Climate Change Response: Input Adjustment in Agriculture*

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Abstract

How do farmers deal with climate change? Using medium-term fluctuations of temperature, precipitation and wildfires in Chile, this research tests the hypothesis of factor adjustment as a mechanism to attenuate the effects of climate change. I find that extreme heat leads to reallocation of land from fruit to forestry (i.e. timber) and primary activities (i.e. cereals). This land reallocation dampens the impact on agricultural output but comes at the cost of job losses and reduced physical capital within the agriculture sector. I conclude that this result is due to the fruit sector being more labor-intensive than the primary and forestry sectors, thus a larger harm of the former relative from the others drives away labor from agriculture. These released workers do not find reallocation in the manufacturing sector.

Keywords: Climate change, adaptation, land reallocation, agriculture.

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1 Introduction

Climate change is predicted to increase the incidence of extreme weather events, rising temperatures, changing precipitation patterns, and increasing wildfire frequency (Collins et al. 2010; Hartmann et al. 2013; Wuebbles et al. 2017; IPCC 2014). Literature suggests significant losses of agricultural productivity in this process (Dell et al. 2014), which are hardly avoided by a lack of adaptability on the part of farmers (Burke and Emerick 2016; Taraz 2018; Schlenker and Roberts 2009; Schlenker and Lobell 2010; Liu et al. 2023).[1]

However, some recent studies find that there are more adaptive strategies to climate change than previously documented. People and firms may adapt to climate change not only through the adoption of new technologies or heat-resistant varieties (Meyer and Keiser 2018; Barreca et al. 2016; Meyers and Rhode 2020) but also by adjusting input allocation in agriculture (Aragon et al. 2019), reallocating factors across productive sectors (Jessoe et al. 2018; Colmer 2020; Liu et al. 2023; Bustos et al. 2023) or migrating to less temperature-sensitive regions (Cattaneo and Peri 2016; Feng et al. 2015; Desmet and Rossi-Hansberg 2015). Therefore, if we expect large economic losses from climate change in the future, they cannot come just from the direct effect of temperature rises on land productivity, but also from a lack of agent adaptation.

In this paper, I investigate whether farmers respond to climate change[2] by adjusting land use and crop variety selection, and how these adaptation strategies impact the labor and physical capital allocation in agriculture and, consequently, agricultural output. Additionally, I explore how wildfires, a phenomenon that is expected to be more frequent with climate change, influence these adaptive processes. Lastly, I examine the extent to which labor reallocation from the agricultural to the manufacturing sector occurs.

For this purpose, I combine the agricultural census with weather, wildfire, and

[1]Long term climate change has the potential to affect agricultural production through alterations in the soil environment that may include organic matter content and quality, as well as the soil temperature regime and soil hydrology. See Wahid et al. (2007)) for a review of the biological evidence.

[2]Despite that some early authors argue that short averaging periods (e.g., annual) only describe the "weather" or "climate variability" and thus have little to say about the impact of climate, most frontier climate change researchers do not agree with this view (Burke et al. 2015a; Schlenker and Lobell 2010; Hsiang 2016; Dell et al. 2014). The explanation for this is that societies experience climatic variables in continuous time and respond to both short-lived and long-term changes, making the frequency of short-lived events an economically-relevant feature of the climate. For example, if hot temperatures harm crops, even if hot temperatures are only experienced for a few hours, then this is important for understanding climate impacts because the frequency of these momentary events might change if the distribution of daily temperatures changes (Burke et al. 2015a). This suggests that climate need not have a fundamental timescale and econometricians might study periods of varying lengths of time (Hsiang 2016).

manufacturing data in Chile, a country where 14.36% of its total GDP comes from agriculture or forestry,[3] and compute the elasticity of input use (land, labor and physical capital) to extreme heat changes through a long differences approach. This empirical strategy offers substantial advantages over cross-sectional and panel approaches to understand medium-term adaptation responses, since people and firms may respond differently to permanent changes in the expected distribution of weather than to short-term and unanticipated fluctuations in the climate variables (Burke and Emerick 2016).

From an economic perspective, farmers respond to changes in temperature, precipitation and wildfire by adjusting their land use, labor and physical capital to maximize profits under the new conditions. In the absence of friction, the factors released in the more affected sectors might be reassigned to the sectors relatively more resistant to climate change until the new value of the marginal product is equalized across sectors.[4] These adjustments could lead to reallocation gains, which may substantially reduce the direct losses from climate change in the long-run. Nevertheless, whether there are frictions involved, this response could not have the desired effects. For example, if there are frictions adjusting land but not labor, labor outflows from areas experiencing adverse productivity shocks would further reduce the marginal product of land. Consequently, even if farmers adjust their input use in response to climate change, the net impact of this mechanism depends on the reallocation capability of the economy. For instance, if there is a transition in land use towards crop varieties highly vulnerable to wildfires, which are projected to increase in frequency in the future (Sun et al. 2019), and if farmers underestimate this heightened risk, the adaptive mechanism could have adverse consequences for long-term societal well-being. Therefore, it is crucial to empirically evaluate the outcomes of climate change adaptation, as these responses can result in both winners and losers.

The empirical findings of this study provide direct evidence of adaptation within the agricultural sector in response to climate change. Specifically, I show that regions experiencing an increase in extreme heat tend to reallocate their land use from fruit production to forestry and primary agricultural activities. The extent of this reallocation varies depending on the severity of temperature changes, aligning with the fact that forestry activities exhibit greater resilience to extreme heat compared to fruit production, unless there are wildfires, as indicated by previous research (see for instance Moriondo et al. 2010). Moreover, I document that extreme heat leads to job

[3]This includes the backward and forward linkages of the primary sectors (ODEPA 2019).

[4]Under the assumption of pareto-efficient equilibrium.

loss and a reduction in the allocation of physical capital in the agricultural sector. Notably, contrary to studies in other contexts (Jessoe et al. 2018; Colmer 2020), this research reveals that workers are not reallocated to the manufacturing sector, which, in theory, could benefit from the growth of the forestry sector through its input-output links (e.g. furniture industry). Finally, my findings suggest that temperature increases, rather than wildfires, are predominantly driving these effects.

While previous research has established the statistically significant and economically meaningful influence of temperature, precipitation, and extreme weather events on various economic outcomes (Guiteras 2009; Feng et al. 2010; Schlenker and Lobell 2010; Dell et al. 2012; Burke et al. 2015a; Burke and Tanutama 2019; Somanathan et al. 2021), it has offered limited insights into strategies for addressing climate change in the coming decades. Recent studies have shifted their focus to explore adaptation mechanisms such as land use reallocation (Aragon et al. 2019; Taraz 2018), labor reallocation (Jessoe et al. 2018; Liu et al. 2023; Colmer 2020), and financial capital reallocation (Bustos et al. 2023). This article contributes to this evolving literature by examining the medium-term impacts of extreme temperatures and wildfires on fruit, primary, and forestry agricultural varieties, as agricultural subsectors (i.e. *inter-subsector* adaptation). This comprehensive approach provides a clearer understanding of adaptation mechanisms compared to examining the agricultural sector as a whole, since aggregation of land use would hide this mechanism.[5] Notably, this study is the first to unveil an adaptation mechanism involving the reallocation of land use to forestry activities due to climate change. This mechanism, conceptualized as a substitution from heat-sensitive to heat-resistant crop varieties, requires careful consideration, as it could potentially be reversed if the frequency of wildfires increases significantly in the forthcoming decades (Sun et al. 2019). Additionally, this research enriches the literature by exploring the interaction of the effects of extreme heat, precipitation, and wildfires on job loss, and whether labor reallocates (or not) in the manufacturing sector, elucidating the influence end of these adjustments in agricultural output by subsector.

The empirical relationship between temperature, precipitation and wildfires is important in light of climate change (Burke et al. 2020; Burke et al. 2021; Wen and Burke 2022). This study enhances our understanding of this relationship by assessing the extent to which temperature changes, in comparison to wildfires, drive more substantial effects on the adaptation mechanisms described earlier. Furthermore, it

[5] When the agricultural land as a whole remains unchanged, but all the adjustments occur within this agricultural frontier, the aggregation of land use hides all the adjustments documented in this paper.

sheds light on the intricate interplay between temperature and wildfires, offering insights into the relative influence of these climatic factors on adaptation within the agricultural sector.

To guide understanding of empirical work, and assess the importance of *inter-subsector* land reallocation, I build a simple model of three sectors and two inputs (land and labor) to illustrate the effects of a productivity shift caused by climate change. In this model, the agricultural sector has two subsectors: heat-sensitive (e.g., fruit) and heat-resistant (e.g., forestry),[6] both use land and labor, and the miscellaneous non-agricultural sector uses only labor. The model predicts that a reduction of the heat-sensitive sector productivity induces a decrease in the size of this sector and an increase of the heat-resistant sector, as land reallocates from the former to the latter. Furthermore, if the heat-sensitive sector is more labor and capital intensive than the heat-resistant sector, workers leave agriculture and physical capital is reduced.[7]

In support of the empirical design, I provide an array of robustness exercises and tests of the validity of my empirical strategy. I present evidence that extreme temperature changes are not correlated with the baseline characteristics of the regions, and also that the main results are unchanged when I add controls and agro-climatic zone fixed-effects, trim the tails of the agricultural output or fruit share changes, drop outliers in different variables, use spatially correlated errors, use different weights schemes, and use alternative thresholds to define the treatment variables. Furthermore, by including wildfires as an alternative (but correlated) treatment, I highlight that the direct effect of extreme heat is the most important margin by which climate change affects the economy.

The rest of the paper proceeds as follows: Section 2 describes the theoretical framework. Section 3 describes the data. Section 4 presents and discusses the econometric specification of the relationship between extreme heat and input adjustment. Section 5 presents the main results. Section 6 explores the relationship between extreme heat, wildfires, and input adaptation. Section 7 shows a set of

[6]Fruit trees are considered particularly vulnerable to climate change. Temperature increase directly affects its photosynthesis, causing alterations in sugars, organic acids, flavonoid contents, firmness, and antioxidant activity. These alterations can reduce the fruit's growth and even cause sunburn, where the skin of the fruit turns brown due to pigment synthesis inhibition (see Moretti et al. 2010 for an agronomical review of the impact of climate change on fruit). In contrast, the forestry industry is not sensitive to extreme heat unless wildfires or outbreaks of insects and pathogens (Kirilenko and Sedjo 2007; Nabuurs et al. 2003 .

[7]This is because of Rybczynski Theorem: An increase in the relative supply of a factor generates an increase of sector using that factor intensively.

robustness checks. Finally, Section 8 concludes. Further robustness checks and proofs are given in the Appendix.

2 Theoretical Framework

In this section, I develop a sectors model that gives rise to a set of predictions that are useful to interpret the empirical evidence. For this, I use the key insights from the model in Bustos et al. (2016), and outline a simple model with three sectors: agricultural heat-sensitive, agricultural heat-resistant and non-agriculture; and two factors: land and labor, which are assumed to be mobile between sectors, immobile across regions and supplied inelastically.

In this framework, an increase in extreme heat implies a negative shock relatively higher in heat-sensitive agricultural activities, such as fruit production, than in heat-resistant activities, such as forestry,[8] or non-agricultural activities. Therefore, extreme heat reduces the relative profitability of the agricultural heat-sensitive sector and generates reallocation of factors away from it. Furthermore, this shock leads to direct losses and reallocation gains, and the net impact on aggregate agricultural sales depends on its relative magnitude.

2.1 Setup

Consider that each municipality is a small open economy where prices of final goods are determined by world markets, and production factors are immobile. Each municipality has an endowment T of land and L residents, which are used in two agricultural activities, heat-sensitive and heat-resistant, or in non-agricultural activities.

There are two production technologies in agriculture:

$$\begin{aligned} q_s &= A_s T_s^{\gamma_s} L_s^{1-\gamma_s} \\ q_r &= A_r T_r^{\gamma_r} L_r^{1-\gamma_r} \end{aligned} \tag{2.1}$$

where A_i is a Hicks-neutral level of productivity of sector $i = \{s, r\}$, T_i and L_i denotes land and labor, and $\gamma_i \in (0,1)$ is the land share.

[8] In Ponce et al. 2014 authors find fruits producer being substantially worst-off than crop producers in Chile. Additionally, as mentioned above, fruit trees are considered particularly vulnerable to climate change (Moretti et al. 2010; Moriondo et al. 2010) while forestry is not sensitive to extreme heat unless wildfires or outbreaks of insects and pathogens (Kirilenko and Sedjo 2007; Nabuurs et al. 2003.

On the other hand, the non-agricultural sector only uses labor:[9]

$$Q_n = A_n L_n^{\alpha_n} \tag{2.2}$$

Market clearing in land and labor requires that the amount of land and labor supplied equals the total demand by the producers of heat-sensitive, heat-resistant and the non-agricultural sector:

$$\begin{aligned} T_s + T_r &= T \\ L_s + L_r + L_n &= L \end{aligned} \tag{2.3}$$

Note that, since only agricultural activities use land as input whereas labor is used in all sectors: $T_s + T_r \equiv T_a = T$ and $L_s + L_r \equiv L_a$.

2.2 Equilibrium

As each municipality is considered as a small open economy and all goods are tradable, the equilibrium production can be determined independently of consumption and income. Profit maximization implies that the value of the marginal product of land must equal the land wage in both agricultural sectors:

$$p_s MPT_s = p_r MPT_r = w_T \tag{2.4}$$

and the value of the marginal product of labor must equal the labor wage in all sectors, considering the non-agricultural sector:

$$p_s MPL_s = p_r MPL_n = p_n MPL_n = w_L \tag{2.5}$$

Then, these optimality conditions and the endowment clearing conditions determine the equilibrium allocation of land and labor in each sector $\{T_s^*, L_s^*, T_r^*, L_r^*, L_n^*\}$ and prices of factors $\{w_T^*, w_L^*\}$, taking as given the productions functions $\{q_s(.), q_r(.), Q_n(.)\}$, technological parameters $\{A_s, A_r, A_n, \gamma_s, \gamma_r, \alpha_n\}$, and world prices $\{p_s, p_r, p_n\}$.

[9] I assume this for simplicity. Hence, to ensure a downward slope demand for labor, this sector has decreasing returns to scale. Nevertheless, this assumption is equivalent to think that this sector has constant returns to scale, but uses another factor which is fixed (e.g., physical capital):

$$Q_n = A_n L_n^{\alpha_n} \bar{K}_n^{1-\alpha_n}$$

2.3 Predictions

If all three sectors are active, the effect of a reduction in the productivity of heat-sensitive sector $dA_s < 0$[10] leads to the following predictions:

(i) *Reduces the land share in the heat-sensitive sector:* $d\frac{T_s^*}{T_a} < 0$

(ii) *Increases the land share in the heat-resistant sector:* $d\frac{T_r^*}{T_a} > 0$

(iii) *Does not change the total amount of land used in agriculture as a whole:* $dT_a^* = 0$

(iv) *Reduces employment in the heat-sensitive sector:* $dL_s^* < 0$

Proof: See Appendix C

These predictions are due to extreme heat reduces, unambiguously, the marginal product of land and labor in the heat-sensitive sector.[11] Then, under the assumption of a pareto-efficient equilibrium, the inputs released in this sector reallocate towards the other sectors.

Additionally, if the heat-sensitive is more labor intensive than the heat-resistant $\gamma_s < \gamma_r$, a reduction in the productivity of heat-sensitive $dA_s < 0$:

(v) *Push workers out of agriculture as a whole:* $dL_a^* < 0$

(vi) *Reduces the labor intensity in agriculture as a whole:* $d\frac{L_a^*}{T_a} < 0$

Proof: See Appendix C

The prediction (v) essentially comes from Rybczynski Theorem: the release of workers from the heat-sensitive sector expands the sector that uses labor more intensively, which may be the non-agriculture if $\gamma_s < \gamma_r$. The prediction (vi) comes from the fact that land is reallocated within the agricultural sector as whole (due to non-agriculture use only labor as input), whereas workers released from the

[10] More generally, extreme heat can be conceptualized as reduction in productivity relatively higher in the heat-sensitive sector: $dA_s < dA_r \leq 0$. However, for simplicity I assume that only hits one sector in the predictions.

[11] This prediction is due to extreme heat is modeled as a Hick-neutral shock in the particular context with Cobb-Douglas production functions (i.e., the elasticity of substitution between land and labor is equal to one). However, if extreme heat would be modeled as a land-bias shock in a context with CES production functions, it reduces land allocation in the affected sector s as long as the land share of output is high (land and labor are sufficient substitutes).

heat-sensitive can not reallocate within the agriculture since the heat-resistant sector do not absorb them under the condition described above.

Moreover, if all sectors are active, these predictions together imply that a reduction in the productivity of heat-sensitive $dA_s < 0$, reduces the output of the heat-sensitive $dq_s^* < 0$, whereas increases output of the heat-resistant sector $dq_r^* > 0$.

With this conceptual framework in mind, in the following sections I will quantify the impact of these effects and test if they display the sign patterns predicted by the model.

3 Data and Summary Statistics

3.1 Data

The empirical analysis utilizes different datasets to obtain agricultural, temperature, precipitation and development measures. First, I obtain information about the factors use and output in agriculture from the Chilean Agricultural Census.[12] This dataset has disaggregated measures at municipality level in 1997 and 2007 of the number of agricultural workers, the number of agricultural machinery, the planted area by crop, number of livestock, and amount harvested by crop, such as fruits, forestry and other primary products.[13] To study the different impacts of extreme heat in agriculture, I group these products in four subsectors: fruit, primary, forestry and livestock. However, this dataset has the main limitation that I do not observe the number of agricultural workers or machinery by subsector. Additionally, to obtain a measure of sales for each agricultural subsector, I complement this data with Cuesta et al. (2015) dataset, where the products of the Agricultural Census are valued at long-term undistorted prices (i.e., the average price in chilean peso (CLP) of each type of product over the 1993-2006 period[14]). Then, for each municipality, I compute the use of factors, its relative intensity, output by subsector, and as productivity measures, output per worker and output per hectare (yield).

Second, temperature measures are obtained from University of Berkeley dataset, which includes daily average, maximum and minimum temperature on a grid of 1×1 degree. The precipitation data is sourced from University of Delaware database

[12] I thank to Felipe González, Francisco Gallego and José Ignacio Cuesta for allowing me to use their agricultural census data.

[13] Primary products include alfalfa, rice, oats, barley, beans, corn, potatoes, beets and wheat.

[14] The information on prices is taken from INE's wholesale prices series.

(Willmott et al. 2010) providing monthly estimates on a 0.5×0.5 degree scale. Since the focus of this research is on the impact of climate on agriculture, I aggregate the gridded weather data at the municipality level, weighting it by the crop presence.[15]

Third, I use the household survey *CASEN* collected by the *Instituto Nacional de Estadísticas* (INE). This survey includes economic variables such as income, years of education, poverty rate, and demographic characteristics such as population density, male percentage, and the share of rural population at the municipality level.

Fourth, I use the *Encuesta Nacional de Industrias Anual* (ENIA). This survey contains relevant information about manufacturing plants, such as the number of workers. The survey is conducted annually and covers the universe of manufacturing plants with 10 or more workers.

Fifth, I use the wildfire data collected by *Corparación Nacional Forestal* (CONAF), which includes the date of each wildfire event between 1990 and 2010, and its intensity in burned-down hectares.

To ensure consistency in the datasets, I collapse the 343 modern municipalities found in the climatic databases and the CASEN survey into 264 pristine municipalities, those that appear in the old agricultural censuses and later were subdivided.[16] Due to five municipalities have missing in weather, agricultural, or development variables, the final sample is 259. I consider these municipalities as approximations of local markets, representing small open economies engaged in agricultural trade.

3.2 Summary Statistics

Summary statistics for weather and agricultural variables are presented in Table 1. For each variable, I report the mean and standard deviation of their level in the baseline year 1997 and of their change between 1997 and 2007.[17]

Panel A presents summmary statistics for weather data. GDD and HDD refer to growing degree-days and harmful degree-days, respectively. Using growing degree-days is a standard practice in agronomics to estimate the growth and development of plants during the growing season and has become popular in economic climate change

[15]See Appendix B for a detailed description of weather variables.

[16]For example, *Lo Prado, Pudahuel, Cerro Navia, Renca, Barrancas* and *Quilicura* compose the pristine municipality number 69 and *La Reina, Nuñoa, Peñalolen* and *Macul* compose the pristine municipality number 72. The data has a set of counties that keep the same information over the time period included in the analysis. This implies that in some cases the data merge modern municipalities to make the data consistent with the old censuses municipalities definitions and boundaries.

[17]Hereafter, $\triangle x \equiv x_{2007} - x_{1997}$.

research.[18] See Appendix B for more details of the weather variables and a description of Chile's climate.

Panel B presents summmary statistics for agricultural data such as total planted land, the number of workers and machinery in agriculture, the output by agricultural subsector, the aggregate output per worker and per hectare.[19] In the baseline year, fruit crops represented the 10% of the total planted land, whereas primary and forestry the 42% and 46%, respectively. On average, the fruit share increased 5 percentage points which is equivalent to 527 hectares, whereas the primary share decreased 17 percentage points and forestry increased by 9 percentage points.

Figure 1 presents the geographical distribution of changes in the main variables. Panel (a) illustrates the change in the number of harmful degree-days HDD, indicating areas where extreme heat has increased, and Panel (b) the change in agricultural output. This figure highlights the significant spatial variability in these variables.

Finally, Figure 2 presents the trends in prices and maximum temperature. Panel (a) shows an increase in commodity prices between 1997 and 2007, particularly in cereals and Panel (b) displays the trends in maximum temperatures, revealing no clear overall trend.

3.3 Input Intensity

As described in the theoretical framework, a key factor to understand the responses to climate change is to know the factor intensity by subsector at baseline. Since data includes the total number of workers and agricultural machinery in agriculture as a whole, but not by subsector, I recover the labor and capital intensity for fruit, primary and forestry with a regression model.

The total labor (capital) allocated in agriculture is composed of fruit, primary and forestry workers

$$L_a = L_{fru} + L_{pri} + L_{for}$$

Hence I can exploit that the data includes the number of hectares planted by

[18] See for instance Burke and Emerick (2016), Feng et al. (2015), Aragon et al. (2019), Colmer (2020) and Meyers and Rhode (2020).

[19] Changes of variables in logs are: $log(variable_{2007} + 1) - log(variable_{1997} + 1)$

agricultural activity as follows:

$$L_a = \frac{L_{fru}}{T_{fru}}T_{fru} + \frac{L_{pri}}{T_{pri}}T_{pri} + \frac{L_{for}}{T_{for}}T_{for}$$

Then, I estimate the following equation to recover the labor (capital) intensity

$$L_{a;m} = \delta + \omega_{fru}T_{fru;m} + \omega_{pri}T_{pri;m} + \omega_{for}T_{for;m} + \zeta_m \tag{3.1}$$

where $L_{a;m}$ is the total amount of agricultural workers in the municipality m in the baseline year 1997 and $T_{i;m}$ is the total surface planted with variety $i = \{$*fruit, primary, forestry*$\}$. The coefficient ω_i captures the labor (capital) intensity for sector i, δ is a constant which captures the labor intensity in other agricultural activities such as livestock, and ζ_m is the error term.

The results in Table 2 show that the fruit sector is the more labor intensive, followed by the primary and forestry sectors: $\frac{L_{for}}{T_{for}} < \frac{L_{pri}}{T_{pri}} < \frac{L_{fru}}{T_{fru}}$. On the other hand, primary sector is the more machinery intensive, followed by the fruit and forestry sectors: $\frac{K_{for}}{T_{for}} < \frac{K_{fru}}{T_{fru}} < \frac{K_{pri}}{T_{pri}}$. Note that the forestry sector is the least labor and capital intensive, indicating that it is the most land intensive. These results are according to the literature that shows fruits crops (as perennial crops), being more labor intensive and less capital intensive than primary crops (Nolte and Ostermeier 2017).[20]

In the theoretical framework the total amount of labor in agriculture is composed of heat-sensitive and heat-resistant workers, while in the empirical analysis, it is composed of fruit, primary, and forestry. Then, hereafter the primary sector could be thought as a "medium-sensitive" sector.

Furthermore, understanding whether these subsectors are substitutes is important for assessing the potential impacts of land use reallocation on other inputs such as labor and machinery. Figure 3 examines the relationship between the land share of the fruit, primary, and forestry sub-sectors, shedding light on these dynamics. Panel (a) reveals a negative correlation between fruit and forestry, Panel (b) shows a negative correlation between fruit and primary, and Panel (c) exhibits a negative correlation between primary and forestry. These correlations provide preliminary insights into the interplay among different agricultural sectors.

[20] In general, fruit harvesting is characterized as non-mechanizable process because of tree damage, fruit damage, non-selectivity, efficiency and cost. For example, almost all citrus fruit, berries and grapes, for both raisins and wine, are typically hand-harvested (Li et al. 2011). Also, perennial varieties are pruned with pruning shears used by workers rather than machines.

With these results in mind, the following section quantifies the productive responses to extreme heat of the different subsectors, which, as mentioned in Section 2, depends substantially on factor intensity of the damaged sector.

4 Empirics

The main objective of the empirical exercise is to estimate the response of the agricultural sector to climate change. In Section 4.1, I start describing the identification strategy to measuring the climate change impact on input adjustment. Next, in Section 4.2, I discuss and present evidence in support of the validity of the empirical strategy. Finally, in Section 4.3 I discuss additional concerns of the empirical approach.

The early literature on the economic effects of climate change on agriculture has followed one of two methodologies, commonly known as the hedonic approach and the Ricardian approach. The first one is based on controlled agricultural laboratory or field experiments, where specific crops are exposed to varying climates, and yields are then compared across climates. The second one, pioneered by Mendelsohn et al. (1994), estimate a cross-sectional relationship between land values (representing the present discontinued value of the future stream of profits) and climate while controlling for other factors.

To deal with the strong assumption of cross-sectional models, that average climate is not correlated with other unobserved factors that also affect the outcomes of interest, most recent researchers have turned to a panel data approach, using presumably random year-to-year variation in temperature and precipitation across counties to estimate the impact of weather on agricultural crop yield and profits (Deschênes and Greenstone 2007, Schlenker and Roberts 2009 and Dell et al. 2012).[21]. Moreover, some recent studies use a semi-parametric specification, which defines temperature and precipitation variables as the number of days in a specific bin (e.g., bins of 3^oC and $40mm$ wide, respectively. See Deschênes and Greenstone 2011, Deryugina and Hsiang 2017, Baysan et al. 2019, and Aragon et al. 2019). This approach is useful for identifying nonlinearities and non-marginal effects of weather variables, but not may be the best to study medium or long-run adaptation responses.[22]

[21]This fixed-effects approach has the advantage of controlling for time-invariant district-level unobservables such as farmer quality, labor productivity or unobservable aspects of soil quality and should better approximate the true effect of climate change than a production function approach that does not allow for adaptation. (See Hsiang 2016 for a climate econometrics review).

[22]Additionally, I am unable to implement this approach since semi-parametric estimates need a large number of observations in each cross-section as well as a large number of cross-sections to estimate the

Motivated by that panel models solve identification problems in the cross-sectional approach at the cost of more poorly approximating the idealized parallel worlds experiment, some recent studies such as Dell et al. (2012), Burke and Emerick (2016) and Burke and Tanutama (2019), argue that exploiting longer-run climate fluctuations through a long differences approach provides a better estimate of how agents will respond to climate change.[23] I proceed to discuss this method below.

4.1 Identification Strategy

There are two advantages to using a long differences approach. First, it simulates better a parallel world's natural experiment, because people and firms may respond differently to permanent changes in the expected distribution of weather than to short-term and unanticipated fluctuations changes in the climate variables, so long differences estimates capture any adaptations that farmers have undertaken to recent trends, unlike panel models, which have little to say about medium or long-term readjustment response since they use year-to-year weather variation.[24] Second, is immune to time-invariant omitted variables, which cross-sectional methods are plagued.

Using a long-difference approach to estimate the climate change impact on input adjustment would be more trustworthy in external validity than panel methods, and in internal validity than those based on cross-sectional methods. To have a better understanding of this specification, I proceed to obtain it as follows.

For each cross-section, variance can be described according to the following process:

$$y_{m,\mathfrak{z},t} = \phi_t + \lambda_m + \psi_{\mathfrak{z},t} + \gamma_{m,\mathfrak{z},t} + \varepsilon^{'}_{m,\mathfrak{z},t} \text{ for } t = \{1997, 2007\} \tag{4.1}$$

where $y_{m,\mathfrak{z},t}$ is some outcome of interest in municipality m in agroclimatic zone $\mathfrak{z}$, at year t, ϕ_t are time-variant factors common through all municipalities i.e. aggregated

large number of parameters involved, besides the tails of temperature distributions in Chile are too thin to detect the nonlinearities.

[23]When long-differences has been implemented to measure the effects of climate on growth (Dell et al. 2012) and crop yields (Burke and Emerick 2016; Lobell and Asner 2003), authors have found that long differences estimate is almost identical to panel estimate, leading them to conclude that gradual changes in climate variable likely induce similar effects to more rapid changes in this climate variable. On the other hand, in Burke and Tanutama (2019) authors find that long difference estimates of the impact of longer-term trends in temperature on per-capita GDP are larger than estimates from annual panel models, suggesting that short-run panel estimates understate the longer-term effects of warming hot years (See Hsiang 2016 and Dell et al. 2014 for a discussion in this topic).

[24]The econometrician's choice of a weather versus a climate measure as an explanatory variable critically affects the interpretation of the estimated coefficients in the econometric model: whether the outcome is an actual climate response or a short run weather elasticity (Hsiang 2016).

shocks, λ_m are time-invariant factors for each municipality, $\psi_{\mathfrak{z},t}$ are time-variant factors of each agroclimatic zone (e.g. prices within the agroclimatic zone), $\gamma_{m,\mathfrak{z},t}$ are observed time-variant factors of each municipality (e.g. weather) and $\varepsilon'_{m,\mathfrak{z},t}$ is an idiosyncratic error term of time-variant unobserved characteristics. If I exploit the time-varying nature of the data in the way of Deschênes and Greenstone (2007), the resulting panel fixed-effects approach is:

$$y_{m,\mathfrak{z},t} = \phi_t + \lambda_m + \psi_{\mathfrak{z}} \times t + \mathbf{Z}_{m,\mathfrak{z},t}\boldsymbol{\beta} + \varepsilon_{m,\mathfrak{z},t} \tag{4.2}$$

where $\psi_{\mathfrak{z}} \times t$ is a linear agro-climatic zone trend and $\mathbf{Z}_{m,\mathfrak{z},t}\boldsymbol{\beta}$ is an additive approximation of the relationship between the row vector $\mathbf{Z}$ of weather variables and the outcome. This fixed-effects approach has the advantage of controlling for time-invariant municipality-level unobservables such as farmer quality, labor productivity or unobservable aspects of soil quality. This approach should better approximate the true effect of climate change than a cross-section models that does not allow for adaptation.

Due to I have only two periods in the case of agricultural outcomes (one for each agricultural census year), this approach leads to the same estimates if I substract both cross-sections described by equation (4.1)[25]

$$\begin{aligned} y_{m,\mathfrak{z},2007} - y_{m,\mathfrak{z},1997} = {} & (\phi_{2007} - \phi_{1997}) + (\lambda_m - \lambda_m) + \psi_{\mathfrak{z}}(2007 - 1997) \\ & + (\mathbf{Z}_{m,\mathfrak{z},2007} - \mathbf{Z}_{m,\mathfrak{z},1997})\boldsymbol{\beta} + (\varepsilon_{m,\mathfrak{z},2007} - \varepsilon_{m,\mathfrak{z},1997}) \end{aligned}$$

the time fixed-effects and agroclimatic zone time-variant characteristics collapse to a constant $\mu_{\mathfrak{z}}$ which captures the average trends across agroclimatic zones, the municipality time-invariant factors (λ_m) drop out and using $\mathbf{Z}_{m,\mathfrak{z},t} = [f(H_{m,\mathfrak{z},t}) \quad g(P_{m,\mathfrak{z},t})]$, I can rewrite (4.2) as a long-difference equation

$$\triangle y_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + [\triangle f(H_{m,\mathfrak{z}}) \quad \triangle g(P_{m,\mathfrak{z}})]\ \boldsymbol{\beta} + \xi_{m,\mathfrak{z}} \tag{4.3}$$

where $\triangle y_{m,\mathfrak{z}}$ is the change in outcome variable between the last two census years in the municipality m (e.g., input measures), and $f(.)$ and $g(.)$ are vector functions of heat H and precipitation P, both weighted by crop area[26]. To deal with non-linearities in the effect of weather variables,[27] I use growing degree-days with an upper threshold, which

[25]Note that First Difference, Within (also know as demeaning or fixed effects) and Least Squared Dummy Variables (LSDV) estimators are exactly equivalent for two periods. This proposition is derived from Frisch–Waugh–Lovell theorem, see Lovell (2008) for the proof.

[26]In Section 7 I show the robustness to alternative weighting.

[27]See Burke et al. 2015b for a discussion about non-linear effects of climate variables.

measure the exposition to extreme heat over the growing season, and use a second order polynomial in the case of precipitation.[28] Additionally, to capture more effectively the change in climate over time, I use weather variables as a three-years average.[29]

Therefore, I can rewrite the equation (4.3) in the way of Burke and Emerick (2016)

$$\begin{aligned} \triangle y_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \beta_1 \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \beta_2 \triangle GDD_{m,\mathfrak{z};\ \ell_0:\ell_1} \\ +\beta_3 \triangle P_{m,\mathfrak{z}} + \beta_4 \triangle P^2_{m,\mathfrak{z}} + \mathbf{X}_{m,\mathfrak{z}1965/96}\ \mathbf{\Omega} + \xi_{m,\mathfrak{z}} \end{aligned} \tag{4.4}$$

where $GDD_{m,\mathfrak{z};\ \ell_0:\ell_1}$ is the sum over the growing season of degree-days between the temperature bounds ℓ_0 and ℓ_1, and $HDD_{m,\mathfrak{z};\ \ell_1:\infty}$ is a measure of the harmful degree-days, which are defined as those upper a threshold ℓ_1. The vector $\mathbf{X}_{m1965/96}$ contains a set of municipality controls at baseline obtained in 1965 and 1996 such as population density, rural population share, mean income, mean years of education, poverty rate, percentage of males, total area and the number of agricultural machinery (e.g., tractors, plows and harvesters).[30] This vector should not include time-varying controls whether these are endogenous and affected by climatic events (e.g., the adoption of new technologies), although this might introduce new biases, a situation known as "bad control" (Angrist and Pischke 2008, Hsiang 2016). If changes in climate variables were randomly assigned through municipalities, I can estimate its effect on the outcome with no need to control for any other variable, and the estimates of $\boldsymbol{\beta}$ have a causal interpretation. Nevertheless, I include baseline controls to increase the estimates' precision and also to control for differential trends across municipalities with different initial levels of development. The initial share in rural population and population density captures differential trends in the outcome variable between rural and urban municipalities, whereas the number of agricultural machinery captures the differential trends between municipalities that are more capital intensive. I also control for the lagged level of income per capita in logs, poverty rate, mean years of education and percentage of males to capture differential trends across municipalities with different initial levels of income, human capital and size of the agricultural labor supply. Since Chile is a country with a large variation in geographical qualities from north to south, I include agro-climatic zone fixed-effects $\mu_{\mathfrak{z}}$, which control for different trends across agro-climatic zones. Normally, Chile is divided into 5 agro-climatic

[28] See Appendix B.1 for the formal definition of growing season degree-days

[29] This is $\triangle z_m = z_{m,2007} - z_{m,1997}$ where $z_{m,1997} = \sum_{t=1995}^{1997} z_{m,t}$ and $z_{m,2007} = \sum_{t=2005}^{2007} z_{m,t}$.

[30] The inclusion of baseline controls in equation (4.3), is identical to the inclusion of baseline controls in the equation (4.2) interacted with a linear time trend:

$y_{m,\mathfrak{z},t} = \phi_t + \lambda_m + \psi_{\mathfrak{z}} \times t + \mathbf{Z}_{m,\mathfrak{z},t}\boldsymbol{\beta} + (\mathbf{X}_{m,\mathfrak{z},1965/96} \times t)\ \mathbf{\Omega} + \varepsilon_{m,\mathfrak{z},t}$

zones: Far North, Near North, Central Zone, Southern Zone and Austral Zone (see Figure 1).[31] Therefore, $\boldsymbol{\beta}$ is identified off within-zone differences in climate changes over time, after having accounted for any differences in trends common to all zones and any differences in initial levels of development captured for the controls vector $\mathbf{X}_{m,\mathfrak{z}1965/96}$. Finally, ξ_m is the error term capturing all omitted factors, which I allow to be correlated at province level, a larger level of geographic aggregation.[32]

4.2 Randomness of HDD trends

The identifying assumption in Equation (4.4) relies on that temperature trends at the municipality level are uncorrelated with other factors that affect trends in agricultural inputs within the agroclimatic zone, once baseline controls are accounted for. Figure 4 shows that within agroclimatic zones, changes from HDD are not strongly correlated with baseline economic and demographic measures, such as population density, income per capita, poverty rate, years of education, municipality size, and agricultural output in 1965 and 1997.[33] Panel (a), shows the correlations and the p-values of the regression coefficient of HDD on the baseline variables and the results after controlling for GDD, precipitation, and its square in the "+ controls" version.

Changes in temperature and precipitation in Chile are hardly due to endogenous factors. Instead, they mainly relate to large events of variation in ocean temperature such as *El Niño*, which relates to more precipitation and higher temperatures and *La Niña*, which relates to dryer and cooler temperatures (Minetti et al. 2003, Haylock et al. (2006)). Since future trends and frequency of these events are not possible to predict,[34] the trends in temperature and precipitation in Chile appear to represent a true natural experiment.

[31] The sample is divided in 5 zones. Each zone is composed by 52 municipalities in average.

[32] As Figure 1 shows, temperature is strongly correlated across moderate distances, so when a specific municipality has warm temperatures it is likely that neighboring municipalities also have warm temperatures. This spatial correlation motivates the use of standard errors that are clustered by province. In the data there are 51 provinces, where each one is composed of 5 municipalities on average. In Section 7 I show the results when I allow errors to be spatially correlated with different geographic cutoffs using Conley (1999)'s method.

[33] This robustness check was proposed in Burke and Emerick (2016).

[34] See Collins et al. (2010) for a discussion about its predictability.

4.3 Additional Concerns

A key issue is to define the value of the upper threshold ℓ_1. Previous studies in U.S. and India set this value between 23-32^{o}C (Deschênes and Greenstone 2007, Schlenker and Roberts 2009, Burke and Emerick 2016 and Colmer 2020). Nevertheless, these estimates are likely to be crop and context-dependent and hence might not be transferable to this case. Econometrically, whether the threshold increases, the heating shock becomes stronger at the cost of a reduction in the *"take up"* of the treatment. In other words, each municipality suffers fewer harmful degree-days, but each harmful degree-day is more intense, and then, in the extensive margin, fewer municipalities are treated. For this reason, I show how the main results vary over all possible thresholds ℓ_1.

Furthermore, differential trends in temperature across municipalities, even exogenous, could just be driven by short-run variation in weather around the chosen endpoint year. Hence, there could have been little "true" medium-run change in temperature to adapt to. To deal with the potential abnormal variation in the endpoint year, I use the treatment variables as three-year average changes. However, this could be a key decision, thus, in Section 7 I show the main results under different numbers of years on the average to construct the treatment variables.

Another concern is that emissions of pollutants could be correlated with both agricultural land planted and weather variables (e.g., the emission of manufacturing plants leads to a change in the temperature, which leads to a change in land productivity). However, long-lived greenhouse gases (e.g., CO_2), are rapidly mixed in the atmosphere, so local emissions lead to a global stock of pollution, which in turn changes local temperatures, but it is not true that they could stay in one municipality for a long time and affect the climate.

Chile is a country with a considerable variation in geographic qualities from north to south. This is why it is important to use agro-climatic fixed effects. However, its inclusion is very challenging to the main specification because it absorbs a significant amount of weather variance and could amplify the measurement error (Fisher et al. 2012, Auffhammer and Schlenker 2014), which could lead to under-rejection of the null hypothesis, especially in a context with a reduced number of the sample. Nevertheless, it provides an insight into how robust are the main estimates, because an omitted relevant variable in equation (4.4) would need to be a zone-level variable whose trend over time differs across the period 1997-2007 in a way correlated with the zone-level difference in climate changes and is not captured for the initial development controls, which is hard to imagine.

Finally, climate measures introduce large measurement errors because of the interpolation through climate stations. Even if the measurement errors are non-classical, the resulting bias will be towards zero as long as the error is not too severe (Auffhammer et al. 2013, Hsiang 2016).[35] This could cause attenuation bias, leading to under-rejection of the null hypothesis. Therefore, hereafter my estimates serve as lower bounds on the true climate change effect.

5 Results

The first part of the analysis focuses on the effect of medium-run changes in the climate on each agricultural sector. In Sections 5.1, I document that extreme heat caused a reduction in the fruit land share and an increase in the share of primary and forestry subsectors, which is consistent with a negative productivity shock in the fruit subsector (conceptualized as heat-sensitive) and a reallocation of this land towards the other sectors. Next, in Sections 5.4, 5.2 and 5.3 I document a large reduction in agricultural labor, and agricultural machinery, but null effects on total land use. Finally, in Section 5.5 I document that these land use, labor, and capital adjustments dampened the potential effects in output and, if there is any effect, it is a slight increase in production of the forestry sector.

5.1 Effects on Land Use by Subsector

As discussed in Section 2, a negative shock in the heat-sensitive sector would release land in this sector which may be absorbed by the heat-resistant sector. The results presented in Table 3 and shown graphically in Figure 5a go in this direction.

The first two columns of Table 3 present the impact of climate variables on fruit land share. Municipalities with an increase of one standard deviation in the harmful degree-day distribution (around 12.5 degree days) experienced a decrease of 4 percentage points in the fruit land share (40% of their initial share, around to 397 hectares in average[36]). The point estimate remains stable when including agro-climatic zone fixed effects and controlling for initial municipality characteristics, which suggests that the estimates are not capturing differential growth trends across

[35] Formally, this condition is *Pr(Type I error) + Pr(Type II error) < 1*

[36] Taking an initial fruit land share of 10%, the reduction is given by $\frac{(0.10-0.04)-0.10}{0.10} = -0.4$

municipalities.[37] In addition, columns (4) and (6) show that, with an increase of one standard deviation in the HDD distribution, the land share of primary and forestry subsectors increased by 2.12 and 2.5 percentage points, respectively.

Figure 5a complements this evidence by presenting the coefficient estimate of HDD in equation (4.4) using different threshold values ranging from 22 to 30. The figure shows that when extreme heat is less severe, the land use reallocates mainly from the fruit sector to the primary sector. However, as the temperature becomes more severe and reaches a threshold of 26^oC, the reallocation is predominantly towards the forestry sector. This trend continues, with the forestry sector receiving all the reallocation beyond a threshold level of 28^oC, indicating its relative resistance to extreme heat.[38]

5.2 Effects on Labor

In the case of agricultural labor, Table 4, Panel (b), columns (1) and (2) present the main findings. An increase of one standard deviation in the HDD distribution results in a significant job loss of 31%, even in the most conservative specification. These results underscore that extreme heat induces not only statistically significant but also economically substantial adjustments in agricultural labor.

Importantly, these point estimates are stable in the Oster (2019)'s way. When including agro-climatic zone fixed effects and controlling for lagged municipality characteristics, the R^2 increases, since controls have a joint significance with a p-value less than 1% in all the models, but the coefficients β_1 do not change significantly.[39]

Complementing this evidence, Figure 5b, Panel (b), illustrates the effects on labor for various thresholds of the HDD definition. As the temperature becomes more extreme, the magnitude of job loss in the agricultural sector increases.

To interpret these findings, I turn to the theoretical framework discussed in Section 2. The model predicts that a negative shock in the heat-sensitive sector reduces labor demand, thus labor goes away from this sector. Then, the ability of the agricultural

[37] Additionally, in Section 7 I add the outcome variable at baseline which leads to a joint significance with p-value less than 5% and keeps the point estimate unchanged.

[38] Figure A.4 presents the coefficient estimate of GDD with different thresholds. Panel (a) shows that an increase in GDD is associated with an increase in the primary sector. This evidence goes in the same line of Burke and Emerick (2016) who shows that an increase in GDD is associated with an increase in corn yields, as opposed to an increase in HDD

[39] Oster (2019) develops a "coefficient stability approach" to understand omitted variable bias from comparing the coefficient of regression with and without controls, showing that: $\hat{\beta}^* = \beta_c - (\beta_{nc} - \beta_c)\frac{R_{max}-R_c}{R_c-R_{nc}}$, where β_c and β_{nc} are coefficients from the regression with and without controls, respectively, with their corresponding R-squared, and R_{max} is an unknown parameter in the interval $[R_c, 1]$. According this approach, the labor coefficient $\hat{\beta}_1^*$ is in the range [-0.0255 , -0.0148].

sector as a whole to absorb these workers depends on the labor intensity of the heat-resistant sector (i.e., primary or forestry in this case). Additionally, in Section 3.3, I provided evidence that the fruit sector is more labor intensive than the primary and forestry sectors. These insights together imply that labor released by the fruit sector will not be absorbed for the primary or forestry sectors. Complementing this, if workers are driven out from agriculture, but land reallocates within agricultural sectors and its endowment is fixed, the overall labor intensity decreases. The results presented above confirm these predictions.[40]

Next, in Figure 6 I explore whether workers displaced from agriculture might be finding employment in the manufacturing sector, potentially benefiting from the growth of the forestry sector (e.g., the furniture industry). Alternatively, it also explores the possibility that workers in both sectors are leaving the labor market (e.g. due to the climate preferences of the population), reflecting a labor supply story rather than a labor demand story. However, these hypotheses are ruled out in light of these results, as they reveal that only agricultural labor experiences a substantial reduction while manufacturing labor remains unaffected by extreme heat.

5.3 Effects on Physical Capital

In the case of capital (agricultural machinery), Table 4, Panel (b), columns (3) and (4), and Figure 5b present the main findings. An increase of one standard deviation in the HDD distribution, results in a decrease of 37.5% or alternatively, exposure to each additional harmful degree-day results in a decrease of 3 percent in capital. These effects are both statistically significant and economically substantial. Notably, as the temperature threshold increases, the effects on capital reduction become more pronounced, similar to the pattern observed with labor.

As previously discussed in the section on input intensity (Section 3.3), it was determined that the primary sector (i.e. cereals) is the most capital-intensive. However, explaining the reduction in capital is more nuanced compared to the labor explanation, as the decrease in the primary sector is not as substantial as in the fruit sector. In this context, the decline in capital can also be attributed to reduced utilization of agricultural machinery within fruit-related activities. There is also the possibility of substitution within the primary sector, where high-capital-intensive crops or varieties may be replaced with low-capital-intensive alternatives (intra-crop adaptation). However, due to data limitations, it is not possible to directly test this

[40] See predictions (v) and (vi) of Section 2.

hypothesis.

5.4 Effects on Agricultural Land Frontier

Furthermore, the estimates reported in columns (5) and (6) of Table 4, Panel (b) show that the aggregate land supply does not change (i.e, there is not a reduction of the agricultural frontier) which is consistent with a fixed land endowment in the economy. This result rules out the possibility that the use of the land is transitioning from an agricultural use to an urban use due to extreme heat. This evidence is complemented with Figure 5b, which shows that total agricultural land use does not respond to any level of temperature increase. To reinforce this evidence, Figure 5b provides a visual representation of the relationship between temperature increases and total agricultural land use. Notably, this figure illustrates that the utilization of agricultural land remains unresponsive to any level of temperature.

Overall, these effects on labor, capital, and land align with the theoretical model. Climate change has a more significant negative impact on the fruit subsector, and consequently on labor, given its status as the most labor-intensive sector, and there is a moderate negative effect on the primary subsector, which falls between the impacts on the fruit and forestry subsectors.

5.5 Effects on Output by Subsector

Given the evidence presented above, in Table 5 and Figure 5c I study the effect of extreme heat on agricultural output by subsector.[41] In the case of the fruit sector, although the estimates are not statistically significant at conventional levels, the point estimate is negative as expected. In contrast, the point estimates of primary and forestry are positive, with the last being substantially higher than the others.[42]

Based on the tables and figures presented above, there is evidence to suggest that adaptive responses to extreme heat in the agricultural sector have mitigated its potential harm to output, potentially driven by substitution, in the margin, from the least productive fruit varieties to heat-resistant cereals and timber varieties. As a result of these adaptive responses, there has been an output increase in the primary and forestry sectors.

[41] As explained above, I refer as output to the value of production or sales. Therefore, to use this outcome, a key assumption is that prices are determined exogenously (i.e. determined by "world" markets), then, only quantities but not prices are a function of extreme heat (i.e., $p_a Q_a(\mathbf{Z})$).

[42] Biological literature shows that the forestry sector is resistant to extreme heat unless wildfires or outbreaks of insects and pathogens (Kirilenko and Sedjo 2007, Nabuurs et al. 2003.)

Finally, it is important to acknowledge two caveats in this approach. First, I observe the area planted by sector, but not the composition of the varieties of each crop. Thus, I cannot distinguish adaptation by planting crops with different advantages or sensitivities to extreme temperatures within each subsector. For example, Meyers and Rhode (2020) document that the substitution from open-pollinated varieties of corn to hybrid corn seeds, led to heat tolerance, and Aragon et al. (2019) show an increase in the use of tubers in response to extreme heat.[43] Second, I do not observe the intensive margin use of these planted areas. This implies that I assume that each unit of land within each subsector has the same yield. Therefore, it is impossible to rule out that behind these results there is another type of adaptation besides extensive land use.

6 Effects Through Other Climate Change Margins

Climate change may influence other climate factors such as drought, sea levels and natural disaster frequencies (e.g. storms, floods and wildfires). In this section, I investigate to what extent the results shown above, which consider only the impact of shifting temperature distributions, may be altered by the effect of wildfire intensity.

Adaptation responses to wildfires could be different than those to extreme heat, especially whether agricultural varieties more proper to wildfire damage are different than those more proper to extreme heat direct damage.

To address this possibility, I estimate a version of equation (4.4) using the wildfire burned down share as an alternative treatment:

$$\triangle y_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \theta \, \triangle Wildfire_{m,\mathfrak{z}} + \mathbf{X}_{m,\mathfrak{z}1965/96} \, \mathbf{\Omega} + \xi_{m,\mathfrak{z}} \tag{6.1}$$

where $Wildfire_{m,\mathfrak{z}}$ is the change in the number of wildfires or burned-down hectares (both in logs) between 1997 and 2007, and the others variables remain the same.

Table 6 presents the estimates. Panel A, Columns (1),(3), and (5) show that wildfires are associated with a decrease in fruit share and an increase in primary share, both statistically significant at conventional levels, and a non-significant reduction in forestry share. Panel B, Columns (1),(3), and (5) show that wildfires are associated with a

[43] This research highlights that the increase in tubers is due to its advantages over other crops, such as short maturity, sequential harvesting, low water and fertilizer requirements, more reliability, and high nutritional content, but not necessary due to heat-tolerance.

decrease in agricultural labor and capital. Finally, Panel C shows that wildfires are not associated with significant effects on output. Overall, these results suggest that wildfires have an effect with the same direction of extreme heat.

However, wildfires could be caused by HDD, and therefore, θ is confounded with the effect of extreme heat. To address this possibility, I estimate the following equation:

$$\begin{aligned}\triangle y_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \theta \ \triangle Wildfire_{m,\mathfrak{z}} + \beta_1 \ \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \beta_2 \ \triangle GDD_{m,\mathfrak{z};\ \ell_0:\ell_1} \\ + \beta_3 \ \triangle P_{m,\mathfrak{z}} + \beta_4 \ \triangle P^2_{m,\mathfrak{z}} + \mathbf{X}_{m,\mathfrak{z}1965/96} \ \mathbf{\Omega} + \xi_{m,\mathfrak{z}}\end{aligned} \tag{6.2}$$

Columns (2),(4) and (6) show that, the wildfires effect dilutes when I add the vector $\mathbf{Z}$ of weather treatment variables (HDD, GDD, P and P^2). These results suggest that extreme heat is the main driver of the input reallocation. Importantly, comparing the results with those obtained in Tables 3, 4 and 5, the HDD coefficient, remains statistically unchanged.

Finally, based on these results, I explore to what extent extreme heat increases wildfire frequency and intensity (Abatzoglou and Williams 2016).

To address this relationship, I estimate the following equation:

$$\begin{aligned}\triangle Wildfire_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \beta_1 \ \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \beta_2 \ \triangle GDD_{m,\mathfrak{z};\ \ell_0:\ell_1} \\ + \beta_3 \ \triangle P_{m,\mathfrak{z}} + \beta_4 \ \triangle P^2_{m,\mathfrak{z}} + \mathbf{X}_{m,\mathfrak{z}1965/96} \ \mathbf{\Omega} + \xi_{m,\mathfrak{z}}\end{aligned} \tag{6.3}$$

Figure 7 presents the estimate of β_1 under different thresholds. As expected, heating degree days increases wildfires in their intensive and extensive margins, an effect that is larger as the threshold of harmful degree days increases.[44]

Overall, these findings align with the notion that the adaptation mechanisms discussed earlier are primarily driven by temperature increases, with only a partial direct influence from wildfires. Furthermore, it's noteworthy that the occurrence of wildfires itself is largely attributed to rising temperatures.

7 Robustness Checks

7.1 Controlling for Initial Dependent Variable

A relevant concern regarding previous estimations is that results are driven by mean-reversion or conditional convergence effects. Therefore, even after controlling for a large

[44]Additionally, Figure A.5 presents the GDD estimates with different thresholds.

set of controls, my estimates could be capturing differential input adjustment trends across municipalities that differ in their initial level of agricultural development. To address this concern, I add as a control the initial level of the outcome as follows:

$$\begin{aligned}\triangle y_{m,\mathfrak{z}} = \rho\ y_{m,\mathfrak{z}1997} + \mu_{\mathfrak{z}} + \beta_1\ \triangle HDD_{m;\ \ell_1:\infty} + \beta_2\ \triangle GDD_{m;\ \ell_0:\ell_1} \\ +\beta_3\ \triangle P_m + \beta_4\ \triangle P_m^2 + \mathbf{X}_{m1965/96}\ \mathbf{\Omega} + \xi_{m,\mathfrak{z}}\end{aligned} \tag{7.1}$$

where all the variables remain the same as in the main equation (4.4) and y_{m1997} is the initial level of the outcome. In Table A.1 I report the main results controlling for this variable. The estimated effects of extreme heat in the fruit share, labor, capital and remain significant and unchanged, despite it improves the joint significance of controls and the precision of the main estimates.

7.2 Outliers

Robustness of the main results to dropping outliers in agricultural output and fruit share changes are presented in Tables A.2 and A.3, respectively. Each Table summarizes Tables 3, 4 and 5 but after dropping the top and bottom tails at 5% in Columns (1), (3) and (5), and at 10% in Columns (2), (4) and (6). Additionally, in Figure A.6 I show the main estimates after dropping each province at a time from north to south. Overall, the results remain virtually unchanged after this sample adjustment.

7.3 Spatial Correlation

Figure 1 suggests that temperature and precipitation are correlated across space. Therefore, in this section I show that the main estimates of the effect of climate change reported above remain statistically significant when I correct standard errors for heteroskedasticity and spatial dependence as suggested by Conley (1999) using Colella et al. 2019's program which builds arbitrary clusters within a given distance. Table **??** report my results. The first row shows for each variable the standard errors clustered at the province level as a benchmark, while the second, third, fourth and fifth rows show Conley standard errors assuming spatial correlation within 25, 50, 100 and 150 kilometers, respectively.[45] In the case of HDD coefficient, the table shows that, although standard errors tend to slightly increase after accounting for spatial correlation within 50 km, all the coefficients which are significant with clusters at province level remain statistically significant with Conley standard errors.

[45]These distances are calculated between the centroids of each municipality.

7.4 Sensitivity to Number of Year Average Election

In Section 4 I defined the harmful degree-days as those above a threshold ℓ_1, and established the number of years used to calculate the cumulative in the case of weather variables. These decisions, however, may be key in the results presented above.

In Figure A.3 I show the sensitivity of the results to the election of the number of endpoint years average in the climatic variables. Estimates using a three-year average do not lead to statistically different results from estimates that use a four-year, two-year average or no average.[46] However, the use of a three-year average increase the precision of the estimates and helps to capture medium-term changes variation in average conditions (i.e., climate change) instead of a short-run variation (i.e., weather shock). The increase in precision is because of two main reasons: First, hot years have persistent effects, thus lags of extreme heat matter accounting for inputs adjustments (Burke and Tanutama 2019; Aragon et al. 2019) and also provide information to farmers about the future trends of extreme heat. Second, averaging the weather variables reduces the abnormal variation in weather variation (e.g., if one year has exceptionally high temperatures), which may not impact the outcomes and adds noise (Burke and Emerick 2016).

In Appendix A, I provide additional robustness checks such as alternative weight schemes.

8 Final Remarks

This paper provides empirical evidence of an unexplored adaptation mechanism, such as land reallocation across agricultural sectors. Using medium-term variations in temperature and precipitation in Chile, I find that farmers change land use, hired labor, and capital to attenuate the effects of extreme heat. Specifically, land use changes from the most sensitive sector, such as the fruit sector, to the most resistant to extreme heat, such as the forestry sector, without changing the total land use (i.e. agricultural frontier). Overall, this response mitigates extreme heat on agricultural output at the social cost of job loss in agriculture and highlights that accounting for land reallocation is essential to quantify the mitigation of the losses associated with climate change.

The advantage of the mechanism highlighted in this research is that farmers and

[46] Despite three coefficients are not statistically significant when I do not use three-years average (fruit and output), they are not statistically different from the main estimates (red points). Note that, due to statistical issues, all the panels of this figure should be interpreted together to get a notion of the performance of this approach.

firms make their own decisions in response to climate change, and without the need for coordination, reallocation gains can lead to substantial mitigation of agricultural output damage. Nevertheless, it is crucial to acknowledge that there are several unsolved issues. First, the land reallocation and the attenuation of negative output effects presented above do not encompass the net social welfare effects of the overall adaptation mechanism. Job losses could have long-lasting negative effects on the economy, and the growth of the forestry sector due to extreme heat adaptation might pose challenges, especially if the frequency of wildfires increases, as observed in other countries (Burke et al. 2021). This could potentially impact health and educational outcomes (Wen and Burke 2022, Arrizaga et al. 2023). Second, due to data limitations, I cannot investigate adaptation through other margins, such as defensive investments or the adoption of new technologies. This implies that behind the results there could be another type of adaptation that complements input adjustment. Third, the estimates capture only the impact of shifting temperature, precipitation and wildfire distributions, although climate change may influence other factors such as sea level rises, floods, and storm frequencies. In principle, it is straightforward to extend this approach to additional dimensions of the climate. Exploring these issues warrants future research.

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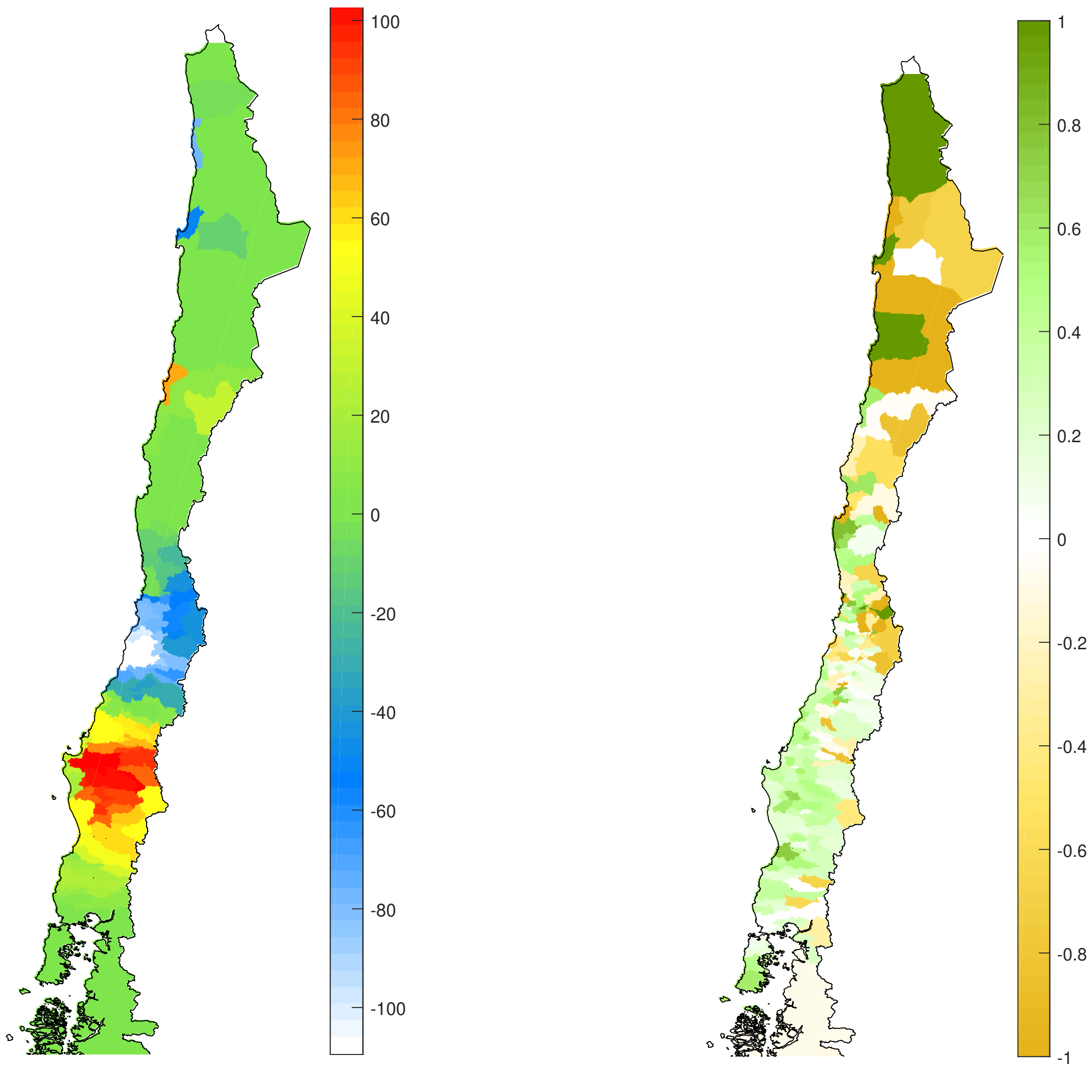
9 Figures

Figure 1: Spatial Distribution of Changes

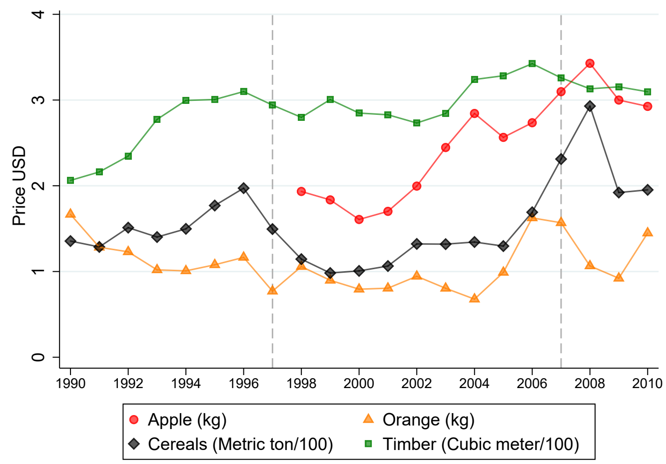
(a) HDD changes **(b)** Agricultural output changes



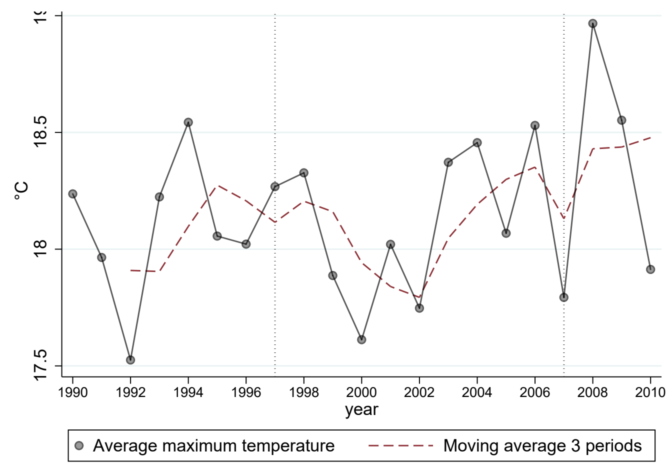
Notes: Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997 in levels in panels (a) and in logs in panel (b). Harmful degree-days are computed over the growing season, using maximum temperature with a threshold of $\ell_0 = 0$ and $\ell_1 = 27$.

Figure 2: Trends

(a) Commodity Prices



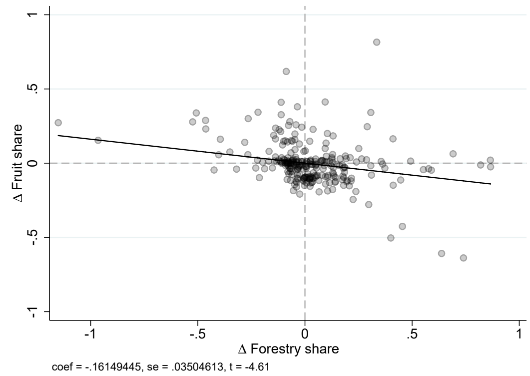
(b) Maximum temperature trends



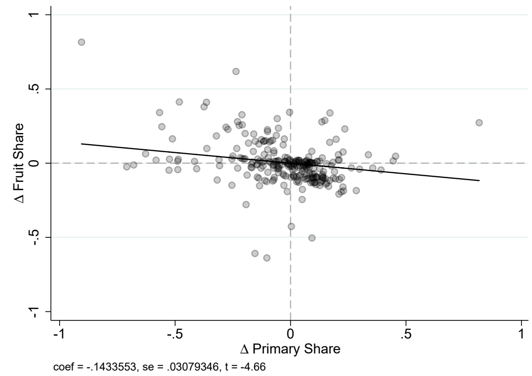
Notes: Data of Panel (a) is from PCPS and Panel (b) is from Berkeley Earth

Figure 3: Correlations in Land use shares

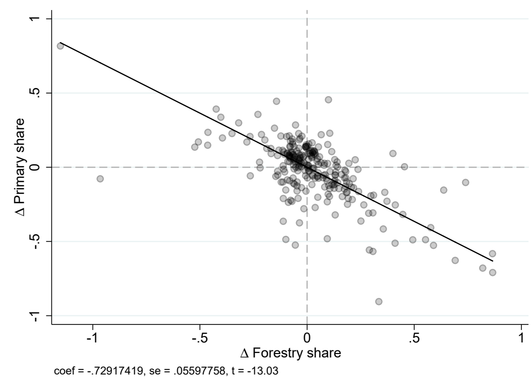
(a)



(b)



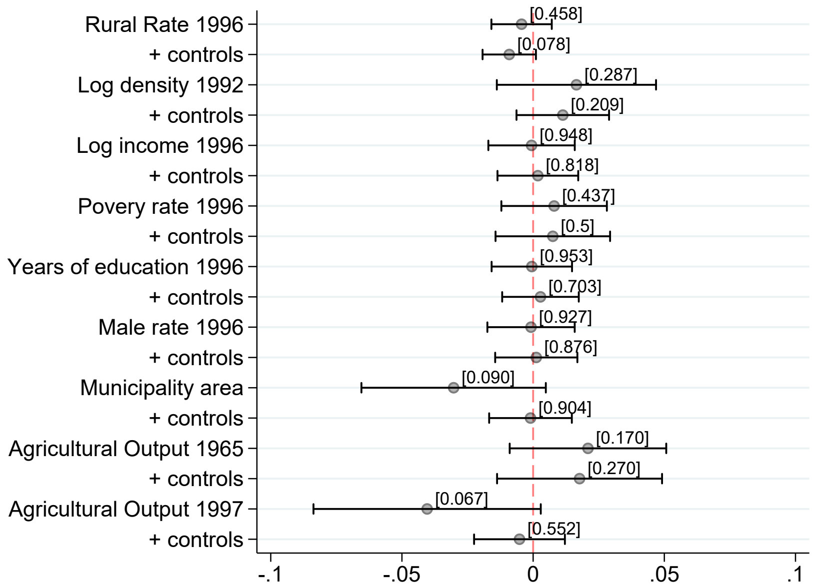
(c)



Notes: Each dot is a municipality and the lines are the fitted values of the linear regression weighted by agricultural output in 1965. These changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997.

Figure 4: Randomness of the HDD changes

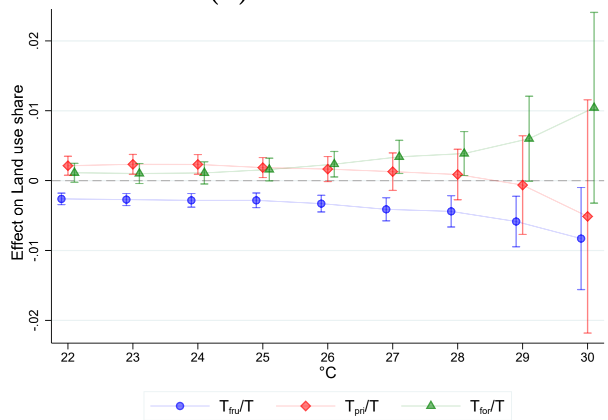
(a) Regression without and with climatic controls



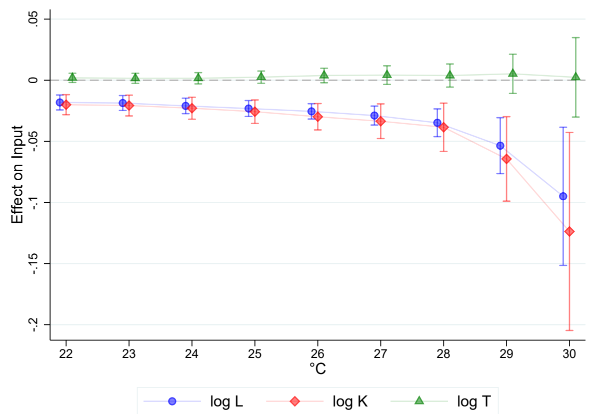
Notes: This figure show the point estimates, the 95% confidence intervals and the p-values in brackets of the β_1 of the equation $x_{m,\mathfrak{z}} = \alpha + \beta_1 \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \xi_{m,\mathfrak{z}}$, and of the equation $x_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \beta_1 \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \beta_2 \triangle GDD_{m,\mathfrak{z};\ \ell_0:\ell_1} + \beta_3 \triangle P_{m,\mathfrak{z}} + \beta_4 \triangle P^2_{m,\mathfrak{z}} + \xi_{m,\mathfrak{z}}$ that is the version "+controls". Both models use an upper threshold of 26^oC.

Figure 5: Upper Threshold Differentiated HDD Effects

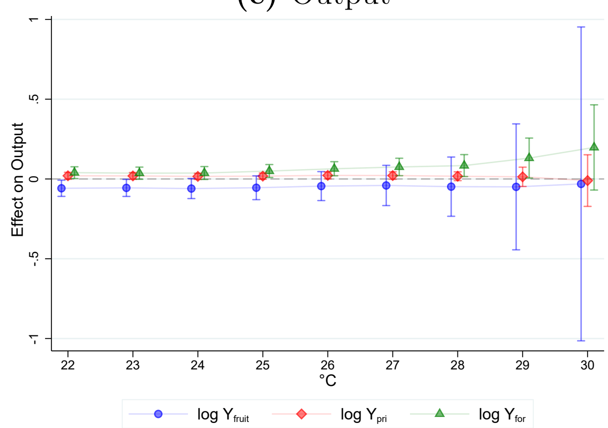
(a) Land Share



(b) Input



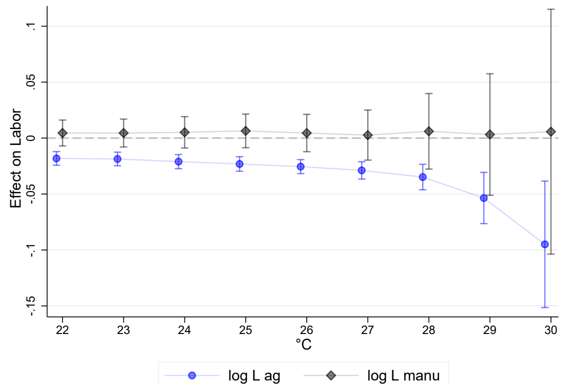
(c) Output



Notes: These figures show the point estimates and 95% confidence intervals of the β_1 in the equation (4.4). Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure 6: Differentiated HDD Effects in Sectoral Labor

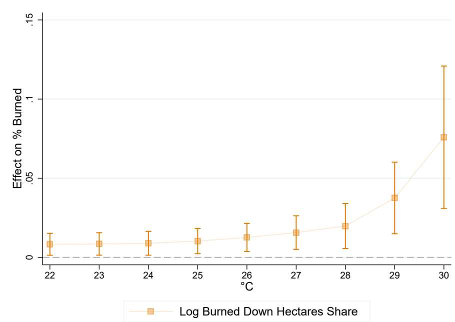
(a) Agriculture vs. Manufacturing



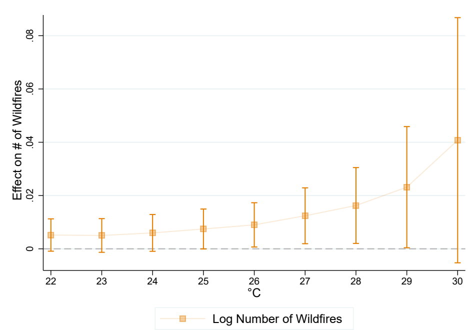
Notes: This figure shows the point estimates and 95% confidence intervals of the β_1 in the equation (4.4). The manufacturing labor estimates come from the ENIA survey database, and the agricultural labor estimates come from the Agricultural Census. Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure 7: Wildfire Upper Threshold Differentiated HDD Effects

(a) Change in Log Burned-down area



(b) Change in Log # of wildfires



Notes: These figures show the point estimates and 95% confidence intervals of the β_1 in the equation (4.4). Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

10 Tables

Table 1: Summary Statistics

	1997		2007-1997		
	Mean	SD	Mean	SD	Observations
Panel A. Weather Data					
Temperature					
$HDD_{\ell_1:\infty}$	81.780	77.276	5.487	17.044	259
$GDD_{\ell_0:\ell_1}$	6,609.403	1,179.454	-23.294	43.333	259
Average Precipitations (100 mm)	456.373	271.889	-12.542	52.062	259
Panel B. Agricultural Data					
Land Use (1000 ha)					
Planted Land	24.120	26.019	-0.537	7.938	259
Fruit Share	0.107	0.214	0.055	0.115	259
Primary Share	0.422	0.323	-0.173	0.214	259
Forestry Share	0.455	0.370	0.091	0.183	259
Log Aggregate Input Use					
Planted Land	8.767	2.666	-0.091	0.607	259
Number of Workers	8.027	1.080	-0.237	0.920	259
Number of Machinery	6.112	1.316	-0.778	0.957	259
Log Output and Productivity					
Aggregate	23.921	1.537	0.133	0.379	259
Fruit	15.167	8.816	0.071	5.852	259
Primary	20.046	2.598	-1.006	3.481	259
Forestry	17.728	9.888	1.380	5.216	259
Livestock	22.485	2.470	-1.156	3.570	259
Output per Worker	15.896	2.079	0.371	1.067	259
Output per Hectare	15.156	3.652	-0.561	4.743	259
Panel C. Manufacturing Data					
Log Number of Workers	4.666	2.869	0.276	1.379	259
Panel D. Wildfires Data					
Log number of events	0.124	0.302	0.445	0.524	259
Log burned-down share	-4.560	0.189	0.139	0.479	259

Notes: The data source is the Berkeley University and Delaware University databases in Panel A, Agricultural Census (1997, 2007) in Panel B, ENIA survey in Panel C and CONAF in Panel D. The unit of observation is the municipality. All variables are weighted by agricultural output in 1965. Weather variables are calculated over the main growing season and as a three-year average. GDD refers to growing degree-days while HDD refers to harmful degree-days, see Appendix for a formal definition of these variables. Thresholds in GDD and HDD variables are $\ell_0 = 0$ and $\ell_1 = 26$.

Table 2: Input Intensity by Sector

	1997	
	$\frac{L_i}{T_i}$	$\frac{K_i}{T_i}$
Fruit	839^{***}	23
	(164)	(23)
Primary	350^{***}	80^{***}
	(103)	(25)
Forestry	46^{*}	11
	(26)	(7)
Other	1,018	116
	(634)	(162)
Observations	259	259
Adjusted R^2	0.588	0.572

Notes: Results come from the estimation of equation (3.1). The "*other*" category is the intercept. The unit of observation is the municipality. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of extreme heat on land use shares.

	Land use share					
	$\triangle\frac{T_{fru}}{T_a}$		$\triangle\frac{T_{pri}}{T_a}$		$\triangle\frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0033^{***}	-0.0033^{***}	0.0025^{***}	0.0017^{*}	0.0016^{*}	0.0024^{**}
	(0.0005)	(0.0006)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0009^{***}	-0.0005	-0.0006	0.0026^{***}	-0.0000	-0.0015^{*}
	(0.0001)	(0.0004)	(0.0007)	(0.0009)	(0.0003)	(0.0008)
Observations	259	259	259	259	259	259
Adjusted R^2	0.406	0.425	0.159	0.345	0.258	0.361
Climatic zone FE	No	Yes	No	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: Results come from the estimation of equation (4.4). All regressions are weighted by agricultural output in 1965. Thresholds in GDD and HDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of extreme heat on input use.

	Input					
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0265^{***}	-0.0255^{***}	-0.0310^{***}	-0.0299^{***}	0.0026	0.0039
	(0.0043)	(0.0032)	(0.0041)	(0.0055)	(0.0019)	(0.0030)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0018	-0.0042	0.0033	-0.0003	-0.0034^{***}	-0.0013
	(0.0017)	(0.0034)	(0.0023)	(0.0040)	(0.0011)	(0.0017)
Observations	259	259	259	259	259	259
Adjusted R^2	0.291	0.352	0.311	0.379	0.333	0.383
Climatic zone FE	No	Yes	No	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: Results come from the estimation of equation (4.4). All regressions are weighted by agricultural output in 1965. Thresholds in GDD and HDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of extreme heat on output.

	Output					
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0266	-0.0447	0.0289^{**}	0.0224^{**}	-0.0089	0.0641^{***}
	(0.0201)	(0.0463)	(0.0138)	(0.0110)	(0.0225)	(0.0226)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0192^{*}	-0.0387	-0.0282	0.0182	0.0013	-0.0106
	(0.0114)	(0.0320)	(0.0176)	(0.0161)	(0.0081)	(0.0175)
Observations	259	259	259	259	259	259
Adjusted R^2	0.034	0.148	0.127	0.227	0.281	0.448
Climatic zone FE	No	Yes	No	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: Results come from the estimation of equation (4.4). All regressions are weighted by agricultural output in 1965. Thresholds in GDD and HDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

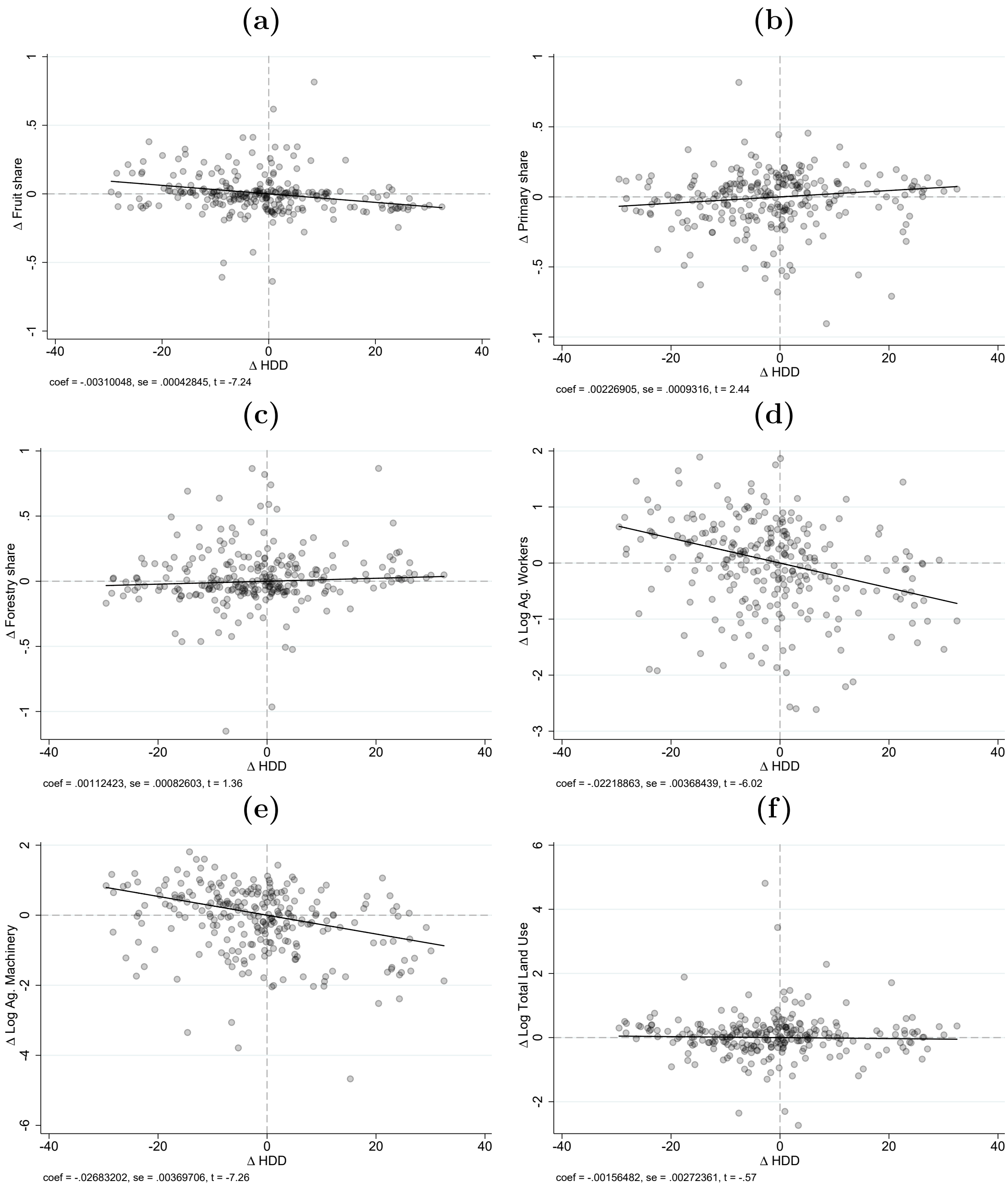
Table 6: Effects of wildfires and extreme heat on agricultural outcomes.

Panel A: Land use share						
	$\triangle \frac{T_{fru}}{T_a}$		$\triangle \frac{T_{pri}}{T_a}$		$\triangle \frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle Wildfire$	-0.0307^{**}	-0.0025	0.0387^{***}	0.0163	-0.0104	-0.0240^{*}
	(0.0144)	(0.0092)	(0.0149)	(0.0110)	(0.0130)	(0.0127)
$\triangle HDD_{\ell_1:\infty}$		-0.0032^{***}		0.0015		0.0027^{***}
		(0.0006)		(0.0009)		(0.0010)
$\triangle GDD_{\ell_0:\ell_1}$		-0.0005		0.0026^{***}		-0.0015^{*}
		(0.0004)		(0.0009)		(0.0008)
Observations	259	259	259	259	259	259
Adjusted R^2	0.312	0.423	0.195	0.344	0.142	0.362
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Input						
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle Wildfire$	-0.2373^{*}	-0.0215	-0.4457^{***}	-0.2193^{**}	0.0552	0.0503
	(0.1265)	(0.0958)	(0.1696)	(0.1022)	(0.0536)	(0.0446)
$\triangle HDD_{\ell_1:\infty}$		-0.0252^{***}		-0.0271^{***}		0.0032
		(0.0034)		(0.0044)		(0.0033)
$\triangle GDD_{\ell_0:\ell_1}$		-0.0042		-0.0001		-0.0013
		(0.0034)		(0.0040)		(0.0017)
Observations	259	259	259	259	259	259
Adjusted R^2	0.244	0.349	0.289	0.387	0.160	0.382
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Output						
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle Wildfire$	-0.7273	-0.3410	0.0966	-0.1309	0.2944	-0.0593
	(0.4663)	(0.2842)	(0.1111)	(0.2362)	(0.2252)	(0.3631)
$\triangle HDD_{\ell_1:\infty}$		-0.0404		0.0241^{*}		0.0648^{***}
		(0.0465)		(0.0133)		(0.0249)
$\triangle GDD_{\ell_0:\ell_1}$		-0.0385		0.0183		-0.0106
		(0.0322)		(0.0162)		(0.0176)
Observations	259	259	259	259	259	259
Adjusted R^2	0.100	0.145	0.210	0.224	0.209	0.446
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results come from the estimation of equation (4.4). $Wildfire$ is the change in burned-down land share between 1997 and 2007 (in logs). All regressions are weighted by agricultural output in 1965. Thresholds in GDD and HDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix: Empirics

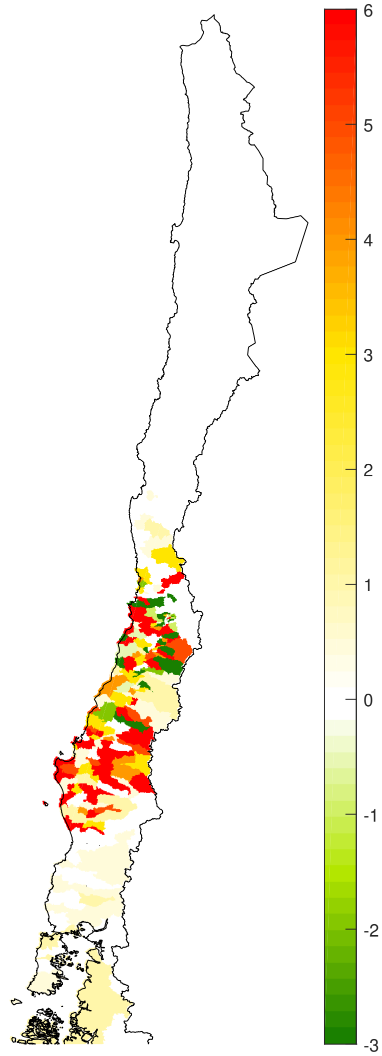
Figure A.1: Correlations in the Data



Notes: Each dot is a municipality and the lines are the fitted values of the linear regression weighted by agricultural output in 1965. These changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997.

Figure A.2: Spatial Distribution of Wildfires

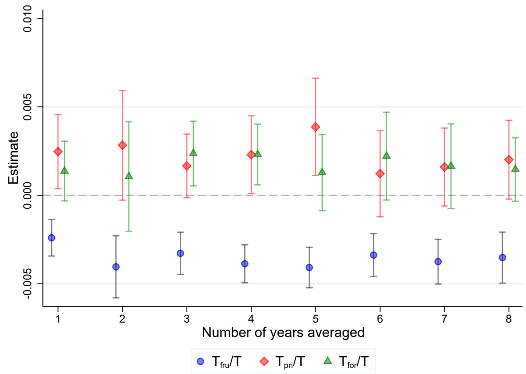
(a) Changes in Wildfire Burned Down Share



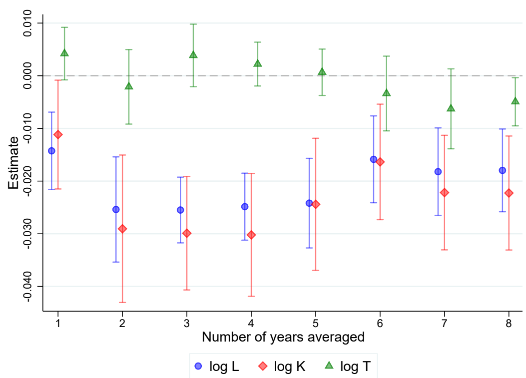
Notes: This figure shows the spatial variability of the changes in burned down share due to wildfire events.

Figure A.3: Sensitivity of Results to n-year average

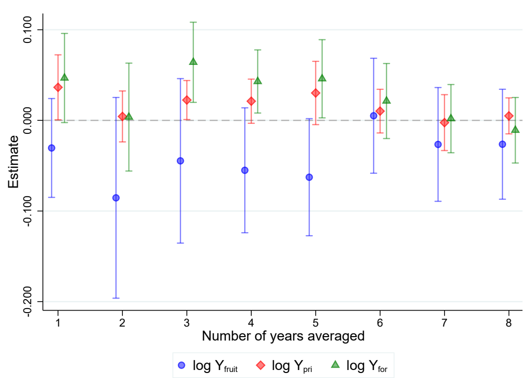
(a) Land Share



(b) Input



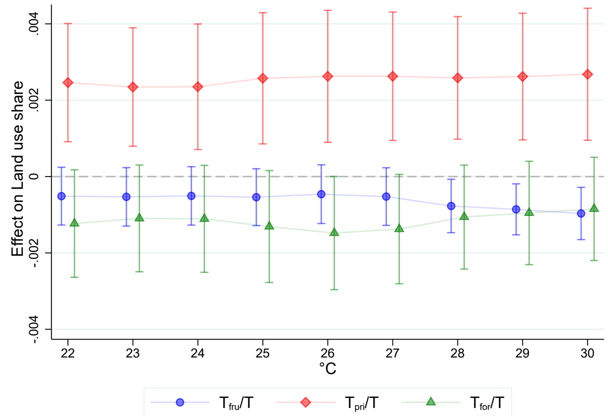
(c) Output



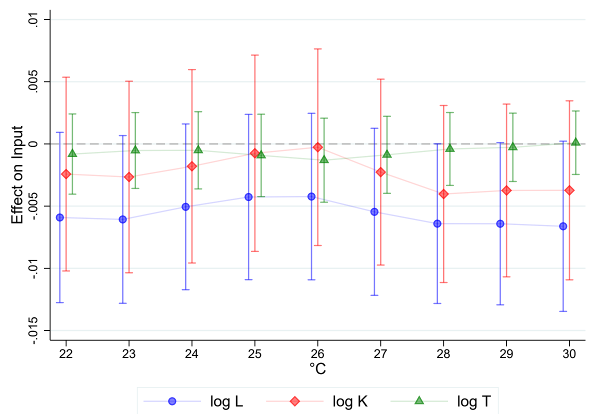
Notes: These figures show the point estimates and 95% confidence intervals of the β_1 in the equation (4.4). Each coefficient comes from a different estimation using different cumulative years. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure A.4: Upper Threshold Differentiated *GDD* Effects

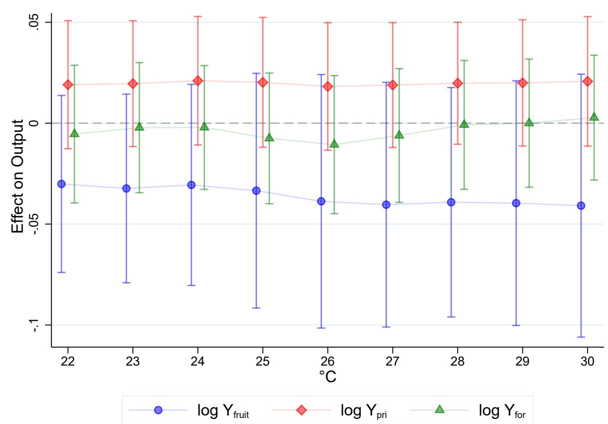
(a) Land Share



(b) Input



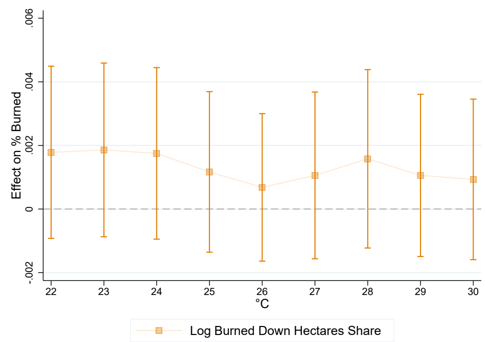
(c) Output



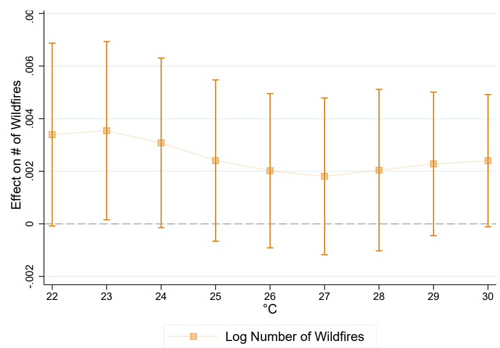
Notes: These figures show the point estimates and 95% confidence intervals of the β_2 in the equation (4.4). Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure A.5: Wildfire Upper Threshold Differentiated GDD Effects

(a) Change in Log Burned-down area



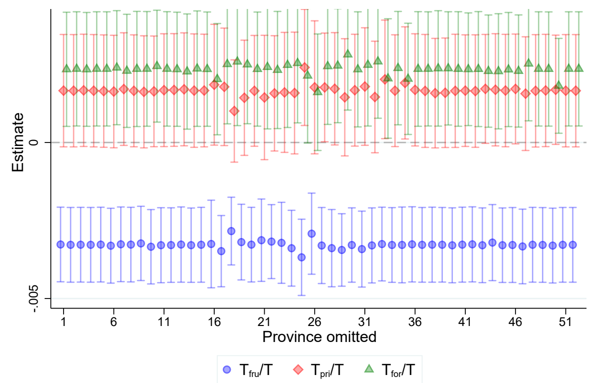
(b) Change in Log # of wildfires



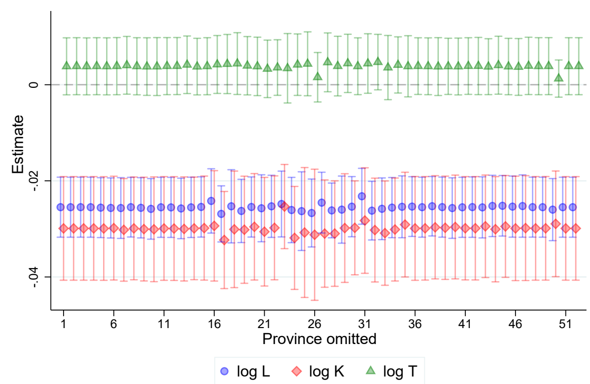
Notes: These figures show the point estimates and 95% confidence intervals of the β_2 in the equation (4.4). Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure A.6: Omitting one province at a time

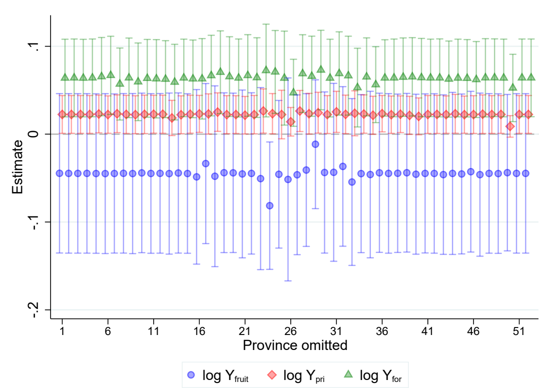
(a) Land Share



(b) Input



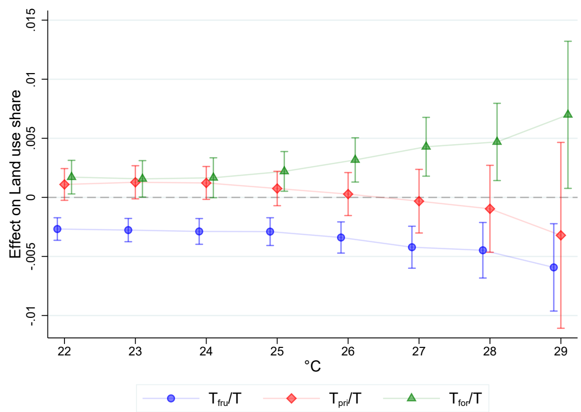
(c) Output



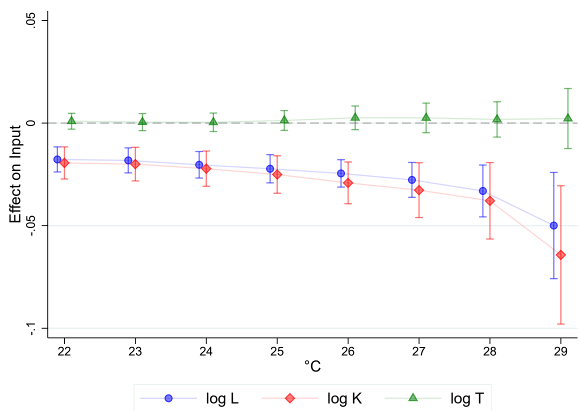
Notes: These figures show the point estimates and 95% confidence intervals of the β_1 in the equation (4.4). All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Figure A.7: Robustness to initial dependent variable as a control: Upper Threshold Differentiated Effects

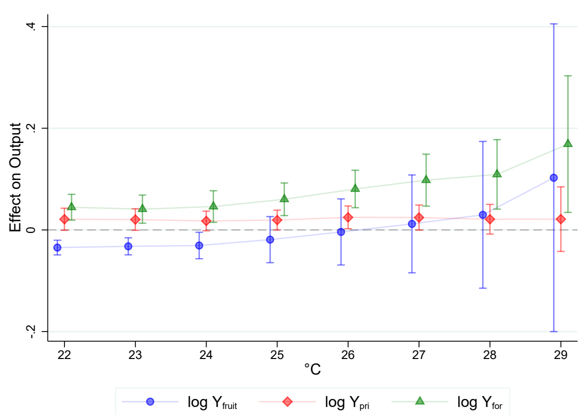
(a) Land Share



(b) Input



(c) Output



Notes: These figures show the point estimates and 95% confidence intervals of the β_1 in the equation (7.1). Each coefficient comes from a different estimation using different ℓ_1 thresholds. All regressions are weighted by agricultural output in 1965. Standard errors clustered at province level.

Table A.1: Robustness to Initial Dependent Variable as a Control.

Panel A: Land use share						
	$\triangle\frac{T_{fru}}{T_a}$		$\triangle\frac{T_{pri}}{T_a}$		$\triangle\frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0033^{***}	-0.0034^{***}	0.0017^{*}	0.0003	0.0024^{**}	0.0032^{***}
	(0.0006)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0010)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0005	-0.0005	0.0026^{***}	0.0026^{***}	-0.0015^{*}	-0.0013
	(0.0004)	(0.0004)	(0.0009)	(0.0010)	(0.0008)	(0.0008)
$\triangle y_{m,1997}$		-0.0352		-0.3575^{***}		-0.1091^{**}
		(0.0533)		(0.0520)		(0.0481)
Observations	259	259	259	259	259	259
Adjusted R^2	0.425	0.425	0.345	0.494	0.361	0.380
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Input						
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0255^{***}	-0.0245^{***}	-0.0299^{***}	-0.0292^{***}	0.0039	0.0026
	(0.0032)	(0.0034)	(0.0055)	(0.0052)	(0.0030)	(0.0029)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0042	-0.0042	-0.0003	-0.0004	-0.0013	-0.0014
	(0.0034)	(0.0033)	(0.0040)	(0.0041)	(0.0017)	(0.0016)
$\triangle y_{m,1997}$		0.2161		-0.2297^{*}		0.0452
		(0.1584)		(0.1273)		(0.0407)
Observations	259	259	259	259	259	259
Adjusted R^2	0.352	0.361	0.379	0.392	0.383	0.385
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Output						
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0447	-0.0040	0.0224^{**}	0.0248^{**}	0.0641^{***}	0.0806^{***}
	(0.0463)	(0.0332)	(0.0110)	(0.0114)	(0.0226)	(0.0188)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0387	-0.0296	0.0182	0.0184	-0.0106	-0.0274
	(0.0320)	(0.0246)	(0.0161)	(0.0161)	(0.0175)	(0.0229)
$\triangle y_{m,1997}$		-0.6636^{***}		0.1773		-0.5804^{***}
		(0.1025)		(0.2216)		(0.1186)
Observations	259	259	259	259	259	259
Adjusted R^2	0.148	0.410	0.227	0.229	0.448	0.617
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results come from the estimation of equation (4.4). Columns (1), (3) and (5), present the main results and columns (2), (4) and (6) after controlling for the initial dependent variable as control.

Table A.2: Robustness to Dropping Output Tails.

	Panel A: Land use share					
	$\triangle\frac{T_{fru}}{T_a}$		$\triangle\frac{T_{pri}}{T_a}$		$\triangle\frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0033^{***}	-0.0031^{***}	0.0017^{*}	0.0017^{*}	0.0023^{**}	0.0021^{**}
	(0.0006)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0006^{*}	-0.0006^{*}	0.0028^{***}	0.0033^{***}	-0.0015^{*}	-0.0019^{**}
	(0.0004)	(0.0003)	(0.0009)	(0.0010)	(0.0008)	(0.0008)
Observations	235	209	235	209	235	209
Adjusted R^2	0.469	0.488	0.355	0.399	0.380	0.446
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%
	Panel B: Input					
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0257^{***}	-0.0261^{***}	-0.0299^{***}	-0.0297^{***}	0.0039	0.0036
	(0.0033)	(0.0036)	(0.0055)	(0.0056)	(0.0031)	(0.0030)
$\triangle GDD_{\ell_0:\ell_1}$	−0.0044	−0.0046	−0.0006	−0.0022	−0.0012	−0.0020
	(0.0035)	(0.0037)	(0.0041)	(0.0039)	(0.0018)	(0.0018)
Observations	235	209	235	209	235	209
Adjusted R^2	0.343	0.337	0.376	0.392	0.394	0.391
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%
	Panel C: Output					
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	−0.0463	−0.0392	0.0221^{**}	0.0228^{*}	0.0580^{***}	0.0542^{***}
	(0.0468)	(0.0463)	(0.0109)	(0.0120)	(0.0217)	(0.0207)
$\triangle GDD_{\ell_0:\ell_1}$	−0.0416	−0.0441	0.0163	0.0187	−0.0175	−0.0245
	(0.0333)	(0.0382)	(0.0164)	(0.0176)	(0.0167)	(0.0178)
Observations	235	209	235	209	235	209
Adjusted R^2	0.146	0.154	0.241	0.239	0.457	0.487
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%

Notes: Results come from the estimation of equation (4.4). Columns (1), (3) and (5), present the results after dropping top and bottom 5% in output changes and columns (2), (4) and (6) after dropping the top and bottom 10% in output changes.

Table A.3: Robustness to Dropping Fruit Share Tails.

Panel A: Land use share						
	$\triangle \frac{T_{fru}}{T_a}$		$\triangle \frac{T_{pri}}{T_a}$		$\triangle \frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0028^{***}	-0.0022^{***}	0.0013	0.0006	0.0022^{**}	0.0023^{**}
	(0.0005)	(0.0005)	(0.0008)	(0.0008)	(0.0010)	(0.0011)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0006^{*}	-0.0005	0.0026^{***}	0.0028^{***}	-0.0012^{*}	-0.0014^{*}
	(0.0003)	(0.0004)	(0.0009)	(0.0009)	(0.0007)	(0.0007)
Observations	235	209	235	209	235	209
Adjusted R^2	0.513	0.529	0.342	0.374	0.362	0.418
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%
Panel B: Input						
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0251^{***}	-0.0209^{***}	-0.0296^{***}	-0.0279^{***}	0.0033	0.0026
	(0.0037)	(0.0045)	(0.0058)	(0.0071)	(0.0034)	(0.0034)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0043	-0.0028	-0.0005	0.0005	-0.0013	-0.0010
	(0.0035)	(0.0040)	(0.0041)	(0.0047)	(0.0018)	(0.0017)
Observations	235	209	235	209	235	209
Adjusted R^2	0.347	0.326	0.376	0.330	0.397	0.434
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%
Panel C: Output						
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0439	-0.0433	0.0203^{*}	0.0222^{*}	0.0591^{***}	0.0680^{***}
	(0.0491)	(0.0559)	(0.0109)	(0.0121)	(0.0223)	(0.0258)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0397	-0.0357	0.0187	0.0249	-0.0032	0.0029
	(0.0339)	(0.0377)	(0.0160)	(0.0178)	(0.0154)	(0.0155)
Observations	235	209	235	209	235	209
Adjusted R^2	0.143	0.163	0.239	0.248	0.425	0.456
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Trimmed	5%	10%	5%	10%	5%	10%

Notes: Results come from the estimation of equation (4.4). Columns (1), (3) and (5), present the results after dropping top and bottom 5% in output changes and columns (2), (4) and (6) after dropping the top and bottom 10% in output changes.

Table A.4: Robustness to Different Weighting Scheme.

Panel A: Land use share						
	$\triangle \frac{T_{fru}}{T_a}$		$\triangle \frac{T_{pri}}{T_a}$		$\triangle \frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0032^{***}	-0.0030^{***}	0.0004	0.0006	0.0038^{***}	0.0033^{***}
	(0.0006)	(0.0006)	(0.0012)	(0.0010)	(0.0010)	(0.0009)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0008^{**}	-0.0007^{**}	0.0031^{***}	0.0029^{***}	-0.0012^{**}	-0.0012^{**}
	(0.0004)	(0.0003)	(0.0009)	(0.0008)	(0.0006)	(0.0006)
Observations	259	259	259	259	259	259
Adjusted R^2	0.431	0.413	0.365	0.354	0.348	0.347
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weight	Area	Pop	Area	Pop	Area	Pop
Panel B: Input						
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0217^{***}	-0.0222^{***}	-0.0262^{***}	-0.0266^{***}	0.0031	0.0037
	(0.0039)	(0.0040)	(0.0050)	(0.0053)	(0.0031)	(0.0029)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0070^{*}	-0.0058^{*}	-0.0045	-0.0032	0.0016	0.0007
	(0.0036)	(0.0035)	(0.0037)	(0.0037)	(0.0017)	(0.0015)
Observations	259	259	259	259	259	259
Adjusted R^2	0.338	0.335	0.350	0.351	0.386	0.395
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weight	Area	Pop	Area	Pop	Area	Pop
Panel C: Output						
	$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle\ log(Y_{for})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0271	-0.0461	0.0284^{**}	0.0280^{**}	0.0855^{***}	0.0801^{***}
	(0.0411)	(0.0474)	(0.0137)	(0.0141)	(0.0249)	(0.0229)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0339	-0.0302	0.0277	0.0225	-0.0087	-0.0095
	(0.0223)	(0.0268)	(0.0182)	(0.0153)	(0.0158)	(0.0154)
Observations	259	259	259	259	259	259
Adjusted R^2	0.168	0.171	0.271	0.263	0.440	0.449
Climatic zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weight	Area	Pop	Area	Pop	Area	Pop

Notes: Results come from the estimation of equation (4.4). Column (1) presents the results using area weighting and column (2) population weighting.

B Appendix: Definition of Treatment Variables

B.1 Definition of Climate Treatment Variables

To capture nonlinear effects of the temperature, is a standard practice in agronomics converting daily mean temperatures to degree-days (See Schlenker and Roberts 2009 for more details). The variable $GDD_{m,t;\ \ell_0:\ell_1}$ is the number of growing season degree-days and $HDD_{m,t;\ \ell_1:\infty}$ is the number of harmful heating degree-days, also know as killing degree-days. This transformation has became very popular in climate change economic research. See for instance Burke and Emerick (2016), Aragon et al. (2019), Jessoe et al. (2018), Colmer (2020) and Meyers and Rhode (2020).

In particular, the construction of these variables is described by the following formula:

$$GDD_{m;\ \ell_0:\ell_1} = \begin{cases} 0 & \text{if } H \leq \ell_0 \\ H - \ell_0 & \text{if } \ell_0 < H < \ell_1 \\ \ell_1 - \ell_0 & \text{if } \ell_1 \leq H \end{cases} \tag{B.1}$$

$$HDD_{m;\ \ell_1:\infty} = \begin{cases} 0 & \text{if } H \leq \ell_1 \\ H - \ell_1 & \text{if } \ell_1 < H \end{cases}$$

Where H is the heat (maximum temperature) in the geographic region m, and ℓ_0 and ℓ_1 are endogenous lower and upper thresholds, respectively (e.g., 0^oC and 26^oC). For example, one day of 10^oC contributes 10 degree days, a day of 11^oC contributes 11 degree days, up to a temperature of 26^oC, which contributes 26 degree days. All the days with temperatures above 26^oC contributes 26^oC degree days, and the difference with the upper threshold ℓ_1, is the number of harmful degree-days. Figure **??** shows graphically the use of an upper threshold to construct of this variable. Then, degree-days are summed over the growing season in Chile (September-April), following Hajek and Gutiérrez (1979). Note that the agricultural year in Chile is cut by the calendar year, so all the agricultural variables are calculated for the "agricultural year". For example, the growing season of the year 1997, is composed of September, October, November and December of 1996, and January, February, March and April of 1997. Nevertheless, for the years where I have census data (1997 and 2007), I use every month of growing season in that year, because the census is computed throughout the year until December. Furthermore, the precipitation are summed over the growing season and its squared is added to deal with its potential nonlinear effect.

Therefore, weather treatment variables vector has the following form:

$$\mathbf{Z}_{m,t} = [f(H_{m,t}) \quad g(P_{m,t})]$$

where $f(.)$ and g(.) are functions that capture nonlinearities of heat and precipitation

$$f(H_{m,t}) = [HDD_{m,t;\ \ell_1:\infty} \quad GDD_{m,t;\ \ell_0:\ell_1}]$$
$$g(P_{m,t}) = [P_{m,t} \quad P^2_{m,t}]$$

When I take first differences:

$$\mathbf{Z}_{m,2007} - \mathbf{Z}_{m,1997} = [\triangle f(H_m) \quad \triangle g(P_m)] = [\triangle HDD_{m;\ \ell_1:\infty} \quad \triangle GDD_{m;\ \ell_0:\ell_1} \quad \triangle P_m \quad \triangle P^2_m]$$

An implicit assumption is the effect of weather variables can be approximated to a linear in parameters function: $F(\mathbf{Z}_{mt}) = \mathbf{Z}_{mt}\boldsymbol{\beta}$. This assumption relies on the empirical results of Schlenker and Roberts (2009).

Furthermore, a possible concern of this empirical strategy is that the differential trends in temperature and precipitation across municipalities are driven by short-run variation in weather around the chosen endpoints years (i.e. 1997 and 2007). In an effort to capture more effectively the change in "average" climate over time, I use weather variables as a n-years average:

$$\triangle z_m = z_{m,2007} - z_{m,1997} \text{ where } z_{m,1997} = \sum_{l=0}^{n-1} \frac{z_{m,1997-l}}{n} \text{ and } z_{m,2007} = \sum_{l=0}^{n-1} \frac{z_{m,2007-l}}{n}$$

The main specification uses $n = 3$, however, as I show in Figure **??**, the results do not depend on this sum but improves the precision of the estimates because the lags are relevant in measuring the extreme heat impact.

C Appendix: Theory

C.1 Equilibrium

Non-Agricultural sector: Profit maximizing implies

$$\max_{L_n} \Pi_n = p_n Q_n - w_L L_n \tag{C.1}$$

$$L_n = \Big(\frac{p_n A_n \alpha_n}{w_L}\Big)^{\frac{1}{1-\alpha_n}} \tag{C.2}$$

Inserting (C.13) in (C.2)

$$L_n^* = \left(\frac{p_n A_n \alpha_n}{\left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}} \left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}} \tag{C.3}$$

$$Q_n^* = A_n\left(\frac{p_n A_n \alpha_n}{\left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}} \left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{\alpha_n}{1-\alpha_n}} \tag{C.4}$$

Agriculture: Heat-sensitive and Heat-resistant goods
For each sector $i = \{s, r\}$, minimizing costs implies

$$\min_{T_i, L_i} C_i = w_T T_i + w_L L_i \qquad s.t. \quad A_i T_i^{\gamma_i} L_i^{1-\gamma_i} = \bar{q}_i \tag{C.5}$$

Using Lagrange multiplier implies

$$\max_{T_i, L_i} \mathcal{L}_i = -w_T T_i - w_L L_i + \lambda_i [A_i T_i^{\gamma_i} L_i^{1-\gamma_i} - \bar{q}_i] \tag{C.6}$$

$$L_i = T_i \Big(\frac{1-\gamma_i}{\gamma_i}\Big)\frac{w_T}{w_L} \tag{C.7}$$

As $\bar{q}_i = A_i T_i^{\gamma_i} L_i^{1-\gamma_i}$, the conditional factor demands are

$$\begin{aligned} T_i^C &= \frac{\bar{q}_i}{A_i}\Big(\frac{\gamma_i}{1-\gamma_i}\Big)^{1-\gamma_i}\Big(\frac{w_L}{w_T}\Big)^{1-\gamma_i} \\ L_i^C &= \frac{\bar{q}_i}{A_i}\Big(\frac{1-\gamma_i}{\gamma_i}\Big)^{\gamma_i}\Big(\frac{w_T}{w_L}\Big)^{\gamma_i} \end{aligned} \tag{C.8}$$

Then, the minimum cost (value) function is

$$CT_i^* = \frac{\bar{q}_i}{A_i} w_T^{\gamma_i} w_L^{1-\gamma_i} \Psi_i \tag{C.9}$$

with $\Psi_i = \frac{1}{\gamma_i^{\gamma_i}(1-\gamma_i)^{1-\gamma_i}}$ to save space.

In equilibrium, the zero profit conditions in each sector implies $MC_i = p_i$, then

$$w_L = w_T^{\frac{-\gamma_i}{1-\gamma_i}} \left(\frac{p_i A_i}{\Psi_i}\right)^{\frac{1}{1-\gamma_i}} \tag{C.10}$$

Using simmetry between s and r

$$\frac{MC_s}{MC_r} = \frac{p_s}{p_r} \quad \Rightarrow \quad \frac{\frac{1}{A_s} w_T^{\gamma_s} w_L^{1-\gamma_s} \Psi_s}{\frac{1}{A_r} w_T^{\gamma_r} w_L^{1-\gamma_r} \Psi_r} = \frac{p_s}{p_r} \tag{C.11}$$

Hence, rearranging terms

$$w_T = w_L \left[\frac{p_s A_s \Psi_r}{p_r A_r \Psi_s}\right]^{\frac{1}{\gamma_s - \gamma_r}} \tag{C.12}$$

Then, inserting (C.10) in (C.12)

$$\begin{aligned} w_L^* &= \left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}} \left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}} \\ w_T^* &= \left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r-1}{\gamma_s-\gamma_r}} \left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s-1}{\gamma_s-\gamma_r}} \end{aligned} \tag{C.13}$$

On the other hand, profit maximizing in each sector implies

$$\max_{T_i, L_i} \Pi_i = p_i q_i - w_T T_i - w_L L_i \tag{C.14}$$

$$\frac{\partial \Pi_i}{\partial T_i} = 0 \quad \Rightarrow \quad MPT_i = \frac{w_T}{p_i} \tag{C.15}$$

Then

$$L_i = T_i \left[\frac{w_T}{p_i A_i \gamma_i}\right]^{\frac{1}{1-\gamma_i}} \tag{C.16}$$

Inserting (C.16) for each sector $i = \{s, r\}$ and (C.3) in the endowment of labor restriction $L = L_s + L_r + L_n$:

$$L = \underbrace{T_s\Big[\frac{w_T}{p_sA_s\gamma_i}\Big]^{\frac{1}{1-\gamma_s}}}_{L_s} + \underbrace{T_r\Big[\frac{w_T}{p_rA_r\gamma_r}\Big]^{\frac{1}{1-\gamma_r}}}_{L_r} + \underbrace{\left(\frac{p_nA_n\alpha_n}{\left(\frac{\Psi_s}{p_sA_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_rA_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}}_{L_n} \tag{C.17}$$

Then, rearranging terms:

$$T_r = \left\{L - T_s\Big[\frac{w_T}{p_sA_s\gamma_i}\Big]^{\frac{1}{1-\gamma_s}} - \left(\frac{p_nA_n\alpha_n}{\left(\frac{\Psi_s}{p_sA_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_rA_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}\right\}\Big[\frac{p_rA_r\gamma_r}{w_T}\Big]^{\frac{1}{1-\gamma_r}} \tag{C.18}$$

Moreover, inserting (C.18) in the endowment of land restriction $T = T_s + T_r$

$$T = T_s + \left\{L - T_s\Big[\frac{w_T}{p_sA_s\gamma_i}\Big]^{\frac{1}{1-\gamma_s}} - \left(\frac{p_nA_n\alpha_n}{\left(\frac{\Psi_s}{p_sA_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_rA_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}\right\}\Big[\frac{w_T}{p_rA_r\gamma_r}\Big]^{\frac{1}{1-\gamma_r}} \tag{C.19}$$

Therefore, rearranging terms:

$$\begin{aligned} T_s^* = &\left\{T - L\Big[\frac{p_rA_r\gamma_r}{w_T^*}\Big]^{\frac{1}{1-\gamma_r}} + \left(\frac{p_nA_n\alpha_n}{w_L^*}\right)^{\frac{1}{1-\alpha_n}}\Big[\frac{p_rA_r\gamma_r}{w_T^*}\Big]^{\frac{1}{1-\gamma_r}}\right\} \\ &\times \frac{(p_sA_s\gamma_s)^{\frac{1}{1-\gamma_s}}}{(p_sA_s\gamma_s)^{\frac{1}{1-\gamma_s}} - (w_T^*)^{\left(\frac{1}{1-\gamma_s}-\frac{1}{1-\gamma_r}\right)}(p_rA_r\gamma_r)^{\frac{1}{1-\gamma_r}}} \end{aligned} \tag{C.20}$$

where w_T^* and w_L^* are given by the equation (C.13).

Since s and r are symmetric, obtaining T_r^* is trivial. Additionally, L_s^* can be obtained using (C.20) and (C.16).

C.2 Proofs

Prediction (i) : A reduction in the agricultural heat-sensitive land productivity A_s, leads to a reduction in the land allocation the heat-sensitive sector.

Proof: From the production function of the heat-sensitive sector, I can compute the marginal product of land

$$MPT_s = A_s\gamma_sT_s^{\gamma_s-1}L_s^{1-\gamma_s}$$

Therefore,

$$\frac{\partial MPT_s}{\partial A_s} = \gamma_sT_s^{\gamma_s-1}L_s^{1-\gamma_s} > 0 \tag{C.21}$$

Prediction (ii): A reduction in the agricultural heat-sensitive productivity A_s, increase the land share in the heat-resistant sector.

Proof: Land market clearing requires $T_s + T_r = T_a$, thus and reduction in T_s is compensated with and increase of T_r such that $dT_s + dT_r = dT = 0$ if land endowment is fixed: $dT_a = dT = 0$

Prediction (iii): A reduction in the agricultural heat-sensitive productivity A_s, remain unchanged the total amount of land used in agriculture as a whole.

Proof: Similar argument to prove prediction (ii). It is sufficient to assume that there is no waste, nor is there expansion of the supply of land.

Prediction (iv): A reduction in the agricultural heat-sensitive productivity A_s, reduces the land share in the heat-sensitive sector:

Proof: Since $0 < \gamma_s < 1$

$$\frac{\partial MPL_s}{\partial A_s} = (1-\gamma_s)L_s^{-\gamma_s}T_s^{\gamma_s} > 0 \tag{C.22}$$

Prediction (v): A reduction in the agricultural heat-sensitive productivity A_s, leads to an increase in labor allocation in non-agricultural sector whether heat-sensitive is more labor intensive than heat-resistant sector. Thus, reduces the labor allocation in agriculture as a whole $L_s + L_r$.

Proof: Using equation (C.3)

$$\begin{aligned} L_n &= \underbrace{(p_n A_n \alpha_n)^{\frac{1}{1-\alpha_n}} \left(\frac{\Psi_r}{p_r A_r}\right)^{\frac{\gamma_s}{\gamma_r-\gamma_s} \times \frac{-1}{1-\alpha_n}}}_{=c_1\ >0} \left(\frac{p_s A_s}{\Psi_s}\right)^{\frac{\gamma_r}{\gamma_r-\gamma_s} \times \frac{-1}{1-\alpha_n}} \\ &= c_1 \left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{(\gamma_r-\gamma_s)(1-\alpha_n)}} \end{aligned} \tag{C.23}$$

$$\frac{\partial L_n}{\partial A_s} = c_1 \frac{\gamma_r}{(\gamma_r-\gamma_s)(1-\alpha_n)} \left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{(\gamma_r-\gamma_s)(1-\alpha_n)}-1} \frac{\Psi_s}{p_s}(-1)A_s^{-2} \tag{C.24}$$

Then

$$\frac{\partial L_n}{\partial A_s} \begin{cases} > 0 & \text{if} \ \ \gamma_s > \gamma_r \\ < 0 & \text{if} \ \ \gamma_s < \gamma_r \end{cases} \tag{C.25}$$

Therefore, if the heat-resistant sector is more land intensive than the heat-sensitive sector $\gamma_s < \gamma_r$, a decrease in the productivity of the latter leads to an increase in the allocation of labor in the non-agricultural sector.

Prediction (vi): A reduction in the agricultural heat-sensitive productivity A_s, reduces the labor intensity in agriculture as a whole.

Proof: As land supply in agriculture is fixed (non-agriculture do not use land), a reduction in $L_s + L_r$ implies a reduction in $(L_s + L_r)/T_a$. (See proof of predictions (ii) and (iii))