Climate Change Response: Input Adjustment in Agriculture*

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Abstract

Can farmers mitigate the impact of climate change? Using medium-term fluctuations of temperature and precipitation in Chile, this research tests the hypothesis of factor adjustment as a mechanism to attenuate the effects of extreme heat. I find that extreme heat leads to reallocation of land from fruit to forestry and primary activities. This readjustment leads to a reduction in labor and physical capital allocation in agriculture but also increases labor productivity and aggregate agricultural output. I conclude that this result is due to fruit sector is more labor-intensive than forestry and primary sectors, thus a reduction of this subsector drives away labor from the agriculture, but also leads to reallocation gains sufficiently high to compensate the direct losses due to extreme heat. These findings are consistent with farmers using input adjustments as a medium-term mechanism to attenuate the effects of extreme heat and highlight that accounting for land reallocation is essential to quantify the mitigation of the damages associated with climate change.

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 and changing precipitation patterns (Collins et al. 2013; Hartmann et al. 2013; Wuebbles et al. 2017; IPCC 2014). Literature suggests significant losses of agricultural productivity in this process (Dell, Jones and Olken 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).[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; Meyers and Rhode 2020) but also adjusting input allocation in agriculture (Aragon, Oteiza and Rud 2020), reallocating factors from agriculture to other productive sectors (Jessoe, Manning and Taylor 2018; Colmer 2020) or migrating to less temperature-sensitive regions (Cattaneo and Peri 2016; Feng, Oppenheimer and Schlenker 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 agents adaptation within agriculture and a limited reallocation of factors through sectors and space.

In particular, farmers may respond to temperature changes by adjusting their land use, labor and physical capital to maximize profit. In the absence of frictions, 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.[2] These adjustments could lead to reallocation gains, which may substantially reduce the direct losses from climate change in the long-run. Nevertheless, if 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.

In contrast to most the previous research, which focuses on outcomes that already include farmer responses such as crop yields or profits, this study focuses on the reallocation of inputs within agriculture and also in the productive responses of agriculture as a whole. In particular, this research studies if farmers respond to weather

[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] Under the assumption of pareto-efficient equilibrium.

shocks or climate change[3] by adjusting its land use, hired labor and physical capital, and if these factors reallocate across agricultural subsectors or leave agriculture. Furthermore, I test whether adaptative responses reduce the effect of extreme heat on agricultural output.

For this purpose, I combine the agricultural census with weather data in Chile, a country where 14.36% of its total GDP comes from agriculture or forestry,[4] and compute the elasticity of input use 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.

To assess the factors reallocation importance as an adaptation mechanism, I build a simple model of three sectors and two inputs to illustrate the effects of a shift in productivity caused by climate change. In this model, the agricultural sector has two subsectors: heat-sensitive (e.g., fruit) and heat-resistant (e.g., forestry),[5] both use land and labor, and the 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 intensive than heat-resistant sector, workers leave agriculture.[6] These adjustments result in reallocation gains that counteract direct losses due to extreme heat, which under

[3]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, Hsiang and Miguel 2015; Schlenker and Lobell 2010; Hsiang 2016; Dell, Jones, and Olken 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, Hsiang and Miguel 2015). This suggests that climate need not have a fundamental timescale and econometricians might study periods of varying lengths of time (Hsiang 2016).

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

[5]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. 2002).

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

certain conditions, could lead to a positive impact on aggregate sales.

My empirical findings provide direct evidence of adaptation in the agricultural sector. I find that municipalities facing an increase in extreme heat reallocated the land use from fruit, to forestry and primary activities. Additionally, I document that extreme heat reduced the total hired labor and physical capital allocation in agriculture. These adjustments led to a slight speed-up in its aggregated agricultural output growth[7] and output per worker. Overall, these findings suggest that farmers may substantially reduce the negative effects of extreme heat on output reallocating the land use, but also this adjustment may reduce employment in agriculture.

In addition, I provide an array of robustness exercises and tests of the validity of my empirical strategy. The results are very similar when I change controls, add agro-climatic zone fixed-effects, use spatially correlated errors, use different weights schemes and use alternative thresholds to define the treatment variables.

This work contributes to the climate change adaptation literature and documents a novel case where reallocation gains are slightly higher than the direct losses from extreme heat. Understanding the underlying mechanisms of these results can be increasingly important in a context where global temperatures are expected to rise substantially in the following decades, especially in developing countries located in low latitudes which will experience rises in temperature earlier (Harrington et al. 2016), and where agriculture is a large portion of the GDP.

The rest of the paper proceeds as follows: Section 2 expose the literature review. Section 3 describes the theoretical framework. Section 4 describes the data. Section 5 presents and discusses the econometric specification of the relationship between extreme heat and input adjustment. Section 6 shows the main results. Section 7 shows a set of robustness checks. Finally, Section 8 concludes. Further robustness checks and proofs are given in the Appendix.

2 Related Literature

This research contributes to three strands of the economics literature: the literature about climate change impact on crops and other output measures, the literature on adaptation to climate change, and the literature on the impact of agricultural technical changes.

There is an extensive body of research which documents that climate change has a negative impact on several economic outcomes. In a novel work, Schlenker and Roberts

[7] Hereafter, I refer as output to the value of the production or sales (i.e., $p_a Q_a$).

(2009) examine a panel model which allows for non-linearities of U.S. agricultural yields using daily temperature data. They find a threshold in output effects starting between 29–32°C, depending on the crop, with temperature being moderately beneficial at temperatures lower than the threshold and sharply harmful above the threshold. In the same line, Guiteras (2009) and Feng, Krueger, and Oppenheimer (2010) show that higher temperatures in a given year reduce agricultural output in India and Mexico, respectively. Moreover, going beyond the subnational level, Schlenker and Lobell (2010) find robust negative impacts of climate change on yields in African countries, and Dell et al. (2012), Hsiang, Burke, and Miguel (2015) and Burke and Tanutama (2019) find negative impacts of temperature in economic growth rates for different panels of countries.[8]

Overall, these studies document that temperature, precipitation, and extreme weather events exert economically meaningful and statistically significant influences on a variety of economic outcomes. Nevertheless, they have little to say about how to deal with climate change in the coming decades. Motivated by this, more recent studies have developed different approaches to test the existence of mitigation responses and their effects.

On the one hand, the influential work of Burke and Emerick (2016) use U.S. yield data to compare estimates of the long run weather–yield relationships through a long differences approach, to estimates based on year-to-year fluctuations with a fixed-effects model. The authors find that the coefficient on temperature trends is statistically the same as on year-to-year fluctuations, interpreting this finding as suggestive evidence of limited long-term adaptation to higher temperatures. Similarly, Taraz (2018) compares crop yields of districts that experience high temperatures more or less frequently to test adaptation. She finds that adaptation appears to be modestly effective only for moderate levels of heat, while extremely high temperatures do grave damage to crops, even in places that experience these extreme temperatures regularly.

On the other hand, some studies test specific mechanisms to deal with extreme heat. In particular, Meyers and Rhode (2020) find evidence of the adoption of hybrid corn seed, a heat-resistant variety, mediated the adverse effects of extreme heat in Iowa, and Meyer and Keiser (2018) document that the adoption of tile drainage may reduce the impact of climate change. Moreover, some studies suggest that a possible response to climate change would be the economic activity reallocation in the form of change in

[8]Despite, Dell et al. (2012) document that annual economic growth rates in poor countries are negatively correlated with annual variations, but no statistically significant correlation appears to exist for richer countries, Hsiang, Burke, and Miguel (2015) and Burke and Tanutama (2019) show that independently of the wealth of the country, workers and crops exhibit highly non-linear responses to temperature.

sectoral employment shares (Jessoe et al. 2018; Colmer, 2020; Liu et al. 2020). For example, Colmer (2020) shows that temperature-driven reductions in the demand for agricultural labor are associated with an increase in manufacturing and services employment shares, benefits which appear to be attenuated by direct adverse effects of temperature on manufacturing activity.[9] Taking a slightly different approach, Aragon et al. (2020) test the hypothesis of input adjustments as a short-term mechanism to attenuate the effect of extreme heat on output. They find that extreme heat reduces agricultural productivity, induces farmers to increase the land use and to change their crop mix during the agricultural season, and a slight tendency to use more intensively domestic and child labor.

Other authors have argued that over the longer run, migration might be an important channel through which people respond. In particular, Feng, Krueger, and Oppenheimer (2010), Cattaneo and Peri (2016) and Feng, Oppenheimer, and Schlenker (2015) document an increase of out-migration as a response to temperatures and precipitation shocks, results that are driven by a change in agricultural productivity rather than direct preference for climate. However, the net impact on welfare of this response is not clear.

Finally, this paper also relates to the rising empirical studies on the impact of agricultural technical change. In a novel work, Foster and Rozenweig (2004, 2008) study the effects of the adoption of high-yielding-varieties (HYV) for some cereals during the Green Revolution in India. They find that villages with larger improvements in crop yields experienced lower manufacturing growth. In this line, Bustos, Caprettini and Ponticelli (2016) provided evidence of the impact on labor and land reallocation of a labor-augmenting technical change as the engineered soybean seed adoption, and a land-augmenting technical change as the introduction of a second harvesting season for maize. Their estimates document that a soy technical change caused the expansion in the share of agricultural area planted with genetically engineered soy, while a maize technical change had a positive effect on the area planted with maize. Additionally, they show that when technical change in agriculture is strongly labor-saving, as in the case of genetically engineered soy, it can foster industrialization, instead, when technical change

[9] There is also evidence about the opposite effect of temperature on labor reallocation in India. Using a panel data between 1961 and 2011, Liu et al. (2020) find that rising temperatures are associated with higher shares of workers in agriculture, lower rates of urbanization, and lower shares of workers in non-agriculture, effects which are concentrated in districts with sparse road infrastructure networks, suggesting that higher temperatures exacerbate liquidity constraints faced by rural, isolated households, and subsequently limit rural-urban and sectoral mobility. The conflicting results between these papers might be due to labor markets are likely to be more integrated in the most recent decades than in the second half of twenty century.

is land-augmenting, as in the case of the production of a second harvesting season in maize, agricultural productivity growth can retard industrialization.

3 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 models in Bustos et al. (2016) and Bustos et al. (2020), 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,[10] 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.

3.1 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:

$$\begin{aligned} q_s &= A_s T_s^{\gamma_s} L_s^{1-\gamma_s} \\ q_r &= A_r T_r^{\gamma_r} L_r^{1-\gamma_r} \end{aligned} \tag{3.1}$$

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.

[10] In Ponce, Blanco and Giupponi (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) while forestry is not sensitive to extreme heat unless wildfires or outbreaks of insects and pathogens (Kirilenko and Sedjo 2007; Nabuurs et al. 2002).

On the other hand, the non-agricultural sector only uses labor:[11]

$$Q_n = A_n L_n^{\alpha_n} \tag{3.2}$$

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:

$$\begin{aligned} T_s + T_r &= T \\ L_s + L_r + L_n &= L \end{aligned} \tag{3.3}$$

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 $L_s + L_r \equiv L_a$.

3.2 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:

$$p_s MPT_s = p_r MPT_r = w_T \tag{3.4}$$

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

$$p_s MPL_s = p_r MPL_n = p_n MPL_n = w_L \tag{3.5}$$

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 $\{p_s, p_r, p_n\}$.

[11] 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):

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

3.3 Predictions

If all three sectors are active, the effect of a reduction in the productivity of heat-sensitive sector $dA_s < 0$[12] 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 B

These predictions are due to extreme heat reduces, unambiguously, the marginal product of land and labor in the heat-sensitive sector.[13] 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 B

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

[12] 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.

[13] 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).

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 $dq_r^* > 0$.

Due to in the empirical analysis I do not observe each sector's output, q_s and q_r, but rather its "sales", the adjustments showed above imply that:

$$\frac{\partial log(Y_a)}{\partial A_s} = \underbrace{\eta_s \frac{\partial log(Y_s)}{\partial A_s}}_{\text{direct losses}} + \underbrace{\eta_r \frac{\partial log(Y_r)}{\partial A_s}}_{\text{reallocation gains}}$$

where $Y_s \equiv p_s q_s$, $Y_r \equiv p_r q_r$ are the sales by agricultural subsector, $Y_a \equiv Y_s + Y_r$ the aggregate agricultural sales, and $\eta_s = \frac{p_s q_s}{p_s q_s + p_r q_r}$ and $\eta_r = \frac{p_r q_r}{p_s q_s + p_r q_r}$ the sales shares.

Then, as a result of this setting, it is crucial to understand how a decrease in the productivity of the heat-sensitive sector may impact the aggregate sales. I summarize this framework with the following theorem.

Theorem 1: *A decrease in the heat-sensitive productivity leads to an increase in aggregate sales, provided that:*

1. The increase in output of the resistant sector is large enough to compensate the decrease in the output of the sensitive sector.

2. Prices of the sensitive sector are not sufficiently high relative to the resistant sector to absorb this effect.

Proof: See Appendix B

This is due to prices could amplify or reduce the effect of the changes in output depending on its relative size. In particular, if the changes in output are exactly compensated $-\frac{\partial q_s^*}{\partial A_s} = \frac{\partial q_r^*}{\partial A_s}$, the net effect on sales depends on the international prices. Then, if $p_s < p_r$ the shock implies an increase in aggregate sales. On the contrary, if $p_s > p_r$ implies a reduction.

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.

4 Data and Summary Statistics

4.1 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.[14] 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.[15] 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, Gallego and González (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[16]). 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, I obtain measures of temperature from University of Berkeley dataset, which includes information of daily average, maximum and minimum temperature on a grid of 1×1 degree, and precipitation from University of Delaware database (Willmott, Matsuura and Legates 2010) which provides monthly estimates on a 0.5×0.5 degree scale. Due to this research aims to study the impact of climate on agriculture, I collapse these gridded data at municipality level weighting by crops presence.[17]

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

In the climatic databases, as in the *CASEN* survey, there are 343 modern municipalities, which are collapsed to the 264 pristine municipalities, those that appear

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

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

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

[17]See Appendix A.2 for a detailed description of weather variables.

in the old agricultural censuses and later were subdivided.[18] Due to five municipalities have missing in weather, agricultural, or development variables, the final sample is 259. I use pristine municipalities (just municipalities hereafter) as an approximation of the local market. They can be thought of as small open economies that trade in agricultural goods.

4.2 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.[19]

Panel A presents summmary statistics for weather data. Heat refers to the yearly average maximum temperature over the growing season, while 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 research.[20] Furthermore, Table A.1 shows the correlation among maximum, minimum and average temperature, and precipitation in 1997 and 2007. See Appendix A 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.[21] In the baseline year, fruit crops represented the 12% of the total planted land, whereas primary and forestry the 41.5% and 49%, respectively. In average, the fruit share increased 5 percentage points which is equivalently to 527 hectares, whereas primary share decreased 15 percentage points and forestry increase 9 percentage points.

Additionally, Figure 1 presents the geographical distribution of changes of the main variables. Panel A shows for each agro-climatic zone the change in the number of harmful degree-days HDD, Panel B the change in precipitation in mm and Panel C the change of agricultural workers in percentage.

[18] 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.

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

[20] See for instance Burke and Emerick (2016); Feng, Oppenheimer and Schlenker (2019); Aragon et al. (2020); Colmer (2020) and Meyers and Rhode (2020).

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

Finally, Figure A.2 shows variables histograms, Figure A.3 the basic correlations in the data and Figure A.4 the annual average precipitation time series.

4.3 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 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

$$L_{a;m} = \delta + \omega_{fru} T_{fru;m} + \omega_{pri} T_{pri;m} + \omega_{for} T_{for;m} + \zeta_m \tag{4.1}$$

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 $i = \{\textit{fruit, primary, forestry}\}$. 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: $\frac{K_{for}}{T_{for}} < \frac{K_{fru}}{T_{fru}} < \frac{K_{pri}}{T_{pri}}$. 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).[22]

[22] 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, Lee and Hsu 2011).

Note that 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.

With these results in mind, the following section quantifies the productive responses to extreme heat of the different subsectors, which, as mentioned in Section 3, depends substantially on factor intensity of the damaged sector.

5 Empirics

The objective of the empirical exercise is to estimate the response of the agricultural sector to climate change. I start describing the existing approaches measuring the climate change impact in Section 5.1. Then, in Section 5.2 I describe my identification strategy to measure the causal impact of climate change on input adjustment. Finally, in Section 5.3 I discuss additional concerns of the empirical approach.

5.1 Existing Approaches

The early literature of 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, Nordhaus, and Shaw (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; Dell et al. 2012). 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^{o}C and 40mm wide, respectively. See Deschênes and Greenstone 2011; Deryugina and Hsiang 2017; Baysan et al. 2019; Aragon et al. 2020). 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.[23]

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 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.[24] I proceed to discuss this method below.

5.2 Identification Strategy

There are two advantages to use 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.[25] Second, is immune to time-invariant omitted variables, which cross-sectional methods are plagued.

Therefore, 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:

$$y_{m,t} = \phi_t + \lambda_m + \mathbf{Z}_{m,t}\boldsymbol{\beta} + \varepsilon_{m,t} \text{ for } t = \{1997, 2007\} \tag{5.1}$$

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

[24]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).

[25]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).

where $y_{m,t}$ is some outcome of interest in municipality m at year t, ϕ_t are time-variant factors common through all municipalities i.e. aggregated shocks, λ_m are time-invariant factors for each municipality, $\mathbf{Z}_{m,t}$ is a row vector of time-variant weather treatment variables defined below and $\varepsilon_{m,t}$ is an idiosyncratic error term of time-variant ommited 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:

$$y_{m,t} = \phi_t + \lambda_m + \mathbf{Z}_{m,t}\boldsymbol{\beta} + \varepsilon_{m,t} \tag{5.2}$$

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 and should better approximate the true effect of climate change than a cross-section approach 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 (5.1)[26]

$$y_{m,2007} - y_{m,1997} = (\phi_{2007} - \phi_{1997}) + (\lambda_m - \lambda_m) + (\mathbf{Z}_{m,2007} - \mathbf{Z}_{m,1997})\boldsymbol{\beta} + (\varepsilon_{m,2007} - \varepsilon_{m,1997})$$

the time fixed-effects collapse to a constant α, the time-invariant factors drop out and using $\mathbf{Z}_{m,t} = [f(H_{m,t}) \quad g(P_{m,t})]$, I can rewrite (5.2) as a long-difference equation

$$\triangle y_m = \alpha + [\triangle f(H_m) \quad \triangle g(P_m)]\ \boldsymbol{\beta} + \xi_m \tag{5.3}$$

where $\triangle y_m$ 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. To deal with non-linearities in the effect of weather variables,[27] I use growing degree-days with an upper threshold, which 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 average climate over time, I use weather variables as a three-years average.[29]

[26]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, M. (2008) for the proof.

[27]See Burke, Hsiang and Miguel (2015) for a discussion about non-linear effects of climate variables.

[28]See Appendix A.1 for the formal definition of growing season degree-days. Figure A.1 graphically shows the construction of this variable.

[29]This is $\triangle z_m = z_{m,2007} - z_{m,1997}$ where $z_{m,1997} = \sum_{t=1995}^{1997} \frac{z_{m,t}}{3}$ and $z_{m,2007} = \sum_{t=2005}^{2007} \frac{z_{m,t}}{3}$.

Therefore, I can rewrite the equation (5.3) in the way of Burke and Emerick (2016)

$$\triangle y_m = \alpha + \beta_1 \triangle HDD_{m;\ \ell_1:\infty} + \beta_2 \triangle GDD_{m;\ \ell_0:\ell_1} + \beta_3 \triangle P_m + \beta_4 \triangle P_m^2 + \mathbf{X}_{m1965/96}\, \boldsymbol{\psi} + \xi_m \tag{5.4}$$

where $GDD_{m;\ \ell_0:\ell_1}$ is the sum over the growing season of degree-days between the temperature bounds ℓ_0 and ℓ_1, and $HDD_{m;\ \ell_1:\infty}$ 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 and the number of agricultural machinery (e.g., tractors, plows and harvesters).[30] This vector should not include time-varying controls if 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 precision of the estimates 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. 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.[31]

A key issue is to define the value of the upper threshold ℓ_1. Previous studies in U.S. set this value between 28-32^{o}C (Deschênes and Greenstone 2007; Schlenker and Roberts 2009, Burke and Emerick 2016, Colmer 2020). Nevertheless, these estimates are likely

[30]The inclusion of baseline controls in equation (5.3), is identical to the inclusion of baseline controls in the equation (5.2) interacted with a linear time trend: $y_{m,t} = \phi_t + \lambda_m + \mathbf{Z}_{m,t}\boldsymbol{\beta} + (\mathbf{X}_{m1965/96} \times t)\ \boldsymbol{\psi} + \varepsilon_{m,t}$

[31]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's (1999) method.

to be crop and context dependent and hence might not be transferable to this case. For this reason, I prefer to use a threshold according to the literature, and then show the robustness of the main results looping over all possible thresholds ℓ_1.[32]

5.3 Additional Concerns

The identifying assumption in equation (5.4) relies on that temperature and precipitation trends at the municipality level are uncorrelated with other factors that affect trends in agricultural inputs, once baseline controls are accounted for. A first, 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 in a change in the temperature, which leads to a change in the productivity of land). 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.

Furthermore, 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 with more precipitation and higher temperatures and *La Niña*, which relates with 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,[33] the trends in temperature and precipitation in Chile appear to represent a true natural experiment.

Another concern is that 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 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 number of years on the average to construct the treatment variables.

Moreover, Chile is a country with a considerable variation in geographical qualities from north to south. The omission of geographic variables could bias the estimates even after accounting for the economic controls if these relates with the trends in climate variables and the outcome. In Section 7, I address this concern controlling for agro-climatic zone fixed effects.

[32] In Section 7 I show the results under different thresholds.

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

Finally, climate measures introduce large measurement errors because of the interpolation through climate stations. Even if the measurement erros 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).[34] 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.

6 Results

The first part of the analysis focuses on the effect of medium-run changes in the climate on each agricultural sector. In Section 6.1, 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 Section 6.2 I document that these land adjustments led to a reduction of the output of fruit subsector in absolute and relative terms, and a slight increase in the output of primary and forestry sectors.

The second part of the analysis examines agriculture as a whole. In Section 6.3, I document that the aggregate land use remains unchanged, whereas there were outflows of workers and physical capital from agriculture. Finally, in Section 6.4 I document a slight positive net-of-adaptation effect on aggregate agricultural output and labor productivity.

6.1 Effects on Land Use by Sector

As discussed in Section 3, 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 shown in Table 3 go in this direction.

The first two columns show the impact of climate variables on fruit land share. In the most conservative specification, municipalities with an increase of one harmful degree-day experienced a decrease of 0.4 percentage points in the fruit land share (3.3 percent of their initial share, around to 67.5 hectares in average[35]). The point estimate remains stable when controlling for initial municipality characteristics, which suggests that the estimates are not capturing differential growth trends across municipalities.[36]

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

[35] Taking an initial fruit land share of 12.3%, the reduction is given by $\frac{(0.123-0.004)-0.123}{0.123} = -0.033$

[36] To address the concern about the non-significance of controls jointly, in Section 7 I add the initial agro-climatic zone fixed-effects, which leads to a joint significance with p-value less than 5% and keeps

In addition, columns (4) and (6) show that extreme heat increased the land share of primary and forestry subsectors 0.2 percentage points each. Despite their point estimate is non-significant, if they would be put together as a "non-fruit" category, they would increase 4 percentage points (significant at 1%), since the reduction in fruit share increases the share in the others sectors ($\triangle \frac{T_{fru}}{T_a} + \triangle \frac{T_{pri}}{T_a} + \triangle \frac{T_{for}}{T_a} = 0$).

Overall, this table suggests responses to climate change according to the predictions of the theoretical framework. There are, however, two important 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 temperature within each subsector. For example, Meyers and Rhode (2020) document that the substitution from open pollinated varieties of corn to hybrid corn seeds, led heat tolerance, or Aragon et al. (2020) show an increase in the use of tubers in response extreme heat.[37] 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.

6.2 Effects on Output by Sector

Given the evidence presented above, in Table 4 I also study the effect of extreme heat in aggregate output and output by sector.[38] Columns (1) and (2) show a slight significant increase in the aggregate output in municipalities more exposed to extreme heat. In terms of magnitude, the exposure to each additional harmful degree-day results in an increase in overall agricultural output of 0.61 percent. This strange estimates raises doubts about which sector is driving this result. Then in columns (3)-(10) I show the results at the disaggregated level.

Although the estimates at the disaggregated level are not statistically significant, the point estimate of the fruit sector is negative as expected. In contrast, the point estimates of primary and forestry are positive, with the last being substantially higher than the others. However, this coefficient is very imprecise. Hence, it is not possible to reject the null hypothesis at any standard levels of confidence, but suggests that forestry sector

the point estimate unchanged.

[37]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.

[38]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" makets), then, only quantities but not prices are a function of extreme heat (i.e., $p_a Q_a(\mathbf{Z})$).

could be the main driver of the result in the aggregate output.[39]

Moreover, columns (11) and (12) show a statistical reduction in the relative size of the fruit sector. Each additional harmful degree-day results in a decrease of 0.16 percentage points in the share of the fruit sector in agricultural output. This implies a reduction of 1.6%, considering an initial output share of 10%.

Taken together, the estimates presented in Table 3 and Table 4, show that the fruit sector experienced not only a reduction in the land share but also a reduction in its relative size in output terms.

6.3 Effects on Aggregate Input Use

As discussed above, there is also relevant to study the aggregate input use adjustments in agriculture in response to extreme heat. Table 5 shows these results.

In Panel A, the columns (1) and (2) show the effect on workers, (3) and (4) on agricultural machinery (i.e. capital), and (5) and (6) in the aggregate planted surface. In the most conservative specification, exposure to each additional harmful degree-day results in a decrease in overall hired labor of 2.44 percent, and a decrease of 2.7 percent in agricultural machinery. Both point estimates remain stable when controlling for lagged municipality characteristics, controls that have a joint significance with a p-value less than 1% in all the models. Furthermore, the estimates reported in columns (5) and (6) show that the aggregate supply of land do not change (i.e, there is not a reduction of the agricultural frontier) which is consistent with a fixed land endowment in the economy.

Next, Panel B shows the change in the relative use of factors. The first two columns show a significant reduction in the labor intensity in municipalities with a larger exposure to extreme heat, and columns (5) and (6) shows a significant reduction in the capital intensity. In contrast, columns (3) and (4) shows that the relative use of capital and labor remain unchanged.

To interpret these findings, I turn to the theoretical framework discussed in Section 3. The model shows that a negative shock in the heat-sensitive sector decreases labor demand, thus labor reallocates away from this sector. Then, the ability of the agricultural 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 4, I provided evidence that the fruit sector is more labor intensive than the primary and forestry sectors. These insights together imply that labor release by the fruit sector will not be absorbed for the primary or forestry sectors. Complementing this, if workers are

[39]Biological litertature show that the forestry sector is resistant to extreme heat unless wildfires or outbreaks of insects and pathogens (Kirilenko and Sedjo 2007; Nabuurs et al. 2002).

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]

However, in the case of the capital, the argument is a little bit more nuanced, since fruit sector is not the most capital intensive. This reduction can be explained from a decrease in the use of capital in the fruit activities, but also from substitution within the primary sector from high capital intensive to low capital intensive crops or varieties. Nevertheless, the data do not allow me to test this hypothesis directly.

6.4 Effects on Aggregate Output and Input Productivity

Finally, to analyze the net-of-adaptation impact of extreme heat, I estimate the main specification (5.4) using aggregate output, output per worker, and yields (i.e., output per hectare) as outcomes. Table 6 shows the results.

Columns (1) and (2) show a slight but significant increase in the aggregate sales in municipalities more exposed to extreme heat of 0.61 percent per each degree-day above 26^{o}C. Despite this effect is small, it suggests that the reallocation gains are higher than the direct losses from extreme heat. As exposed in Section 3, this particular case requires two conditions described by the Theorem 1: The increase in the output of primary and forestry sectors should be large enough to compensate the decrease in the output of the fruit sector, and prices of the fruit sector should not be sufficiently high relative to the prices of primary and forestry sectors to absorb this effect.

Since each agricultural subsector is an aggregate, I cannot explore the changes in quantities or prices separately. Nevertheless, alternative explanations to these results could be thinking that extreme heat generates a positive effect on the plants by itself, which may be substantially less trustworthy considering the bast literature that documents the negative impact.

Next, in columns (3)-(6) I present the results of the measures of input productivity. Columns (3) and (4) show that municipalities more exposed to extreme heat experienced a larger increase in the labor productivity, while columns (5) and (6) show a non-significant effect on aggregated yield.[41]

The results presented above should be interpreted with caution. They do not suggest that climate change leads to an increase in agricultural output and productivity by itself.

[40] See predictions (v) and (vi) of Section 3.

[41] Using crop yields and output per worker as productivity measures may be less informative in contexts in which farmers respond to weather shocks by changing land and labor use, but do not require the assumption of a production function form. A limitation of this approach is that yields are a measure of partial productivity that reflect changes in TFP and land use.

In contrast, they support the hypothesis of an increase in aggregate agricultural output and labor productivity caused by adaptation responses, such as land reallocation across sectors and its consequent impact on the agricultural output composition. In particular, the increase in labor productivity is not due to each worker has become more productive, but because there was a reduction of the labor intensive sector, so there were outflows of workers from the agriculture.[42]

In sum, these findings suggest that responses such as adjustment within the agricultural subsectors and changes in input allocation in the agricultural sector as whole, have the capability to attenuate the negative effect of extreme heat on output.

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 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:

$$\begin{aligned} \triangle y_m = \rho\ y_{m1997} + \alpha + \beta_1\ \triangle HDD_{m;\ \ell_1:\infty} + \beta_2\ \triangle GDD_{m;\ \ell_0:\ell_1} \\ +\beta_3\ \triangle P_m + \beta_4\ \triangle P_m^2 + \mathbf{X}_{m1965/96}\ \boldsymbol{\psi} + \xi_m \end{aligned} \tag{7.1}$$

where all the variables remain the same as in the main equation (5.4) and y_{m1997} is the initial level of the outcome. In Table 7 I report the main results controlling for this variable. The estimated effects of extreme heat in the fruit share, labor, capital, output and output per worker remain significant and unchanged, and in the case of column (5) the estimates improves its significance to 1%. The estimates of land use and yield (i.e., output per hactare) remain non-significant. Finally, note that the inclusion of this variable as a control improves the joint significance of controls.

[42] In terms of the theoretical framework, the sales per worker are defined as $\frac{Y_a}{L_a} = \frac{Y_s}{L_s}\frac{L_s}{L_a} + \frac{Y_r}{L_r}\frac{L_r}{L_a}$, then if the heat-resistant sector is less labor intensive $\frac{T_r}{L_r} > \frac{T_s}{L_s}$, and due to zero profit conditions imply that $\frac{Y_i}{L_i} = w_T\frac{T_i}{L_i} + w_L$ for $i = \{s, r\}$, the sales per worker are higher in the heat-resistant sector $\frac{Y_r}{L_r} > \frac{Y_s}{L_s}$. Therefore, land reallocation towards the heat-resistant sector increases sales per worker (Bustos et al. 2016).

7.2 Controlling for Common Trends Across Agro-climatic Zones

Since Chile is a country with a large variation in geographical qualities from north to south, a relevant concern regarding previous estimations is they would be biased in the presence of across zone time-varying unobservables correlated with both climate and input adjustment measures. A possible approach to deal with this concern is with an agro-climatic zone fixed-effect model.

Including agro-climatic fixed-effects, not only helps to address ommited variable concerns, but also can indicate what type of adaptation we are in the presence of. If the main coefficients decrease significantly in the fixed-effect estimates, this could suggest that the effects reported above come from adaptations across agro-climatic zones. In contrast, if the estimates remain unchanged, this suggest that the effects come from within-agro-climatic zone adaptation.

Normally, Chile is divided into 5 agro-climatic zones: Far North, Near North, Central Zone, Southern Zone and Austral Zone (see Figure 1).[43] I use this grouping to estimate the following fixed-effects model:

$$\begin{aligned} \triangle y_{m,\mathfrak{z}} = \mu_{\mathfrak{z}} + \beta_1 \triangle HDD_{m,\mathfrak{z};\ \ell_1:\infty} + \beta_2 \triangle GDD_{m,\mathfrak{z};\ \ell_0:\ell_1} \\ + \beta_3 \triangle P_{m,\mathfrak{z}} + \beta_4 \triangle P^2_{m,\mathfrak{z}} + \mathbf{X}_{m,\mathfrak{z}1965/96}\ \boldsymbol{\psi} + \xi_{m,\mathfrak{z}} \end{aligned} \tag{7.2}$$

where all the variables remain the same as in the main equation (5.4) and $\mu_{\mathfrak{z}}$ is a set of agro-climatic zone fixed-effects which controls for any unobserved zone-level trends. This implies that identification comes only from within-zone variation, eliminating any concerns of time-trending unobservables at the zone level. Therefore, $\boldsymbol{\beta}$ is now 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 $\mathbf{X}_{m,\mathfrak{z}1965/96}$. In Table 8, I report the main results with agro-climatic zone fixed-effects. In all models the effects of extreme heat β_1 remains with the same sign and significant after the inclusion of zone fixed-effects. Although the point estimates are slightly smaller, these estimators are not statistically different from the main ones. This suggest that the main estimates are not biased from within-zone time-varying ommited variables and also, that the effects reported in Section 6 come from within-agro-climatic zone adaptation.

The inclusion of zone-level fixed-effects as a robustness exercise 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

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

2014), which could lead to under-rejection of the null hypothesis, specially in a context with a reduced number of the sample. Nevertheless, it provides an insight about how robust are the main estimates, because an omitted relevant variable in equation (7.2) 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, an alternative method to control for climatic heterogeneity could be adding latitude and longitude as controls to the main equation (5.4). In Table A.2, I show these results. Comparing both methods provides evidence of the fixed-effects approach being more challenging.

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 Collela et al. (2019)'s program which builds arbitrary clusters within a given distance. Table 9 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.[44] 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.

7.4 Sensitivity to Upper Threshold and Number of Year Average Election

In Section 5 I defined the harmful degree-days as those above a threshold ℓ_1, and established the number of years used to calculate the average in the case of weather variables. These decisions, however, may be key in the results presented above.

In Figure 2 I show the sensitivity of the main results to the upper threshold ℓ_1 election. Each dot shows the point estimate of the coefficient of HDD obtained in the estimate of equation (5.4) with a different ℓ_1 ranging from 24 to 30, and the red dot indicates the main estimation presented in Tables 3, 5 and 6 (i.e., $\ell_1 = 26$). Higher thresholds increase

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

the magnitude of the estimates but reduce their precision due to a reduction in the *"take up"* of the treatment.[45]

On the other hand, in Figure 3 I show the sensitivity of the results to the election of the number of years average in the climatic variables. Estimates using a three-year average (in red) do not lead to statistically different results from estimates that use a 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. 2020) 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.3, I provide additional robustness checks such as alternative weight schemes and dropping outliers in aggregate output.

8 Final Remarks

This paper provides empirical evidence of an unexplored adaptation mechanism, such as land reallocation across agricultural sectors. Using medium-term variation in temperature and precipitation in Chile, I find that farmers change land use, hired labor, and capital to attenuate the effects of extreme heat. These adjustments, drive to reallocation in the land use from the most sensitive sectors to the more resistant. Overall, this response mitigates extreme heat on output 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 individuals and firms make their own decisions in response to climate change, and without the need for coordination, reallocation gains can lead to substantial mitigation of damage.

However, this mechanism may not operate in the future if climate change exacerbate frictions to the reallocations of factors (Liu et al. 2020). In that case, the policy design

[45] If ℓ_1 increases, each municipality suffer less harmful degree-days, but each harmful degree-day is more intense, then, in the extensive margin, fewer municipalities are treated.

[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.

should go in the direction to remove these frictions.

Finally, it is crucial to acknowledge that there are several unsolved issues. First, the reallocation of land presented above does say nothing about if reallocation of workers exists, which raises doubts about the net impact of these findings in the overall economy and welfare. 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 distributions, although climate change may influence other climatic factors such as drought, wildfires 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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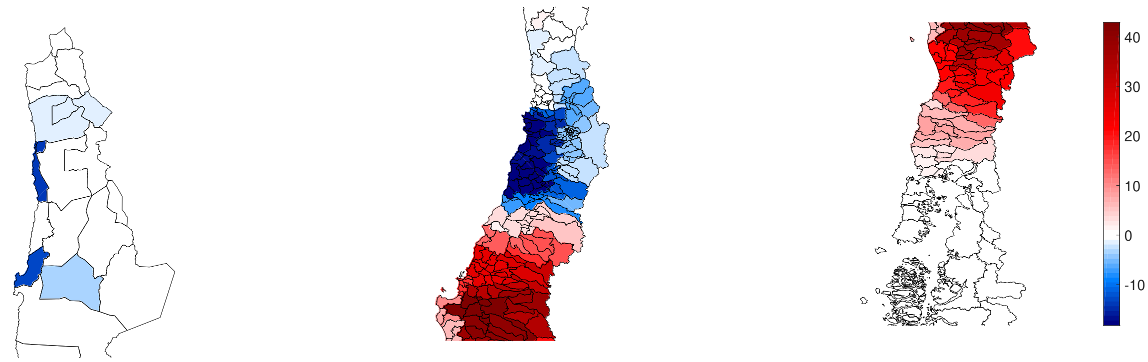
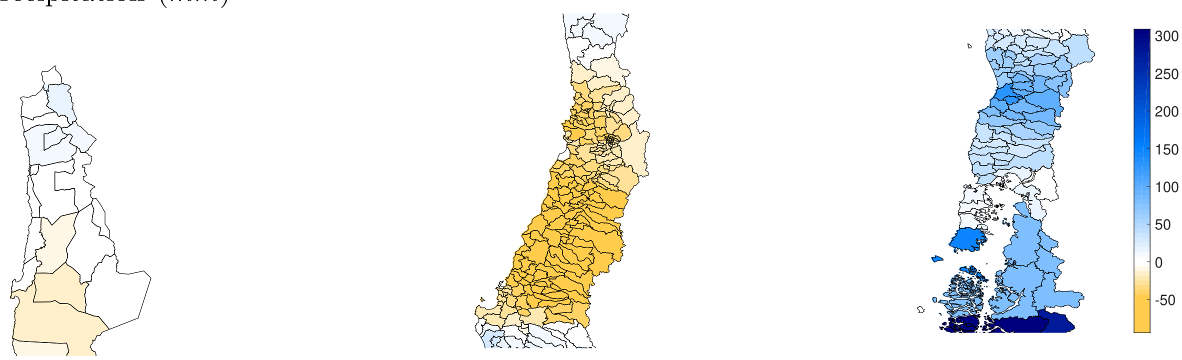
Figure 1: Spatial Distribution of Changes

Panel A. Harmful degree-days

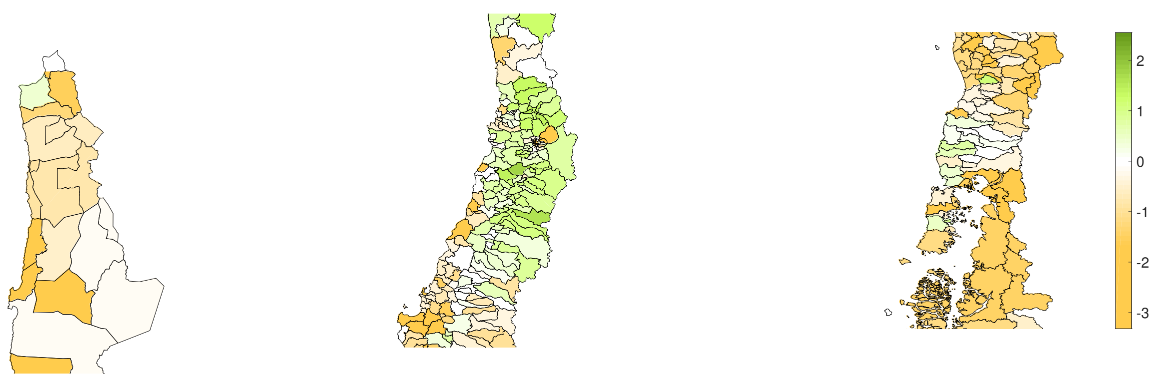
Norther Zone | Central Zone | Southern Zone



Panel B. Precipitation (mm)

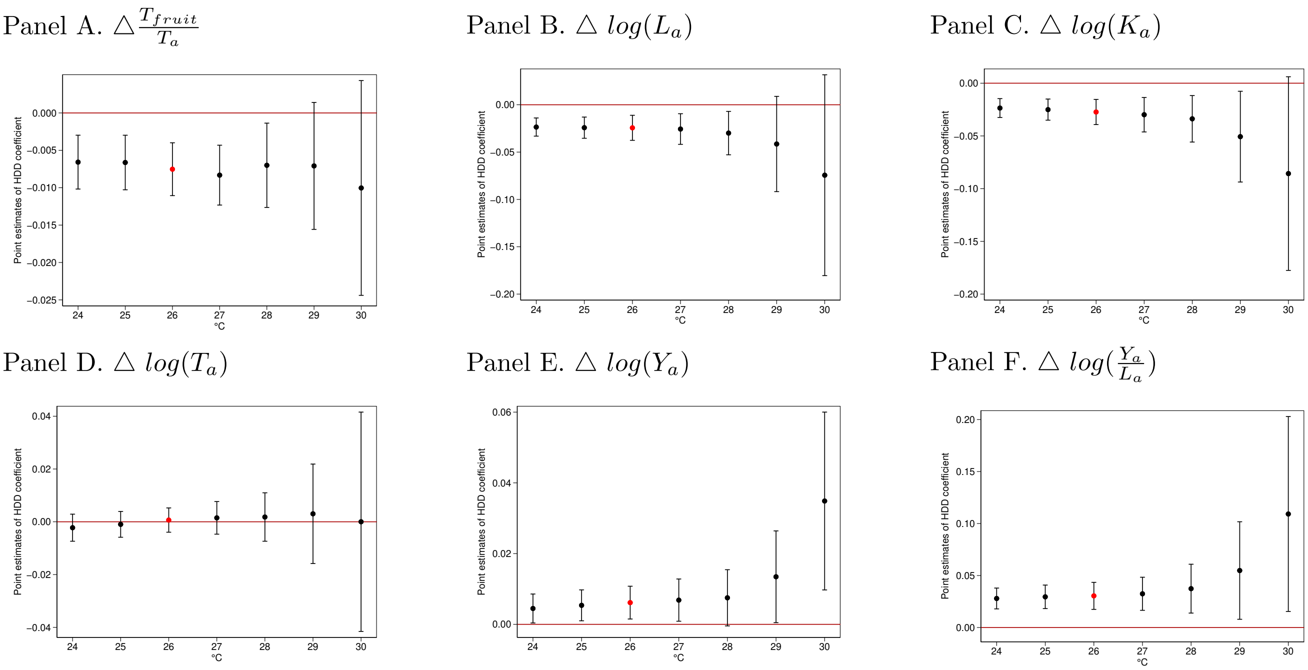


Panel C. Agricultural workers



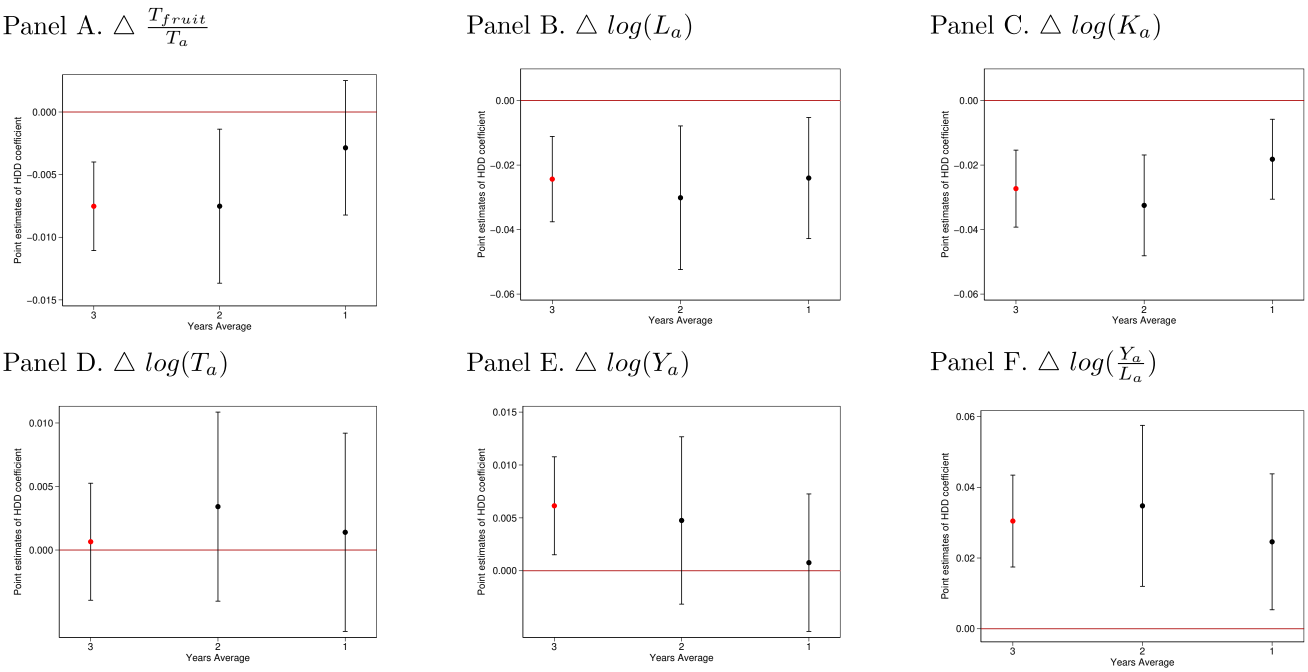
Notes: Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997 in levels in Panels A and B, and in logs in Panel C. Harmful degree-days are computed over the growing season, as a three-year average and using maximum temperature with a threshold of $\ell_0 = 0$ and $\ell_1 = 26$.

Figure 2: Sensitivity of Results to Upper Threshold Election



Notes: This figure shows the sensitivity of the coefficient of HDD to the election of the upper threshold ℓ_1. In each Panel, the red dot is the point estimate of HDD of the main specification using $\ell_1 = 26$ (e.g., in Panel A, the red dot shows the point estimate of column (2) in Table 3). Harmful degree-days are computed over the growing season and using maximum temperature with a threshold of $\ell_0 = 0$ and $\ell_1 = 26$. Whiskers are 95 percent confidence intervals of the point estimate. All the models include the full set of controls.

Figure 3: Sensitivity of Results to n-year Average



Notes: In each Panel, the red dot is the point estimate using three-year average (main specification), the second dot is the estimate using two-years average (i.e. $\triangle z_m = \sum_{t=2006}^{2007} \frac{z_{m,t}}{2} - \sum_{t=1996}^{1997} \frac{z_{m,t}}{2}$) and the third dot is the estimate using only 2007-1997 differences. Whiskers are 95 percent confidence intervals of the point estimate. All the models include the full set of baseline controls.

Table 1: Summary Statistics of the Sample

	1997		2007-1997		
	Mean	SD	Mean	SD	Observations
Panel A. Weather Data					
Temperature					
Heat (^{o}C)	20.69	3.16	0.07	0.127	259
$GDD_{\ell_0:\ell_1}$	4327.43	629.00	5.34	20.33	259
$HDD_{\ell_1:\infty}$	64.64	57.66	4.34	13.09	259
Average Precipitations (100mm)	3.70	2.18	-0.088	0.61	259
Panel B. Agricultural Data					
Land Use (1000 ha)					
Planted Land	25.42	26.08	-0.56	8.14	259
Fruit	2.047	1.867	0.527	1.18	259
Primary	8.18	10.48	-3.592	6.751	259
Forestry	18.188	20.97	2.498	6.403	259
Fruit Share	0.123	0.218	0.058	0.117	259
Primary Share	0.415	0.325	-0.153	0.189	259
Forestry Share	0.490	0.363	0.095	0.187	259
Log Aggregate Input Use					
Planted Land	9.10	2.19	-0.071	0.546	259
Number of Workers	8.16	0.93	-0.257	0.940	259
Number of Machinery	6.28	1.10	-0.846	0.931	259
Log Output and Productivity					
Aggregate	23.79	1.42	0.146	0.386	259
Fruit	16.75	6.35	0.127	4.763	259
Primary	20.32	2.31	-0.482	1.318	259
Forestry	19.45	7.22	1.248	4.349	259
Livestock	22.27	2.32	-1.103	2.986	259
Output per Worker	15.63	1.72	0.397	1.088	259
Output per Hectare	14.68	2.87	0.212	0.605	259

Notes: The data source is the Berkeley University and Delaware University databases in Panel A, and Agricultural Census (1997, 2007) in Panel B. 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 A.1 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	823.545***	20.874
	(164.081)	(23.412)
Primary	347.817***	80.065***
	(103.976)	(25.466)
Forestry	44.177	11.058
	(27.819)	(7.214)
Other	-98.679	17.195
	(861.088)	(215.587)
Observations	259	259
Adjusted R^2	0.572	0.561

Notes: Results come from the estimation of equation (4.1). The "*other*" category is the intercept. The unit of observation is the pristine 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: The Effect on Land Use

	$\triangle \frac{T_{fru}}{T_a}$		$\triangle \frac{T_{pri}}{T_a}$		$\triangle \frac{T_{for}}{T_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0039***	-0.0040***	0.0013	0.0020	0.0025**	0.0020
	(0.0007)	(0.0008)	(0.0013)	(0.0017)	(0.0012)	(0.0014)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0018***	-0.0016**	0.0014*	0.0027*	0.0004	-0.0013
	(0.0005)	(0.0007)	(0.0008)	(0.0014)	(0.0008)	(0.0013)
Controls	No	Yes	No	Yes	No	Yes
p-value Controls		0.059		0.008		0.024
Observations	259	259	259	259	259	259
Adjusted R^2	0.410	0.422	0.286	0.329	0.320	0.391

Notes: $T_a = T_{fru} + T_{pri} + T_{for}$. The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include precipitation, its square and constant. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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: The Effect on Agricultural Output by Sector

	$\triangle\ log(Y_a)$		$\triangle\ log(Y_{fru})$		$\triangle\ log(Y_{pri})$		$\triangle log(Y_{for})$		$\triangle\ log(Y_{livestock})$		$\triangle\ \frac{Y_{fru}}{Y_a}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\triangle HDD_{\ell_1:\infty}$	0.0097***	0.0061**	-0.0173	-0.0052	0.0204**	0.0031	-0.0038	0.0158	0.0231*	-0.0031	-0.0022***	-0.0016**
	(0.0020)	(0.0024)	(0.0338)	(0.0371)	(0.0076)	(0.0092)	(0.0264)	(0.0236)	(0.0128)	(0.0182)	(0.0005)	(0.0006)
$\triangle GDD_{\ell_0:\ell_1}$	0.0003	0.0025	-0.0426	-0.0572	-0.0118*	-0.0088	-0.0332	-0.0980*	0.0398**	0.0490**	-0.0022***	-0.0033***
	(0.0020)	(0.0030)	(0.0303)	(0.0449)	(0.0067)	(0.0072)	(0.0364)	(0.0507)	(0.0163)	(0.0233)	(0.0007)	(0.0009)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
p-value Controls		0.018		0.526		0.000		0.043		0.049		0.046
Observations	259	259	259	259	259	259	259	259	259	259	259	259
Adjusted R^2	0.091	0.104	0.019	0.076	0.033	0.109	0.270	0.377	0.083	0.146	0.223	0.253

Notes: $Y_a = Y_{fru} + Y_{pri} + Y_{for} + Y_{livestock}$. Each of the products 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). Information on prices taken from INE's wholesale prices series. Aggregate output includes forestry, fruits and other primary products such as alfalfa, rice, oats, barley, beans, corn, potatoes, beets, wheat and livestock. The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include precipitation, its square and constant. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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: The Effect on Aggregate Input Use

	Panel A: Input Use					
	$\triangle\ log(L_a)$		$\triangle\ log(K_a)$		$\triangle\ log(T_a)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0319***	-0.0244***	-0.0400***	-0.0273***	0.0048*	0.0007
	(0.0061)	(0.0067)	(0.0058)	(0.0061)	(0.0027)	(0.0023)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0065	-0.0114**	0.0009	-0.0029	-0.0043*	-0.0055
	(0.0059)	(0.0046)	(0.0055)	(0.0055)	(0.0025)	(0.0041)
Controls	No	Yes	No	Yes	No	Yes
p-value Controls		0.000		0.000		0.000
Observations	259	259	259	259	259	259
Adjusted R^2	0.288	0.483	0.293	0.715	0.357	0.424
	Panel B: Input Intensity					
	$\triangle\ log(\frac{L_a}{T_a})$		$\triangle\ log(\frac{K_a}{L_a})$		$\triangle\ log(\frac{K_a}{T_a})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0367***	-0.0250***	-0.0081	-0.0029	-0.0448***	-0.0280***
	(0.0063)	(0.0070)	(0.0052)	(0.0052)	(0.0067)	(0.0070)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0022	-0.0058	0.0074***	0.0084**	0.0052	0.0026
	(0.0075)	(0.0061)	(0.0023)	(0.0040)	(0.0073)	(0.0068)
Controls	No	Yes	No	Yes	No	Yes
p-value Controls		0.000		0.000		0.000
Observations	259	259	259	259	259	259
Adjusted R^2	0.324	0.551	0.056	0.201	0.316	0.723

Notes: The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include precipitation, its square and a constant. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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: The Effect on Aggregate Output and Input Productivity

	$\triangle\ log(Y_a)$		$\triangle\ log(\frac{Y_a}{L_a})$		$\triangle\ log(\frac{Y_a}{T_a})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	0.0097***	0.0061**	0.0416***	0.0305***	0.0049	0.0055
	(0.0020)	(0.0024)	(0.0067)	(0.0066)	(0.0035)	(0.0034)
$\triangle GDD_{\ell_0:\ell_1}$	0.0003	0.0025	0.0068	0.0138**	0.0046*	0.0080*
	(0.0020)	(0.0030)	(0.0070)	(0.0058)	(0.0026)	(0.0047)
Controls	No	Yes	No	Yes	No	Yes
p-value Controls		0.018		0.000		0.029
Observations	259	259	259	259	259	259
Adjusted R^2	0.091	0.104	0.327	0.495	0.299	0.350

Notes: $Y_a = Y_{fru} + Y_{pri} + Y_{for} + Y_{livestock}$. The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include precipitation, its square and a constant. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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 7: Robustness to Initial Dependent Variable as a Control

	$\triangle \frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0040***	-0.0245***	-0.0144***	0.0007	0.0063***	0.0315***
	(0.0009)	(0.0068)	(0.0035)	(0.0024)	(0.0023)	(0.0073)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0017**	-0.0114**	0.0015	-0.0055	0.0054	0.0184**
	(0.0008)	(0.0047)	(0.0036)	(0.0041)	(0.0042)	(0.0084)
y_{m1997}	-0.0205	-0.0195	0.5855***	-0.0031	-0.0567	-0.0834
	(0.0462)	(0.1378)	(0.0634)	(0.0349)	(0.0465)	(0.0965)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
p-value Controls	0.097	0.000	0.000	0.000	0.034	0.000
Observations	259	259	259	259	259	259
Adjusted R^2	0.420	0.481	0.808	0.421	0.115	0.497

Notes: The table shows the estimates of the following regression:

$$\triangle y_m = \rho\ y_{m1997} + \alpha + \beta_1\ \triangle HDD_{m;\ \ell_1:\infty} + \beta_2\ \triangle GDD_{m;\ \ell_0:\ell_1} + \beta_3\ \triangle P_m + \beta_4\ \triangle P_m^2 + \mathbf{X}_{m1965/96}\ \boldsymbol{\psi} + \xi_m$$

The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include precipitation, its square a constant, and the full set of baseline controls which are population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). Thresholds in GDD 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 8: Robustness to Agro-climatic Zone Fixed Effects

	$\triangle \frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0044***	-0.0239***	-0.0285***	0.0025	0.0042*	0.0281***
	(0.0008)	(0.0064)	(0.0078)	(0.0024)	(0.0021)	(0.0064)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0017**	-0.0052	0.0016	0.0009	0.0026	0.0078
	(0.0007)	(0.0070)	(0.0081)	(0.0054)	(0.0022)	(0.0070)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
p-value Controls and FE	0.027	0.000	0.000	0.000	0.000	0.000
Observations	259	259	259	259	259	259
Adjusted R^2	0.447	0.512	0.720	0.439	0.185	0.548

Notes: The table shows the estimates of the following regression:

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

The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965 and include precipitation, its square and a constant. The p-value of the controls comes from the joint significance test of all the baseline controls and the zone fixed-effects. Thresholds in GDD 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 9: Robustness to Spatial Correlation

	$\triangle \frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.00395	-0.02436	-0.02730	0.00065	0.00614	0.03050
Clusters	(0.00083)***	(0.00675)***	(0.00609)***	(0.00235)	(0.00236)**	(0.00663)***
25 *km*	[0.00077]***	[0.00631]***	[0.00541]***	[0.00295]	[0.00210]***	[0.00622]***
50 *km*	{0.00082}***	{0.00657}***	{0.00609}***	{0.00303}	{0.00195}***	{0.00659}***
100 *km*	⟨0.00079⟩***	⟨0.00524⟩***	⟨0.00660⟩***	⟨0.00214⟩	⟨0.00224⟩***	⟨0.00597⟩***
150 *km*	|0.00054|***	|0.00343|***	|0.00605|***	|0.00199|	|0.00155|***	|0.00565|***
$\triangle GDD_{\ell_0:\ell_1}$	-0.00163	-0.01138	-0.00295	-0.00553	0.00247	0.01385
Clusters	(0.00074)**	(0.00459)**	(0.00548)	(0.00411)	(0.00295)	(0.00583)**
25 *km*	[0.00060]***	[0.00405]***	[0.00472]	[0.00375]	[0.00245]	[0.00499]***
50 *km*	{0.00070}**	{0.00408}***	{0.00501}	{0.00384}	{0.00186}	{0.00465}***
100 *km*	⟨0.00068⟩**	⟨0.00477⟩**	⟨0.00397⟩	⟨0.00393⟩	⟨0.00251⟩	⟨0.00596⟩**
150 *km*	|0.00050|***	|0.00498|**	|0.00338|	|0.00372|	|0.00266|	|0.00645|**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	259	259	259	259	259	259

Notes: The unit of observation is the pristine municipality. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. All regressions are weighted by agricultural output in 1965, include a constant, precipitation, its square and the full set of baseline controls which are population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery in 1965 (in logs). Thresholds in GDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level in round parentheses and Conley standard errors within 25 km in square brackets, 50 km in curly brackets, 100 km in angle brackets and 150 km in vertical bars. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix: Empirics

A.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, Feng, Oppenheimer and Schlenker 2019, Aragon et al. 2020, Jessoe et al. 2018, Colmer 2020 and Meyers and Rhode 2020.

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

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

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

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 A.1 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 Gutierrez (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

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

When I take first differences:

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

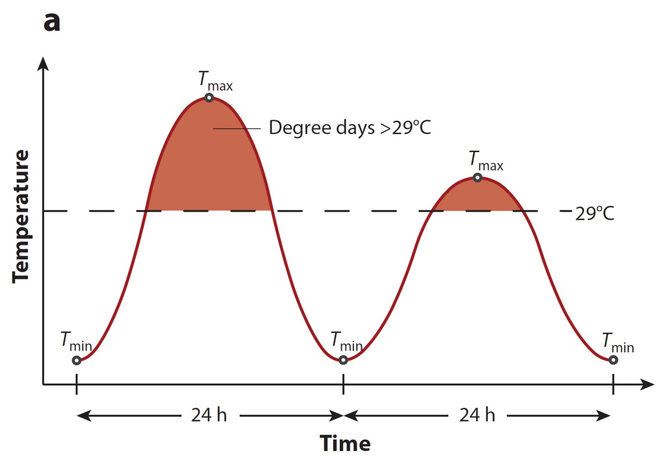
An implicit assumption is the effect of weather variables can be approximated to a linear in parameters function: $F(\mathbf{Z}_{mt}) = \mathbf{Z}_{mt}\boldsymbol{\beta}$. This assumption relies on the empirical results of Schlenker and Roberts (2009).

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:

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

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

Figure A.1: Construction of Harmful Degree-Days Measure



Notes: Construction of harmful degree-days measure using hourly temperature data interpolated between daily minimum and maximum temperature in Schlenker & Roberts (2009). Source: Hsiang (2016)

A.2 Understanding Weather and Economic Variables

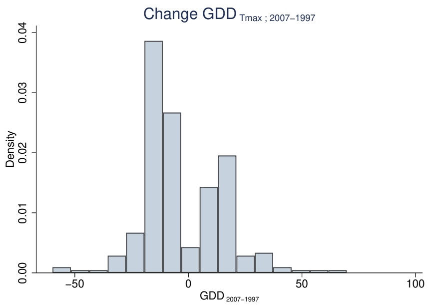
This section aims to understand the patterns of the changes in the main weather and economic variables and the relationship between them.

Figure A.2 shows the distributions of the changes between 1997 and 2007 of GDD and HDD in days, precipitation in 100's mm, fruit land share in percentage points, and agricultural workers, machinery, total planted land and aggregate output in percentage. Figure A.3 plots the basic correlations in the data between 1997-2007. Panel A plots the changes in GDD and HDD for the sample municipalities. This plot shows that increases in "beneficial" days GDD and harmful days HDD are positively correlated. However, there are also municipalities that experienced increases in HDD and decreases in the GDD. Panel B and C show that there is a negative correlation between the changes in GDD and the porcentual change in agricultural workers, as well as with HDD. This suggest that an increase in the numbers of GDD may not be good for labor intensive crops. Next, Panel D shows that a decrease in HDD is related with an increase in the share of fruit planted land. Finally, Panels E and F show the correlations of changes in HDD with changes in log capital use and log aggregate ouput, respectively.

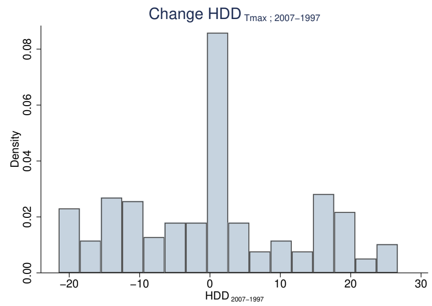
Finally, to understand the climate patterns in Chile, Table A.1 shows the correlations among minimum, maximum and average temperature, and precipitation in 1997 and 2007. A positive correlation between average temperature and precipitation is generally observed in cooler areas because increased precipitation is associated with the import of warm and humid tropical air, and cloud cover keeps the underlying surface warmer. In order to obtain unbiased estimates of the effects of changes in temperature and precipitation, which are historically correlated, both variables must be included in the regression equation (Auffhammer et al. 2013). On the other hand, a negative correlation between average temperature and precipitation indicates that warmer zones tend to be dryer, which is the case of Chile due to its long coastline, the arid deserts and dry summers. Additionally, Figure A.4 plots the time series of annual average precipitation between 1950 and 2013 for top fruit producers and for a random sample municipalities for each climatic zone. In the period under study (marked with dashed lines), the precipitation does not appear to have particular patterns such as drought. However, from 2007, there is a clear pattern of drought in the top fruit producer municipalities and other municipalities belonging to northern and central zones.

Figure A.2: Histograms

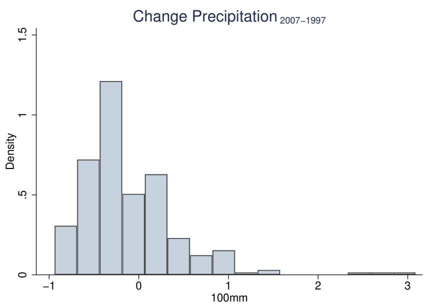
Panel A.



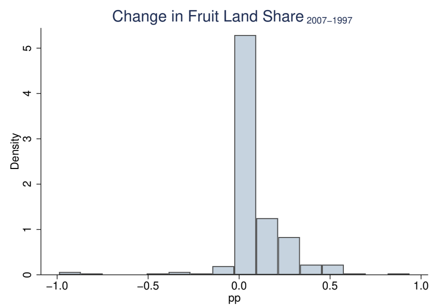
Panel B.



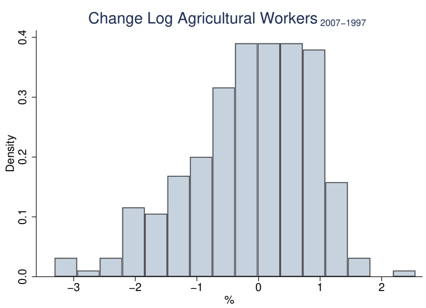
Panel C.



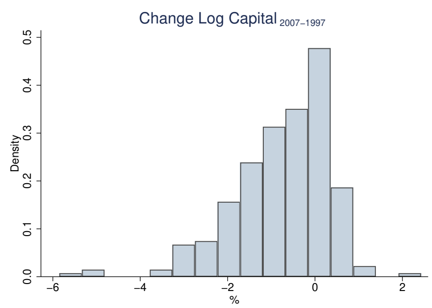
Panel D.



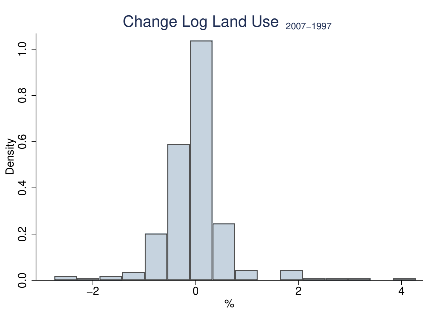
Panel E.



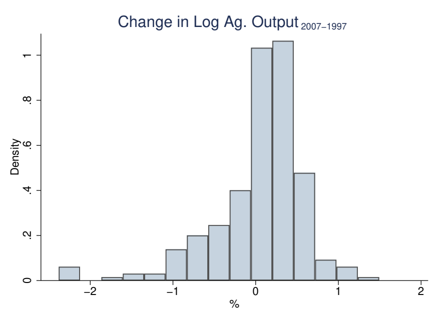
Panel F.



Panel G.

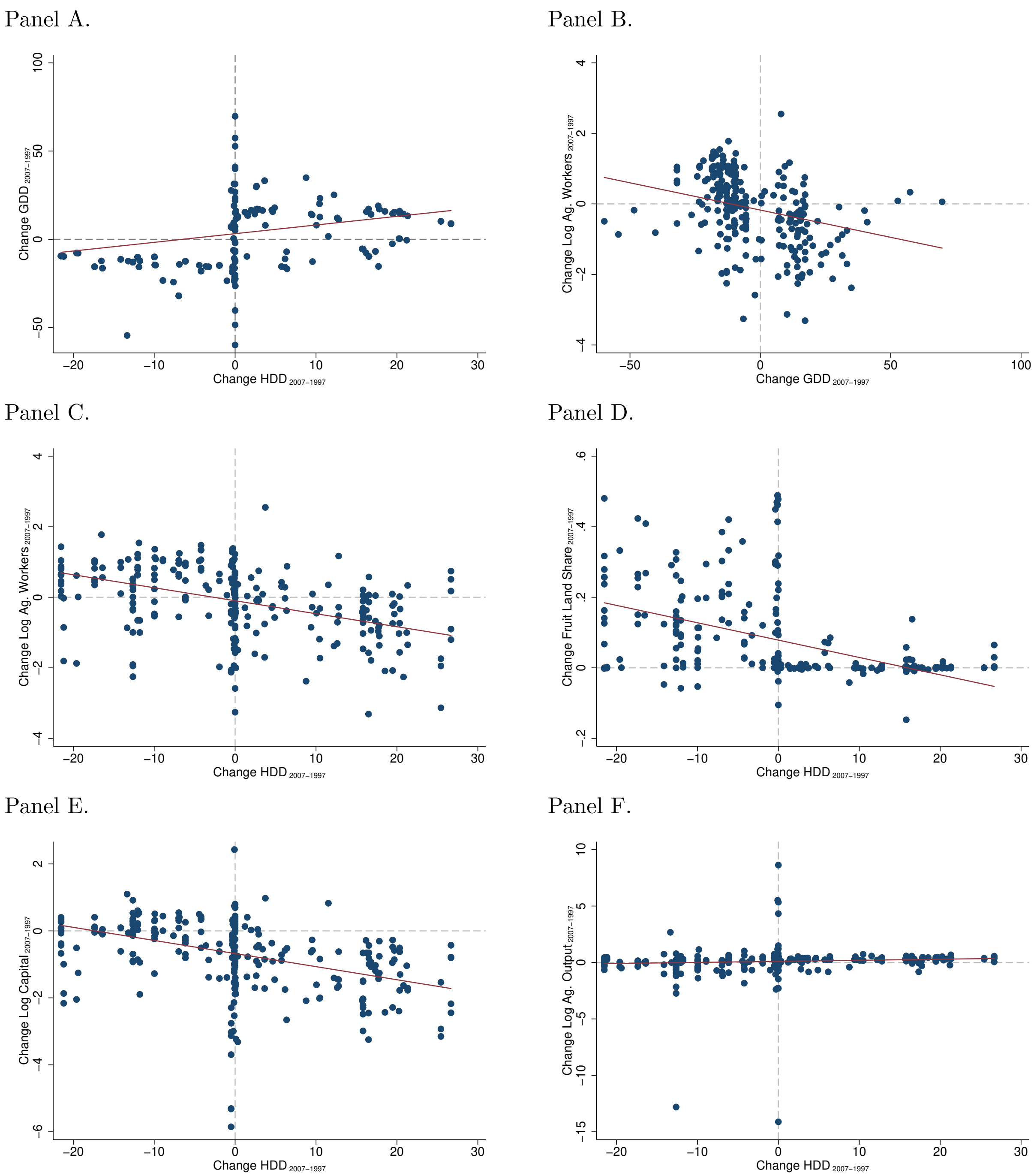


Panel H.



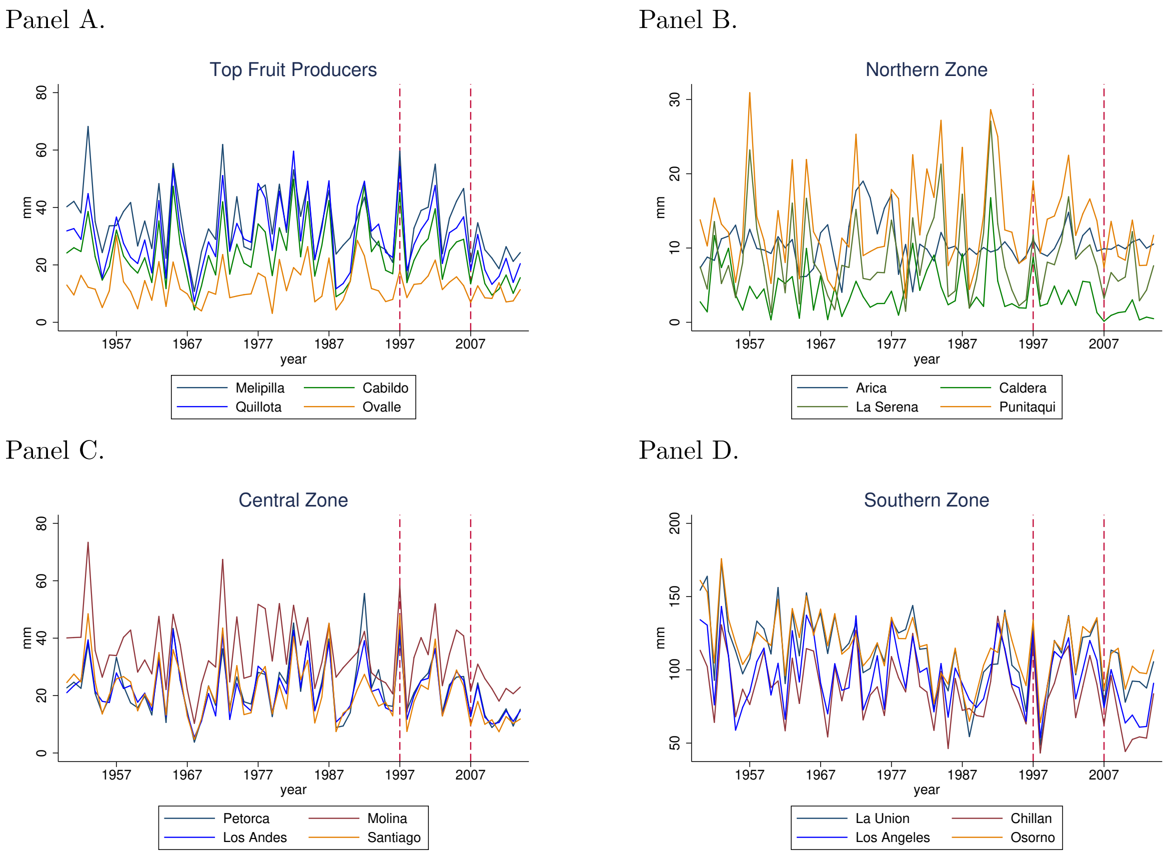
Notes: Each municipality is an observation. Changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. Panel A, B and C show histograms of the growing degree days, harmful heating degree days, and precipitation (mm), respectively. Panels D, E, F and G show the change in the input use. Finally, Panel H shows the change in the agricultural output. Weather variables are calculated over growing season and as a three-year average.

Figure A.3: Basic Correlations in the Data



Notes: Each dot is a municipality and the red lines are the fitted values of the linear regression weighted by agricultural output in 1965. Panel A show the correlation among GDD and HDD, Panel B show the correlation among GDD and agricultural workers, whereas Panels C, D, E and F show the correlation among the change HDD and fruit land share, agricultural workers, capital and agricultural output. These changes are computed by subtracting the value of each variable in 2007 from the corresponding value in 1997. Weather variables are calculated as three-year average and thresholds in GDD variables are $\ell_0 = 0$ and $\ell_1 = 26$.

Figure A.4: Municipality Annual Average Precipitation Time Series 1950-2014



Notes: Dashed vertical lines show the period under study. Panel A show the precipitation time series for top fruit producers, while Panels B, C and D show a random sample of municipalities from each zone in Chile.

Table A.1: Correlations Among Weather Variables

1997			
	H_{min}	H_{max}	H_{avg}
H_{max}	0.509	-	-
H_{avg}	0.840	0.825	-
P	-0.207	-0.437	-0.222
2007			
H_{max}	0.449	-	-
H_{avg}	0.823	0.808	-
P	-0.223	-0.474	-0.263

Notes: The unit of observation is the municipality. All variables are calculated over growing season and as a three-year average.

A.3 Additional Robustness Checks

In Section 7 I diccussed about that the fixed-effects approach could absorb a significant amount of weather variance and amplify the measurement error, which could lead to under-rejection of the null hypothesis (Fisher et al. 2012; Auffhammer and Schlenker 2014). Another possible method to control for geographical heterogeneity is adding latitude and longitude as controls. Table A.2 shows these results. The points estimates and their significance are very similar to the main results.

The use of weights aims to compare agricultural municipalities in the estimates and avoid to include in the analysis entirely urban or arid municipalities. Nevertheless, another concern is that the use of weights by agricultural output in 1965 is driving the results due to an overweight of the crops with higher prices. In Table A.3, I show that the main results remain unchanged using weights by aggregate planted land in 1965 instead of agricultural output.

However, although the use of weights by the lagged agricultural output or planted area is standard in agricultural economics literature, doubts may persist about its use. Therefore, in Table A.4 I show the robustness of the main estimates to remove weights. The results remain unchanged except for the value of the output coefficient and its standard error. This point estimate increases twice and its standard error about four times. These changes avoids rejecting the null hypothesis due to a dramatic decrease in the precision of the estimate, but no due to a (precise) reduction of the point estimate. Note that these models have a poor performance in goodness of fit relative to the models with output or land weights. Therefore, these results do not invalidate the arguments previously raised, because it is still striking that when the inputs decrease, the change in the output is non-negative.

Finally, Figure A.3 Panel F, could raise concerns that outliers drive the results. Table A.5 shows that the main results remain unchanged when I trim the 2% tails of changes in log. agricultural output.

Table A.2: Robustness to Controlling for Latitude and Longitude

	$\triangle \frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0036***	-0.0208***	-0.0229***	0.0017	0.0057**	0.0266***
	(0.0008)	(0.0075)	(0.0049)	(0.0028)	(0.0024)	(0.0077)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0016**	-0.0074	0.0087	0.0019	0.0050*	0.0125*
	(0.0007)	(0.0063)	(0.0078)	(0.0066)	(0.0028)	(0.0062)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Latitude and Longitude	Yes	Yes	Yes	Yes	Yes	Yes
p-value Controls	0.000	0.000	0.000	0.002	0.000	0.000
Observations	259	259	259	259	259	259
Adjusted R^2	0.457	0.526	0.770	0.444	0.124	0.546

Notes: All regressions are weighted by agricultural output in 1965, include a constant, precipitation, its square and the full set of baseline controls which are population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery (in logs). The p-value of the controls comes from the joint significance test of baseline controls and geographic controls. Thresholds in GDD 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 A.3: Robustness to Alternative Weighting Scheme

	$\triangle \frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0038***	-0.0200***	-0.0250***	-0.0003	0.0052**	0.0251***
	(0.0009)	(0.0072)	(0.0059)	(0.0023)	(0.0020)	(0.0076)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0025**	-0.0135*	-0.0001	0.0060*	0.0044	0.0179**
	(0.0011)	(0.0078)	(0.0081)	(0.0034)	(0.0033)	(0.0083)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	259	259	259	259	259	259
Adjusted R^2	0.423	0.533	0.752	0.275	0.125	0.557

Notes: All regressions are weighted by agricultural output in 1965, include a constant, precipitation, its square and the full set of baseline controls which are population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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 A.4: Robustness to Removing Weights

	$\triangle\frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0033**	-0.0217***	-0.0251***	-0.0002	0.0117	0.0334***
	(0.0014)	(0.0065)	(0.0047)	(0.0037)	(0.0081)	(0.0107)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0013	-0.0156***	-0.0070	-0.0019	-0.0078	0.0078
	(0.0014)	(0.0050)	(0.0043)	(0.0055)	(0.0067)	(0.0089)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	259	259	259	259	259	259
Adjusted R^2	0.128	0.375	0.760	0.194	0.170	0.257

Notes: All regressions include a constant. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD 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 A.5: Robustness to Dropping Outliers in Output

	$\triangle\frac{T_{fru}}{T_a}$	$\triangle\ log(L_a)$	$\triangle\ log(K_a)$	$\triangle\ log(T_a)$	$\triangle\ log(Y_a)$	$\triangle\ log(\frac{Y_a}{L_a})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle HDD_{\ell_1:\infty}$	-0.0040***	-0.0244***	-0.0273***	0.0010	0.0060***	0.0303***
	(0.0008)	(0.0069)	(0.0060)	(0.0024)	(0.0021)	(0.0069)
$\triangle GDD_{\ell_0:\ell_1}$	-0.0015*	-0.0117**	-0.0023	-0.0060	0.0022	0.0140***
	(0.0008)	(0.0047)	(0.0055)	(0.0043)	(0.0021)	(0.0050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248	248	248	248	248	248
Adjusted R^2	0.427	0.484	0.715	0.438	0.143	0.518

Notes: This table shows the main result with the trimmed sample after dropping the top and bottom two percentiles of agricultural output. All regressions are weighted by agricultural output in 1965, include a constant, precipitation and its square. The regression with controls includes the lagged population density (in logs), the share of rural population, poverty rate, mean education level, percentage of males, mean income (in logs), and the number of agricultural machinery (in logs). The p-value of the controls comes from the joint significance test of all the baseline controls. Thresholds in GDD variables are $\ell_0 = 0$ and $\ell_1 = 26$. Standard errors clustered at province level reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Appendix: Theory

B.1 Equilibrium

Non-Agricultural sector: Profit maximizing implies

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

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

Inserting (B.13) in (B.2)

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

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

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

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

Using Lagrange multiplier implies

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

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

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

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

Then, the minimum cost (value) function is

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

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

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

Using simmetry between s and r

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

Hence, rearranging terms

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

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

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

On the other hand, profit maximizing in each sector implies

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

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

Then

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

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

$$L = \underbrace{T_s\Big[\frac{w_T}{p_s A_s \gamma_i}\Big]^{\frac{1}{1-\gamma_s}}}_{L_s} + \underbrace{T_r\Big[\frac{w_T}{p_r A_r \gamma_r}\Big]^{\frac{1}{1-\gamma_r}}}_{L_r} + \underbrace{\left(\frac{p_n A_n \alpha_n}{\left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}}_{L_n} \tag{B.17}$$

Then, rearranging terms:

$$T_r = \left\{L - T_s\Big[\frac{w_T}{p_s A_s \gamma_i}\Big]^{\frac{1}{1-\gamma_s}} - \left(\frac{p_n A_n \alpha_n}{\left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}\right\}\Big[\frac{p_r A_r \gamma_r}{w_T}\Big]^{\frac{1}{1-\gamma_r}} \tag{B.18}$$

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

$$T = T_s + \left\{L - T_s\Big[\frac{w_T}{p_s A_s \gamma_i}\Big]^{\frac{1}{1-\gamma_s}} - \left(\frac{p_n A_n \alpha_n}{\left(\frac{\Psi_s}{p_s A_s}\right)^{\frac{\gamma_r}{\gamma_s-\gamma_r}}\left(\frac{p_r A_r}{\Psi_r}\right)^{\frac{\gamma_s}{\gamma_s-\gamma_r}}}\right)^{\frac{1}{1-\alpha_n}}\right\}\Big[\frac{w_T}{p_r A_r \gamma_r}\Big]^{\frac{1}{1-\gamma_r}} \tag{B.19}$$

Therefore, rearranging terms:

$$\begin{aligned} T_s^* = &\left\{T - L\Big[\frac{p_r A_r \gamma_r}{w_T^*}\Big]^{\frac{1}{1-\gamma_r}} + \left(\frac{p_n A_n \alpha_n}{w_L^*}\right)^{\frac{1}{1-\alpha_n}}\Big[\frac{p_r A_r \gamma_r}{w_T^*}\Big]^{\frac{1}{1-\gamma_r}}\right\} \\ &\times \frac{(p_s A_s \gamma_s)^{\frac{1}{1-\gamma_s}}}{(p_s A_s \gamma_s)^{\frac{1}{1-\gamma_s}} - (w_T^*)^{(\frac{1}{1-\gamma_s}-\frac{1}{1-\gamma_r})}(p_r A_r \gamma_r)^{\frac{1}{1-\gamma_r}}} \end{aligned} \tag{B.20}$$

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

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

B.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

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

Therefore,

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

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 $0 < \gamma_s < 1$

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

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 (B.3)

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

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

Then

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

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))

Theorem 1: The reallocation gains could increase aggregate sales only if the increase in output of the heat-resistant is large enough, and prices in the heat-sensitive sector are not sufficiently high relative to the heat-resistant good to absorb this effect.

Proof:

$$\begin{aligned}
\frac{\partial log(Y_a)}{\partial A_s} =& \frac{\partial log(p_s q_s + p_r q_r)}{\partial A_s} \\
=& \frac{1}{p_s q_s + p_r q_r} \left(\frac{\partial p_s q_s}{\partial A_s} + \frac{\partial p_r q_r}{\partial A_s} \right) \\
=& \frac{1}{p_s q_s + p_r q_r} \frac{\partial p_s q_s}{\partial A_s} + \frac{1}{p_s q_s + p_r q_r} \frac{\partial p_r q_r}{\partial A_s} \\
=& \frac{p_s}{p_s q_s + p_r q_r} \underbrace{\frac{\partial q_s}{\partial A_s}}_{<0} + \frac{p_r}{p_s q_s + p_r q_r} \underbrace{\frac{\partial q_r}{\partial A_s}}_{>0}
\end{aligned} \tag{B.26}$$

Then, $\frac{\partial log(Y_a)}{\partial A_s} > 0$ iff

$$\begin{aligned}\frac{\partial log(Y_a)}{\partial A_s} = \frac{p_s}{p_s q_s + p_r q_r}\frac{\partial q_s}{\partial A_s} + \frac{p_r}{p_s q_s + p_r q_r}\frac{\partial q_r}{\partial A_s} > 0 \\ \frac{p_r}{p_s q_s + p_r q_r}\frac{\partial q_r}{\partial A_s} > \frac{-p_s}{p_s q_s + p_r q_r}\frac{\partial q_s}{\partial A_s} \\ p_r\frac{\partial q_r}{\partial A_s} > -p_s\frac{\partial q_s}{\partial A_s}\end{aligned} \tag{B.27}$$

therefore, the net impact on aggregate sales depends on the magnitude of the changes in output and the international prices, which could amplify or reduce this effect.

Hence, in the particular case that changes in output are exactly compensated $-\frac{\partial q_s}{\partial A_s} = \frac{\partial q_r}{\partial A_s}$, aggregate sales could increase iff

$$p_r > p_s \tag{B.28}$$

This mechanism can be summarized as

$$\frac{\partial log(Y_a)}{\partial A_s} = \frac{p_s q_s}{p_s q_s + p_r q_r}\frac{1}{p_s q_s}\frac{\partial p_s q_s}{\partial A_s} + \frac{p_r q_r}{p_s q_s + p_r q_r}\frac{1}{p_r q_r}\frac{\partial p_r q_r}{\partial A_s} \tag{B.29}$$

as $\frac{1}{p_i q_i}\frac{\partial p_i q_i}{\partial A_s} = \frac{\partial log(p_i q_i)}{\partial A_s}$, rearranging terms of (B.29)

$$\frac{\partial log(Y_a)}{\partial A_s} = \underbrace{\frac{p_s q_s}{p_s q_s + p_r q_r}\frac{\partial log(p_s q_s)}{\partial A_s}}_{\text{direct losses}} + \underbrace{\frac{p_r q_r}{p_s q_s + p_r q_r}\frac{\partial log(p_r q_r)}{\partial A_s}}_{\text{reallocation gains}} \tag{B.30}$$

where $Y_s \equiv p_s q_s$, $Y_r \equiv p_r q_r$, $Y_a \equiv Y_s + Y_r$, $\eta_s = \frac{p_s q_s}{p_s q_s + p_r q_r}$ and $\eta_r = \frac{p_r q_r}{p_s q_s + p_r q_r}$.