pacific	4.84	5.47	-0.00189%	0.00362%	1.53	-0.0029%	0.0056%
OMN	Arab States	6.41	6.94	0.0119%	0.0164%	305	3.62%	5.02%
PAK	Asia and the Pacific	2.57	3.13	-0.0217%	-0.0169%	286	-6.22%	-4.83%
PAN	Americas	5.77	6.53	0.0062%	0.0129%	340	2.11%	4.39%
PER	Americas	2.38	2.92	-0.0234%	-0.0186%	102	-2.40%	-1.91%
PHL	Asia and the Pacific	3.13	3.99	-0.0168%	-0.0093%	302	-5.08%	-2.82%
POL	Europe and Central Asia	4.45	5.35	-0.0053%	0.0026%	22.9	-0.121%	0.0586%
PRT	Europe and Central Asia	5.36	5.79	0.0026%	0.0064%	46.1	0.121%	0.296%
PRY	Americas	4.53	5.27	-0.0046%	0.00185%	276	-1.26%	0.510%
QAT	Arab States	7.07	7.41	0.0176%	0.0205%	396	6.96%	8.13%
ROU	Europe and Central Asia	4.94	5.40	-0.0010%	0.00297%	78.4	-0.0795%	0.233%
RUS	Europe and Central Asia	4.37	4.78	-0.0061%	-0.0024%	43.1	-0.261%	-0.103%
RWA	Africa	1.32	1.74	-0.0327%	-0.0290%	35.8	-1.17%	-1.04%
SAU	Arab States	5.81	6.44	0.0066%	0.0120%	415	2.72%	5.00%
SEN	Africa	2.53	2.85	-0.0220%	-0.0193%	394	-8.69%	-7.60%
SGP	Asia and the Pacific	7.10	7.32	0.0178%	0.0198%	353	6.29%	6.98%
SLV	Americas	2.87	3.61	-0.0191%	-0.0126%	330	-6.31%	-4.17%
SVK	Europe and Central Asia	6.12	6.38	0.0093%	0.0115%	34.8	0.323%	0.400%
SVN	Europe and Central Asia	5.75	6.11	0.0061%	0.0092%	38.7	0.235%	0.356%
SWE	Europe and Central Asia	5.04	5.63	-0.0002%	0.00496%	3.69	-0.00065%	0.0183%
SYR	Arab States	2.60	NaN	-0.0215%	NaN	254	-5.45%	NaN
TGO	Africa	2.49	2.14	-0.0225%	-0.0255%	384	-8.61%	-9.79%
THA	Asia and the Pacific	3.88	4.74	-0.0103%	-0.0027%	368	-3.80%	-1.01%
TJK	Europe and Central Asia	3.29	3.36	-0.0155%	-0.0148%	114	-1.77%	-1.70%
TTO	Americas	4.83	5.63	-0.0020%	0.00498%	328	-0.657%	1.64%
TUN	Africa	4.18	4.40	-0.0077%	-0.0057%	217	-1.66%	-1.24%
TUR	Europe and Central Asia	4.40	4.92	-0.0057%	-0.0012%	136	-0.776%	-0.168%
TZA	Africa	2.06	2.23	-0.0262%	-0.0247%	231	-6.06%	-5.71%
UGA	Africa	1.20	1.29	-0.0337%	-0.0330%	249	-8.38%	-8.20%

Table 36: *(continued)*

Country	Region	LM	L19	MELM	ME19	DCDDs	PILM	PIL19
UKR	Europe and Central Asia	4.14	4.43	-0.0080%	-0.0055%	67.5	-0.541%	-0.369%
URY	Americas	4.22	4.85	-0.0073%	-0.0019%	64.3	-0.468%	-0.119%
USA	Americas	4.49	5.22	-0.00499%	0.00142%	134	-0.668%	0.190%
VEN	Americas	3.56	NaN	-0.0131%	NaN	357	-4.69%	NaN
VNM	Asia and the Pacific	4.83	5.10	-0.0020%	0.00034%	319	-0.646%	0.108%
YEM	Arab States	2.33	NaN	-0.0238%	NaN	163	-3.88%	NaN
ZAF	Africa	4.07	4.16	-0.0087%	-0.0078%	107	-0.927%	-0.835%
ZMB	Africa	1.61	2.22	-0.0301%	-0.0248%	257	-7.76%	-6.39%
ZWE	Africa	2.49	1.68	-0.0224%	-0.0295%	217	-4.87%	-6.39%