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TWO ESSAYS ON AGRICULTURE, TRADE AND CLIMATE CHANGE

PAOLO NOTA

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CONTENTS

1 INTRODUCTION 1
2 CLIMATE INSTABILITY, WEATHER SHOCKS, AND AGRICULTURAL PRODUCTION 3
2.1 Introduction 3
2.2 Background and Conceptual Framework 5
2.2.1 Climate Change as Increasing Climate Instability 5
2.2.2 Model of Agricultural Production 7
2.3 Methodology and Data 8
2.3.1 Empirical Specification 8
2.3.2 Data 11
2.4 Results 11
2.4.1 Heterogeneity Between Countries 14
2.4.2 Counterfactual Analysis for Future Climate . . 15
2.5 Conclusions 18
3 ADAPTATION TO CLIMATE CHANGE THROUGH MARKET INTEGRATION: EVIDENCE FROM AGRICULTURAL TRADE IN THE EU 21
3.1 Introduction 21
3.2 Methods 24
3.2.1 Model 25
3.2.2 Productivity-to-Exports Elasticity 27
3.2.3 Counterfactual Productivity 28
3.3 Data 29
3.4 Results 31
3.4.1 Estimates of the Trade Elasticity 31
3.4.2 Productivity and Climate 33
3.4.3 Trade Adjustments and Welfare 35
3.5 Conclusions 41

I APPENDIX 43
A APPENDIX A 45
A.1 Methodology 45
B APPENDIX B 53

BIBLIOGRAPHY 59

LIST OF FIGURES

Figure 1	Marginal Effect of Positive Temperature Anomaly on Agricultural Output	16
Figure 2	Cumulative Change (%) in Agricultural Output in 2070: RCP 6.0	18
Figure 3	Marginal Effect of Temperature and Precipitation on Productivity	33
Figure 4	Change (%) in Agricultural Productivity (2081-2100, RCP4.5)	34
Figure 5	Change (%) in Consumer Surplus in the Mediterranean Region	40
Figure A1	Robustness Check: different values of m	51
Figure A2	Evolution of an Agriculture-based Gini Index 2016-2070	52
Figure B1	Estimates of θ using different years	56

LIST OF TABLES

Table 1	Impact of Weather Anomalies on Agricultural Production	13
Table 2	Cumulative Change (%) of Agricultural Output in 2070	17
Table 3	Descriptive Statistics	30
Table 4	Estimate of the Trade Elasticity (θ)	32
Table 5	Results from the Model Simulations (% changes)	37
Table 6	Sensitivity analysis	40
Table A1	Descriptive Statistics	46
Table A2	Variables' description and source	47
Table A3	Robustness Checks	48
Table A4	Heterogeneity between Income Groups	49
Table A5	Heterogeneity between Average Temperature Groups	50
Table B1	Estimate of the Climate-Productivity Relationship	53
Table B2	Results for all regions - RCP 4.5	53
Table B3	Welfare Results: Country Level	57

ACRONYMS

ACC Anthropogenic Climate Change

CC Climate Change

EU European Union

GDP Gross Domestic Product

IPCC Intergovernmental Panel on Climate Change

NDVI Normalized Difference Vegetation Index

NUTS Nomenclature of Territorial Units for Statistics

RCP Representative Concentration Pathway

SSP Shared Socioeconomic Path

TFP Total Factor Productivity

WDI World Development Indicators

WMO World Meteorological Organization

1 INTRODUCTION

In this thesis, I present two research articles that connect different branches of the vast economic discipline, namely, agricultural, international trade, and climate economics.

In the first chapter, I present the paper "Climate Instability, Weather Shocks, and Agricultural Production", coauthored with my supervisor Prof. Alessandro Olper. Here, we follow the climate-economy literature that uses econometric methods to assess the impact of climate change on economic activities (e.g. Dell, Jones, and Olken, 2014), to quantify the climate-driven consequences in global agricultural production caused by future climatic changes.
The agricultural economic literature starts early to address this topic (see the milestone article by Mendelsohn, Nordhaus, and Shaw, 1994) because of the peculiarity of agricultural productions that are particularly sensitive to climatic conditions (for an extensive review see Ortiz-Bobea, 2021). After describing common methodologies, we develop a theoretical framework to assess the impact of changing climatic conditions on aggregate agricultural production, accounting for adaptation within the sector. Using panel data techniques and historical observations for a large sample of countries, we estimate the relationship between agricultural production and weather shocks.
We show that when annual temperature and precipitation deviate from their historical norm, they have a negative effect on agricultural production. These negative effects are different among countries and, using differences in income levels, it is possible to estimate a heterogeneous damage function. Simple counterfactual analyses, using future climatic conditions according to different GHGs emissions scenarios, show that climate change will substantially reduce agricultural production if the target of the so-called Paris Agreement will not be reached. Low-income and developing countries will be particularly affected with likely consequences on global inequality.

In the second chapter, I present the paper "Adaptation to Climate Change through Market Integration: Evidence from Agricultural Trade in the EU", which constitutes the single-author article of the thesis. Here, I analyze the role of trade and market integration as an adaptation mechanism to cope with climate change. This research question is not particularly new (see Reilly and Hohmann, 1993), however, it has been recently renewed in the context of new quantitative trade models (see Costinot and Rodríguez-Clare, 2014 for an overview of this literature) by recent contributions (Costinot, Donaldson, and Smith, 2016; Gouel and Laborde, 2021).

Because of the heterogeneous impact of climate change on agricultural productivity, the structure of comparative advantage will change, inducing new patterns of trade among regions. Therefore, I build a partial equilibrium model, based on the trade literature of Ricardian models (Eaton and Kortum, 2002), to simulate different degrees of trade adjustment to a productivity shock induced by climate change. I use detailed trade data for the agricultural sector of intra-EU subnational regions (NUTS2) to feed the quantitative model. I estimate in a consistent manner a key parameter, i.e. the trade elasticity, that in these types of models governs comparative advantage. Using econometric techniques and detailed territorial (NUTS3) data on agricultural productivity and climatic conditions, I estimate the relationship between the two and predict future productivity changes according to climate change scenarios. Using such changes as an exogenous shock in the model, I run simulations to quantify the role of trade and its impact on welfare.
The results show that, on average, trade adjustments play little role in defining the welfare effect within the EU. However, heterogeneity is large both between consumers and producers and among the different regions. In particular, trade would play a substantial role in alleviating consumers' losses for those regions where the productivity shock would increase local prices (e.g. Mediterranean area).

The two essays are not directly connected and I present them in chronological order. The next Section (2) presents the paper "Climate Instability, Weather Shocks, and Agricultural Production". Section 3 presents the paper "Adaptation to Climate Change through Market Integration: Evidence from Agricultural Trade in the EU". Appendix A refers to the first article, while Appendix B refers to the second one.

2 CLIMATE INSTABILITY, WEATHER SHOCKS, AND AGRICULTURAL PRODUCTION

ABSTRACT

We study the relationship between aggregate agricultural production and weather anomalies in a panel data setting with a global sample of countries in the period 1968-2016. Using an aggregate measure allows us to account for intra-sector and within-country adjustments, while the use of deviations from the historical climatology (i.e. anomalies) better represents the shocks that a changing climate imposes on the agricultural system. Our results suggest a negative, non-linear and significant relationship between agricultural output and our measure of the weather. We find that less developed countries experience stronger negative impacts of temperature anomalies. Development and income levels play an important role in reducing these negative effects. Counterfactual analyses of potential future impacts caused by climate change show that losses would be substantial in high-emission scenarios and the gap between developing and developed regions would further increase.

Keywords: Agriculture, Climate Change, Economic Impact
JEL Classification: Q1, Q51, Q54

2.1 INTRODUCTION

The relationship between agriculture, weather, and climate is well documented. A rich literature exists on the subject and the most recent developments are related to the consequences that Climate Change (CC) has on the sector (for a review see Auffhammer and Schlenker, 2014; Ortiz-Bobea, 2021). CC impact assessment has acquired particular importance for the distinctive role that the agricultural system has in the economy. Indeed, agriculture provides the largest amount of food consumed by the population and employs a large share of the world's labor force (especially in developing countries). Thus, weather and climate impacts on the agricultural sector have repercussions on important issues such as food security (Wheeler and Braun, 2013), labor mobility and migration (Falco, Galeotti, and Olper, 2019), and political stability (Burke, Hsiang, and Miguel, 2015a). Our understanding of the phenomenon plays a crucial role in leading to proper mitigation, adaptation, and sustainable development policies.

In the economic literature, the terms "climate" and "weather" refer to different concepts that bring to develop different methodologies. The former regards the atmospheric conditions in a given location over a long period of time that allows the economic agents to form expectations and choose their management practices based on these. The second term refers to the actual realization of atmospheric conditions over a short period of time. In this case, changes in weather are not easily predictable by the economic agents and are therefore considered exogenous (Hsiang, 2016). In this paper, we mainly refer to the literature based on the second concept and describe the different methodologies in the subsection 2.2.

Many studies analyze crop productions since they represent a quantitatively important share of the entire agricultural sector and they use crop yield as the main outcome variable (e.g. Schlenker and Roberts, 2009; Burke and Emerick, 2016; Gammans, Mérel, and Ortiz-Bobea, 2017, among many others). These estimates are of particular value because they provide the direction and magnitude of the effects that weather variations have on agricultural productivity and are often used to be implemented in quantitative economic models to derive future scenarios under CC.

Despite its remarkable contribution to the literature, the vast majority of studies that focus only on staple crop yields limits the overall analysis. Hertel and Lima (2020) highlight the importance of estimating weather and climate impacts on the overall agricultural system and focusing the attention on other proxies for productivity (in particular labor and Total Factor Productivity, TFP) that represent better the historical evolution of the agricultural sector (see also Fuglie, 2015). The recent paper by Ortiz-Bobea et al. (2021) represents a clear example that overcomes these shortcomings. In particular, they estimate the relationship between weather variables and agricultural TFP on a global sample of countries in order to quantify the impact of Anthropogenic Climate Change (ACC) of the past decades (from 1962 to 2020). They find that on average ACC had a negative impact of 21% in global TFP (corresponding to the last 7 years of lost growth), with even higher effects in the hottest regions of the world.

Instructed by the above-mentioned analyses, we focus our attention on the aggregate agricultural sector and on the future impact of CC. Using an aggregate measure allows us to account for intra-sectoral and within-country adjustments to changing climatic conditions (i.e. adaptation). In fact, not all crops are affected by adverse weather conditions in the same way, also because farmers may select those that are more resilient. Differences exist between the subsectors, for example animal and non-animal productions, that can induce farmers to rearrange the mix of their agricultural activities in a proper way. Furthermore, some countries may further exploit their lands and move the production sites toward more suitable regions (Costinot, Donaldson, and Smith, 2016) or benefit from competitive input prices in the national (Dall'Erba, Chen, and Nava, 2021) and international markets (Garcia-Verdu et al., 2021).

We develop a conceptual framework in which the weather extremes, in the form of anomalies, affect the production function of the farmers. We translate the theoretical framework into an empirical specification and, using data for 172 countries in the period 1968-2016, we estimate the relationship between aggregate agricultural production and weather anomalies. The results confirm our hypothesis and suggest a negative, non-linear and significant relationship between agricultural production and our measure of the weather. In particular, when the temperature is above the historical norm (positive anomaly) and the precipitation is below (negative anomaly), aggregate agricultural production decreases significantly. We also estimate a heterogeneous damage function to assess countries' ability to cope with adverse climatic conditions (see Auffhammer, 2018). We find that the marginal effect of temperature anomaly is proportional to GDP per capita. Consequently, future CC impacts (considering only temperature changes) result in sizeable losses for less developed countries and almost no losses for advanced economies.

The paper is organized as follows. In Section 2.2, we present the conceptual framework that informs and motivates our empirical application. Section 2.3 shows how our theoretical structure can be translated into an empirical specification, discussing the underline econometric identification properties. Section 2.4 presents the results. Finally, Section 2.5 concludes.

2.2 BACKGROUND AND CONCEPTUAL FRAMEWORK

2.2.1 *Climate Change as Increasing Climate Instability*

The weather is a complex phenomenon that describes the atmospheric conditions at a given time and location. The economic literature often relies on multi-variable simple statistics, e.g. average temperature and precipitation. Climate is therefore defined by the joint distribution of these weather variables and is represented by their long-term averages (e.g. 20-year temperature average represents a climate-normal or climatology). Climate change is consequently seen as a change in this distribution (for a review of the climate-economy relationship see Dell, Jones, and Olken, 2014; Hsiang, 2016; Kolstad and Moore, 2020, among others).

Directly estimating the impact of a changing climate is not easy. Cross-sectional Ricardian studies (see Mendelsohn, Nordhaus, and Shaw, 1994) essentially compare economic outcomes of interest in different climates. As a result, they establish a relationship between the two variables that accounts for full adaptation. However, the reliability of this approach is questionable for two main reasons. First, it may be subject to omitted variable bias because its cross-sectional nature does not allow accounting for unobservable heterogeneity. Second, comparing economic outcomes between hot and cold climates is essentially a static exercise. Indeed, it does not consider the fact that the adaptation process from one state to the other may take time, can be costly, or may not take place at all in practice, as recently shown by Burke and Emerick (2016) for the US corn yields, and confirmed by Wing, De Cian, and Mistry (2021) at the global level.

Panel fixed effects models (see Schlenker and Roberts, 2006; Deschênes and Greenstone, 2007) overcome the omitted variable bias, but if climatic norms are used as independent variables, identification problems emerge because of their low year-to-year variability that is largely subsumed in the fixed effects. For this reason, one common approach in estimating the climate-economy relationship is to exploit interannual fluctuations of weather variables (e.g. average annual temperature) using fixed effects to account for time-invariant unobservable factors. In such a case, the econometrician compares the response of the economic outcome within the same unit of analysis in warmer and colder years. For this reason, this approach is often seen as a short-run estimate of the weather impact, i.e. it cannot incorporate long-run adaptation.[1]

Having considered previous methodologies, we focus on weather extremes in the form of anomalies. An anomaly is defined as the difference between the current weather statistic (e.g. annual average temperature) and its historical norm (e.g. 20-year average). We define the weather as the annual observation of the anomaly and the climate as its probability distribution, while climate change is seen as a change in this distribution. Importantly, we describe CC as a transition process of continuous change in the weather that characterizes an unstable climate. Given the inertia of the climate response to greenhouse gasses (GHG) emissions, only after some time, the climate (in particular the temperature) will reach a new stable path, consisting of natural fluctuations around a certain norm. We characterize a stable climate with an expected value of the anomaly (w) in unit i at time t equal to zero, $\mathbb{E}[w_{i,t}] = 0$, in a given long-time period. Vice versa, an unstable climate is represented by $\mathbb{E}[w_{i,t}] \neq 0$.

This approach presents three important advantages. First, it better describes the direct and indirect impacts of a changing climate on agricultural output. Both farmers and the crops they choose to plant are adapted to a specific climate. When the seasonal weather differs from the expected one, the production can suffer losses directly due

1 When also a quadratic term of the weather variable is added to the specification, the interpretation is in favor of a medium-long term effect because the changes in weather vary with the mean level of the variables, i.e. the climate (see Mérel and Gammans, 2021).

to the shock (e.g. a reduction in the water content of the soil, caused by higher temperatures) or indirectly due to the inability to cope with the unexpected weather (e.g. impossibility to irrigate due to the lack of an irrigation system). Second, in the literature that uses the level of the weather variable, we observe large heterogeneity in climates (e.g. Norway vs. Qatar) while the use of anomalies allows better comparability among countries. In the traditional quadratic models that use average temperature, the marginal effect depends on the level of the weather variable with the consequence that a warmer year would have a greater impact in a hot place. For this reason, estimates of CC often show a larger impact in hot countries and lower (or even positive) in cold ones (e.g. Burke, Hsiang, and Miguel, 2015b; Ortiz-Bobea et al., 2021). Using the anomalies, as in our empirical specification, allows us to account for a non-linear effect of the weather shock, but the impact of CC does not depend *a priori* on the level of temperature in the considered country. Moreover, in the traditional quadratic approach, the optimal temperature for the economic outcome (i.e. the temperature at which a further increase would reduce it) is estimated with uncertainty and falls into a relatively large range. This translates into further uncertainty in the magnitude and direction of the impacts caused by a warmer climate (Burke, Davis, and Diffenbaugh, 2018). In our setting, the optimal temperature is country-specific and it is supposed to be reached when it approaches the expected climate (represented by the historical norm). Third, in this framework, adaptation to the climate is embedded in our estimations. Indeed, the use of the anomalies (particularly when scaled by country-specific standard deviations of the variable) consists in an implicit model of adaptation where farmers adapt to the climate but they have only limited possibility to cope with continuous changes in the weather. Thus, we are able to provide more reliable estimates for the evaluation of weather extremes in future climatic scenarios.

2.2.2 *Model of Agricultural Production*

We hypothesize that agricultural production is affected by weather conditions when they deviate from their historical norms. Farmers adapt their production to the local climate (e.g. type of crop, calendar of agricultural works, machinery). Thus, they choose the main inputs according to the climatic conditions and they can adjust them consequently. Contrary, they can change the inputs to the current weather only to some little extent and they may suffer losses when the weather differs from the usual climate. Hence, we link agricultural production to weather anomalies considering the following aggregate production function:

$$Y_{i,t} = F(w_{i,t}, I_{i,t}) \tag{1}$$

where $w_{i,t} = x_{i,t} - \mu_{i,t}$ is the weather anomaly (x is the annual mean, μ is the climatology) and $I_{i,t}$ is a vector of inputs such as labor, land, capital and intermediate inputs. The weather enters directly into the production function. We allow both the annual mean and the climatology to change over time, but the latter changes substantially only over a longer period. Critically, we assume that farmers can adapt to these small changes in the climate. Indeed, some intrinsic adaptation mechanisms can take place during time with the diffusion of technology and the advancement of new knowledge (only to mention some examples).

The inputs used in the current production function are by themselves a function of farmer's previous actions:

$$I_{i,t} = f(\alpha_{i,t-1}) \tag{2}$$

where actions $\alpha_{i,t-1}$ are adjusted according to the climatic conditions expected by farmers, and not in response to annual weather variations, i.e.:

$$\alpha_{i,t-1} = f(\mathbb{E}[\mu_{i,t}]) \tag{3}$$

Thus, if the annual weather is consistent with the usual climate, the input choice leads to a potentially optimal output. Vice versa, when the two variables differ significantly, the absence of input adjustment would induce sub-optimal production. Similar to Mérel and Gammans (2021), we account for this effect using a "penalty term" and we assume that farmers choose actions $\alpha_{i,t-1}$ in order to maximize the expected output:

$$\begin{aligned} \alpha_{i,t-1} &\in \operatorname{argmax} \mathbb{E}\left[F(w_{i,t}, f(\alpha_{i,t-1}))\right] \\ &= \operatorname{argmin} \mathbb{E}\left[(x_{i,t} - f(\alpha_{i,t-1}))\right] \\ &= \operatorname{argmin} \mathbb{E}\left[(x_{i,t} - \mu_{i,t} + \mu_{i,t} - f(\alpha_{i,t-1}))\right] \\ &= \operatorname{argmin} \mathbb{E}\left[(\mu_{i,t} - f(\alpha_{i,t-1}))\right] = f^{-1}(\mu_{i,t}), \end{aligned} \tag{4}$$

where $\mathbb{E}[x_{i,t}] = \mu_{i,t}$. To say it simply, the farmers' actions maximize the expected output when they are in line with the local climatic conditions. This occurs when the expected anomaly is equal to zero, $\mathbb{E}[w_{i,t}] = 0$, meaning that a stable climate is a precondition for optimal agricultural outcomes. Climate change (considered here only in the form of weather anomalies) is modifying these climatic conditions making sub-optimal the actions of the farmers.

2.3 METHODOLOGY AND DATA

2.3.1 *Empirical Specification*

We translate our conceptual framework in a reduced-form panel approach using fixed effects, in line with the new climate-economy literature (Dell, Jones, and Olken, 2014), that allows us to capture both direct and indirect effects. The basic idea is to exploit the year-to-year variability of the (exogenous) weather anomalies and of the agricultural production, comparing a country's performance when the annual weather is close or not to the historic climate. We use as weather variables both temperature and precipitation (see Auffhammer et al., 2013). We divide the anomalies by the standard deviation of the annual average of the variables during the entire period for each country. This process is important for two reasons. First, it allows us to give more weight to those weather shocks that are relevant with respect to the distribution of the weather in the specific country (as suggested in Dell, Jones, and Olken, 2014). As mentioned before, in our framework the weather variations matters with respect to the expectations of the current climate and its variability is an important factor to be considered. Indeed, it allows us to account for an implicit model of adaptation since we are interacting our weather measure with a climatic feature such as its long-term variability (Tol, 2021). Second, with "standardized" measures we can directly compare the effect of temperature and precipitation anomalies since both of them may have important consequences in the agricultural sector.

We compute the weather anomalies as $T\_an_{i,t} = (T_{i,t} - T^*_{i,t-1})/\tau_i$ and $P\_an_{i,t} = (P_{i,t} - P^*_{i,t-1})/\rho_i$, representing the country-year deviations of temperature ($T_{i,t}$) and precipitation ($P_{i,t}$) from their respective historical norms ($T^*_{i,t-1}$, $P^*_{i,t-1}$). These are defined as $T^*_{i,t-1} = m^{-1}\sum_{j=1}^{m} T_{i,t-j-1}$ and $P^*_{i,t-1} = m^{-1}\sum_{j=1}^{m} P_{i,t-j-1}$, i.e. as moving averages of the annual temperature and precipitation. m represents the past time period upon which farmers base their expectations about the current weather and they adjust the inputs accordingly. In other words, its value means that farmers expect the current year's weather to be similar to the mean of the past m years. The lower the m, the higher their willingness to change the inputs according to the recent weather observations. As the baseline value of m, we use 20 years. We think this time period is long enough to represent the climate but still coherent with the expectations and adaptation potentials of the farmers (results are unchanged for different values of m, see Figure A1). τ_i and ρ_i depict the country-specific standard deviations of annual temperature and precipitation over the entire period. Finally, in order to account for non-linear and asymmetric effects induced by weather shocks, we follow Kahn et al. (2021) and consider both positive and negative anomalies separately. This is a natural choice (instead of using higher polynomial functional forms) since the potential optimal outcome occurs when the anomaly is zero and both positive and negative deviations from the expected climate may have detrimental effects.

We estimate the following empirical specification:

$$\Delta y_{i,t} = \beta^{'} \Delta Wpos_{i,t} + \gamma^{'} \Delta Wneg_{i,t} + \alpha_i + \theta_{r \times t} + \epsilon_{i,t} \qquad (5)$$

where $\Delta y_{i,t}$ is the change of (log) agricultural output for country i at year t. It enters in first difference representing the growth rate. This allows us to estimate the impact on agricultural production and overcome the issue of non-stationarity due to the upward trend of the variable. We know from previous literature that the impact of the weather on agricultural outcomes is a level effect, meaning that the consequences are not persistent in time and once the weather shock has ended, a fast recovery occurs in the following year (assuming no further shock). For this reason, we estimate a static model and focus on the contemporaneous time period. Coherently, we also differentiate the left-hand side of our equation considering the first difference of the weather variables (see Newell, Prest, and Sexton, 2021). $Wpos_{i,t}$ represents a vector of positive weather anomalies, i.e. positive deviation of annual temperature and precipitation from their historical norms (e.g. $T_{i,t} > T^{*}_{i,t-1}$). Contrary, $Wneg_{i,t}$ represents a vector of negative weather anomalies. Negative temperature and negative precipitation anomalies enter in absolute values to ease the interpretation of the sign of the coefficients. Indeed, we expect that each departure from the expected climate would induce a negative effect (i.e. a negative sign).

α_i represents a (growth) country fixed effect and implies that the identification comes from the exogenous deviation of the weather anomaly growth from its mean. As a result, β_s and γ_s pick up the anomaly impact on output that are departures from agricultural trend growth. In other words, this is equivalent to controlling for a linear country-specific time trend in the log of output (a standard approach in the literature, see Newell, Prest, and Sexton, 2021 and Ortiz-Bobea et al., 2021).

$\theta_{r \times t}$ is region-year fixed effects and captures common regional shocks. We prefer this set of time fixed effects in our baseline specification, instead of simple year fixed effects, because the agricultural markets are better integrated at the regional level instead of at global.[2]

We follow the literature using a parsimonious number of controls to avoid the so-called "over-controlling" problem (Dell, Jones, and Olken, 2014). However, we acknowledge that there is a recent literature trying to determine if omitted variable bias could be an issue in this standard setting. For example, there is growing evidence of the role played by soil moisture (Ortiz-Bobea et al., 2019) and spatial spillover effects (Bae and Dall'erba, 2021; Dall'Erba, Chen, and Nava, 2021).

Finally, $\epsilon_{i,t}$ represents the idiosyncratic error term. In the baseline specification, we clustered standard errors simultaneously at country and region-year levels to account for serial and spatial correlation in the error terms.

2 We define the regions as Sub-Saharan Africa, Asia, Europe, ex-USSR, Latin America and the Caribbean, West Asia and North Africa, North America, Oceania.

2.3.2 *Data*

We collect national agricultural data from the USDA/ERS International Agricultural Productivity database (2019 version, USDA / ERS, 2019) that provides annual observations for 196 countries for the period 1961-2016 on different agricultural variables. It represents one of the most accurate sources for cross-country data comparison on aggregate agricultural measures. In particular, we use as the main dependent variable the gross value of agricultural output that accounts for both crop and animal production. Others useful variables in the data set are Total Factor Productivity (TFP) and inputs data such as labor, land, and machinery (among others). This information is useful to build other measures of productivity such as labor productivity.
We also collect agricultural variables from the World Development Indicators (WDI) database from the World Bank, such as agricultural value added, food production index and Gross Domestic Product (GDP) per capita.
We collect historic weather data from Ortiz-Bobea et al. (2021). They built seasonal average temperature and total precipitation weighted by cropland area within each country for the period 1948-2016 based on the Global Meteorological Forcing Dataset. The seasonal weather variables (named green season) are built using a five-month period centered around the month of the year where the Normalized Difference Vegetation Index (NDVI) shows its maximum value. This is intended to proxy the main productive season, when most of the agricultural production takes place, and help us to better identify the direct relationship between agricultural production and weather anomalies.
The temperature data used for the counterfactual analyses of the future impact of CC comes from the KNMI Climate Change Atlas provided by the Royal Netherlands Meteorological Institute (KNMI) and World Meteorological Organization (WMO) (KNMI, 2013). We collect the linear trend of temperature according to the mean ensemble of the Global Circulation Models (GCM) of the CMIP5 (Coupled Model Intercomparison Project, phase 5) for the four Representative Concentration Pathways (RCPs) used in IPCC (2014).
Our final sample with agricultural and weather variables is an unbalanced panel with 172 countries that spans from 1968 to 2016. Table A1 shows the descriptive statistics of the main variables and Table A2 provides the definition and the source for each of them.

2.4 RESULTS

Table 1 shows the results from the estimation of Equation (5). Weather anomalies negatively affect aggregate agricultural output in our sample of countries. In Column (1), we observe these effects on the growth rate of real agricultural production. All the coefficients have a negative sign, but only those associated with positive temperature anomaly and negative precipitation anomaly are significant at standard levels ($< 10\%$). This would imply that when the temperature is warmer or precipitation is lower than expected, agricultural production suffers a loss (in ceteris paribus conditions). In particular, when the temperature in the main productive season is higher than the historical norm of one standard deviation (average of 0.62 °C), aggregate output decreases by 0.9 percentage points (ppt); when precipitation is lower than the historical norm of one standard deviation (average of 40 mm) output decreases by 0.8 ppt.[3]

Using these coefficients we can derive the marginal effect of the weather anomalies on the aggregate agricultural output, i.e. a 1°C rise of temperature and 100 mm decrease in precipitation with respect to the climatology. In the case of temperature anomaly, we find a marginal effect of -1.5 ppt, while in the case of precipitation anomaly we find a marginal effect of -2 ppt.[4]

In our baseline result, we use as dependent variable the gross value of the aggregate agricultural production. Since it is expressed in monetary terms, this may hide the direct link between the food produced and the weather, leading us to underestimate the true impact on the supply. For this reason, we also estimate the effects of weather anomalies on a quantity-based measure of food production such as the Food Production Index, which represents the relative level of the aggregate volume of production for each year in comparison with the base period 2014-2016. The overall results, presented in Column (2), are substantially unchanged.

In our framework, we assume that farmers cannot significantly adjust the inputs in the short run. However, in practice, they have the possibility to change their composition to avoid excessive losses (see for example Aragón, Oteiza, and Rud, 2021). For this reason, we estimate Equation (5) using three other dependent variables. In Column (3) we use agricultural value added that measures the difference between the gross value of production and the costs of intermediate inputs. Thus, if the farmers adjust the inputs to the weather shock, this would be reflected in the costs paid for them. In the case of temperature, we observe similar coefficients, while in the case of precipitation, the coefficients are slightly different.[5] In Column (4) we use output per worker as dependent variable since labor is a crucial input for the agricultural system, especially in developing countries. Again, the co-

3 Table A3 and Figure A1 show some robustness checks.

4 These values are computed using a simple proportion between the estimated coefficients and the standard deviations of within-country temperature and precipitation annual variables (e.g. 1°C * -0.9 ppt / 0.62°C).

5 Differently from the variable of aggregate agricultural output, the VA also incorporates fish and forestry production making the two estimates only partially comparable.

Table 1: Impact of Weather Anomalies on Agricultural Production

	(1) Δ(ln) Output	(2) Δ(ln)Food Index	(3) Δ(ln) VA	(4) Δ(ln)Output per worker	(5) Δ(ln) TFP
ΔTpos	-0.00944***	-0.00947***	-0.00981***	-0.0107***	-0.00821***
	(0.00175)	(0.00187)	(0.00289)	(0.00190)	(0.00163)
ΔTneg	-0.00181	-0.00181	-0.00111	-0.00222	-0.00400*
	(0.00223)	(0.00245)	(0.00377)	(0.00233)	(0.00234)
ΔPpos	-0.00145	-0.00102	0.00115	-0.00249**	-0.00244**
	(0.00106)	(0.00118)	(0.00262)	(0.00125)	(0.00111)
ΔPneg	-0.00780***	-0.00766***	-0.00469*	-0.00800***	-0.00658***
	(0.00177)	(0.00202)	(0.00283)	(0.00195)	(0.00175)
Cons	0.0195***	0.0210***	-0.0219***	0.0162***	0.00846***
	(0.0000230)	(0.0000249)	(0.0000749)	(0.0000232)	(0.0000225)
N	8232	7422	5695	8088	8232
R^2	0.155	0.138	0.131	0.149	0.125

Notes: estimated model as Equation (5). Historical norms are computed using 20-years moving averages. Standard errors (in parentheses) are clustered at country and region-year levels. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

efficients associated with positive temperature (-1 ppt) and negative precipitation anomalies (-0.8 ppt) are fairly similar to our baseline estimate. Finally, in Column (5) we use TFP as dependent variable. It considers the overall inputs productivity and account for annual inputs changes. Also in this case weather anomalies negatively affect aggregate TFP and we find significant coefficients associated with positive temperature and negative precipitation anomalies, with similar magnitudes.

Overall, these results are in line with previous estimates of the impact of climatic shocks on agricultural outcomes. For example, the coefficients estimated in Ortiz-Bobea et al. (2021), which use a quadratic formulation, imply a marginal effect of temperature at 20°C of about -1.6%. However, our approach allows accounting for non-linearity without imposing a specific functional form and without linking the magnitude of the coefficient to the level of the variables. This important feature allows us to better identify heterogeneity among countries, as described in the next subsection. [6]

6 We also tried to understand how much our model captures adaptation by estimating a short-run linear "levels" model and comparing it with our results. In the former case, a 1°C increase in temperature, decreases output by 2.3% suggesting that adap-

2.4.1 *Heterogeneity Between Countries*

An important question concerning the impact of climate change on economic outcomes is related to what extent the direction and magnitude of the estimated effect differ between countries. Possible sources of heterogeneity are the development level of the countries (Dell, Jones, and Olken, 2012), their degree of integration in the global economy (Garcia-Verdu et al., 2021), or geographical conditions. For instance, high-income countries may have better adaptive capabilities to cope with adverse weather shocks, while less developed ones may lack crucial conditions (such as infrastructures, credit market imperfections, risk diversification tools, institutional mechanisms, and public subsidies) to reduce these negative effects. We assess the heterogeneous effects of weather anomalies on aggregate agricultural production using differences in GDP per capita, in order to account explicitly for vulnerability and adaptation potential (see Auffhammer, 2018). Far from being perfect, this measure is a good proxy for the level of development as it correlates with most of the characteristics that can play an important role in detecting differences among countries. [7] We interact our measure of weather extremes with the GDP per capita of each country to verify that with higher levels of income, the negative impact of the weather anomalies decreases (and vice versa). We also divide our sample considering the average GDP per capita distribution (over the entire period) and attribute a dummy variable to three groups, corresponding to those countries with values lower than the 25th percentile, lower than the 50th percentile, and higher than the 75th percentile. We then estimate separately Equation (5) interacting the dummy with the weather anomalies. These results are shown in Table A4 and show heterogeneous effects for temperature anomalies and precipitation negative anomaly, with the magnitude of the coefficients proportional to the level of income.

Focusing on temperature, Figure 1 shows the marginal effect of a unit increase in positive temperature anomaly according to the GDP per capita distribution, as estimated in Column (1) of Table A4. The marginal effect is negative and significant when the level of income is low and reduces its magnitude to zero (and not significant) with higher incomes. At the bottom of Figure 1, we also plot the histograms representing the distributions of GDP per capita, population, and agricultural production, along with the level of GDP per capita. Note that most of the world's population and agricultural production

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tation (captured by our approach) could reduce this negative effect by 0.8 percentage points.

7 GDP per capita is considered, to some extent, correlated with geographic conditions. We investigate, as a further source of heterogeneity, the differences in countries' climates and in particular the differences between hot and cold countries. The type of analysis is the same used in the case of GDP per capita and the results show no heterogeneous effects (Table A5).

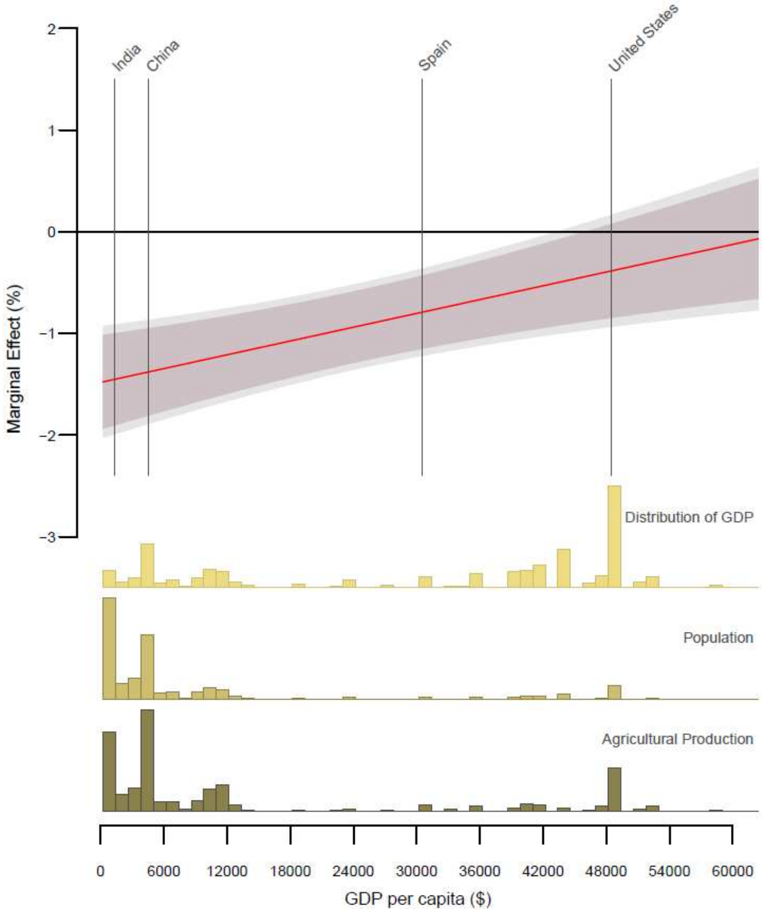
is concentrated where the marginal effect is the highest in magnitude. This result underlines two important facts: the climate instability induced by CC would affect most of the world's agricultural production and population; it would amplify even more the gap between wealthy nations and less developed countries as has been recently shown by Callahan and Mankin (2022) and Palagi et al. (2022).
These heterogeneous effects are in line with previous literature focusing on the GDP-climate relationship (Dell, Jones, and Olken, 2012, Letta and Tol, 2019, Newell, Prest, and Sexton, 2021). However, the agricultural literature shows mixed results. Country-specific analyses based on crop yields find negative effects also in high-income countries (e.g. Schlenker and Roberts, 2006, Burke and Emerick, 2016 for the USA; Gammans, Mérel, and Ortiz-Bobea, 2017 for France). Focusing on aggregate TFP in the USA, Ortiz-Bobea, Knippenberg, and Chambers (2018) find heterogeneous effects of climatic shocks with detrimental results in the Midwest and Southeast. They show that such heterogeneity is due to the sensitivity of non-irrigated crop production in those areas, while regions specialized in livestock production do not suffer the same effects.

2.4.2 *Counterfactual Analysis for Future Climate*

We use the described results to build counterfactual scenarios, helping us to understand what are the possible consequences of pursuing further climate instability in the future. Our aim here is not to forecast the future, but to give a sense of the direction, distribution, and magnitude of potential impacts of the weather extremes induced by climate change in a *ceteris paribus* condition. Therefore, we compute future temperature anomalies using the four Representative Concentration Pathways (RCP 8.5, RCP 6.0, RCP 4.5, and RCP 2.6) used in IPCC (2014) for the period 2017-2070.[8] We estimate future changes in countries' agricultural production considering the heterogeneity of the impacts with respect to their income level as shown in the previous subsection. We allow countries to increase their future income level according to projected economic growth rates for the period 2017-2070. To this end, we use the Shared Socioeconomic Path 2 (SSP2) "Middle of the Road" scenario and the country-specific growth rates computed by the OECD's ENV-Growth Model. We use RCP2.6 as the reference scenario. It represents an emissions path that is in line with the Paris Climate Agreement target. Therefore the results are interpreted as potential changes in production given by failing to

8 We focus only on temperature because it shows a clear upward trend that will continue also in future years. In the case of precipitation, the trend derived by RCP scenarios is very often not statistically significant at the country level and for this reason, we do not present them. However, this must not be interpreted as a non-relevant issue (see e.g. Damania, Desbureaux, and Zaveri, 2020).

Figure 1: Marginal Effect of Positive Temperature Anomaly on Agricultural Output



Notes: the graph shows the marginal effect of a unit increase in positive temperature anomaly on agricultural output (y-axis), associated with different levels of GDP per capita (x-axis). Gray bands show the 95% and 90% confidence intervals. The histograms represent GDP per capita, population, and agricultural production distributions in 2010, according to specific income levels shown in the x-axis (Norway, Switzerland, and Qatar are omitted because of their high values).

meet the established goal. We detail the methodology in Appendix A.1.

Table 2 describes the cumulative percentage change in aggregate agricultural production in 2070 (a medium-long run horizon), divided by world regions and RCPs scenarios. In the case of RCP 8.5 (Column 1), the highest emissions scenario, losses are particularly large (average of -18%) with Africa, Asia and Ex-USSR territories being the most affected. In this scenario, the gap between income groups is particularly pronounced, with emerging and low-income countries suffering substantial losses (-21% and -29% respectively). [9]

9 RCP 8.5 scenario is potentially catastrophic (Woillez, Giraud, and Godin, 2020) but highly unlikely (Hausfather and Peters, 2020). We report it here because it is standard in the literature and it represents a particularly unstable climate.

Table 2: Cumulative Change (%) of Agricultural Output in 2070

Region	(1) RCP 8.5	(2) RCP 6.0	(3) RCP 4.5
Africa	**-26**	**-11**	**-11**
	(-38, -14)	(-16, -6)	(-16, -6)
Asia	**-19**	**-7**	**-8**
	(-32, -6)	(-12, -2)	(-14, -2)
Europe	-1	0	0
	(-27, 26)	(-12, 12)	(-10, 10)
Ex USSR	**-29**	**-13**	**-12**
	(-49, -8)	(-22, -4)	(-21, -4)
Latin America and the Caribbean	**-18**	**-7**	**-7**
	(-31, -4)	(-12, -2)	(-13, -2)
Near East and North Africa	-18	-7	-7
	(-41, 5)	(-17, 2)	(-16, 2)
North America	7	3	3
	(-34, 49)	(-13, 20)	(-14, 21)
Oceania	5	2	2
	(-21,31)	(-10, 14)	(-9, 13)
Advanced Economies	2	1	1
	(-27, 31)	(-12, 14)	(-11, 13)
Emerging Markets	**-21**	**-9**	**-8**
	(-38, -3)	(-16, -1)	(-16, -1)
Low-Income Countries	**-29**	**-12**	**-12**
	(-41, -16)	(-17, -7)	(-17, -7)
Average	**-18**	**-7**	**-8**
	(-35, -1)	(-15, 0)	(-15, -1)

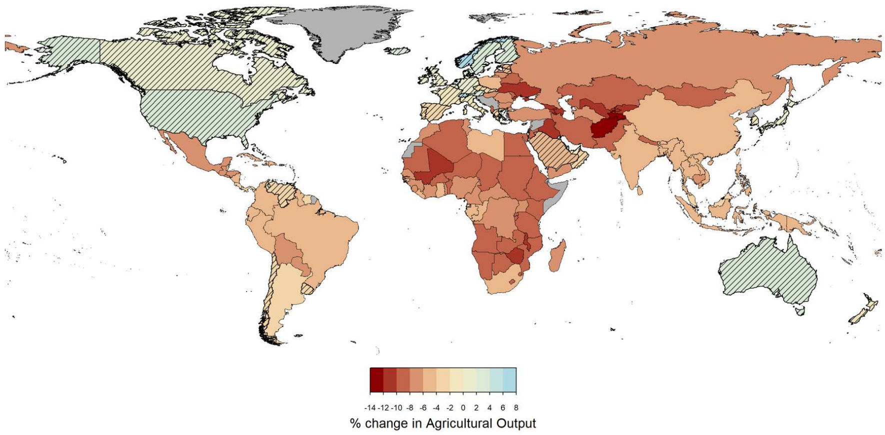
Notes: RCP 2.6 is the reference scenario. Appendix A.1 shows the methodology. Values in parenthesis are the upper and lower bounds, accounting for uncertainty from the estimates (95% level). Bold numbers are those where the confidence interval does not cross zero.

Columns (2) and (3) show the results for the RCP 6.0 and RCP 4.5 scenarios, the ones that better represent the emissions trend in recent years. The results between the two are similar, with an average loss of about -8%. Also in this case, low-income countries and emerging markets are the most affected (about -12% and -9% respectively) and the gap between advanced economies and the rest of the world is marked.[10]

Finally, in Figure 2 we plot the percentage changes in agricultural pro-

10 In Figure A2 we show the evolution of a Gini Index based on agricultural output per worker. The median value among the different scenarios is about 0.77 in 2070 with an increase of about 10% from the initial year (2016).

Figure 2: Cumulative Change (%) in Agricultural Output in 2070: RCP 6.0



Notes: the methodology to compute future anomalies and consequent changes in agricultural output is presented in the Appendix A. Striped areas indicate non-significant estimates at 90% confidence interval.

duction according to the RCP 6.0 scenario on a world map, showing the geographical distribution of the predicted impacts. Africa and West Asia are the most affected areas with production losses ranging from -6 to -14%. Contrary, high-income regions, such as Europe, North America, and Oceania have positive (although not statistically significant) effects. The overall results show that limiting climate instability following the Paris Climate Agreement could substantially benefit the world's agricultural production, particularly in the most vulnerable regions.

2.5 CONCLUSIONS

In this paper, we analyze the relationship between aggregate agricultural production and weather anomalies using country-level data from a global sample of countries in the last decades. Differently from a large share of the previous literature, we focus our attention on an aggregate measure of agricultural production that allows us to account for within-country and sectoral adjustments to climate change. We also use a novel methodological approach, that emerged recently (see Kahn et al., 2021), exploiting weather departures from the historical climatology which better represents the shocks that a changing and unstable climate imposes on farmers. Indeed, the agricultural production system is adapted to the local climate, but it is affected by unforeseeable weather anomalies that make suboptimal farmers' choices. This is particularly important since CC is constantly modifying the climatic conditions under which farmers are operating.

Our results suggest a negative, non-linear and significant relationship between aggregate agricultural production and weather anomalies. Temperatures higher than the historical norm cause negative effects on aggregate agricultural production and productivity. The same is true when there is a reduction in total precipitation. Importantly, we find that the structural characteristics of countries (that we proxy with income) play a key role in defining the magnitude of the impacts caused by the temperature anomalies on their agricultural production. These results renew the discussion on the distributional effects of CC damages and, consequently, policies (Hsiang, Oliva, and Walker, 2019). In absence of substantial mitigation, adaptation, and development, future CC projections show sizeable losses in those regions that have the larger share of agricultural production and population. The distribution of these losses shows that low and middle-income countries would be the most affected and that further inequalities between them and the advanced economies would emerge.

We derive three interdependent policy considerations from our analysis. First, sustainable development policies, e.g. increase the productivity of small agricultural producers, foster innovation, and sustain inclusive economic growth (UN, 2015), should be considered as an integral part of the CC policy agenda, together with mitigation and adaptation policies. Those countries that face major challenges should focus their climate policy on insulating their economy (and particularly their agricultural system) from weather shocks, implementing development and adaptation policies. Second, advanced economies should make any effort to fulfill the targets posed by the Paris Agreement, namely, reduce GHGs emissions limiting global warming to 1.5°C and finance the Green Climate Fund with USD 100 billion per year to support developing countries (UNFCCC, 2015). In a similar direction goes the recent agreement on the "Loss and Damage" Fund for vulnerable countries decided at the COP27. Third, policies must be implemented immediately to stabilize the climate, avoid the foreseen large losses in the food production system, and not compromise efforts in reaching other goals such as reducing global hunger and inequality.

3

ADAPTATION TO CLIMATE CHANGE THROUGH MARKET INTEGRATION: EVIDENCE FROM AGRICULTURAL TRADE IN THE EU

ABSTRACT

Understanding the trade potential in reducing the negative effects caused by climate change in agriculture is a hotly debated topic, especially because of the high levels of protection in this sector. My analysis provides additional evidence of the role played by market integration as an adaptation mechanism. Exploiting a rich data set of trade flows between sub-national administrative units in the European Union, I run counterfactual analyses using a neo-Ricardian quantitative trade model. I consistently estimate the productivity-to-exports elasticity, as well as the impact of future climate change on agricultural productivity. Comparing simulations with different degrees of trade adjustments, the results show that market integration has little effect on overall welfare in the EU. However, large heterogeneity exists among regions, and in some cases, trade has a substantial role in defining welfare changes. Furthermore, looking at the welfare decomposition, I show that consumers and producers react differently and consumers in regions where climate change induces a reduction in productivity would benefit from import adjustments.

Keywords: Agriculture, Trade, Climate Change, Europe
JEL Classification: D58, F18, Q17, Q54

3.1 INTRODUCTION

The climate is a fundamental input in the agricultural sector and, to large extent, determines what is profitable to be produced in a specific geographic area. Because of climate change (CC), production patterns are changing and will change further if greenhouse gas emissions (GHGs) will not stop substantially in the next years. Some countries will have an advantage from warmer temperatures and longer growing seasons and they will be able to produce new or more abundant crops. Contrary, in other regions, heat stress and water scarcity will reduce productivity if the adaptation investments are too costly.
A direct consequence of such a phenomenon is the change in absolute and comparative advantages in the agricultural sector. The consequences of evolving comparative advantage induced by climate

change are gaining interest in the agricultural trade literature (Gaigné and Gouel, 2022). With heterogeneous impacts, a changing climate would induce different types of specialization. These new patterns of comparative advantage would involve specialization in new varieties of products and changes in land allocation, and trade flows would consequently adjust to them. Therefore, a natural question that has emerged is related to what extent new patterns of trade from regions that benefit from a relatively more suitable climate toward those negatively affected could reduce their welfare losses.[1]

As an early example, Reilly and Hohmann (1993) investigate the role of agricultural international trade in the case of future climate change scenarios. They recognize that for open economies, the effects of climate change on agricultural markets cannot be considered in isolation from the rest of the global economy. Using a partial equilibrium model and yield changes predicted by crop modelers, they find that international trade adjustments tend to buffer the impact of climate change but with relatively small effects on domestic economies.

Contrary, Randhir and Hertel (2000) reach the opposite conclusion that international trade would have a detrimental welfare effect. Their result is driven by positive yield changes induced by climate change in developed countries that have high levels of protection. Assuming similar levels of agricultural subsidies also in future scenarios, they show that increased price transmission would reduce global welfare.

Recently, Costinot, Donaldson, and Smith (2016) make an important attempt at quantifying the adaptive role of within-country production and between-country trade adjustments arising from changes in comparative advantage for some of the most important cultivated crops. They build a quantitative model suited to exploit a micro-level data set on agricultural productivity that uses high-resolution information on geographic and climatic conditions to predict crop yields. These data are available both under contemporary growing conditions and under climate change scenarios and, by comparing them, it is possible to observe directly the evolution of comparative advantage across space, as predicted by climatologists and agronomists. Their results show a negligible role played by international trade compared to within-country production adjustments.

Following the previous work, Gouel and Laborde (2021) build a very similar model that incorporates also the livestock sector and uses parameters from the literature. They show that, with these new features, international trade could contribute substantially to reducing global welfare losses, although production adjustments make a larger contri-

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1 The economic literature on agricultural trade and CC is generally divided in two temporal scales (Baldos and Hertel, 2015): short-run shocks from (extreme) weather events on seasonal production with consequent trade flows from "surplus to deficit" regions (e.g. Dall'Erba, Chen, and Nava, 2021); and long-run shift in climate suitability for agriculture that induces Ricardian specialization (e.g. Costinot, Donaldson, and Smith, 2016). My focus is on the second one.

bution.[2]

Although the mentioned literature provides critical information on the potential role of trade as an adaptation mechanism for climate change, it also presents some limitations. First, most of the previous works focus on cross-country international trade where trade barriers are substantial. Second, often the literature relies on crop models (developed by agronomists) to simulate the future impact of CC that are based on future potential environmental conditions (especially of the soil), with little relation to actual farmers' behavior.

Given these limitations and the renewed debate on such an important topic, the aim of the present work is to shed new light on it. I decided to focus on a particular geographic area, i.e. Europe. The EU represents a well-integrated market with limited barriers to trade and it has a vast climatic heterogeneity.[3] Considering its high technological development it is also reasonable to think that important changes to the production structure will be put in place in order to adapt to a warmer future. Exploiting a rich data set of productivity, weather variables, and trade flows for sub-national administrative units, I use econometric methods to estimate the changes in agricultural productivity due to CC and build a partial equilibrium model that allows me to simulate the future consequence on trade and welfare.

The analysis goes as follows: I build a partial equilibrium model of agricultural trade between European sub-national NUTS2 units (I refer to them as "regions"). Describing the model in terms of changes, I simulate how an exogenous shock in productivity due to climate change would impact the sector. Finally, to quantify the role of market integration as an adaptation mechanism, I simulate different degrees of trade adjustments and compare the results. Importantly, I estimate the trade elasticity (a key parameter of the model) that, in the neo-Ricardian literature, governs the comparative advantage. I also calculate the counterfactual productivity changes using detailed information at the local level following the climate-econometrics literature. This allows me to quantify the impact of climate change considering the historical economic behavior of the farmers and not only the soil potential predicted by agronomic models.

Results show that specialization induced by new climatic conditions would change trade patterns. On average, welfare changes are small. Limiting the possibility to fully adjust the trade flows, by fixing the bilateral import shares, does not change substantially the results. This would imply a small role of trade as an adaptation mechanism to climate change. However, large heterogeneity exists among regions and

2 Other important contributions to the literature come from quantitative models of partial and general equilibrium such as Janssens et al. (2020) and Baldos and Hertel (2015).

3 Although I refer to market integration, my empirical exercise is focused specifically on trade adjustments which represent a narrow component of it (Lence and Falk, 2005)

between consumers and producers. Producers in the northern part of Europe, where agricultural productivity is predicted to increase, would have significant benefits from full trade adjustment. In a similar manner, consumers in the Mediterranean regions, where the impact of climate change would reduce productivity, could benefit from importing agricultural goods at lower prices.
The paper is presented as follows: in Section 3.2, I describe the three steps that allow me to perform the simulations, namely, the quantitative model (subsection 3.2.1), the estimation of the trade elasticity (3.2.2) and of the productivity change (3.2.3); in Section 3.3, I describe the data used in the analyses; in Section 3.4, I present the results from the estimations and simulations; finally, Section 3.5 concludes.

3.2 METHODS

To understand which role trade plays as an adaptation mechanism, we build a quantitative neo-Ricardian model of trade that describes the relationship between agricultural productivity, trade flows, and welfare. In the standard Ricardian model (Dornbusch, Fischer, and Samuelson, 1977), the comparative advantage, i.e. the difference in relative autarky prices caused by cross-country productivity differences, is the rationale for trade. Qualitative predictions of the Ricardian model are not easy to be tested, but results in line with the theory can be found in Bernhofen and Brown (2005) and Costinot, Donaldson, and Komunjer (2012). Since CC has heterogeneous impacts on countries' agricultural productivity, this theoretical model is a natural choice for my purposes.[4]
Exploiting an ingenious choice for the distribution of technology within each country, Eaton and Kortum (2002) develop a multi-country neo-Ricardian model where estimation of parameters and counterfactual analyses are possible. Dekle, Eaton, and Kortum (2007) and Dekle, Eaton, and Kortum (2008), further develop their previous model and describe how to identify the minimum set of information necessary to obtain counterfactual results (this approach has been called "exact hat algebra"). Based on these works, Costinot, Donaldson, and Komunjer (2012) build a multi-country and multi-sector model providing theoretical justification for the estimate of the trade elasticity (a key parameter in the model). Finally, Costinot, Donaldson, and Smith (2016) and Gouel and Laborde (2021) build computable general equilibrium models precisely to evaluate the role of production and trade adjustments to CC.
Based on this literature, I develop a theoretical model that allows me to quantify (a) how productivity affects trade flows; and (b) how

4 Other trade models in which varieties are distinguished by firms rather than countries such as in Krugman (1980) and Melitz (2003) are not considered here because, in this setting, I cannot derive firm-level (heterogeneous) impacts of climate change.

an exogenous agricultural productivity shock, induced by CC, affects trade flows and welfare. In the next subsections, I describe the theoretical model (3.2.1), the empirical strategy to estimate the trade elasticity (3.2.2), and the counterfactual productivity induced by new climatic conditions (3.2.3).

3.2.1 *Model*

Consider the European agricultural market formed by N regions (those within the member states and a "Rest of the World" region), indexed by i for the origin and j for the destination. For each region, I assume a constant-elasticity demand function such as:

$$D_j = \alpha_j P_j^{-\epsilon} \tag{6}$$

where D_j is the quantity demanded, P_j is the consumer price index of the agricultural products, and α_j is a shift parameter. Similarly, I assume a constant-elasticity supply function:

$$S_i = A_i p_i^{\eta} \tag{7}$$

where S_i is the quantity produced, p_i is the producer price, A_i is sectoral productivity that represent a supply-shift parameter and η is the supply elasticity.
In neo-Ricardian trade models (Eaton and Kortum, 2002, Costinot, Donaldson, and Komunjer, 2012), productivity in origin i is drawn from a Fréchet distribution, such as:

$$F_i(a) = exp\left[-\left(\frac{a}{A_i}\right)^{-\theta}\right]$$

where cross-regional variability in the parameter $A_i > 0$ pins down differences in absolute advantage, while the parameter $\theta > 1$ regulates the dispersion of efficiency within the distribution. A lower value of θ implies a stronger role for comparative advantage and trade. Since in autarky consumers must consume even their region's worst draws, gains from trade emerge because they can import from other regions and benefit from a favorable productivity draw there. This also implies that producers can specialize in goods for which they have the best productivity draws.
From this framework, I derive a standard gravity equation that determines trade flows:

$$x_{i,j} = \gamma_{i,j} \left(\frac{\tau_{i,j} p_i}{P_j}\right)^{-\theta} E_j \tag{8}$$

where $x_{i,j}$ is the value of trade from i to j, $\gamma_{i,j}$ is a constant, $\tau_{i,j}$ are bilateral trade costs and $E_j = P_j D_j$ is the expenditure for agricultural products in the importer region j. The consumer price index (P_j) is given by:

$$P_j = \left[\sum_i^N \gamma_{i,j} (\tau_{i,j} p_i)^{-\theta} \right]^{-1/\theta} \tag{9}$$

where θ substitutes $\sigma - 1$ in demand-side Armington models (with σ being the elasticity of substitution between origin-differentiated goods).
Market equilibrium is given by the equality between the value of production in origin i and the value of demand from all the regions:

$$p_i S_i = \sum_{j=1}^N x_{i,j} \tag{10}$$

I link directly agricultural productivity with the climatic conditions in the region of origin (C_i) such that:

$$A_i = F(C_i) \tag{11}$$

I will use this relationship to estimate the impact of the historical climate on agricultural productivity and to simulate the future impact of climate change on it. Following Dekle, Eaton, and Kortum (2008), I reformulate the model in terms of changes using as an exogenous shock the change in agricultural productivity, $\hat{A}_i = \frac{A_i^{'}}{A_i}$ (with $A^{'}$ being the new value). The model is composed by the following system of equations:

$$\hat{D}_j = \hat{P}_j^{-\epsilon} \tag{12}$$

$$\hat{S}_i = \hat{A}_i \hat{p}_i^{\eta} \tag{13}$$

$$\hat{x}_{i,j} = \left(\frac{\hat{p}_i}{\hat{P}_j} \right)^{-\theta} \hat{E}_j \tag{14}$$

$$\hat{P}_j = \left[\sum_i^N \pi_{i,j} (\hat{p}_i)^{-\theta} \right]^{-1/\theta} \tag{15}$$

$$p_i Q_i \ \hat{p}_i \hat{Q}_i = \sum_{j=1}^N x_{i,j} \hat{x}_{i,j} \tag{16}$$

where $\pi_{i,j} = x_{i,j}/E_j$ represents the bilateral import share, and in Equation (16) I use the fact that for a generic variable ν, the following holds: $\nu^{'} = \nu \cdot \hat{\nu}$. $\pi_{i,j}$ captures the interrelation between region i and j such as bilateral costs, preferences, etc., that are not explicitly modeled. Although this simplifies the analytical framework, it assumes that counterfactual bilateral characteristics evolve in a similar way as in the historical period. I acknowledge that, in the EU context, this assumption is relatively innocuous while in the case of extra EU regions (RoW) it is not.[5]

3.2.2 *Productivity-to-Exports Elasticity*

One important parameter in the model is the trade elasticity θ, which regulates the relationship between productivity and trade. I exploit my model setting to consistently estimate this parameter. I derive the econometric equation from the gravity equation such as:

$$x_{i,j} = \frac{(\tau_{i,j} p_i)^{-\theta}}{\sum_{i=1}^{N} (\tau_{i,j} p_i)^{-\theta}} E_j \tag{17}$$

Given that I do not observe producer prices, I assume that they are proportional to the production costs (c_i) and inversely proportional to productivity, such that $p_i = c_i/A_i$. Substituting it in the previous equation and dividing by by $x_{n,j}$ (for a general exporter/competitor n) I obtain (in logarithm):

$$\ln\left(\frac{x_{i,j}}{x_{n,j}}\right) = \theta \ln\left(\frac{A_i}{A_n}\right) - \theta \ln\left(\frac{c_i \tau_{i,j}}{c_n \tau_{n,j}}\right) \tag{18}$$

This equation shows that to estimate the coefficient that regulates the relationship between relative productivity and exports in this Ricardian world, we need to account also for production and trade costs.
Estimating directly this equation raises issues of reverse causality. Therefore, I model agricultural productivity as a function of innovation and rainfall and I rely on an instrumental variable approach. This method helps also to eliminate possible omitted variable bias and measurement errors. I estimate the following specification:

$$\log x_{i,j} = \theta \log \tilde{A}_i + \alpha_j + \beta' \mathbf{c}_i + \gamma' \mathcal{T}_{i,j} + \epsilon_{i,j} \tag{19}$$

where $\log x_{i,j}$ is the (logarithm) value of exports from region i to region j; $\log \tilde{A}_i$ is the predicted value of productivity in origin i instrumented using the number of agricultural patents and total rainfall attributed to that specific region[6]; α_j is the importer fixed effects that account for destination-specific characteristics; $\mathbf{c}_j$ is a vector of control variables for the exporter; $\mathcal{T}_{i,j}$ is a vector of bilateral trade costs; and $\epsilon_{i,j}$ represents the error term.
This estimation relies on the identifying assumption that innovation and rainfall are correlated with bilateral trade flows only through their impact on productivity, which is used as a proxy for producer prices. Given the structure of this specification, the identification of

5 Notice that the RoW contribution on EU food consumption is not particularly relevant, being only 0.2% of the EU imports.
6 The results are similar when lagged values of the instruments are used.

the parameter θ comes from cross-sectional variability in exports and productivity levels between regions, in line with the Ricardian nature of the model.

To estimate Equation (19), I use bilateral trade and productivity data for 212 sub-national units (NUTS2) within the EU averaged for the years 2009-2010 (details in subsection 3.3). Within the EU, trade and institutional barriers are limited and this allows to avoid possible bias related to them.

3.2.3 *Counterfactual Productivity*

The next step to understand the role played by trade adjustments in the context of climate change is to compute the counterfactual productivity in agriculture that would be used as an exogenous shock in the trade model simulations. To do that, I follow the empirical literature on climate change impacts in agriculture where productivity is modeled as a function of the weather (Ortiz-Bobea, 2021). Mérel and Gammans (2021) show that, under specific conditions, the use of weather variables in a non-linear panel fixed effect approach is able to capture long-run climatic response. Therefore I estimate the following baseline specification:

$$\Delta \log A_{i,t} = \beta_1 \Delta T_{i,t} + \beta_2 \Delta T^2_{i,t} + \gamma_1 \Delta P_{i,t} + \gamma_2 \Delta P^2_{i,t} + \delta_i + \rho_{c \times t} + \epsilon_{i,t} \tag{20}$$

where $\log A_{i,t}$ is the (logarithm) agricultural productivity in region i in year t. The weather is represented by temperature ($T_{i,t}$) and precipitation ($P_{i,t}$) and enters with a linear and a quadratic term. The inclusion of the squared variables allows the effect of the inter-annual variations in weather to change with their (cross-sectional) baseline level, i.e. the climate, and to capture non-linearities (Mérel and Gammans, 2021). δ_i are region fixed effects and controls for average regional productivity. Given that the model is expressed in first difference, the inclusion of δ_i is equivalent to controlling for a region-specific linear time trend in $\log A$. $\rho_{c \times t}$ are country-year fixed effects that control for common shocks within the same country. $\epsilon_{i,t}$ is the error term that incorporates unobserved changes in inputs not absorbed by fixed effects and measurement errors.

To estimate Equation (20), I use productivity and weather data for about 1172 sub-national (NUTS3) provinces (further discussion in section 3.3). This level of detail allows us to clearly identify the climate-productivity nexus accounting for within-country heterogeneity.

We use the estimated relationship to compute the counterfactual productivity change ($\hat{A}_i$) in a future scenario of climate change. To do that, we use the following formula:

$$\hat{A}_i = \hat{\beta}_1 (\bar{T}'_i - \bar{T}_i) + \hat{\beta}_2 (\bar{T}'^2_i - \bar{T}^2_i) + \hat{\gamma}_1 (\bar{P}'_i - \bar{P}_i) + \hat{\gamma}_2 (\bar{P}'^2_i - \bar{P}^2_i) \tag{21}$$

where the future ($\bar{T}_i'$, $\bar{P}_i'$) and historic ($\bar{T}_i$, $\bar{P}_i$) climatic variables are expressed as 20-years-averages in the periods 2081-2100 and 1981-2000 (predicted by the same regional climate model) and $\hat{\beta}_s$ and $\hat{\gamma}_s$ are the estimated coefficients from Equation (20). The future projections are computed using the Representative Concentration Pathways (RCP) 4.5 and 8.5. Further discussion is presented in the following section (3.3).

3.3 DATA

Trade data comes from the PBL EUREGIO database provided by the PBL Netherlands Environmental Assessment Agency (Thissen et al., 2018). It provides Input-Output tables spanning from 2000 to 2010 with regional information at NUTS2 level for the European Union member states and other external countries. For each region, the data are disaggregated into 14 sectors. I collect output data (exports) for the agricultural sector from the region of origin, and I aggregate the inputs (imports) for the 14 sectors of each destination region. In this way, I have information on the value of agricultural production traded from region i to region j. I then use the average value between the years 2009-2010 to calibrate the model and to estimate Equation (19). These are the last two available years of the data and represent the period of maximum European integration. The final sample has 212 EU sub-national regions and the "Rest of the World" with the extra-EU territories aggregated. Seven countries (Bulgaria, Cyprus, Estonia, Latvia, Lithuania, Malta, and Romania) do not have information at NUTS2 level, therefore I consider the national values.

To proxy agricultural productivity, I use the sectoral (NACE2) Gross Value Added (GVA) divided by the number of employees in the same sector. The source of these data is the Annual Regional Database of the European Commission (ARDECO) (European Commission, 2022). The category "Agriculture" refers to agricultural, forestry, and fishing products, the same of the trade data. ARDECO provides data at both NUTS2 and NUTS3 territorial levels for the period 1980 to 2020. I use the former to match the trade data and estimate the parameter θ. Contrary, for the estimation of the climate-productivity relationship I use the more detailed information at NUTS3.

In the estimation of the trade elasticity, I use an IV approach where the instruments are the number of agricultural patents and/or rainfalls for each region of production. The former data come from the Organisation for Economic Co-operation and Development (OECD) RegPat database (release version January 2021, Maraut et al., 2008), while the rainfall data are from the ERA5-land database (Muñoz Sabater, 2019). I collect also data on bilateral trade costs, such as common currency, common language, and distance. The currency and language information is collected at the national level from the CEPII gravity

database (Conte, Cotterlaz, and Mayer, 2022), while the last is computed as the distance between the centroid of the regions.
To estimate the productivity-climate relationship, I rely on the proxy of agricultural productivity (discussed before) and climatic variables such as temperature and precipitation. I collect these data for the period 1980 to 2020 from the ERA5-land database (Muñoz Sabater, 2019). It provides grid-level monthly information with a cell size of about 9 x 9 kilometers (0.1° x 0.1°). I compute the region-specific annual average temperature and total precipitation weighting them by the agricultural land distribution in each sub-region (NUTS3). The gridded data on crop and pasture areas (which I aggregate to form the agriculture land share) come from Ramankutty et al. (2008) and refers to the year 2000.
Finally, for future climatic projections, I rely on the KNMI-RACMO22E regional climate model for the European continent provided by the Netherlands Environmental Assessment Agency. This model falls in the framework of the Coordinated Regional Climate Downscaling Experiment (CORDEX) that aims at providing climate change information on regional scales in fine detail, which cannot be obtained from coarse-scale Global Circulation Models (GCMs). The data are provided at 0.11° x 0.11° resolution on a monthly bases both for historic and future periods (called experiments). Future projections are provided assuming greenhouse gas emissions based on the RCP 4.5 and 8.5. The former represents a scenario where CO2-equivalent emissions stabilize approximately at 650 ppm in the year 2100, while in the second they will exceed 1000 ppm. In order to have perfect comparability, I compute 20-year long-term averages for temperature and precipitation in the periods 1981-2000 and 2081-2100 for each NUTS2 region (using again land weights). The difference between the two represents the change in climatic conditions.
Table 3 summarizes descriptive statistics for key variables.

Table 3: Descriptive Statistics

	Mean	Median	S.D.	Min	Max	Territory
Exports (Mln €)	2.17	0.16	14.34	0	915.22	NUTS2
Patents	6.34	1	17.38	0	187	NUTS2
Distance (Km)	1274	1156	761	17	5269	NUTS2
Productivity (€/Empl)	24348	21680	18779	42	897750	NUTS3
Temperature (°C)	10.11	9.94	2.72	-1.83	19.56	NUTS3
Precipitation (cm)	80.54	76.54	25.94	3.68	300.58	NUTS3

Notes: own elaboration of the variables presented in Section 3.3 .

3.4 RESULTS

In this section, I show the results from each step of the analysis. First, I show the results from the estimation of the trade elasticity; second, I present the changes in agricultural productivity predicted for new climatic conditions; and finally I simulate the counterfactual scenarios to quantify the welfare effect induced by trade adjustments.

3.4.1 *Estimates of the Trade Elasticity*

The first step is to estimate the value of θ, the parameter that governs comparative advantage. Table 4 shows these results. Column (1) shows the reduced form of Equation (19). The associated coefficient of interest is positive and significant, but its magnitude is not reliable due to reverse causality and omitted variable bias. Columns (2) to (4) show the 2SLS results using patents, rainfall, and both of them as instruments, respectively. All the estimates are statistically significant with coefficients ranging between 1.9 and 3.1. Finally, Column (5) shows the results using a three years panel dataset (from 2008 to 2010) instead of the average values in the period 2009-2010. This allows me to increase the number of observations and use the importer-year fixed effects to account for time-variant factors. The coefficient associated with productivity is very similar to the other estimates (about 2.1).

Our preferred estimate for the trade elasticity is 2.2 from Column (4) and it is lower than previous estimates in the literature. For example, Costinot, Donaldson, and Komunjer (2012) develop a Ricardian quantitative trade model and, using producer price data for 13 manufacturing sectors in the OECD countries, estimate a value of 6.53. When they reduce the sample to only EU member states, to avoid the issue related to endogenous trade protections, their estimates decrease to 4.62. They also use other proxies for productivity, such as labor and multi-factor productivity, and the resulting estimates are always lower than their preferred estimate (2.7 - 4.3). They warn that such results could possibly be caused by measurement error that is not entirely obviated by the instrumental variable procedure.

In the case of agriculture, estimates change substantially. Donaldson (2018) uses a trade costs approach with data for 15 commodities in colonial India and estimates a range of values from -9.6 (not significantly different from 0) to 29.21 with an average of 7.8. Caliendo and Parro (2015) build a multi-country, multi-sector Ricardian model and, with a method based on trade and tariff data, estimate a trade elasticity for agriculture of 8.11. Finally, Tombe (2015) focuses specifically on the differences between the manufacturing and agricultural sectors. He estimates trade elasticities using country-level data on trade and tariffs and his preferred estimate for agriculture is 4.06.

Table 4: Estimate of the Trade Elasticity (θ)

	(1) ln Exports	(2) ln Exports	(3) ln Exports	(4) ln Exports	(5) ln Exports
(ln) Productivity	0.7889***	1.8657***	3.0892***	2.1719***	2.1264***
	(0.0143)	(0.0494)	(0.1275)	(0.0474)	(0.0508)
(ln) Employees	0.7260***	1.0815***	1.4855***	1.1826***	1.1484***
	(0.0093)	(0.0187)	(0.0445)	(0.0186)	(0.0193)
Distance	-0.1383***	-0.1280***	-0.1163***	-0.1251***	-0.1262***
	(0.0016)	(0.0018)	(0.0024)	(0.0019)	(0.0019)
Same Country	0.3323***	0.2789***	0.2182***	0.2637***	0.3494***
	(0.0503)	(0.0517)	(0.0608)	(0.0533)	(0.0509)
Currency	-0.1870***	-0.6739***	-1.2273***	-0.8124***	-0.7232***
	(0.0257)	(0.0374)	(0.0705)	(0.0386)	(0.0392)
Language	1.0817***	1.2539***	1.4496***	1.3029***	1.2383***
	(0.0313)	(0.0344)	(0.0474)	(0.0360)	(0.0353)
Observations	41361	41361	41361	41361	123674
R^2	0.5459	0.5067	0.5103	0.5103	0.5213
F-stat (1^{st} stage)	-	33	22	23	41
Instrument	None	Patents	Rainfall	Both	Both
FEs	importer	importer	importer	importer	importer-year

Notes: Columns (2)-(5) use patents and/or rainfall as instruments for productivity. Both have strong predictive power, with the heteroskedasticity-robust t-statistic in the first stage of column (4) equal to 4.8 and 3.3, respectively. The F-statistics refers to the first stage run only across exporters, i.e. utilizing only the meaningful variation of the exporter-specific productivity and instruments. "Same country", "Currency", and "Language" are dummy variables and are equal to 1 if the regions share the same feature. Standard errors (in parentheses) are clustered by exporter-importer pair. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

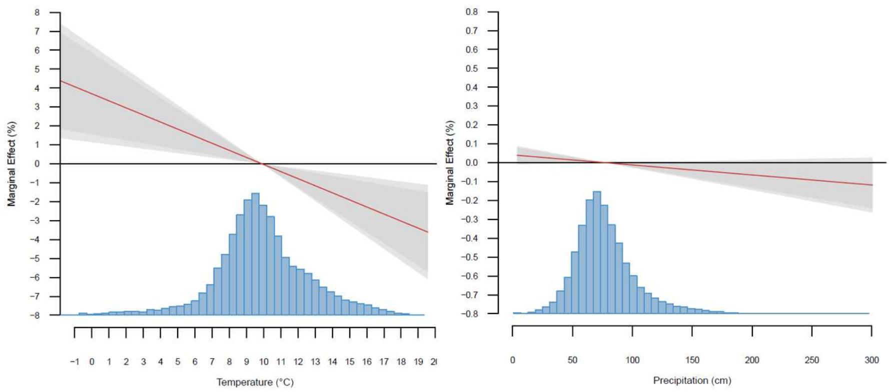
As noticed in Costinot, Donaldson, and Komunjer (2012), the fact that my estimate is relatively low could be caused by measurement error. However, it is also plausible to assume that using intra-national within Europe data where barriers to trade are limited, allows us to account for possible confounding factors such as endogenous trade protections (particularly relevant in the agricultural sector) that could bias previous estimates. To support this hypothesis, in Figure B1, I plot the coefficients estimated for every single year in the period 2000-2010. The value of θ in the year 2000 is 5.8 and decreases since then.

This could suggest that with further integration the comparative advantage exerts a stronger force.

3.4.2 *Productivity and Climate*

In the second step, I compute the climate change-induced shock on productivity. I start by determining the relationship between climate variables and productivity using Equation (20). The estimated marginal effect of temperature and precipitation is shown in Figure 3, while the associated coefficients are shown in Table B1. Both variables affect European agricultural productivity with a non-linear behavior, reflected in a non-constant marginal effect. At cold and mild temperatures, the marginal effect is positive, while for warm climates a further increase in temperature leads to a negative effect. For example, an increase of 1°C corresponds to a change in the productivity of about 0.8% at the 25th percentile of the distribution (8.7°C), but -0.2% at the 75th percentile (11.6°C). At more extreme values, the positive and negative effects become substantial. In the case of precipitation, the marginal effect is lower by about two orders of magnitude with respect to temperature and the precision of the estimate is less statistically significant. This could reflect the small size of rainfed crops and the inclusion of animal production in the measure of agricultural productivity.

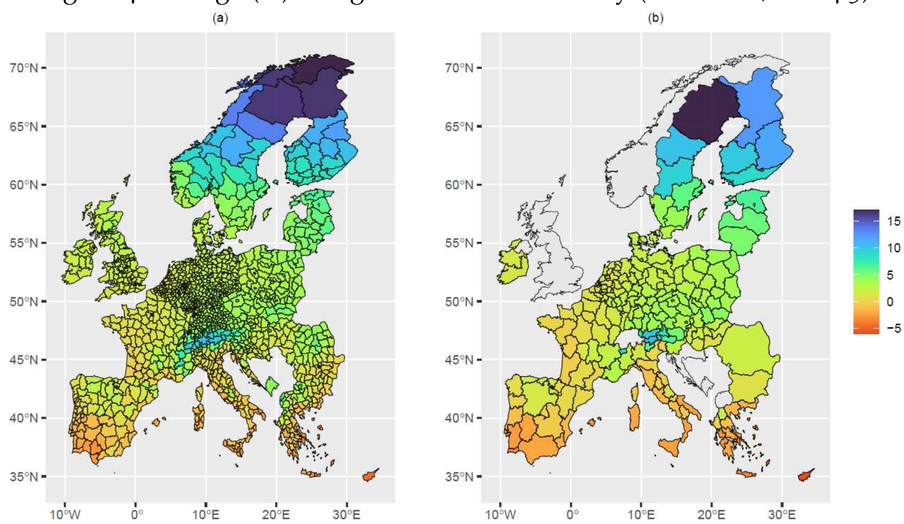
Figure 3: Marginal Effect of Temperature and Precipitation on Productivity



Notes: the red lines show the exposure-weighted marginal effects computed using estimates from Eq. (20). Grey bands represent confidence intervals at 90% and 95% levels. The blue histograms represent the NUTS3-level distribution of annual average temperature and precipitation over the sample period 1980–2019.

I use the estimated relationship to compute the change in productivity induced by new climatic conditions caused by climate change. To this end, I consider only the change in long-term averages of temperature and precipitation, neglecting all possible consequences induced by climate change (e.g. extreme weather events, sea-level rise, etc.). Considering a detailed regional climate model (NMI-RACMO22E) for the RCP 4.5 and RCP 8.5 emission scenarios, I compute 20-years climatologies for the reference (1981-2000) and future (2081-2100) periods. The change in productivity is given by applying Equation (21). Figure 4 shows the results using the RCP 4.5 emissions scenario. In panel (a) the administrative boundaries represent the NUTS3 subnational regions. Productivity changes range from -6% to +18% with a median value of about +2%. The map shows that northeast (e.g. Scandinavia) and high-altitude (e.g. the Alps) regions would potentially benefit from warmer temperatures. Vice-versa, regions in the southern part of Europe (southern Spain, Italy, Greece, and Cyprus) would be negatively affected by warmer temperatures with changes in productivity rates from 0 to -6%. These negative effects are induced primarily by increasing temperatures, but also because of a lower amount of precipitation.

Figure 4: Change (%) in Agricultural Productivity (2081-2100, RCP4.5)



Notes: panel (a) shows NUTS3 boundaries, while panel (b) shows NUTS2 boundaries for which trade data are available.

In order to match these results with the available trade data from the EUREGIO database, I aggregate the productivity changes at NUTS2 (or country) level, weighting by the share of agricultural GVA within each sub-national unit. Panel (b) presents the outcome. Contrary to productivity data from ARDECO, trade data are missing for Croatia, Norway, Switzerland, and the UK, therefore their corresponding productivity changes are not used in the subsequent analysis. In the case of Bulgaria, Cyprus, Estonia, Latvia, Lithuania, Malta, and Romania trade data are only available at the national level. For all other countries, productivity changes are shown for each NUTS2 region.
Although it is difficult to directly compare the results with the literature, the predictions described above are in line with the previous analyses. For example, the most recent JRC PESETA reports (num-

ber IV) about the climate change impact on EU agriculture in 2050 (Hristov et al., 2020) shows that different biophysical crop models tend to agree on predicting positive yield changes in Northern Europe and negative changes in Southern Europe for wheat and grain maize (two of the most important crops). Similarly, Van Passel, Massetti, and Mendelsohn (2017), using a large sample of European farms, perform a so-called Ricardian analysis to estimate the climate change impact on farmers' land values. Using the coefficients estimated with a median quantile regression and three different climate models, they predict that farmland value would decreases in Southern European regions (NUTS3) and increase in the Northern ones in 2100. Using similar econometric methods, Moore and Lobell (2014) estimate the impact of climate change on EU farms' profit and yields for wheat, maize, barley, sugarbeet, and oilseed. They show that by 2040, the average farm profit would increase by 1.5% if adaptation occurs. However, they show that even with adaptation, southern (warm) regions could potentially suffer losses up to 10%.

3.4.3 *Trade Adjustments and Welfare*

In the final step, I use the previous results on counterfactual productivities for the EU regions as exogenous shocks in the partial equilibrium model presented in Section 3.2.1.[7] Quantities, trade flows, and prices endogenously adjust to this shock and consequently, induce a change in welfare. The welfare change is computed as the sum of consumer and producer surplus, i.e. the sum of the defined integrals of demand and supply functions from the initial prices to the new ones. To quantify the adjustment role of trade, the model must be slightly changed. Because climate change affects regions' comparative advantage and creates new opportunities to trade, I focus on the possibility that importing regions have on changing their sources of supply (i.e. importing from new regions). Therefore, in order to restrict trade adjustments, I fix the bilateral import shares to their initial values and replace the (gravity) equation (14) with $\hat{x}_{i,j} = \hat{E}_j$. This equation states that the change in the value of imports of the region j from origin i is equal to the change in its own expenditure. Thus, the value of the imports is allowed to change, but the source is not. This implies that the bilateral import shares stay fixed, i.e. $\pi'_{i,j} = \pi_{i,j}$.
My quantitative model is transparent enough to understand clearly the underlying mechanisms that drive the results. A positive (negative) change in local productivity $A_i \uparrow$ ($A_i \downarrow$) induces an increase (decrease) in the quantity produced $Q_i \uparrow$ ($Q_i \downarrow$) and a reduction (increase) in the producer price $p_i \downarrow$ ($p_i \uparrow$). The consumer price index

7 The change in productivity for the "Rest of the World" comes from Cline (2007) where the author shows single country estimates that I aggregate using as weights the import shares with the EU in 2010.

P_j, the demand D_j and the trade flows x_{ij} adjust consequently. Trade transmits the local shocks from the exporter to the importer according to the bilateral relationships between them and changes in prices determine consumer surplus, producer surplus, and welfare changes. Therefore, the net price effect in one region is caused directly by the productivity shock and indirectly by what happens to its trade partners. For example, southern regions, where the average productivity decreases, would see an increase in local consumer prices. However, this effect could be mitigated by the increase (or the milder reduction) of productivity in their trade partners. Therefore, the more a region trades with partners that gain (or have lower losses) from warmer temperatures the more the local consumers would benefit.[8] This effect is particularly relevant for small regions that heavily depend on imports because the net price effect is mainly driven by trade transmission. For example, a region that trades most of its food with partners where the producer price goes down would see its consumer price decreased (and *vice versa*).

Table 5 shows the results of the simulations for both RCP 4.5 and RCP 8.5, comparing the "full trade adjustment" and the "partial trade adjustment" scenarios. Given the large number of regions, I sort the welfare change in the first scenario and only show the first and the last five regions, and the median of that distribution (the results for all regions are shown in Table B2, while Table B3 presents the results aggregated at country level). The last row of each panel shows the average among all the regions weighted by the value of production. The values are in percentage change. The third column shows the predicted change in productivity for each region ($\hat{A}$). The following columns show the ratio of price changes ($\hat{p}/\hat{P}$), the change in consumer and producer surplus ($\hat{CS}, \hat{PS}$), and the change in welfare ($\hat{W}$) for the two simulations. The "Full Adjustment" scenario gives the reference results, while the "Partial Adjustment" shows the results for the counterfactual simulation where bilateral import shares are constrained.

Looking at the reference simulation, the average increase in agricultural productivity in the EU (1.72%; 1.79%) would reduce the producer prices. This would induce an increase in consumer surplus (1.19%; 0.98%) and a reduction in producer surplus (-1.22%; -1.04%). The net effect on welfare is close to zero (-0.03%; -0.06%). Fixing the bilateral import shares, i.e. limiting the possibility to change importer partners, does not change substantially the results. Reduced trade interactions would reduce even further the consumer price that depends more on the local producer price, increasing the consumer surplus (1.42%; 1.37%) and decreasing the producer surplus (-1.46%; -

8 The trade relationship between partners is given by bilateral frictions such as distance, language (etc.). I do not model directly such characteristics and their information is captured by the initial trade shares π_{ij}.

Table 5: Results from the Model Simulations (% changes)

			RCP 4.5							
			Full Adjustment				Partial Adjustment			
Region	Code	$\hat{A}$	$\hat{p}/\hat{P}$	$\widehat{CS}$	$\widehat{PS}$	$\hat{W}$	$\hat{p}/\hat{P}$	$\widehat{CS}$	$\widehat{PS}$	$\hat{W}$
Vienna	AT13	2.17	1.44	2.59	-1.19	1.40	1.58	3.22	-1.69	1.53
Cyprus	CYP	-5.98	1.24	-1.41	2.53	1.12	2.13	-2.53	4.50	1.98
Aland	FI20	5.99	1.23	6.62	-5.58	1.04	2.57	8.10	-5.79	2.31
Melilla	ES64	-3.86	0.99	-0.14	1.09	0.95	2.24	-0.34	2.51	2.17
Attiki	GR30	-3.92	1.00	-1.22	2.17	0.95	1.35	-1.75	3.03	1.28
...										
Nyugat Dunantul	HU22	1.69	-0.01	1.23	-1.25	-0.02	-0.01	1.44	-1.46	-0.03
...										
Trento	ITD2	6.10	-1.28	0.69	-2.06	-1.38	-3.01	0.94	-4.11	-3.17
Mellersta Norrland	SE32	10.20	-1.03	4.69	-6.08	-1.39	-1.83	5.95	-8.16	-2.22
Övre Norrland	SE33	17.06	-1.29	6.67	-8.87	-2.20	-2.30	9.74	-13.09	-3.35
Bolzano	ITD1	10.20	-2.19	1.07	-3.53	-2.46	-4.88	1.65	-6.97	-5.32
Valle d'Aosta	ITC2	8.92	-2.29	0.61	-3.11	-2.51	-4.95	0.79	-6.11	-5.32
Weighted Average		1.72	0.01	1.19	-1.22	-0.03	0.00	1.42	-1.46	-0.03
			RCP 8.5							
			Full Adjustment				Partial Adjustment			
Region	Code	$\hat{A}$	$\hat{p}/\hat{P}$	$\widehat{CS}$	$\widehat{PS}$	$\hat{W}$	$\hat{p}/\hat{P}$	$\widehat{CS}$	$\widehat{PS}$	$\hat{W}$
Vienna	AT13	2.33	2.59	3.53	-1.01	2.52	2.98	4.64	-1.77	2.87
Cyprus	CYP	-12.09	2.33	-3.73	5.53	1.80	4.13	-5.80	9.28	3.48
Melilla	ES64	-8.93	1.83	-1.66	3.24	1.58	4.34	-2.17	6.13	3.96
Attiki	GR30	-7.87	1.76	-3.15	4.66	1.51	2.44	-4.04	6.22	2.18
Aland	FI20	7.30	1.80	8.42	-6.91	1.50	3.80	10.57	-7.20	3.37
...										
Detmold	DEA4	2.69	-0.02	1.53	-1.57	-0.04	0.03	2.26	-2.26	-0.01
...										
Tirol	AT33	17.48	-1.83	5.66	-8.40	-2.74	-3.29	8.92	-13.29	-4.37
Trento	ITD2	11.75	-2.64	0.40	-3.35	-2.95	-6.04	1.05	-7.70	-6.65
Övre Norrland	SE33	24.29	-1.76	9.05	-12.57	-3.52	-3.08	13.44	-18.54	-5.11
Bolzano	ITD1	18.57	-4.04	1.03	-5.87	-4.85	-8.83	2.20	-12.45	-10.25
Valle d'Aosta	ITC2	17.30	-4.51	0.16	-5.40	-5.24	-9.64	0.57	-11.57	-11.00
Weighted Average		1.79	0.01	0.98	-1.04	-0.06	0.02	1.37	-1.44	-0.07

Notes: the table shows the first five, the median, and the last five regions of the welfare change distribution from the "Full Adjustment" simulation. The values are in % change. The "Full Adjustment" simulation (used as reference) provides results allowing trade flows to change in size and direction, while the "Partial Adjustment" simulation shows the results constraining bilateral import shares.

1.44%).

Looking at the extremes of the welfare change distribution, the re-

sults are heterogeneous. In the first rows of the panels, I show the regions with the highest welfare change according to the "full adjustment" scenario, while at the bottom there are the five regions with the lowest one. In the first case, welfare changes are about 1% (max 1.40) and are driven by two different mechanisms. First, regions with negative productivity changes (e.g. Cyprus) would have an increase in prices with a positive effect on local producers but a negative one on consumers. The net effect on welfare is positive, showing that the producer's gains are higher. In such a case, fixing import shares would benefit even further local producers at the expense of consumers. Therefore, the role of trade here is asymmetric: it gives consumers the possibility to obtain lower prices from imported goods ($\hat{CS}$ is lower in the "partial" scenario) at the expense of local producers ($\hat{PS}$ is higher). Second, regions with positive productivity changes (e.g. Vienna) would see a reduction in producer surplus (given lower prices) and an increase in consumer surplus. When such regions trade a substantial amount of products from regions where prices also decrease, the net welfare effect will be positive because the consumer price index would decrease less than the producer price ($\hat{p}/\hat{P} \uparrow$). Limiting trade would benefit further the consumers that can enjoy lower prices induced by higher local productivity.
On the opposite side, there are regions with higher productivity gains that would see a reduction in the producer price and this would induce a negative effect on the producer surplus. The net effect on welfare is negative given that the increase in consumer surplus does not offset completely the producer surplus reduction. Also in this case, results are driven by price transmissions. For example, regions such as Trento, Bolzano, and Valle d'Aosta are all placed in northern Italy where productivity is expected to increase, but their main trade partners are from southern Italy where prices are predicted to rise. Therefore, consumer surplus does not increase as much as in regions with similar productivity changes. Limiting trade would induce larger welfare losses driven by lower consumer surplus.
Although these results show little percentage point variation from one scenario to the other (especially for the weighted average), in relative terms, changes can be substantial. For some regions, trade could reduce welfare losses by two times (e.g. ITC2, ITD1), while for others it could reduce welfare gains by the same amount (e.g. FI20, ES64). The same is true when looking at consumer and producer surplus. Comparing the two RCP scenarios, they show qualitatively similar results, although larger productivity shocks in the RCP 8.5 would induce a larger welfare response.

Table 6 shows the results of a sensitivity analysis. As before, the welfare change decomposition in percentage is shown but, in this case, I show only the average value among the EU regions. Each row shows the results from a simulation where only one parameter has been changed compared to the baseline one (reported in the first row).

The second and the third rows have a larger value of θ (the trade elasticity) that reflects estimated values in Tombe (2015) and Caliendo and Parro (2015), respectively. The larger the value, the lower the changes associated with consumer and producer surplus in the full adjustment scenario. Also the welfare change is reduced (in absolute value). This is coherent with the fact that higher values of the trade elasticity imply reduced sensitivity of trade flows to the productivity shock and therefore lower price transmissions. When trade is limited, the results associated with different values of θ are similar because we imposed a different trade equation that does not depend on the trade elasticity.

Assuming inelastic demand and supply ($\epsilon = 0.2, \eta = 0.2$), the change in consumer and producer surplus is slightly larger but the net welfare change is mostly unchanged. Limiting trade would induce a slightly larger consumer surplus and lower producer surplus. Contrary, assuming elastic demand and supply ($\epsilon = 0.9, \eta = 0.9$), consumer and producer surplus reduce slightly their magnitude with no substantial change in welfare.

The sensitivity results show that, on average, the value attributed to the parameters does not substantially change the overall results (although they could be significantly different for specific regions).

Finally, I directly address one specific question related to this literature, namely, could consumers located in regions with a negative impact on agricultural productivity benefit from imported goods? (e.g. Janssens et al., 2020). In the European continent, productivity in regions placed in the Mediterranean area is predicted to decline, causing an increase in local prices. In Figure 5, I plot the percentage change of consumer surplus for both simulations and both RCP scenarios. On average, consumers see a negative change in their surpluses that increases with the intensity of the productivity decline (RCP 8.5). Comparing the full adjustment scenario (panels a and c) with the partial one (b and d), we can observe that in the second case the negative effect is even higher. This implies that allowing them to trade with partners that offer lower prices could reduce their losses. For most of the regions, the difference is not trivial and, in relative terms, the trade adjustment mechanism could lead to more than halving the reduction in consumer surplus. For example, for the median region in this sub-sample of Mediterranean areas (GR42), the loss reduction ranges from 43% to 56%.

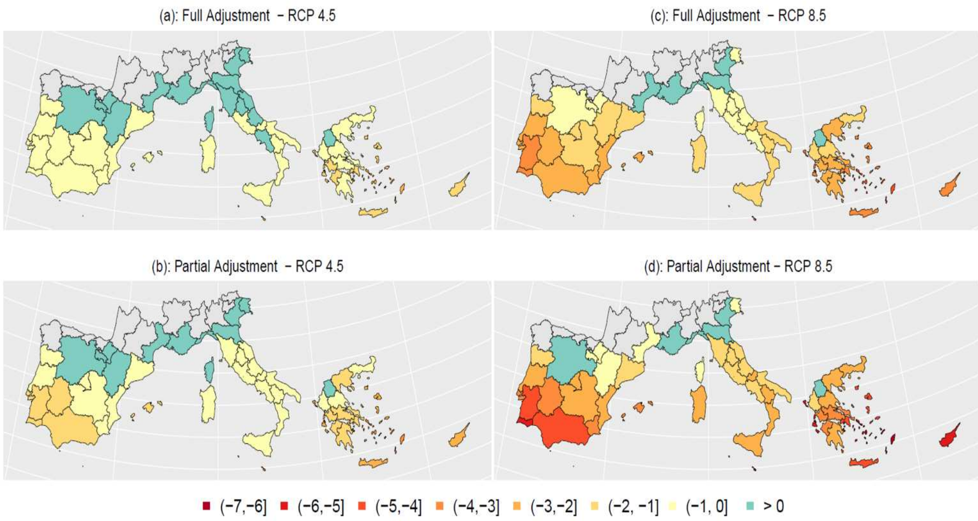
The results presented in this subsection show that on average trade adjustments within the EU would play a relatively small role in adapting to climate change. However, heterogeneous results are shown when welfare is decomposed into consumer and producer surpluses and when focusing on specific areas. This shows that when looking

Table 6: Sensitivity analysis

	RCP 4.5					
	Full Adjustment			Partial Adjustment		
	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
Baseline (θ = 2.2, ϵ = 0.57, η = 0.5)	1.19	-1.22	-0.03	1.42	-1.46	-0.03
$\theta = 4$	1.00	-1.02	-0.02	1.43	-1.46	-0.03
$\theta = 8.1$	0.65	-0.66	0.03	1.46	-1.47	-0.01
$\epsilon = 0.2$	1.47	-1.50	-0.03	1.96	-2.00	-0.03
$\epsilon = 0.9$	1.00	-1.02	-0.02	1.14	-1.17	-0.03
$\eta = 0.2$	1.55	-1.58	-0.03	2.03	-2.07	-0.04
$\eta = 0.9$	0.96	-0.98	-0.02	1.09	-1.12	-0.03
	RCP 8.5					
	Full Adjustment			Partial Adjustment		
	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
Baseline (θ = 2.2, ϵ = 0.57, η = 0.5)	0.98	-1.04	-0.06	1.37	-1.44	-0.07
$\theta = 4$	0.65	-0.69	-0.04	1.41	-1.45	-0.04
$\theta = 8.1$	0.01	-0.02	-0.01	1.48	-1.47	0.01
$\epsilon = 0.2$	0.90	-0.96	-0.05	1.77	-1.83	-0.06
$\epsilon = 0.9$	0.90	-0.96	-0.06	1.14	-1.20	-0.07
$\eta = 0.2$	1.10	-1.16	-0.07	1.94	-2.02	-0.07
$\eta = 0.9$	0.84	-0.89	-0.05	1.06	-1.12	-0.06

Notes: results refers to the weighted average value of all the EU regions.

Figure 5: Change (%) in Consumer Surplus in the Mediterranean Region



Notes: panels (a) and (c) show the "full adjustment" simulations for RCP 4.5 and RCP 8.5, while panels (b) and (d) show the "partial adjustment" ones.

at the disaggregated level and focusing on both sides of the market, the trade adjustment mechanism leads to very different conclusions.
Direct comparison with previous works is not possible, but it can be useful to find differences and analogies with them. For example, Costinot, Donaldson, and Smith (2016), accounting for ten major crops, find welfare consequences of climate change of about 0.27 percent loss in global GDP. Simulating a partial adjustment of trade (holding fixed the shares of crop output exported), they find very similar results, suggesting that international trade plays a minor role in reducing CC impacts on the global economy. Looking at European countries, they find little variation as well from comparing the two simulations. Germany and Poland are the only examples of countries that would benefit from limited trade (difference of 0.1 percentage point), while countries such as Spain, France, and Romania would see their welfare slightly reduced (maximum difference of -0.3 pp for Spain). Gouel and Laborde (2021), using a similar model but a different trade adjustment mechanism (i.e. fixing the bilateral import shares) find that trade has a non-trivial role in adapting to climate change. At the world level, they show that this margin of adjustment reduces losses from -1.30% of world GDP to -1%. In Europe, this mechanism is slightly larger in relative terms (from -1.12% to -0.80%). At the country level, all the considered EU members, but Spain, would see their welfare decreased in the scenario where trade is limited.

3.5 Conclusions

In this paper, I discuss the potential role that agricultural trade and market integration could play as adaptation mechanisms to cope with climate change. I build a partial equilibrium model, based on the neo-Ricardian quantitative trade literature, and run counterfactual simulations where trade adjusts to different extents. I contextualize the analysis within the European Union, exploiting sub-national data and the fact that trade barriers between regions are limited. This allows me to estimate a key parameter in the model, i.e. the trade elasticity, avoiding bias connected to unobserved trade frictions. Using detailed data and a panel econometrics approach, I quantify the predicted change in agricultural productivity according to different emission scenarios. This productivity change is used as an exogenous shock in the model. I run simulations allowing the trade patterns to adjust completely (reference simulation) or only partially (fixing the bilateral import share). Comparing the two counterfactuals provide us with a measure of the extent to which trade can help to attenuate the consequences of climate change.
Results show that, on average, trade adjustments play a little role in defining the welfare effect within the EU. However, heterogeneity is

large both between consumers and producers and among the different regions. In relative terms, exploiting new patterns of trade could avoid substantial losses for producers that see a substantial reduction in their local prices. In a similar vein, trade would play a substantial role in alleviating consumers' losses for those regions where productivity changes would increase local prices (e.g. Mediterranean area).
From these results, important insights emerge when widening the perspective at the global scale where climate change impacts will be larger and more heterogeneous. Lowering trade frictions, similarly to the EU levels, would provide a significant reduction in consumers' losses. This is particularly relevant for those areas where food security represents an important issue.
Finally, my analysis also presents some limitations. Importantly, I use a relatively simple partial equilibrium modeling approach that allows for transparent identification of the underlying mechanisms. However, it does not consider other important factors that may affect the results, such as accounting for the intermediate inputs, the income structure, the role played by other sectors (e.g. food manufacturing), and general equilibrium effects.

Part I

APPENDIX

APPENDIX A

A.1 METHODOLOGY

Following Kahn et al. (2021), we consider future annual temperatures over the counterfactual period (from 2017 to 2070) as:

$$T_{i,h+j} = a_i + b_{i,j}(h+j) + \nu_{i,h+j}, \quad \text{for } j = 1, 2, \ldots, H \tag{22}$$

where a_i is a constant, $b_{i,j}$ is the yearly average increase in temperature, $\nu_{i,h+j}$ is the stochastic weather component, h is the last year of our analysis, i.e. 2016 and H is the number of years from h to 2070 i.e. 55. We consider the historical norm as in Section 2.2 and we write the future temperature anomaly as:

$$\begin{aligned} T_{i,h+j} - T^*_{i,h+j-1} &= T_{i,h+j} - m^{-1}\sum_{s=1}^{m} T_{i,h+j-s} \\ &= \left(\frac{m+1}{2}\right) b_{i,j} + (\nu_{i,h+j} - \bar{\nu}_{i,h+j-1}) \end{aligned} \tag{23}$$

where $\bar{\nu}_{i,h+j-1} = m^{-1}\sum_{s=1}^{m} \nu_{i,h+j-s}$. In this way, the future annual anomaly is given by the trend change $b_{i,j}$ in temperature and by the distribution of the temperature shocks $\nu_{i,h+j}$. Since the purpose of our counterfactual analysis is related to future Anthropogenic Climate Change, we compute the anomaly based only on the temperature trend and disregard the stochastic fluctuation that also incorporates a natural component.
We collect data on the country-specific year average increase in temperature according to the RCPs scenarios as a constant linear trend estimated using the mean ensemble of the Global Circulation Models (GCMs) forming the CMIP5. Data are collected from the KNMI Climate Change Atlas (KNMI, 2013). In order to allow the temperature trends to change in time we define them as:

$$b_{i,j} = T_{i,h+j} - T_{i,h+j-1} = b_i^0 + j d_i \tag{24}$$

where b_i^0 is the historical average increase (from 1968 to 2016) predicted by the climate models and d_i is the average incremental change in temperature between the historical and the future trend according to the RCPs considered in each counterfactual exercise, i.e.:

$$d_i = \frac{2(b_i^1 - b_i^0)}{H+1} \tag{25}$$

In order to have a reliable comparison, we use the historical value predicted by the same climate model used to compute the future

anomaly.
Therefore, we can compute the temperature anomalies according to the trends shown by the different scenarios and we can apply the following loss function to estimate the difference between the historic and future patterns:

$$\Delta Y_{i,h+j} = \delta(\Delta T\_an_{i,h+j}) \tag{26}$$

where $\Delta Y_{i,h+j}$ the is the counterfactual change in the aggregate value of agricultural production, δ is the marginal effect of 1°C rise in temperature derived by the estimated coefficient associated with positive anomaly (β_1 in eq. 5) and $\Delta T\_an_{i,h+j}$ is the difference between the temperature anomaly computed for the RCP8.5, RCP6.0, RCP4.5 and the anomaly in the reference scenario RCP2.6, i.e. $T\_an^{RCP\#}_{i,h+j} - T\_an^{RCP26}_{i,h+j}$.
To be coherent with our results that find heterogeneous impacts of the temperature anomaly between income levels, in the counterfactual analysis we compute the marginal effect using the estimates from the interacted model (column 1 of A4) that consider GDP per capita. To compute the future level of GDP per capita we use the SSP2 scenario and the country-specific growth rates computed by the OECD's ENV-Growth Model. Finally, we sum the future annual changes of $Y_{i,h+j}$ to get the cumulate change in the year 2070 according to the different RCPs compared to the baseline scenario, i.e.:

$$\sum_{j=1}^{H} \Delta Y_{i,h+j} = \delta \sum_{j=1}^{H} \left(T\_an^{RCP\#}_{i,h+j} - T\_an^{RCP2.6}_{i,h+j}\right) \tag{27}$$

Table A1: Descriptive Statistics

	mean	median	sd	min	max
Output ($)	9642342	1773864	3.38e+07	0	6.23e+08
Output growth	0.019	0.021	0.068	-0.247	0.258
Temperature (°C)	21.03	22.76	5.43	4.58	30.58
Precipitation (mm)	219.03	190.33	153.24	0.05	982.23
Δ Temp pos	-0.0020	0	0.7677	-3.2849	3.2869
Δ Temp neg	0.0107	0	0.5405	-2.5642	2.9103
Δ Prec pos	0.0002	0	0.8693	-4.7677	4.4798
Δ Prec neg	-0.0007	0	0.7694	-3.7033	3.9105

Notes: variables are described in Subsection 2.3.2.

Table A2: Variables' description and source

Variable	Description	Source
Gross Agricultural Production	Total value of crop and animal production using constant 2004-2006 global average farmgate prices, in $1000 purchasing-power-parity dollars.	USDA/ERS
Agricultural Total Factor Productivity Index	Derived from output growth minus input growth.	USDA/ERS
Agricultural Labor	Persons (with age higher than 15) economically active in agriculture.	USDA/ERS
Agricultural Value Added	Agriculture, forestry, and fishing, value added (constant 2010 US$).	WDI
Food Index	Food production index (food crops that are considered edible and that contain nutrients).	WDI
GDP per capita	Gross Domestic Product per person (constant 2015 US$)	WDI
Temperature	Annual and green season average temperature (°C).	Ortiz-Bobea et al. (2021)
Precipitation	Annual and green season average precipitations (mm).	Ortiz-Bobea et al. (2021)

Table A3: Robustness Checks

	(1)	(2)	(3)	(4)
	Δ(ln) Output	Δ(ln) Output	Δ(ln) Output	Δ(ln) Output
$\Delta Tpos$	-0.00976***	-0.0100***	-0.0110***	-0.00913***
	(0.00179)	(0.00178)	(0.00209)	(0.00223)
$\Delta Tneg$	-0.00349	-0.00278	-0.00477	-0.00615
	(0.00285)	(0.00186)	(0.00285)	(0.00404)
$\Delta Ppos$	-0.00176	-0.00244**	-0.00320**	-0.00301**
	(0.00114)	(0.00120)	(0.00128)	(0.00144)
$\Delta Pneg$	-0.00738***	-0.00845***	-0.00794***	-0.00894***
	(0.00182)	(0.00173)	(0.00194)	(0.00183)
L.$\Delta Tpos$				0.00154
				(0.00207)
L.$\Delta Tneg$				-0.00545
				(0.00336)
L.$\Delta Ppos$				-0.00136
				(0.00184)
L.$\Delta Pneg$				-0.00422**
				(0.00202)
L.Δ(ln)Output				-0.177***
				(0.0421)
N	8232	8232	8232	7641
R^2	0.181	0.079	0.085	0.122
Weights	yes	no	yes	yes
Region-Year FE	yes	no	no	no
Year FE	no	yes	yes	yes
Clust. SE	region-year	year	year	region-year

Notes: All the estimates account for country Fixed Effects and clustered standard errors at the country level. They vary in terms of additional FEs and additional clusterization (two-way). Weights in column (1) refer to shares of global output among the countries in the sample. Column (4) is estimated using an ARDL(2,2) but only the first lag (L) is shown. Standard errors in parentheses. Statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A4: Heterogeneity between Income Groups

	(1)	(2)	(3)	(4)
	$\Delta(\ln)$	$\Delta(\ln)$	$\Delta(\ln)$	$\Delta(\ln)$
	Output	Output	Output	Output
$\text{dummy} = 1$		GDP $< 25^{th}$	GDP $< 50^{th}$	GDP $> 75^{th}$
ΔTpos	-0.0148***	-0.0111***	-0.0108***	-0.0144***
	(0.00283)	(0.00239)	(0.00283)	(0.00282)
ΔTneg	-0.00612**	-0.00300	-0.00283	-0.00295
	(0.00285)	(0.00344)	(0.00317)	(0.00279)
ΔPpos	0.00277*	-0.00165	-0.00255	0.00233
	(0.00153)	(0.00158)	(0.00188)	(0.00160)
ΔPneg	-0.0123***	-0.00692***	-0.00526**	-0.0119***
	(0.00278)	(0.00204)	(0.00255)	(0.00280)
ΔTpos $\times$ GDP	0.000226***			
	(0.0000755)			
ΔTneg $\times$ GDP	0.000251*			
	(0.000149)			
ΔPpos $\times$ GDP	-0.000267***			
	(0.0000665)			
ΔPneg $\times$ GDP	0.000302***			
	(0.000104)			
ΔTpos $\times$ dummy		-0.00515	-0.00339	0.00818**
		(0.00482)	(0.00365)	(0.00338)
ΔTneg $\times$ dummy		-0.00409	-0.00137	-0.00122
		(0.00438)	(0.00349)	(0.00485)
ΔPpos $\times$ dummy		0.00725	0.00544**	-0.00854***
		(0.00443)	(0.00258)	(0.00282)
ΔPneg $\times$ dummy		-0.0110	-0.00826*	0.00888**
		(0.00690)	(0.00454)	(0.00411)
ΔTpos net effect		-0.01622***	-0.01421***	-0.00626**
		(0.00481)	(0.00315)	(0.002749)
ΔTneg net effect		-0.00709***	-0.0042	-0.00418
		(0.002568)	(0.003215)	(0.004658)
ΔPpos net effect		0.005596	0.002893	-0.00621**
		(0.004018)	(0.002028)	(0.002584)
ΔPneg net effect		-0.01789***	-0.01352***	-0.00298
		(0.006623)	(0.003727)	(0.003079)

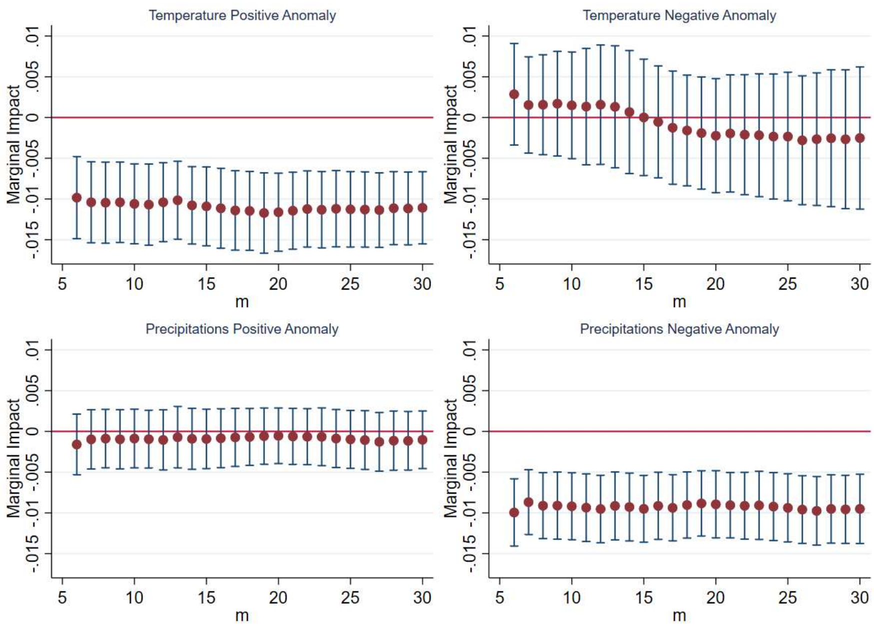
Notes: estimated model in (1) is $\Delta y_{i,t} = \beta' \Delta W'_{i,t} + \rho GDP_{i,t} + \gamma' \Delta W'_{i,t} \times GDP_{i,t} + \alpha_i + \theta_{r \times t} + \epsilon_{i,t}$ where W' represents our vector of weather variables and GDP represents the GDP per capita (the associated coefficient ρ is omitted from the table). Estimated model from (2) to (4) is $\Delta y_{i,t} = \beta' \Delta W'_{i,t} + \gamma' \Delta W'_{i,t} \times D_{i,t} + \alpha_i + \theta_{r \times t} + \epsilon_{i,t}$ where D' is the vector of dummy variables described as in the main text. Standard errors (in parentheses) are clustered at country and region-year level. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A5: Heterogeneity between Average Temperature Groups

	(1) $\Delta(\ln)$ Output	(2) $\Delta(\ln)$ Output	(3) $\Delta(\ln)$ Output	(4) $\Delta(\ln)$ Output
$dummy = 1$		$Temp < 25^{th}$	$Temp < 50^{th}$	$Temp > 75^{th}$
$\Delta Tpos$	-0.0152**	-0.00925***	-0.00689***	-0.0108***
	(0.00638)	(0.00202)	(0.00223)	(0.00197)
$\Delta Tneg$	0.00192	-0.00342	-0.000537	-0.00345
	(0.00838)	(0.00230)	(0.00232)	(0.00265)
$\Delta Ppos$	-0.00826*	-0.000555	0.0000522	-0.00159
	(0.00428)	(0.00126)	(0.00143)	(0.00129)
$\Delta Pneg$	-0.00396	-0.00799***	-0.00878***	-0.00614***
	(0.00648)	(0.00214)	(0.00263)	(0.00202)
$\Delta Tpos \times Temp$	0.000278			
	(0.000288)			
$\Delta Tneg \times Temp$	-0.000186			
	(0.000368)			
$\Delta Ppos \times Temp$	0.000322			
	(0.000196)			
$\Delta Pneg \times Temp$	-0.000184			
	(0.000307)			
$\Delta Tpos \times dummy$		-0.0000628	-0.00517	0.00477
		(0.00349)	(0.00322)	(0.00327)
$\Delta Tneg \times dummy$		0.00607	-0.00235	0.00681
		(0.00457)	(0.00350)	(0.00420)
$\Delta Ppos \times dummy$		-0.00344	-0.00309	0.000411
		(0.00267)	(0.00213)	(0.00215)
$\Delta Pneg \times dummy$		0.000698	0.00202	-0.00673*
		(0.00369)	(0.00360)	(0.00353)

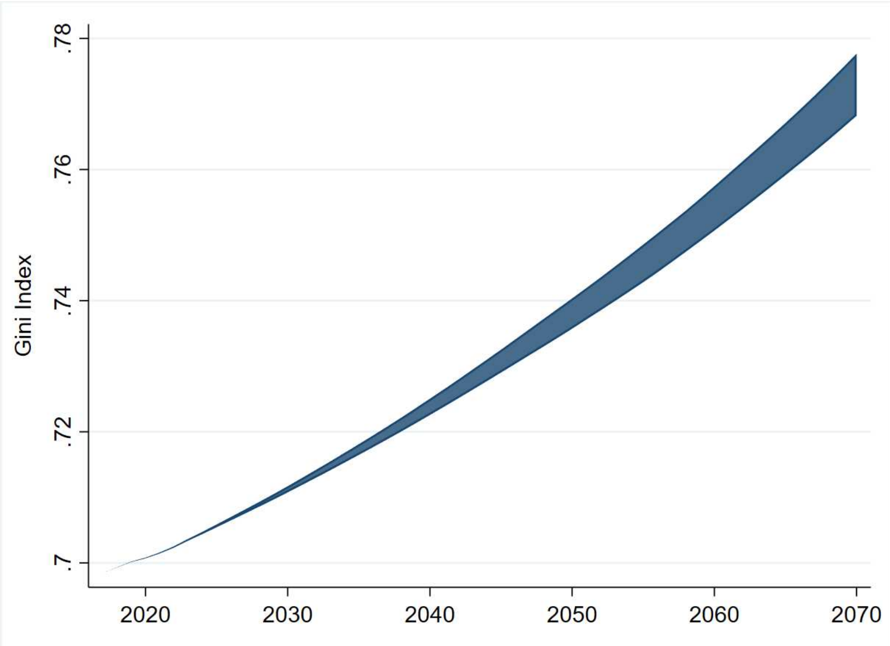
Notes: estimated model in (1) is $\Delta y_{i,t} = \beta' \Delta W'_{i,t} + \rho Temp_{i,t} + \gamma' \Delta W'_{i,t} \times Temp_{i,t} + \alpha_i + \theta_{r \times t} + \epsilon_{i,t}$ where W' represents our vector of weather variables and $Temp$ represents the 20-years moving average (the associated coefficient ρ is omitted from the table). Estimated model from (2) to (4) is $\Delta y_{i,t} = \beta' \Delta W'_{i,t} + \gamma' \Delta W'_{i,t} \times D_{i,t} + \alpha_i + \theta_{r \times t} + \epsilon_{i,t}$ where D' is the vector of dummy variables described as in the main text. Standard errors (in parentheses) are clustered at country and region-year level. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Figure A1: Robustness Check: different values of m



Notes: We estimate Equation (5) using different values of m (from 6 to 30) in computing the moving averages (MA) of the weather variables. The time dimension has been reduced from 1977 to 2016 to allow computation of MA higher than 20 years. The red dots show the estimated coefficients of the weather anomalies, while the blue bands show the 95th confidence interval.

Figure A2: Evolution of an Agriculture-based Gini Index 2016-2070



Notes: the Gini Index is computed considering the value of agricultural output per worker taking into consideration the evolution of the population (UN projections), the share of the agricultural labor force, and the output growth rate (using historical trends). The range of values represents the different impacts of climate change according to the RCPs scenarios.

APPENDIX B

Table B1: Estimate of the Climate-Productivity Relationship

Dependent variable: Δ (ln) Productivity		
	Coefficient	Std. Error
Δ Temperature	0.0406^{***}	(0.0151)
Δ Temperature^2	-0.0019^{***}	(0.0007)
Δ Precipitation	0.0006	(0.0005)
Δ Precipitation^2	-2.65×10^{-6}	(1.67×10^{-6})
N	39849	
R2	0.2897	

Notes: Standard errors are adjusted to reflect spatial dependence (up to 1000 km) as modeled in Conley (1999) and serial correlation (up to a lag of 7 years) as modeled in Newey and West (1987). Province (NUTS3) coordinates refer to province centroid.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Results for all regions - RCP 4.5

	Full			Partial				Full			Partial		
Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
AT11	2.2	-2.3	0.0	2.4	-2.2	0.1	FR43	1.0	-1.1	-0.1	1.3	-1.4	-0.1
AT12	2.4	-2.5	-0.1	2.8	-2.8	0.0	FR51	0.4	-0.4	0.0	0.4	-0.3	0.1
AT13	2.6	-1.2	1.4	3.2	-1.7	1.5	FR52	0.5	-0.4	0.0	0.4	-0.4	0.1
AT21	3.2	-3.8	-0.6	4.3	-5.2	-0.9	FR53	0.4	-0.3	0.1	0.2	-0.1	0.1
AT22	2.9	-3.3	-0.4	3.7	-4.3	-0.6	FR61	0.3	-0.3	0.0	0.1	0.0	0.1
AT31	2.6	-2.8	-0.2	3.2	-3.4	-0.2	FR62	0.5	-0.5	0.0	0.5	-0.5	0.0
AT32	3.4	-4.3	-0.9	4.8	-6.3	-1.5	FR63	0.8	-0.8	0.0	0.9	-1.0	-0.1
AT33	3.7	-4.9	-1.3	5.4	-7.5	-2.1	FR71	1.0	-1.2	-0.2	1.4	-1.9	-0.4
AT34	2.9	-3.8	-1.0	3.8	-5.8	-1.9	FR72	1.0	-1.2	-0.1	1.4	-1.6	-0.2
BE10	0.8	-0.6	0.2	1.1	-0.9	0.2	FR81	0.6	-0.5	0.0	0.5	-0.5	0.1
BE21	0.8	-0.6	0.2	1.1	-0.9	0.2	FR82	1.3	-1.5	-0.2	2.0	-2.4	-0.4
BE22	0.8	-0.8	0.0	1.1	-1.0	0.1	FR83	0.4	-0.2	0.2	0.2	0.1	0.3
BE23	0.8	-0.7	0.1	1.1	-0.9	0.2	GR11	-0.5	0.7	0.2	-0.8	1.0	0.3
BE24	0.8	-0.5	0.3	1.1	-0.8	0.3	GR12	-0.8	1.0	0.2	-1.0	1.2	0.2
BE25	0.8	-0.8	0.0	1.1	-0.9	0.2	GR13	0.9	-1.2	-0.3	1.4	-1.9	-0.5
BE31	0.8	-0.7	0.1	1.1	-1.0	0.2	GR14	-0.5	0.6	0.1	-0.7	0.8	0.1
BE32	0.8	-0.8	0.1	1.1	-1.0	0.1	GR21	-0.1	0.1	0.0	0.0	0.0	-0.1

Table B2 – continued from previous page

	Full			Partial				Full			Partial		
Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
BE33	0.9	-0.9	0.0	1.2	-1.4	-0.2	GR22	-1.8	2.3	0.5	-2.8	3.6	0.7
BE34	1.0	-1.1	-0.2	1.4	-1.7	-0.4	GR23	-1.1	1.4	0.3	-1.6	2.2	0.5
BE35	0.9	-0.9	0.0	1.2	-1.3	-0.1	GR24	-0.9	1.0	0.2	-1.2	1.5	0.3
BGR	0.1	-0.2	0.0	0.6	-0.6	-0.1	GR25	-0.7	1.0	0.3	-1.0	1.5	0.5
CYP	-1.4	2.5	1.1	-2.5	4.5	2.0	GR30	-1.2	2.2	0.9	-1.7	3.0	1.3
CZ01	2.4	-1.9	0.5	2.9	-2.6	0.3	GR41	-1.5	2.1	0.6	-2.4	3.3	0.9
CZ02	2.4	-2.5	-0.1	2.8	-2.9	-0.1	GR42	-2.2	2.8	0.5	-3.4	4.3	0.9
CZ03	2.6	-2.8	-0.2	3.1	-3.3	-0.2	GR43	-1.4	1.8	0.5	-2.2	2.9	0.7
CZ04	2.5	-2.7	-0.1	3.0	-3.2	-0.2	HU10	1.1	-1.0	0.2	1.4	-1.4	0.0
CZ05	2.5	-2.7	-0.1	3.0	-3.1	-0.1	HU21	1.2	-1.3	0.0	1.5	-1.5	-0.1
CZ06	2.5	-2.7	-0.1	3.0	-3.1	-0.1	HU22	1.2	-1.2	0.0	1.4	-1.5	0.0
CZ07	2.5	-2.7	-0.2	3.0	-3.2	-0.2	HU23	1.1	-1.1	0.0	1.2	-1.1	0.1
CZ08	2.5	-2.6	-0.1	3.0	-3.1	-0.1	HU31	1.4	-1.5	-0.1	1.7	-2.0	-0.2
DE11	1.5	-1.5	-0.1	2.0	-2.1	-0.1	HU32	1.2	-1.2	0.0	1.4	-1.4	0.0
DE12	1.4	-1.3	0.1	1.8	-1.7	0.1	HU33	1.1	-1.0	0.1	1.1	-0.9	0.1
DE13	1.6	-1.8	-0.2	2.2	-2.4	-0.3	IE01	0.7	-0.8	0.0	1.3	-1.3	0.0
DE14	1.7	-2.1	-0.3	2.5	-3.0	-0.5	IE02	0.5	-0.4	0.1	1.1	-1.1	0.0
DE21	1.7	-2.0	-0.3	2.5	-3.0	-0.6	ITC1	0.9	-1.2	-0.2	1.3	-1.8	-0.5
DE22	1.8	-2.1	-0.3	2.5	-3.0	-0.5	ITC2	0.6	-3.1	-2.5	0.8	-6.1	-5.3
DE23	1.7	-2.0	-0.3	2.4	-2.9	-0.5	ITC3	0.8	-0.5	0.3	1.0	-0.1	0.9
DE24	1.7	-1.9	-0.3	2.3	-2.7	-0.4	ITC4	1.0	-1.0	0.1	1.4	-1.2	0.2
DE25	1.6	-1.7	-0.1	2.1	-2.4	-0.2	ITD1	1.1	-3.5	-2.5	1.6	-7.0	-5.3
DE26	1.6	-1.7	-0.1	2.0	-2.2	-0.2	ITD2	0.7	-2.1	-1.4	0.9	-4.1	-3.2
DE27	1.8	-2.2	-0.4	2.6	-3.2	-0.6	ITD3	0.6	-0.5	0.1	0.6	-0.5	0.1
DE30	1.4	-0.7	0.8	1.8	-1.4	0.4	ITD4	0.4	-0.4	0.1	0.3	-0.1	0.2
DE41	1.5	-1.5	-0.1	1.8	-1.8	0.0	ITD5	0.6	-0.4	0.2	0.6	-0.1	0.5
DE42	1.2	-1.4	-0.2	1.6	-1.7	-0.1	ITE1	0.1	0.1	0.2	-0.2	0.5	0.3
DE50	1.4	-0.6	0.8	1.7	-1.2	0.5	ITE2	0.1	0.0	0.0	-0.2	0.0	-0.2
DE60	1.4	-0.6	0.8	1.8	-1.3	0.5	ITE3	0.1	0.0	0.1	-0.2	0.1	-0.1
DE71	1.4	-1.1	0.2	1.8	-1.7	0.1	ITE4	0.0	0.3	0.3	-0.3	0.8	0.5
DE72	1.5	-1.6	-0.1	1.9	-2.1	-0.2	ITF1	0.1	-0.3	-0.2	-0.2	-0.5	-0.7
DE73	1.5	-1.6	-0.1	2.0	-2.2	-0.2	ITF2	-0.1	0.0	-0.2	-0.6	0.0	-0.6
DE80	1.4	-1.5	-0.1	1.8	-1.9	-0.1	ITF3	0.0	0.1	0.1	-0.3	0.5	0.2
DE91	1.4	-1.4	0.0	1.8	-1.8	0.0	ITF4	0.0	0.4	0.4	-0.4	1.3	1.0
DE92	1.3	-1.3	0.0	1.6	-1.6	0.0	ITF5	-0.3	0.1	-0.1	-0.9	0.4	-0.5
DE93	1.4	-1.4	-0.1	1.6	-1.6	0.0	ITF6	-0.1	0.6	0.5	-0.7	1.6	0.8
DE94	1.3	-1.3	0.0	1.5	-1.5	0.1	ITG1	-0.2	0.7	0.5	-0.7	1.7	0.9
DEA1	1.2	-1.0	0.2	1.5	-1.1	0.4	ITG2	0.0	0.4	0.4	-0.6	1.3	0.7
DEA2	1.3	-1.0	0.2	1.6	-1.4	0.2	LT00	2.6	-2.8	-0.1	3.8	-4.0	-0.2
DEA3	1.3	-1.2	0.0	1.5	-1.4	0.1	LU00	0.9	-1.1	-0.2	1.3	-1.7	-0.4
DEA4	1.3	-1.3	0.0	1.7	-1.6	0.1	LV00	3.2	-3.5	-0.3	4.3	-4.7	-0.4
DEA5	1.3	-1.2	0.2	1.7	-1.6	0.1	MT00	-2.0	2.8	0.8	-3.1	4.3	1.2

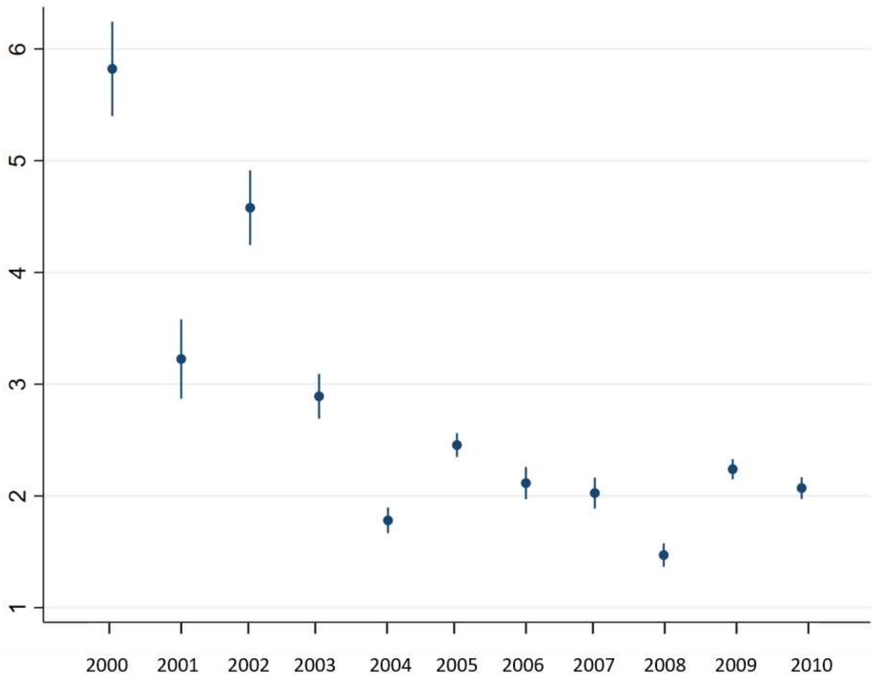
Table B2 – continued from previous page

	Full			Partial				Full			Partial		
Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
DEB1	1.4	-1.5	-0.1	1.9	-2.0	-0.1	NL11	0.9	-0.7	0.1	1.2	-1.2	0.1
DEB2	1.5	-1.6	-0.1	1.9	-2.0	-0.1	NL12	0.9	-0.9	0.0	1.2	-1.1	0.1
DEB3	1.4	-1.4	0.0	1.7	-1.7	0.0	NL13	0.9	-0.9	0.1	1.3	-1.2	0.1
DEC0	1.2	-0.9	0.3	1.6	-1.5	0.1	NL21	0.9	-0.8	0.1	1.2	-1.2	0.1
DED1	1.6	-1.8	-0.2	2.2	-2.6	-0.4	NL22	0.9	-0.8	0.1	1.2	-1.1	0.1
DED2	1.5	-1.6	-0.1	2.0	-2.2	-0.2	NL23	0.9	-0.7	0.1	1.2	-1.0	0.2
DED3	1.4	-1.5	-0.1	1.8	-1.9	0.0	NL31	0.9	-0.5	0.3	1.2	-1.0	0.2
DEE0	1.1	-1.4	-0.3	1.5	-1.8	-0.3	NL32	0.8	-0.5	0.3	1.1	-0.8	0.3
DEF0	1.4	-1.5	-0.1	1.8	-1.8	0.0	NL33	0.8	-0.7	0.2	1.1	-0.9	0.2
DEG0	1.5	-1.7	-0.2	2.0	-2.3	-0.3	NL34	0.8	-0.6	0.2	1.1	-0.7	0.4
DK01	1.5	-1.0	0.5	1.9	-1.8	0.2	NL41	0.8	-0.6	0.2	1.2	-0.9	0.2
DK02	1.5	-1.5	0.0	1.9	-1.9	0.0	NL42	0.9	-0.7	0.1	1.2	-1.0	0.2
DK03	1.5	-1.5	0.0	1.9	-1.9	0.0	PL11	2.3	-2.4	-0.1	2.6	-2.6	0.0
EE00	4.3	-4.6	-0.3	5.3	-5.6	-0.3	PL12	2.4	-2.5	-0.1	2.8	-3.0	-0.1
ES11	0.2	-0.3	0.0	0.4	-0.5	-0.1	PL21	2.3	-2.6	-0.3	2.9	-3.2	-0.4
ES12	0.5	-0.8	-0.3	0.9	-1.3	-0.4	PL22	2.2	-2.3	0.0	2.7	-2.8	-0.1
ES13	0.6	-0.8	-0.2	1.0	-1.4	-0.4	PL31	2.6	-2.7	-0.2	3.0	-3.2	-0.2
ES21	0.2	-0.4	-0.2	0.3	-0.8	-0.5	PL32	2.5	-2.6	-0.2	2.9	-3.1	-0.2
ES22	0.2	-0.3	-0.1	0.3	-0.5	-0.2	PL33	2.5	-2.6	-0.2	2.9	-3.1	-0.2
ES23	0.3	-0.4	-0.1	0.5	-0.8	-0.3	PL34	2.8	-3.0	-0.2	3.3	-3.6	-0.2
ES24	0.1	-0.2	0.0	0.3	-0.4	-0.1	PL41	2.1	-2.2	0.0	2.3	-2.3	0.0
ES30	-0.2	0.3	0.1	-0.4	0.0	-0.4	PL42	2.1	-2.2	0.0	2.3	-2.3	0.0
ES41	0.6	-0.7	-0.1	0.9	-1.2	-0.2	PL43	2.1	-2.0	0.0	2.2	-2.0	0.1
ES42	-0.2	0.3	0.1	-0.3	0.3	0.1	PL51	2.2	-2.2	0.0	2.5	-2.5	0.0
ES43	-0.5	0.8	0.3	-1.0	1.5	0.5	PL52	2.3	-2.3	-0.1	2.5	-2.6	0.0
ES51	0.0	0.0	0.0	-0.1	-0.3	-0.4	PL61	2.3	-2.4	-0.1	2.6	-2.7	-0.1
ES52	-0.4	0.5	0.2	-0.7	1.0	0.3	PL62	2.7	-2.9	-0.2	3.2	-3.4	-0.2
ES53	-0.6	1.0	0.5	-1.1	2.0	0.9	PL63	2.4	-2.5	-0.1	2.8	-3.0	-0.2
ES61	-0.6	0.9	0.3	-1.2	1.6	0.5	PT11	-0.2	0.1	-0.1	-0.2	-0.1	-0.3
ES62	-0.4	0.7	0.2	-0.9	1.3	0.4	PT15	-1.0	1.4	0.4	-1.7	2.4	0.7
ES63	-0.2	1.1	0.8	-0.5	2.4	2.0	PT16	-0.4	0.6	0.1	-0.6	0.8	0.2
ES64	-0.1	1.1	1.0	-0.3	2.5	2.2	PT17	-0.7	1.0	0.3	-1.2	1.8	0.7
FI13	6.9	-7.8	-0.9	8.6	-9.6	-1.0	PT18	-0.8	1.1	0.3	-1.4	1.9	0.5
FI18	5.9	-6.1	-0.2	7.3	-7.4	-0.1	ROU	1.3	-1.4	0.0	1.6	-1.7	-0.1
FI19	6.2	-6.7	-0.6	7.6	-8.2	-0.6	SE11	4.4	-4.1	0.4	5.5	-5.2	0.3
FI1A	6.8	-7.8	-1.0	8.7	-9.9	-1.3	SE12	4.0	-4.4	-0.3	4.6	-5.1	-0.4
FI20	6.6	-5.6	1.0	8.1	-5.8	2.3	SE21	3.7	-3.9	-0.2	3.8	-3.9	-0.1
FR10	0.6	-0.3	0.4	0.7	-0.5	0.1	SE22	3.2	-3.2	0.0	3.0	-2.9	0.1
FR21	0.8	-0.8	0.0	1.0	-1.0	0.0	SE23	3.8	-3.9	-0.1	4.0	-3.9	0.1
FR22	0.8	-0.8	0.0	0.9	-0.9	0.0	SE31	4.8	-5.9	-1.0	6.1	-7.6	-1.5
FR23	0.7	-0.7	0.0	0.8	-0.8	0.0	SE32	4.7	-6.1	-1.4	5.9	-8.2	-2.2
FR24	0.6	-0.6	0.0	0.6	-0.6	0.0	SE33	6.7	-8.9	-2.2	9.7	-13.1	-3.4

Table B2 – continued from previous page

	Full			Partial				Full			Partial		
Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
FR25	0.6	-0.6	0.0	0.7	-0.7	0.0	SI00	1.6	-1.7	-0.1	2.1	-2.2	-0.1
FR26	0.8	-0.8	0.0	1.0	-1.0	0.0	SK01	2.1	-2.0	0.1	2.4	-2.1	0.3
FR30	0.7	-0.7	0.0	0.8	-0.8	0.0	SK02	2.2	-2.2	0.0	2.4	-2.4	0.0
FR41	1.0	-1.1	-0.1	1.3	-1.4	-0.1	SK03	2.7	-2.9	-0.3	3.4	-3.8	-0.4
FR42	1.0	-1.1	-0.1	1.3	-1.5	-0.2	SK04	2.7	-2.9	-0.2	3.5	-3.8	-0.3

Figure B1: Estimates of θ using different years



Notes: the figure shows point estimates and 95% confidence intervals from Equation (19) using single years observations.

Table B3: Welfare Results: Country Level

	RCP 4.5						RCP 8.5					
	Full			Partial			Full			Partial		
Code	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$	$\hat{CS}$	$\hat{PS}$	$\hat{W}$
AT	2.8	-3.1	-0.4	3.5	-4.0	-0.5	3.8	-4.6	-0.7	5.1	-6.1	-0.9
BE	0.8	-0.8	0.1	1.1	-1.0	0.1	0.6	-0.5	0.1	1.2	-1.1	0.1
BG	0.1	-0.2	0.0	0.6	-0.6	-0.1	-0.9	0.8	0.0	-0.2	0.1	-0.1
CY	-1.4	2.5	1.1	-2.5	4.5	2.0	-3.7	5.5	1.8	-5.8	9.3	3.5
CZ	2.5	-2.6	-0.1	3.0	-3.1	-0.1	3.3	-3.5	-0.2	4.1	-4.3	-0.2
DE	1.5	-1.5	-0.1	1.9	-2.0	-0.1	1.7	-1.9	-0.2	2.6	-2.9	-0.3
DK	1.5	-1.5	0.0	1.9	-1.9	0.0	1.7	-1.7	0.0	2.5	-2.5	0.0
EE	4.3	-4.6	-0.3	5.3	-5.6	-0.3	5.6	-6.0	-0.4	7.1	-7.6	-0.5
ES	-0.1	0.2	0.1	-0.2	0.3	0.1	-1.6	1.8	0.1	-2.0	2.2	0.2
FI	6.3	-6.9	-0.6	7.9	-8.5	-0.6	8.0	-8.9	-0.9	10.3	-11.3	-1.0
FR	0.7	-0.7	0.0	0.8	-0.8	0.0	0.3	-0.4	0.0	0.6	-0.6	-0.1
GR	-0.9	1.3	0.4	-1.4	1.9	0.6	-2.7	3.3	0.6	-3.4	4.3	0.9
HU	1.2	-1.1	0.0	1.4	-1.4	0.0	0.7	-0.6	0.1	0.9	-0.8	0.1
IE	0.6	-0.5	0.1	1.2	-1.1	0.0	0.6	-0.5	0.0	1.8	-1.8	-0.1
IT	0.4	-0.3	0.1	0.3	-0.2	0.1	-0.3	0.3	0.1	-0.4	0.6	0.2
LT	2.6	-2.8	-0.1	3.8	-4.0	-0.2	3.2	-3.4	-0.2	5.0	-5.4	-0.3
LU	0.9	-1.1	-0.2	1.3	-1.7	-0.4	0.7	-1.2	-0.4	1.5	-2.4	-0.9
LV	3.2	-3.5	-0.3	4.3	-4.7	-0.4	4.0	-4.5	-0.5	5.7	-6.3	-0.6
MT	-2.0	2.8	0.8	-3.1	4.3	1.2	-4.6	5.8	1.2	-6.6	8.7	2.1
NL	0.9	-0.7	0.2	1.2	-1.0	0.2	0.6	-0.3	0.3	1.3	-1.0	0.3
PL	2.3	-2.4	-0.1	2.7	-2.8	-0.1	2.9	-3.0	-0.2	3.5	-3.6	-0.2
PT	-0.5	0.7	0.1	-0.8	1.0	0.2	-2.5	2.8	0.2	-3.2	3.6	0.4
RO	1.3	-1.4	0.0	1.6	-1.7	-0.1	1.0	-1.0	-0.1	1.5	-1.6	-0.1
SE	4.1	-4.6	-0.4	4.7	-5.2	-0.5	5.6	-6.3	-0.7	6.5	-7.3	-0.8
SI	1.6	-1.7	-0.1	2.1	-2.2	-0.1	2.1	-2.2	-0.2	3.1	-3.3	-0.2
SK	2.4	-2.5	-0.1	2.9	-3.0	-0.1	2.9	-3.0	-0.1	3.5	-3.7	-0.1

Notes: the values have been aggregated considering the share of each region (NUTS2) in the country's total production.

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