Weather Shocks, Income and Inequality

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Abstract

Most of the attention brought towards the uneven economic effects of climate change has been devoted to inequalities between countries. Nonetheless, it is very likely that these effects will be unequally shared within countries as well. This paper measures the economic effect of weather shocks on the average level of income and the distribution of income within Metropolitan France. I combine French fiscal data with climate data from weather stations. Allowing for non-linear effects of weather and using historical data, I am able to compute the marginal effect of weather shocks on income. I find that an additional day above 30 ° C reduces the yearly income by 0.1%. This loss is equivalent to 37% of the average daily contribution to yearly income. I then use RCM to predict potential effects of global warming. I found a reduction of GDP growth of 0.1 percentage point over the medium run and of 0.3 percentage point for the last decades of the century due to additional warm days. Despite, higher point estimates in magnitude for first deciles, I lack statistical power to conclude that the first deciles are significantly more affected than the other ones. One major insight of this paper is nevertheless to conclude that every single decile is affected by the occurrence of extremely hot days.

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La chaleur du climat peut être si excessive que le corps y sera absolument sans force. Pour lors l'abattement passera à l'esprit même; aucune curiosité, aucune noble entreprise, aucun sentiment généreux.

Charles de Montesquieu, *De l'Esprit des lois*, 1748.

1 Introduction

1.1 Motivation

Without falling into Montesquieu's Climate Theory which advances that international differences in economic development and political institutions could be explained solely by temperature differences, the question of an economy's sensitivity to temperatures remains crucial, especially in a context of global warming.

Having a precise idea of the future costs associated with climate change is more than necessary in order to take rational decisions towards climate change and reduction of gas emissions. Lively debates have arose on predicted level of emission, predicted costs and discount rates associated with future damages. However, knowing the precise effect on the aggregate level of income is not enough. This effect goes hand in hand with the effect on inequalities.

Most of the attention brought towards the uneven economic effects of climate change has been devoted to inequalities between countries. Nonetheless, it is likely that these effects will be very unequally shared within countries as well. These unequal effects may be due either to unequal exposition to climate risks (due to the geography or job) or unequal ability to cope with and adapt to climate change (due to individual resources, public provisions or job). Understanding the impacts of climate change notably on inequality levels is of major importance as it pinpoints the population that should be targeted for specific adaptation programs. Moreover, each measure that aims to tackle climate change has an impact in itself on the distribution of income. Several mitigation and adaptation measures have indeed often been accused of being anti-poor and/or regressive.

Another motivation to study differentiated within-country climate change effects is the existence of an effect of inequality *per se* on climate change, leading to the so-called "environment-inequality nexus". Inequalities may reinforce climate change through the richest population's irresponsible consumption and through a higher demand and a higher need for economic growth for the rest of the population. Moreover, inequality harms the willingness of the poorest to accept costly climate change mitigation programs and more generally reduces the ability to collectively organize the mitigation of climate change (Laurent, 2015).

This paper studies the average and differentiated income response to weather shocks in France. My approach in this paper is to study historical short-run reactions to marginal weather shocks to get a benchmark of predicted economic impacts of global warming. I chose here to focus mainly on one unique aspect of climate change which is global warming. Also, I do not consider climate change's other specific aspects such as sea rise and natural disaster. This for two main reasons: (1) The pre-existence of temperature deviations, on the contrary to other aspects, render possible an estimate for global warming effects. (2) Climatic projection models provide clear projections (though with uncertainty) in terms of warming which may not be the case for other aspects.

1.2 Related Literature

There has been a recent development in literature which aims to assess the link between weather and income. However, this literature only scarcely covered the question of differentiated climate change impacts. I will first present studies focusing on an aggregate impact of weather and second on more sectoral and individual-centered approaches[1].

Methodological advances helped to go beyond the simple correlation that "hot countries tend to be poor". Dell et al. (2009) estimated that in 2000 one additional degree Celsius was associated on average with 8.5 % lower income per capita. Not much can nevertheless be inferred from this relationship measured in cross-section, using therefore only between-country fluctuations. Indeed, it is more than likely that some omitted variable may induce this correlation to be spurious. For instance, Acemoğlu et al. (2001) argued that disease risk and mortality rate of settlers in the colonial time (that is influenced by local weather) impacted subsequent economic development. It therefore turned out to be necessary to use panel estimates to compute unbiased reaction functions.

Panel estimates based on year-to-year fluctuations and within-country variations exploit weather *deviations* from average conditions which are assumed to be exogenous. And this, to obtain an unbiased response function. Panel studies also find a negative impact of hot temperatures both on the GDP in level and on its growth. Dell et al. (2012) found a large negative effect of higher temperatures on growth but only in poor countries. They estimate that an increase of temperature by 1°C reduces aggregate annual growth by 1.3 percentage point. They argue that they find an effect on growth (and not only on the level of GDP) which could

[1] Only a small share of this literature will be presented here, with a specific focus on temperature effects in developed countries. Dell et al. (2014) wrote a very clear and (more) exhaustive presentation of the "New Climate-Economy literature".

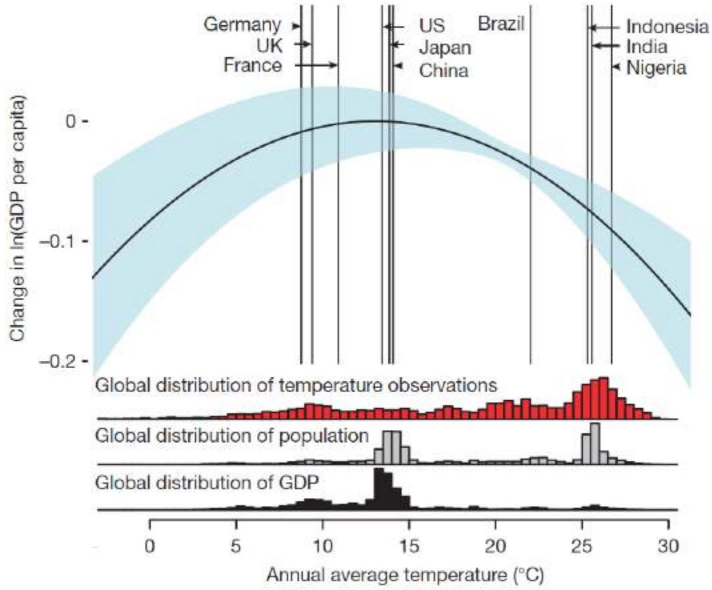

Figure 1: Global Relationship between GDP and Temperatures.

Source: Burke et al. (2015)

lead to large cumulative effects of global warming.

Burke et al. (2015) all the while using a similar methodology also took into account non-linear effects and thus found an impact of temperatures both on poor and rich countries. These non-linear effects can be understood as the fact that an increase of temperature by one degree from 12°C to 13°C does not have the same effect than an increase from 30°C to 31°C. Figure 1 presents the relationship they estimated between income and temperatures. They found that there is an inverted-U shape curve between temperature and income with an optimal temperature for output and productivity at 13°C. Above this threshold, they then observe the non-linear negative impacts of temperature. According to them, this relationship is global (holds for every country) and has not been mitigated since 1960. However, because poor countries will be more severely hit by global warming and some rich countries may gain from the increase in temperatures, they found that global warming will exacerbate global inequalities. They nevertheless did not mention any effect on within-country inequalities.

One small country of indomitable Gauls still holds out against the impact of temperatures: France is the only country in the world for which Burke et al. (2015) found no significant impact (neither positive nor negative) of global warming on the economy. This result may nevertheless not be precise enough for at least two reasons: (1) Their specification may not be flexible enough to allow for non-linear effects and notably effects of particularly high temperatures[2]. (2)

[2]Their main specification is to use a quadratic term in temperature as an independent variable.

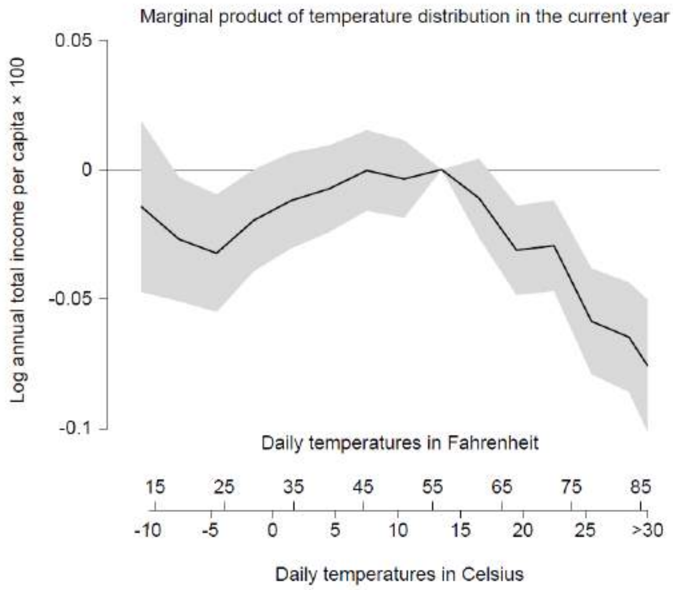

Figure 2: Local relationship between county GDP and daily temperatures in the US.

Source: Deryugina and Hsiang (2017)

Aggregating the impact of temperatures may hide some detrimental effects for sub-groups of the population (either depending on the geography, occupation, quality of housing or income level). No *net* impact does not mean no impact for *everyone*.

Several studies also use local instead of national weather deviations to estimate a response function of income to weather. Dell et al. (2009) use sub-national data for 12 American countries (including the U.S.) and find a significant negative relationship between temperatures and income (an additional degree Celsius in the yearly mean is associated on average with a decrease by 1.2-1.9% of per-capita income) using both within-country and between-country variations.

Deryugina and Hsiang (2017) went further in the study of non-linear effects than Burke et al. (2015). Because global warming is not only an increase in the average temperature but also of its variance, using only means may hide some impacts of temperatures in the tails of the distribution. Deryugina and Hsiang (2017) therefore use as variables for temperatures the number of days in 3°C temperature bins which is closer to a non-parametric specification. study the impact of temperature and precipitation on the county income per capita in the United States. As can be seen on Figure 2, their principal result is that "*The log personal income per capita increases slightly as temperatures rise from cool to moderate, then declines approximately linearly at temperatures above* $15°C$".Their study is focused on the United States, using local temperature deviations at the county scale. The order of magnitude is the same than the one found by Dell et al. (2009).

These sub-national studies brought to light some within-country differentiated impacts as well. For instance, Hsiang et al. (2017) underlined the importance of looking at redistributive impacts of climate change in the United States. From the aggregation of several market and non-market damages across sectors, they conclude that climate change will foster national inequality in the U.S. Using the initial geographic distribution of income across the U.S. combined with predicted climate change impact for every U.S. county, they found that poorer counties (mainly in the Midwest) will suffer more from climate change than the richer ones, therefore, leading to an increase in *between*-county inequality. Despite providing a first idea of a differentiated within-country climate change impact, their paper explores only one aspect of the sensitivity of inequalities to climate change. This aspect is an unequal severity of climate change depending on the place of living; *ie*: they compute a unique response function per county but found that counties are unequally hit by climate change. In other words, they look only at geographical and not at social inequalities. However, it is more than likely that within a county, people may have different response functions to climate change, depending either on their job, quality of housing, education or even simply income. That is why, it seems quite important to consider inequalities within a geographical area, such as the county, and not only between geographical regions.

Papers that have found an impact on the aggregate output are supported by studies on sectoral outputs which help to decompose the aggregate impact. This can be done either by decomposing the output per sector or by conducting sector-focused studies directly.

There is plenty of evidence of the negative impact of climate shocks, notably temperature shocks, on agricultural income. This relationship applies both to developing countries (*e.g.* Skoufias et al. (2013)) and to developed countries (*e.g.* Schlenker and Roberts (2009)). One major insight in terms of methodology brought by the later is the importance of allowing for non-linear and asymmetric temperature effects (ie: increase by one degree from 10 to 11 °C does not have the same impact than an increase from 30 to 31 °C). To estimate these non-linear impacts they use the number of days in several temperature bins (number of days between 20 and 23 °C for instance) as explanatory variables for weather. It therefore allows for non-linearity in the level of temperature[3].

There are fewer studies on non-agricultural output, some strong evidence nevertheless exists. The two aforementioned papers isolated the impact on the agricultural sector from the rest of the economy. Dell et al. (2009), in their sub-national study, found that the negative effect of temperatures is not concentrated on agricultural output but affects other economic sectors as well such as the industrial output. Deryugina and Hsiang (2017) isolate the effect of climate

[3]As it will be underlined later, it however does not allow for non-linearity in the number of days in one specific temperature bin

variations on agricultural income separately from non-agricultural income and found that both were impacted by warmer temperatures, though their estimates for non-farm income are less precise.

More precisely, Hsiang (2010) finds that unusual warm periods have large negative effects for three out of six non-agricultural sectors in Caribbean countries. Moreover, he finds that the impact on non-agricultural sectors exceeds the impact on the agricultural sector (decrease of 2.4% per additional degree Celsius vs. decrease of 0.1% in production of agricultural sector). These output losses are driven by heat shocks during the hottest season. Two out of three of the affected sectors are service-oriented and provide the majority of output in these Caribbean economies, while the other affected sectors are industrial (mining and utilities).

If for the agricultural output, it seems quite straightforward that hot weather or scarce precipitation negatively impact farmland productivity, the channels through which weather impacts non-agricultural income are more subtle.

These channels roughly fall into two groups:

- The impact of temperature on labour productivity or effort as observed by Somanathan et al. (2015) in firms in India. This comforts previous lab experiment results which found that one additional degree above 25° C would be associated with a 2% decrease of human productivity in the US (see e.g. Seppanen et al. (2003)).

- The effects of hot temperatures on the labour supply, notably a reduction of time allocated to work (see e.g. Graff Zivin and Neidell (2014)). Higher temperatures may reduce time allocated to work because of reduced labour productivity or changing marginal utility of non-work activities[4].

Other studies also found effects on non-market outcomes such as health and mortality (see e.g. Deschenes (2014)), energy consumption (see e.g. Deschenes and Greenstone (2011)), crime rate and political conflict (see e.g. Hsiang et al. (2013)). These non-market effects that do not affect income directly are, however, likely to be indirectly linked to the average level of income and its distribution. For instance, temperature effects on health may have additional impact on labour supply and productivity.

A fourth channel between weather and income which may play a non-negligible role, which is harder to estimate precisely, are general equilibrium effects (e.g. extremely hot weather leading to a shift in aggregate demand). These effects may be particularly crucial when looking at a distributional impact. These effects seem difficult to seize when only using sectoral approaches.

[4]Note that temperatures that matter may not only those of the working environment but also nightly temperatures.

Evidence of effects on specific sectors or on individuals to temperatures is difficult to translate into a single aggregate effect. Doing so supposes one knows exactly which sector is affected and which is not. What is more, it leads to questions on how different sectors interact with each other and on potential general equilibrium effects. Using macro studies does not require specific assumptions on how sectors interact with each other or how they aggregate. Such studies rather use reduced-form estimators of climate effects which cannot be restricted *ex-ante* to any specific channel.

Based on all this aforementioned literature, several methodological challenges arise as crucial for an unbiased estimation of weather impact on income. (1) Using panel estimates rather than cross-section allow to get rid of unobservable characteristics and the risk of an omitted variable bias. (2) Using a non-parametric specification in temperature and precipitation in order to not constrain weather impact on income to be linear. (3) There seem to be a trade-off between estimating a precise aggregate effect (with reduced-form estimators) may come at the price of hiding a detrimental effect for certain sub-population or sectors.

In addition, among all these different branches of the literature, very little attention has been brought towards uneven within-country weather effects. However, in the light of the four channels aforementioned, the whole population is probably not exposed in the same extent to weather shocks.

My approach is therefore to study the impact of random, local and marginal year-to-year variations of weather on income per capita, allowing for non-linear effects. This strategy, defined above as close to a reduced-form approach, is related to the work of Deryugina and Hsiang (2017) mentioned above.

Nevertheless, one can fear that this specification using local variations can lead to spurious correlations. For instance, income may increase more in Montpellier than in Charleville-Mézières during the chosen period all the while temperatures rising in Montpellier more than in Charleville-Mézières without a causal relationship between these two trends. To guard against this risk, I *de-trend* income evolution by first using a unique trend over the period and by secondly using seven-year moving averages to keep only income deviations.

Finally, this data allows me to further explore the analysis by studying a differentiated effect by deciles of income. This approach towards uneven within-country effects in a developed country has scarcely been explored by the literature to the best of my knowledge[5].

[5]Note that my approach presents the reverse drawback compared to Hsiang et al. (2017): I am not able to estimate between-county inequality (unequal shocks) but only an unequal response function to a common shock.

Combining French local fiscal data to get the average income for each French municipality from 1990 to 2015 and indicators on the distribution of income since 2000 at the *canton* level (approx. 10 *communes*) with the weather interpolation model SIM provided by *Météo France*, I am able to use local random deviations of income to estimate marginal responses to change in the current weather. These estimates are then used as inputs with climate simulation models to get projections of climate change impacts.

I find that the response function of income with respect to temperature is quite flat but declines severely for days above 30°C. An additional day above 30° C is associated on average with a decrease of the yearly income by 0.1%. It is equivalent to 37% of the average daily contribution to yearly income. Note that the average temperature corresponds to an average over nightly and daily temperatures. The maximum daily temperature of a day with average temperature at 30°C therefore often exceeds 35°C.

Surprisingly, the results seem to not be concentrated on agricultural income. The point estimation for first deciles indicates a most severe effect. However, I lack statistical power to conclude to a significantly more detrimental effect on low deciles compared to the rest of the population. One major insight of this paper is nevertheless to prove that every single decile of income is affected by the occurrence of extremely hot days.

These results bring more precision to the estimation of the impact of global warming in France and emphasizes the importance of non-linear effects and various sub-populations. The results are in line both with the literature and with a report of the French Senate (Sénat, 2004) which estimated the detrimental impact of the 2003 heat wave on French added value to be between 0.1 and 0.2 percent of GDP (1,5 to 3 billion Euros)[6]. The population-weighted national average number of days above 30°C in 2003 was indeed 2.04 days which would, according to my estimate, have a negative impact of 0.2% of GDP.

I finally test the robustness of the results through Randomized Inference. Indeed, studies that use weather (and its randomness) either as an instrument variable or an explanatory one have been recently criticized for the spurious correlation it may contain (see *e.g.* Cooperman (2017) or Lind (2015)). This, notably, as a consequence of the spatial auto-correlation of the data: weather and income of two neighbour *communes* cannot be seen as independent from each other. Randomized Inference (also called Permutation Tests) allows me to assess the extent of this issue in my setting.

[6]Note that in the report, it is mentioned that the 2003 heat wave had an impact 0,1 to 0,2 percent of GDP in relative terms and 15 to 30 billion Euros in absolute terms (which is in fact 1 to 2 percent of GDP). I interpret this incoherence between the two figures as a typo and use the smaller one as a benchmark.

Using the historical estimates on the average level of income, I am able to assess potential impact of global warming in France using a Regional Climate Model (RCM). Under the RCP 8.5 scenario of the IPCC, French GDP would be reduced by 0.1% every year in the medium term (2050-2080) and almost 0.3% every year in the long-term (2080-2100).

The remaining of this paper is organized as follows: Section 2 describes the data used and provides descriptive statistics, Section 3 presents my estimation strategy, Section 4 presents my main results, Section 5 tests the robustness of the results, Section 6 uses these results to assess global warming potential impacts for the French economy and Section 7 concludes and discusses the results.

2 Data and Descriptive Statistics

This paper uses two main categories of data: climate data and income and socio-demographic data. The description of the climate simulation models will be described in the projection section (6).

2.1 Climate Data

I am using a dataset provided by Météo France named Safran-Isba-Moscou (SIM) computed by the Centre National de Recherches Météorologiques (CNRM) and the Centre de géosciences de Mines ParisTech. It gives 9 000 points of gridded data for Metropolitan France obtained from an interpolation of the 554 weather stations and corrected by weather models. I then interpolate this data to obtain the weather of each *commune* as a weighted-average of the four neighbouring points.

Mean daily temperatures over the period are going from -25 ° C to + 35 ° C. The particularly cold temperatures are not representative of temperatures of any *commune* because they correspond to points in very high uninhabited mountains. This is nevertheless not the case of particularly warm temperatures which occurred in inhabited areas. The highest mean daily temperature has been observed on the 13^{th} of August 2003 in Perpignan (near the Spanish border). Figure 4 taken from Météo France illustrates the evolution of the temperatures in France since the beginning of the twentieth century. A striking increase of temperature of about 1° C since 1990 (which is the first year of my study) can be seen on Figure 4.

This increase in average French temperatures can also be observed in the data used for this study by comparing average temperatures of 2010-2015 vs. those of 1990-1995 on Figure 4 for each French Metropolitan *commune*.

Figure 5 displays the average number of days in each temperature bin. Extreme weather and notably extremely warm days are quite rare (on average 1 day above 30° every 10 years). However, out of the total of observations (950 000), 22 000 indicate at least a day above 30°C in the sample.

All *communes* have experienced days with a daily mean temperatures above 26° C. For days above 30° C which will be my main variable of interest, only half of the *communes* are concerned. As can be seen of Figure 6 these *communes* are not localized specifically in the South. Also, they do not show significant differences in income, size or composition of labour force compared to *communes* which did not experienced any days above 30°C. 10 *départements* (over 100) do not have any *communes* which experienced a day above 30° C: Haute-Alpes (05), Ardennes (08),

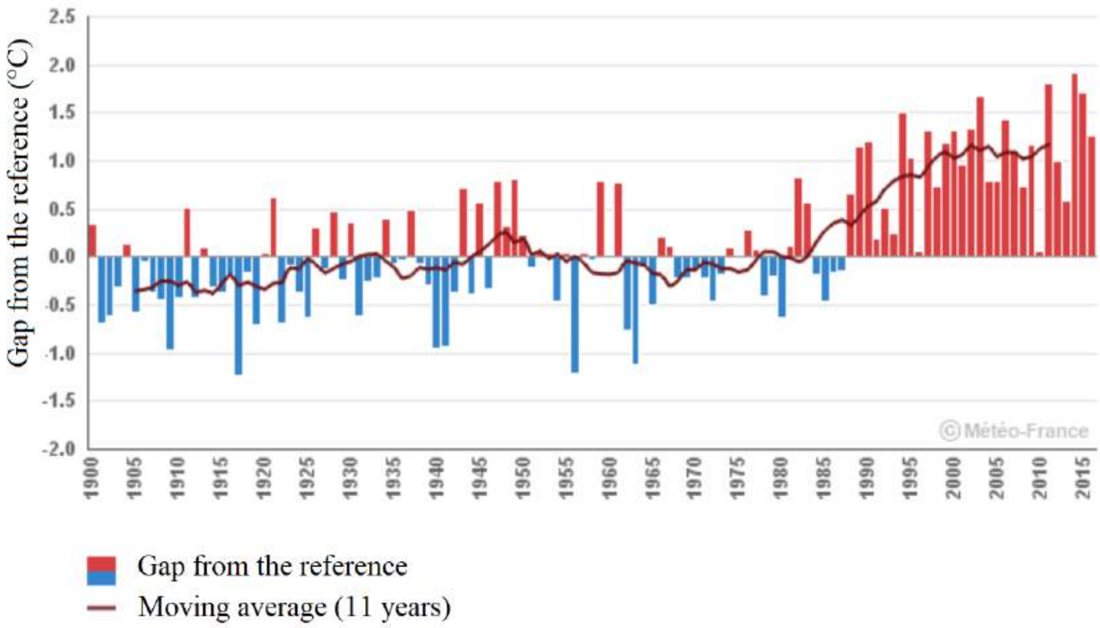

Figure 3: Evolution of the temperature between 1900 and 2015

Source: Météo France
Lecture: In 2003, the yearly average of temperature was 1.6 °C above the long-term average whereas the moving average for 1998-2008 was 1°C above the long-term average.

Haute-Loire (43), Nord(59), Pas-de-Calais (62), Haute-Savoie (74), Seine Maritime (76), Somme (80), Vosges (88) and Territoire de Belfort (90). Figure 20 in the Appendix shows the differences between these communes. These *départements* are either in mountainous area or in the very North of the country. This fact that only half of the *communes* experienced days above 30°C may question the external validity of the estimates. This will be discussed in detail in the last section.

2.2 Income Data

2.2.1 Average Income

I use income data at the municipal level provided by the *Direction Générale des Finances Publiques* (DGFiP) that gives the average level of income per fiscal household per *commune* (approx. 36 000) for each year from 1990 to 2015[7].

Values before 2002 are converted from Francs to Euros and values for each year are converted

[7]Note that the definition for the income variable varies slightly over time. It corresponds to the *revenu net moyen des foyers fiscaux* for the period 1990-1993, *revenu imposable net des foyers fiscaux* for 1994-2009 and *revenu fiscal de référence* for 2010-2015.

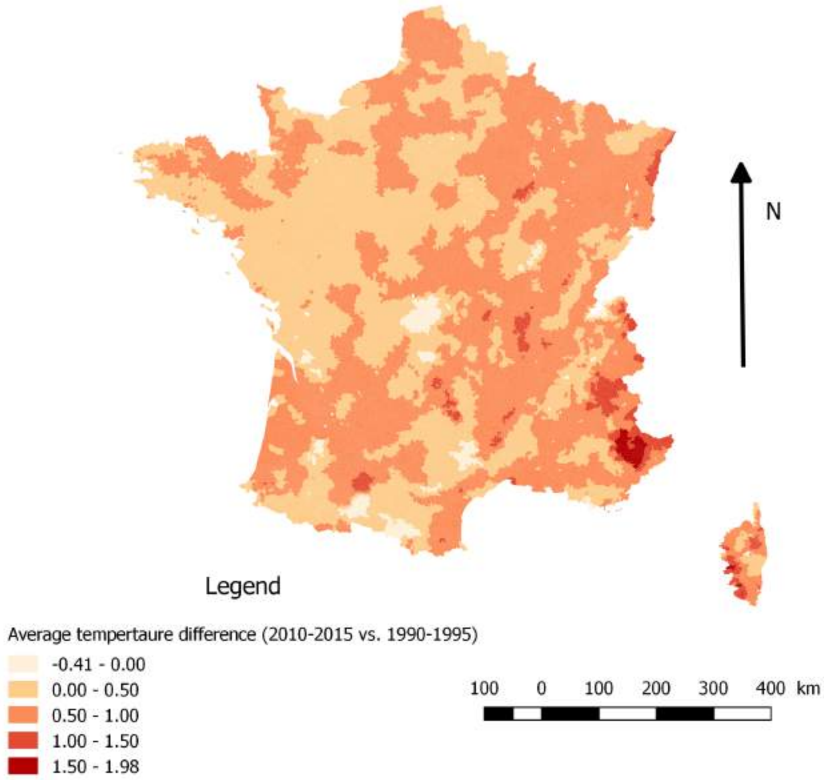

Figure 4: Evolution of the temperature between 1990-1995 and 2010-2015.

Data from Météo France

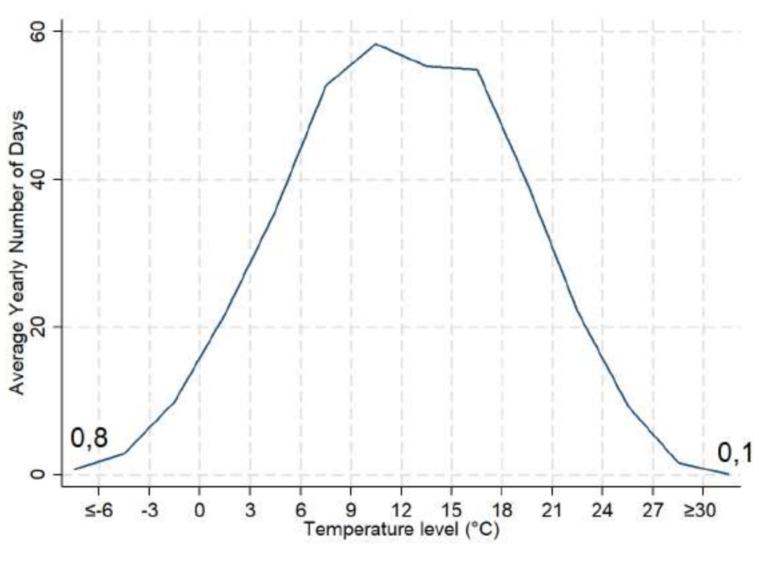

Figure 5: Average yearly number of days in each temperature bin (1990-2015).

Data from Météo France

into Euro of 2015. To get rid of national institutional changes[8] that occurred twice, data is

[8]For instance, in 2006, the tax relief of 20% on wages was suppressed.

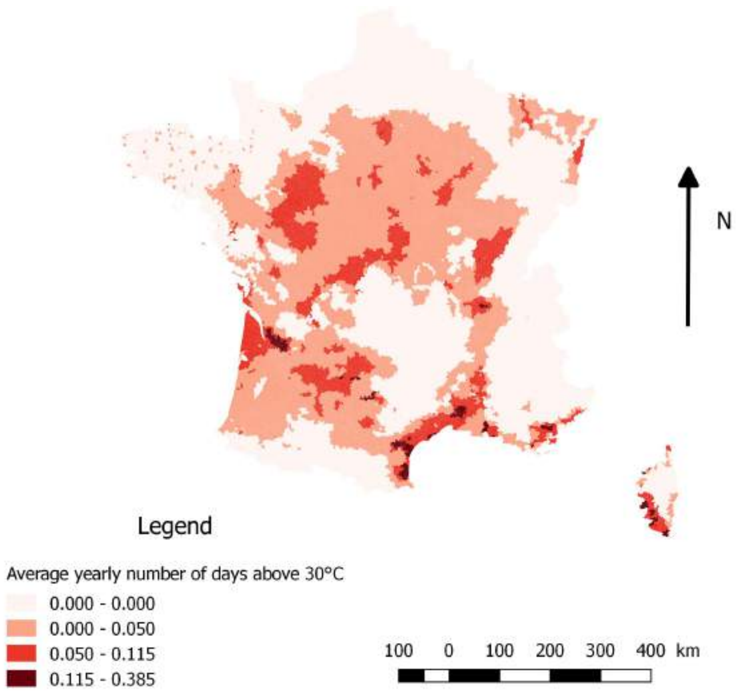

Figure 6: Average yearly number of days above 30 by *commune* (1990-2015).

Data from Météo France

normalized to evolve yearly in the same way as income provided by the World Inequality Lab[9]. This normalization has no impact on the estimation because of the use of year fixed-effects.

The local fiscal data is slightly noisy, notably for small *communes*. This noise may be due to either measurement errors or for instance a rich fiscal household moving in or out of the *commune*. Both of these reasons will add noise to my estimates. Measurement errors can lead to under-estimating the true coefficients. I therefore decided to exclude *observations* that have a gap of (log) income from the 7-year moving-average above the median and three standard-deviations or below the median and three-standard deviations. This excludes only 13 000 observations (1.3% of the sample). The *communes* with these outliers are on average smaller (average population of 205 vs. 1 524 for the whole sample), have thus a higher proportion of farmers (9% vs. 2.5 % for the whole sample) and are a bit poorer (19 513 Euros of average income vs. 22 274 for the whole sample). See Table 5 in the Appendix for more details. Nevertheless, running the main regressions without excluding outliers, gives the same estimates for the main parameters of interest and therefore do not alter the main insights of these papers, though makes it more noisy.

[9] www.wid.world

22 000 observations have missing values in average income (2.3%) and/or have zero reported fiscal households. This issue concerns only 3 000 *communes* (ie: the other 33 000 have information for all years). These missing values are mainly due to institutional changes, for instance two *communes* that merge together and therefore change identifiers or a *commune* that is split in two. The remaining observations for the *communes* are therefore consecutive. For instance, a lot of *communes* do not have information for the period 1990-1999 but have it for 2000-2015. Even, if institutional change or non-reporting may be considered to some extent as endogenous, it seems quite unlikely to be correlated with the weather. Moreover, for years with full information, these *communes* do not have a significantly different average income than the rest and are spread all across French territory. I thus consider these missing values as random and do not take it into account in my specification. The panel dataset is therefore unbalanced.

Figure 7 describes the evolution of the weighted-average income by *communes* during the period 1990-2015. The average income growth rate over the period is 0.73% per year, ie: the

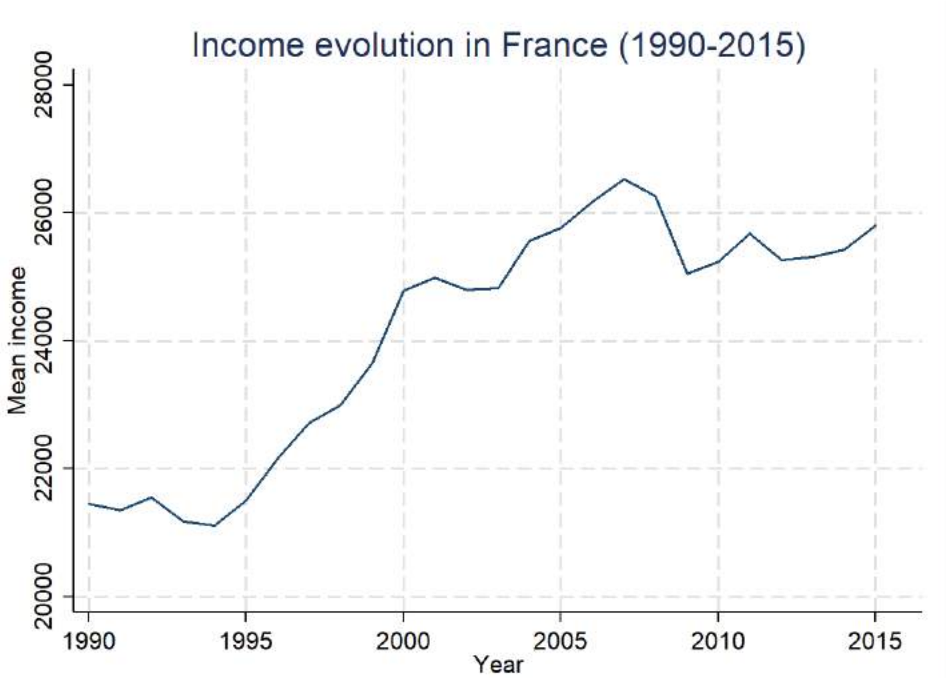

Figure 7: Evolution of the average income by *communes* (1990-2015)

Note: All figures are expressed in constant Euro of 2015. Figures correspond to the population-weighted per-*commune* average income per fiscal household

real average per household income of 2015 is around 20% higher than in 1990.

This evolution can be decomposed by *département* (see Figure 8). There is a divergent trajectory across French territories. For instance, Haute-Savoie had a growth rate of average income over the period of 1.06% each year compared to Seine-Saint Denis which exhibited a decrease in average income of 0.75% each year. In 2015, its average income was 17% lower than in 1990. One nevertheless has to be careful in the interpretation of these figures. Indeed, this divergence in trajectory, does not imply that the same people are affected by a real decrease in average income within a *département*. This, because the composition of the population of these *départements* is very likely to have changed during the last decades. The uneven evolution of income within

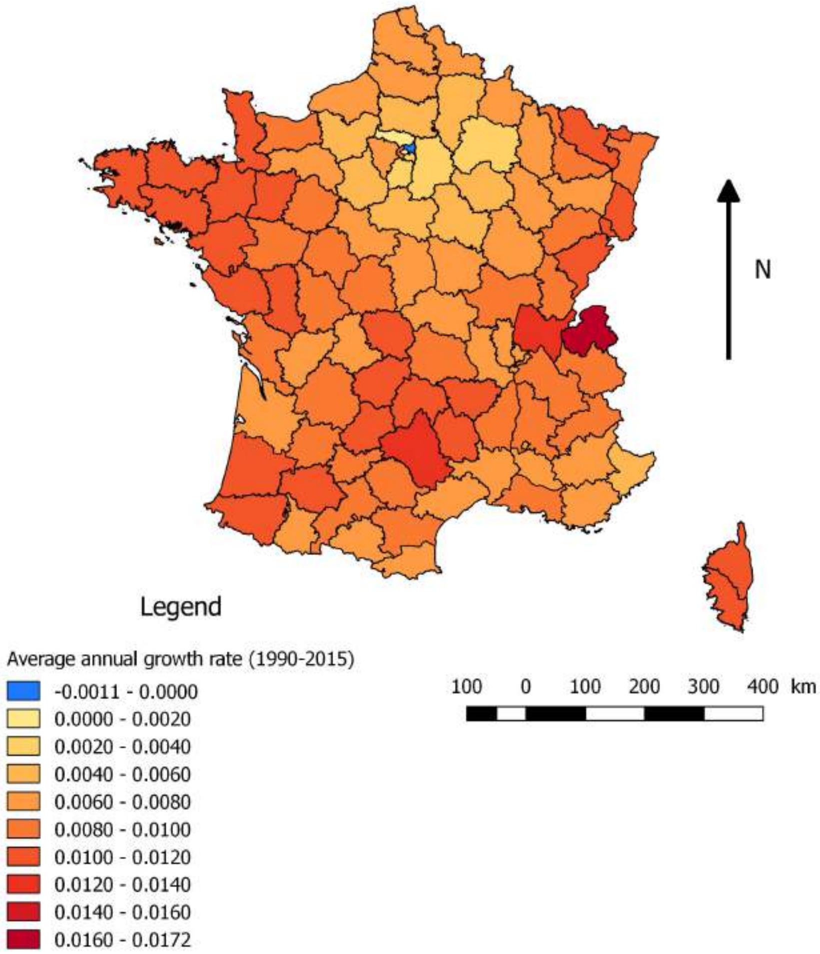

Figure 8: Evolution of the average income by *département* (1990-2015)

Data from the DGFiP

France is a further justification for using not only (log) income but also de-trend (log) income as dependent variables to avoid capturing spurious correlations with trends in weather and in income.

2.2.2 Distribution of Income

For the second part on inequality, I use the same data provided by the DGFiP and distributed by the French Statistical Institute (INSEE[10]) but at the *canton* level (approx. 10 *communes*). This data gives the threshold for each decile of income. I choose to work at a larger scale to approach the question of inequality because a lot of information is hidden in the source file at the *commune* level for statistical confidentiality reasons.

The data provided at the *canton* scale is nevertheless only available for a smaller period of time (2000-2011). I therefore have a lower cross-section and time dimension which reduces the statistical power of the analysis.

This data gives the deciles (*ie:* the threshold at which a share s of the population is below 10% for instance). From this data I can get the average income by group and the share of total income earned by this group using Pareto interpolation as described in Blanchet et al. (2017).

Note that I will not estimate inequality at the national level. Indeed, I use deciles *within cantons* as indicators of inequality. And, as can be seen on Figure 8, there are also high inequalities *between cantons*. If global warming fosters these inequalities, this will not be estimated in my coefficients. This may be a particularly critical issue if poorer *cantons* are more severely hit by temperature shocks than richer ones.

Figure 9 shows the share owned by the top 10 % by *département* for year 2011. The national weighted average for 2011 is of 29.5 %.

2.3 Socio-demographic Data

As covariates I also use data provided by the French Statistics Institute (INSEE) which traces the evolution of the composition of French *communes* in terms of unemployment rates, education levels, etc. Finally, I use data from the *Recenssement agricole* provided by the French Ministry of agriculture to obtain the share of people working in agriculture by *communes* for years 1990, 1997, 2004 and 2010. I then compute for each year of my study (1990-2015) the weighted average of these values depending on the distance to the date with available information[11].

[10] Data named Revenus Fiscaux localisés des ménages (RFL) and Fichier Localisé Social et Fiscal (FiLoSoFi).

[11] For instance: $share_{agri,1994} = (\frac{1}{4} + \frac{1}{3})^{-1} \times (\frac{share_{agri,1990}}{4} + \frac{share_{agri,1997}}{3})$

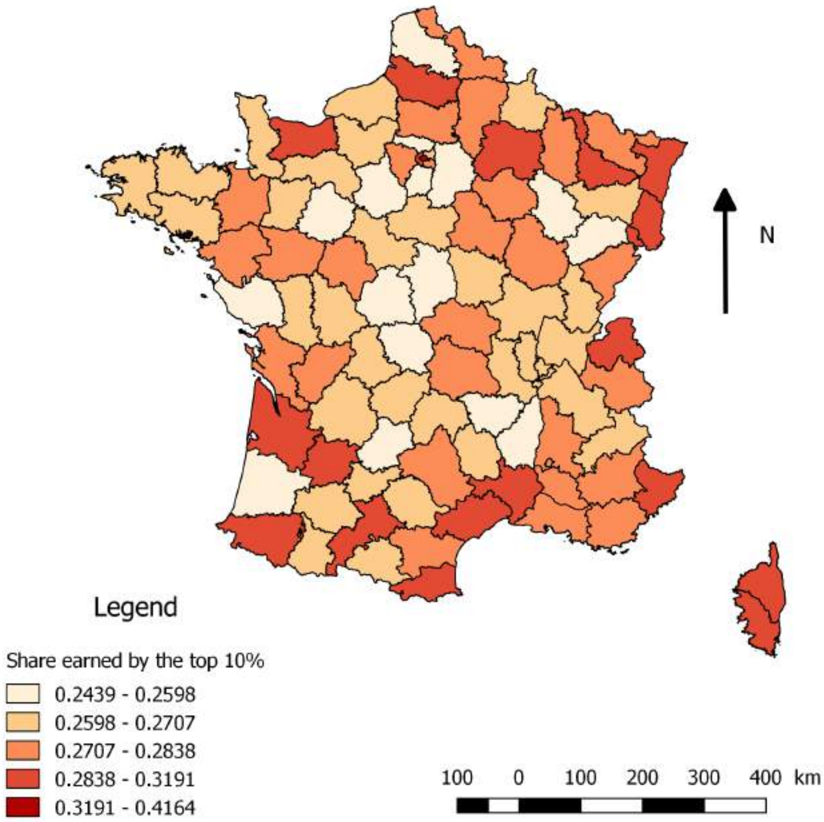

Figure 9: Share of income earned by the top 10% by *département* (2011)

Data from the DGFiP

3 Empirical Strategy

My main equation of interest estimates by *Ordinary Least Squares* (OLS) the (log) average income per fiscal household as a function of the (log) lag income, current and previous weather, *commune* and year specific observables and finally *commune* and year fixed effects. This is summarized by equation (1) below.

$$Y_{i,t} = \rho Y_{i,t-1} + \sum_m (\beta^m T^m_{i,t} + \phi^m T_{i,t-1}) + \sum_n (\gamma^n P^n_{i,t} + \psi^n P^n_{i,t-1}) + X_{i,t} + \mu_i + \theta_t + \epsilon_{i,t} \quad (1)$$

With:

- $Y_{i,t}$ is a measure of average income per fiscal household. Depending on the specification, either:
  - (log) income per capita of *commune* i in year t;
  - Gap between (log) income and the (log) income predicted from the a constant trend;
  - Gap between (log) income and the (log) 7-year moving-average income.
- $T^m_{i,t}$ the number of days of year t for which mean daily temperature have been in the interval m in commune i. These intervals are 3° C intervals : $]-\infty; -6°C[$, $[-6°C; -3°C[$,...,$[+27°C; +30°C[$, $[+30°C; +\infty[$ (the interval $[9; 12]$ is omitted and considered as reference);
- $P^n_{i,t}$ the number of days in year t for which mean precipitations have been in interval n of 40mm: [0;40mm[, [40mm; 80mm[, ..., [400mm, $+\infty$[. The interval [0;40mm[is omitted;
- $X_{i,t}$ is a set of covariates (unemployment rate, share of people with at least an undergraduate diploma, share of people with less education than the *Brevet des collèges* (BEPC), share of people working in agriculture);
- μ_i *communes* fixed effects;
- θ_t year fixed effects;
- $\epsilon_{i,t}$ the error term.

The principal coefficients of interest are here β^m and γ^n. They may be interpreted as the impact on the level of income of having one additional day in a given temperature interval compared to the interval of reference. This equation may be augmented by interaction terms between temperatures and precipitations[12].

[12]Note that I will not make all bins of temperature interact with all bins of precipitation as it would add 140 variables to the specification and present risks of multicolinearity. I will rather compute the number of days inside a temperature bin with substantive rain (ie: with rain higher than 1mm).

This specification allows for an estimation of the non-linear impacts of temperature and precipitation on income which are crucial. Indeed, it seems unlikely that a temperature rise from 12 to 13 °C would have the same impact than from 29 to 30°C. These non-linear impacts may be confounded using only means and quadratic terms (as has been done by Burke et al. (2015)). This equation is related to the work of Deryugina and Hsiang (2017).

The fixed-effects approach controls for both observable and unobservable characteristics of each *commune* that do not vary over time. I therefore compare a *commune* to itself when it experienced several types of weather. For instance, I control for the fact that temperature may be on average higher in Montpellier than in Charleville Mézières and local income higher as well without any causal relationship between the two. I also use fixed-effects for each year which will estimate all observable and unobservable characteristics that vary over time but are the same across all *communes*. In other words, the coefficients will not be biased by the fact that some years, such as 2009, may experience highest temperatures than usual as well as economic recessions at the national level. In brief, the coefficients estimated are computed on local idiosyncratic deviations of each *commune* compared to the usual conditions. Note that despite the several methodological advantages of using such specification, it has also some drawbacks. Because global warming is as its name suggests *global*, I may miss some effects when all *communes* are experiencing higher temperatures at the same time. This will be discussed in more details in Section 7.

Following the work of Cameron et al. (2011), I am clustering my standard-errors in two dimensions (two-way clustering). First, within *communes* across years to take into account the serial correlation and allow for heteroskedasticity. Second, within regions by year to take into account the spatial auto-correlation[13].

It is important to mention the several hypotheses that underlie this specification.

- As in all fixed-effects specifications, in order for $\hat{\beta}^m$ to be a consistent estimator of β^m; the unobservable characteristics of a commune need to not change over time in a way which is correlated with the weather. This assumption would for instance be violated if insurance against weather shocks was available in a *commune* where weather get warmer rather than in another. However, given that most policies are set at the national level, such changes would probably not be specific to a *commune*. Furthermore, because there

[13] I will discuss in more details issues related to spatial auto-correlation in the Section 5 on robustness checks and notably randomized inference.

have been no drastic changes in weather during the period it would be quite unlikely to observe such idiosyncratic changes. Finally, two additional properties of my specification make me think that this assumption is likely to hold:

  – Weather and notably temperature and precipitation can be considered as locally perfectly exogenous[14]. Thus, no unobserved characteristics could drive temperature changes which therefore removes the danger of reverse causality.

  – My coefficient of interest β^m may be seen as a reduced-form estimator. In other words, I do not focus on one specific channel through which temperature can affect income. Therefore, having an impact that may transit through unobserved characteristics is not only more than likely but also desirable in this paper.

- The main coefficient of interest β^m is not indexed neither by i nor by t. I thus assume constant treatment effect over *communes* and over time periods. This will be slightly relaxed later in the study of heterogenous effects.

- Lastly, note that if I allow for non-linearity in temperature level, I do not allow for non-linearity in the number of days in a temperature bin (ie: one additional day above 30 is assumed to have the same effect whether the commune experiences on average one day above 30 per year or 3 days).

As can be seen on Figure 8, there are differentiated trends in income and in weather inside France, one could therefore be afraid that these trends will be spuriously associated with the weather. For example, income may increase more in Montpellier than in Charleville-Mézières during the chosen period whilst weather became warmer in Montpellier than in Charleville-Mézières, and this without there being a causal relationship between these two trends. To tackle this issue, I take two alternative income variables. First, the gap from the (log) predicted income over the period. It can nevertheless be argued that over the period 1990-2015 *communes* may have experienced differentiated trends which could as well lead to spurious correlations. I therefore use the gap from the (log) moving-average income over a seven-year period as a second alternative income variable.

[14]This property may nevertheless be challenged in some cases. For instance, Salamanca et al. (2014) showed that air conditioning in US urban locations, night temperature could increase by more than 1° C as a consequence of air conditioning thus violating the exogeneity of temperatures. Nonetheless, in France in 2009 only 3.6% of the housing were equipped with air conditioning (Figure from the Centre d'Etudes et de Recherches Economiques sur l'Energie (CEREN)) which makes this effect not likely to be really sizable.
A second example of potential endogeneity would be if growth impacts temperatures through urbanization (see e.g. Jones et al. (2008)). Nonetheless, because urbanization takes time, this effect will rather be captured by previous income than by temperature.

The gap from the (log) predicted income $\tilde{y_{i,t}}$ can be written as:

$$\begin{aligned}
\tilde{y}_{i,t} &= y_{i,t} - \hat{y}_{i,t} \\
&= y_{i,t} - y_{i,t_0} \times (1 + g_i)^{(t-t_0)} \\
&= y_{i,t} - y_{i,t_0} \times (1 + \frac{y_{i,T} - y_{i,t_0}}{y_{i,t_0}})^{\frac{t-t_0}{T-t_0}}
\end{aligned}$$

The gap from the (log) moving-average income $\tilde{y}_{i,t}^{MA}$ can be written as:

$$\begin{aligned}
\tilde{y}_{i,t}^{MA} &= y_{i,t} - \hat{y}_{i,t}^{MA} \\
&= y_{i,t} - \frac{1}{7} \sum_{p=t-3}^{t+3} y_{i,p}
\end{aligned}$$

This last alternative income variable can be seen as the most robust and less likely to capture spurious correlations. It is therefore my preferred specification.

To assess the impact on inequality, the same regression will be run on the average income for each decile and on the share of total income earned by this decile.

4 Results

4.1 Impact on the Average Level of Income

Table 6 presents the results of Equation 1. Note that the standard-errors are clustered by *communes* and region×year (two-way clustering) to take into account both the serial and the spatial auto-correlation and heteroskedasticity. Figure 10 presents the coefficients for temperature and Figure 21 in Appendix for precipitation. There are three different specifications. Column (1) regresses (log) Income on the different temperature and precipitation bins (Temperature in $[9; 12]$ and precipitation in $[0; 40]$ are taken as references). Column (2) regresses the gap of (log) income from a predicted income with a constant trend over the whole period. This predicted income corresponds to an income resulting from a constant growth by *communes* from 1990 to 2015. Column (3) presents the results of the regression of the gap (log) income from a 7-year moving average (ie: non-constant trend of growth in the period). All specifications include lag weather and an interaction term between precipitation and temperature . I control for the share of farmers in the *commune*, the percentage of people with no diploma at all, the percentage of people with a diploma higher than an undergraduate and the percentage of unemployed. Each observation is weighted by its population in 1999 to get an average effect for the French metropolitan population[15].

Note that all bins have been divided by 365 in order to have an easier interpretation of the coefficients. Coefficients may therefore be interpreted as: an additional day with a temperature above 30°C reduces the yearly income by 0.1%. Because the average daily contribution to yearly income is $\frac{1}{365} = 0.27\%$, this is equivalent to 37% of the average daily contribution to yearly income (column 3). The idea behind dividing bins by 365 is not to say that the yearly income can be decomposed in 365 daily incomes of equal share nor that the effect of warm days must occur only on the current day but rather to have a order of magnitude in mind when looking at the coefficients. The interpretation would usually be to compare these results with the reference interval (ie: one additional day above 30° C has an impact *compare to a day in the reference bin (here: [9° C;12° C])*. Nevertheless, because here quasi all coefficients for bins under 30 are not significantly different from zero or rather precisely estimated at zero, I can directly interpret my coefficients as the impact of one additional day above 30°C compared to a day below 30°C.

As can be seen on Figure 21, in comparison with temperatures, precipitations do not have a significant effect. It seems that there is no clear-cut conclusion for rainfall. This is in line with

[15]The results can therefore be interpreted as for the average French taxpayer, unweighted results would rather be interpreted as for the average *commune*.

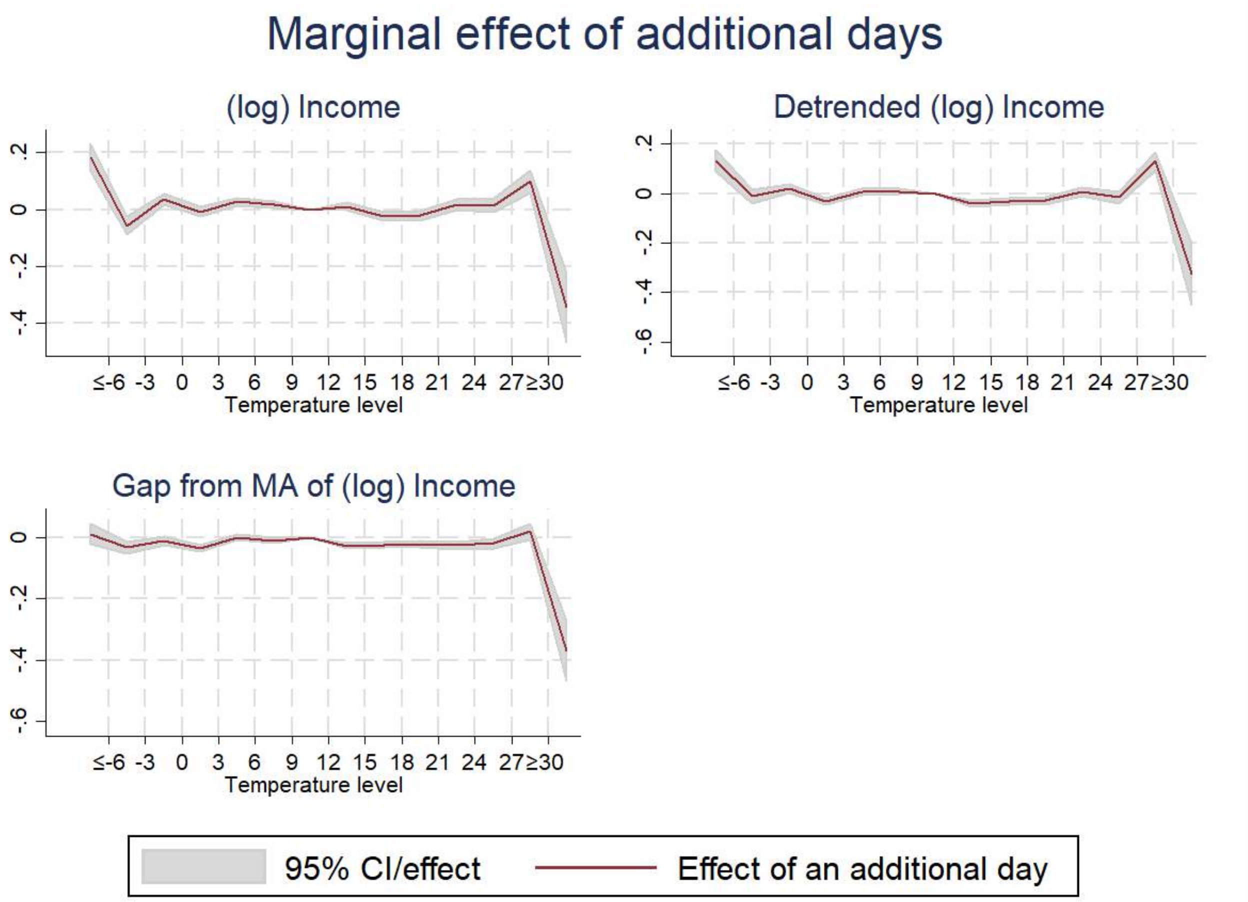

Figure 10: Marginal effect of an additional day in one temperature bin

Note: Results of the equation 1 estimated by OLS with in top-left: (log) income as a dependent variable, top-right: gap from a constant trend in (log) income, bottom-left: gap from the 7-year moving average in (log) income. All coefficients have been multiplied by 365 to be compared with the average daily contribution to yearly income.
Lecture: One additional day above 30°C is associated on average with a decrease of the yearly income by 37% of average daily contribution to yearly income (bottom-left).

what has been found by Dell et al. (2014) and Deryugina and Hsiang (2017).

From column (1) to column (3), all coefficients except the one for days above 30 are reduced in magnitude but are gaining in statistical significance. It is illustrated on Figure 10 on which it can be seen that the graph is flattening out until 30. Notably, the positive effects observed for negative temperatures and for days in bin $[27;30[$ disappear. I interpret the significance of these coefficients in column (1) and (2) as spurious. Indeed, as has been emphasized on Figure 8 above, some mountainous *départments* such as the Haute-Savoie have been the *départements* with the most increasing income over the period. These are also the only places where such cold days occur. With a naive estimator such as in column (1) and to a less extent in column (2) I could capture this trend and interpret it as a spurious causation of the temperature.

The coefficient for days above 30 is not only statistically but also economically significant. Indeed, it means that on a day with average temperature above 30° C, the average income by commune is reduced by approximately a third of the average daily income contribution compared to a day with cooler temperatures. Once again, the idea is not to make the hypothesis that all the effects of a day above 30°C occur only on the given day but rather to have an order of magnitude in mind when looking at the results.

These results differ slightly from the results of Deryugina and Hsiang (2017) who find a negative effect of temperature as temperature grows from 15°C. Here the effect appears only for average temperatures above 30°C. The effect for days with temperatures above 30 is in the same range than their estimates (-0.076%) compared to -0.093% for my corresponding estimate. These two estimators are nevertheless probably not significantly different from one another. The chosen estimator is also in line with Schlenker and Roberts (2009) who found a sharp non-linearity from the same threshold. Their work is nevertheless only focused on agricultural output[16] which will be analyzed in more details in the next part.

4.2 Heterogenous Effects

4.2.1 Impact on Agriculture

Interaction terms with the labour force composition of the *commune* can be added to the specification of Equation 1, notably the share of people working in agriculture. It will allow me to control if the impact is only located in the agricultural sector or if non-farm income is impacted as well.

The results with the interaction term are displayed in Table 8. Column (1) added an interaction term for each temperature bin with the share of farmers. Column (2) is the initial effect without interaction terms, displayed for comparison. The first insight is that coefficients are not heavily impacted by the inclusion of interaction terms. The main coefficient of interest (#days in [30° C;+ ∞[) increases in magnitude by 4 percentage points. The interaction term of days above 30 with the share of people working in agriculture is significant and positive.

It can be interpreted as: 1 percentage point more farmers in the *commune* decreases the magnitude of the impact of an additional day above 30°C on the daily contribution to yearly income by 3.8 percentage point (0,01% in term of yearly income). This is quite a sizable effect. Nevertheless, the median share of farmers in the *communes* is relatively low (at 5%) for an

[16] They found strong non-linear effect from 29° C for corn, 30° C for soybeans and 32° C for corn.

average share across the period around 2.5%. Thus, even for a *commune* that is at the median in terms of share of farmers, the coefficient is still negative and significant (as can be seen on Table 1 which shows the linear combination of the two coefficients). The effect becomes null for a *commune* that has more than 11% of farmers (less than 20% of the *communes*).

Gap (log) Income from MA	Coef.	P-value	[95% Conf. Interval]
# days above 30$\times$ 0.05 $\times$ $share_{farmers}$	-0.234	0.000	[-0.322;-0.147]

Table 1: Linear combination of the impact of an additional day above 30°C on the average daily contribution to yearly income for a commune with the median share of farmers

Note: All temperature bins have been divided by 365. To obtain a coefficient on the yearly income they should therefore be divided by 365.
Details: Results of the estimation by OLS of Equation 1 with an interaction term of the # days above 30°C with the share of farmers.
Lecture: One additional day above 30°C reduces on average the yearly income by 23% of the average daily contribution in a *commune* that has the median share of farmers (5%).

To be more precise, I can also compare the estimated coefficients between the *communes* that have more agricultural workers than the median and those that have less workers than the median. These results are presented on Figure 11.

It is important to keep in mind that the interacted term is the share of people working in agriculture in the *commune* and not the income of those working in agriculture in the *communes* by themselves. This only means that *communes* which have higher share of farmers may be less sensitive to weather variations. However, these *communes* may also have other specifics characteristics that protect them from weather shocks.

Despite the fact that at first sight these results appear counter-intuitive, it is quite in line with a report conducted by the French Senate (Sénat, 2004) which estimated the impact of the 2003 heatwave on farmers' income in France. They find an ambiguous impact on agriculture,. Indeed, they underline that heat waves in the late summer lead notably to early and good quality wine harvest or hardening of wood. Moreover, cereal prices responded to the supply scarcity[17] which led to an ambiguous impact on farmer's income. The same report underlines a sizable detrimental impact on industrial, transport, energy, and distribution sectors.

These results can furthermore be explained both by compensation mechanisms and institutional aspects.

[17]Wheat prices were higher by 20% in October 2003 compared to October 2002 for a total cereal production that was 21.5% under the 2002 production. Nectarine prices were higher by 44% compared to 2002

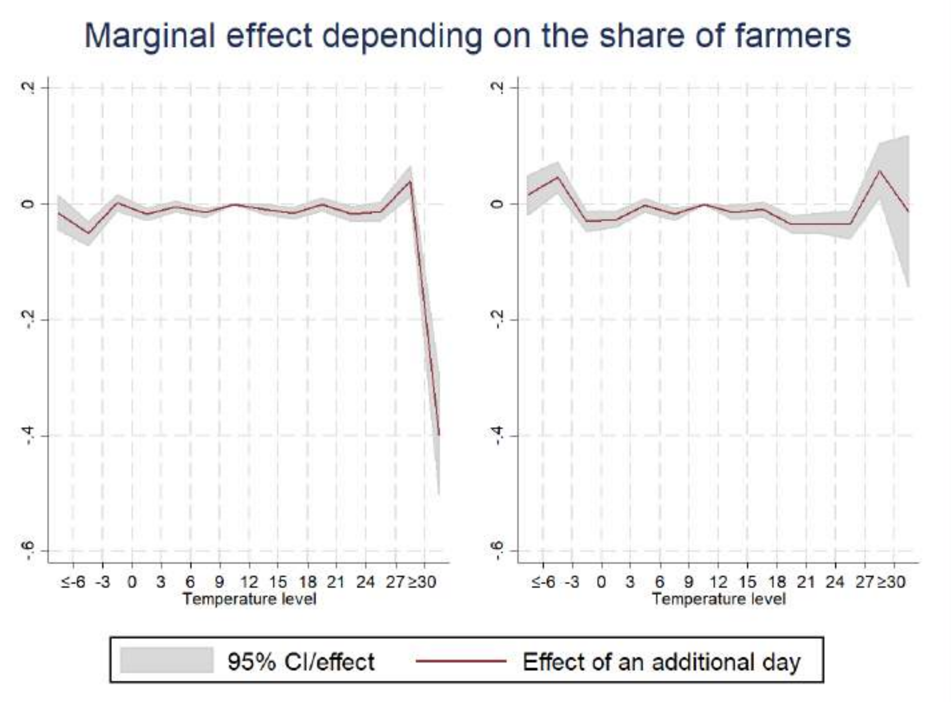

Figure 11: Marginal effect of an additional day in one temperature bin on gap (log) income depending on the *communes* composition.

Note: Results of the estimation by OLS of Equation 1 for *communes* below the median proportion of farmers (left) vs. *communes* above the median proportion of farmers (right). All coefficients have been multiplied by 365 to be compared with the average daily contribution to yearly income (0.27%)
Lecture: One additional day above 30°C is associated on average with a decrease of the income per *commune* by 40% of the average daily contribution to yearly income in *commune* with a share of farmers below the median and has a non-significant impact in *commune* with a share of farmers above the median.

Farmers usually subscribe to insurance that compensates them in case of extreme weather, notably drought. Moreover, in case of drought, the State may also decide to compensate farmers for their losses[18]. These compensations either publicly or privately funded are included in the farmers' earnings and are therefore included in the reported income, which is my dependent variable.

Several institutional aspects can also justify the fact that farmers' reported income may be less responsive to weather shocks than their real income. Indeed, farmers have the possibility in France to declare in year n not only the income of year $n-1$ (as all other French) but the average over the three previous years (*Moyenne triennale*) in order to smooth their taxes. Moreover, they can also choose to report the income of year $n-2$ in year n and not the one of year $n-1$ as the rest of the population do. Lastly, farmers are allowed to differ the inclusion of investment expenses in their tax reports, again in order to smooth the level of their taxes.

These compensation mechanisms and tax reporting types may explain why those who are *a priori* the more sensitive to weather seem to be the ones for whom the income responds less.

Nonetheless, it is important to note that observing a low impact for *communes* with farmers does not imply that French farmers' income do not vary with weather. Indeed, deferring the costs of a climate shock to the following year or smoothing it across three years does not imply that the farmer does not end up paying these costs.

Secondly, even when the farmer has been compensated by the insurance, this is likely to be translated into a more expensive insurance policy for following years which can also be considered as a negative impact on the net actualized income.

Thirdly, taking a more macro approach, compensating farmers for weather shocks still represents a cost for society that is not estimated here. These costs may however become critical and unbearable for taxpayers and for private insurances in the context of climate change.

Lastly, it should be kept in mind that the timing of the heat waves may be very crucial as well, *ie:* if days above 30°C occur in the early summer or in spring it can have a much more detrimental impact on land yields than in the late summer (as the 2003 heatwave). Climate change may lead to earlier hot days which would have an impact that I do not seize here because I do not make any distinction of when hot days occur. This aspect is true not only for farmers but may apply to the whole population and thus to my previous estimates. This will be discussed in more details in section 7.

[18]For instance, see the Arrêtés interministériels d'indemnisation du 9 septembre 2003

To conclude, I do not consider the fact that farmers are less impacted by hot days in France as a main finding of this paper. And this for the three reasons mentioned above. (1) The variable of reported income may not be adequate in seizing an impact on the real income of farmers. (2) Compensation mechanisms may hide more long term detrimental effects. (3) With a macro view, a non-responding farmer's income to hot days does not mean that the costs of agriculture in France are increasing (need more subventions and compensation mechanisms).

One strong implication of these elements is therefore that the average effect computed in section 4.1 is likely to only very scarcely take into account the impact on agriculture and therefore to under-estimate the true average impact.

4.2.2 Impact on the Distribution of Income

From the deciles provided in the data, I can get the average income by decile and the share of total income earned by this group. This by using Pareto interpolations as described by Blanchet et al. (2017).

As mentioned above, the data is not at the same scale than the one used in section 4.1 to compute the average effect. I now work at the *canton* level (approx. 10 *communes*). Nevertheless, running the same regression on the average income by *canton* gives the same results as the ones on the average income by *commune*.

The same regression can be run on the average income by deciles in order to better understand if all economic agents in the income distribution are impacted in the same proportions.

Figure 12 plots the distribution (without confidence interval) for each decile[19]. Two aspects have to be noted when looking at this distribution: (1) The two first deciles seem to be the most affected in terms of log income[20]. Their reaction functions of the first deciles seem to look closer at what Deryugina and Hsiang (2017) found (*ie:* progressive negative effects of temperatures higher than 15° C). (2) Even the highest deciles seem to have an income sensitivity to weather shocks and notably to hot days.

Nevertheless, there is no clear-cut evidence of a differentiated effect depending on the decile of income. Indeed, estimates for the first decile are very noisy (see Figure 22 in the Appendix for more details). The first decile may be subject to more income variability in general and more measurement errors (more unemployment, part-time job, etc.). Moreover, the differences between coefficients are typically not very significant (fail to reject the t-test of unequal coeffi-

[19] The graph with all confidence intervals is displayed on Figure 22 in the Appendix.
[20] Note that in absolute terms, the higher deciles remain the most affected

cients). All these elements hinder premature conclusions[21].

The only null hypothesis one can reject with strong confidence is that one specific decile is not affected (*ie:* all deciles have a coefficient for temperature above 30 that is significantly negative). In other words, all income groups in France seem to be affected by the occurrence of hot days. Even if it remains unclear if it is in unequal proportions, it is already a strong finding that one specific decile will not bear all the costs of global warming.

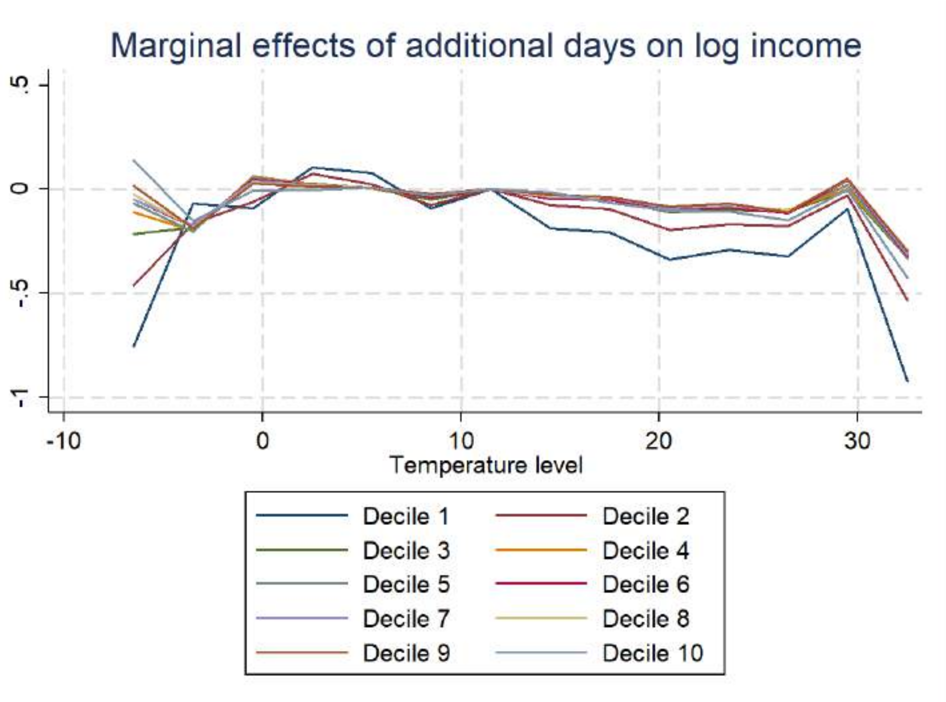

Figure 12: Marginal effect of an additional day in one temperature bin by deciles

Note: Results of the estimation by OLS of Equation 1 for each decile separately.
Lecture: An additional day above 30°C is associated on average with a decrease of the yearly income of the first decile (10% poorest of the commune population) by 80% of the average daily contribution to yearly income. This effect is only of -30% of the sixth decile.
The same graph with confidence interval is displayed in the Appendix (see Figure 22).

I can also study the impact of weather shocks on the share of income earned by each decile in every *canton*. These figures are also obtained thanks to Pareto interpolation from the thresholds available in the fiscal data. Regressing the year-to-year variation of the share of income earned by each decile does not give any significant results for any decile except for the 9^{th} decile. The latter has a coefficient of +0.005 for an additional day above 30°C. This would mean that an additional day above 30°C increases by 0.5 percentage point the share earned by the 9^{th} decile

[21] Note that the coefficients are much more noisy for at least two reasons: (1) less observation for each year because work at a higher scale (3 500 cantons vs. 36 000 communes) and (2) only 11 years of observations vs. 26 years in the study on the average level of income

(from a baseline average of 15%; *ie:* relative increase of $\frac{1}{30}$). Nevertheless, regarding issues of multi-testing, it is very likely that when I test 10 different coefficients at least one would reveal to be falsely significant. After having adjusted by the Bonferroni correction, this coefficient does not remain significant.

Despite having no clear-cut conclusions, there are several justifications for a more severe effect of warm days for first deciles. This, evidently, depends on the channel through which the effect occurs. First deciles may be more affected because their jobs are more sensitive to hot weather (for instance more outdoor activities, more physical activities, less air-conditioned working environment). Moreover, first deciles may have a lower housing quality (notably less well-insulated home or less access to air conditioning[22]). Finally, they may also suffer more from general equilibrium effects (less demand for goods produced or sold by first deciles for instance).

Note that, as mentioned above, I cannot really estimate differentiated effects depending on the place of living (*ie:* geographical inequalities). Nevertheless, households of first deciles may live (now or in the future) in *cantons* that are more subject to particularly warm (and therefore detrimental) temperatures. This inequality will however only be translated in an increase in national but not local inequality.

[22]Note nevertheless that only 3.6% of the housing were equipped with air conditioned in France in 2009 (Figure from the Centre d'Etudes et de Recherches Economiques sur l'Energie (CEREN)).

5 Robustness Checks

5.1 Other Intervals

One potential (and legitimate) criticism to the above findings would be that the results are specific to the intervals chosen. I therefore tested if I find the same results (or at least the same insights) when the intervals vary. For the three specifications presented above I re-estimated the results switching the temperature bins by 1° C (ie: instead of using bins $[0°C; +3°C[$, $[+3°C; +6°C[$, etc.; I use $[-1°C; +2°C[$, $[+2°C; +5°C[$, etc. and $[+1°C; +4°C[$, $[+4°C; +7°C[$, etc.). The coefficients obtained are plotted on Figure 13.

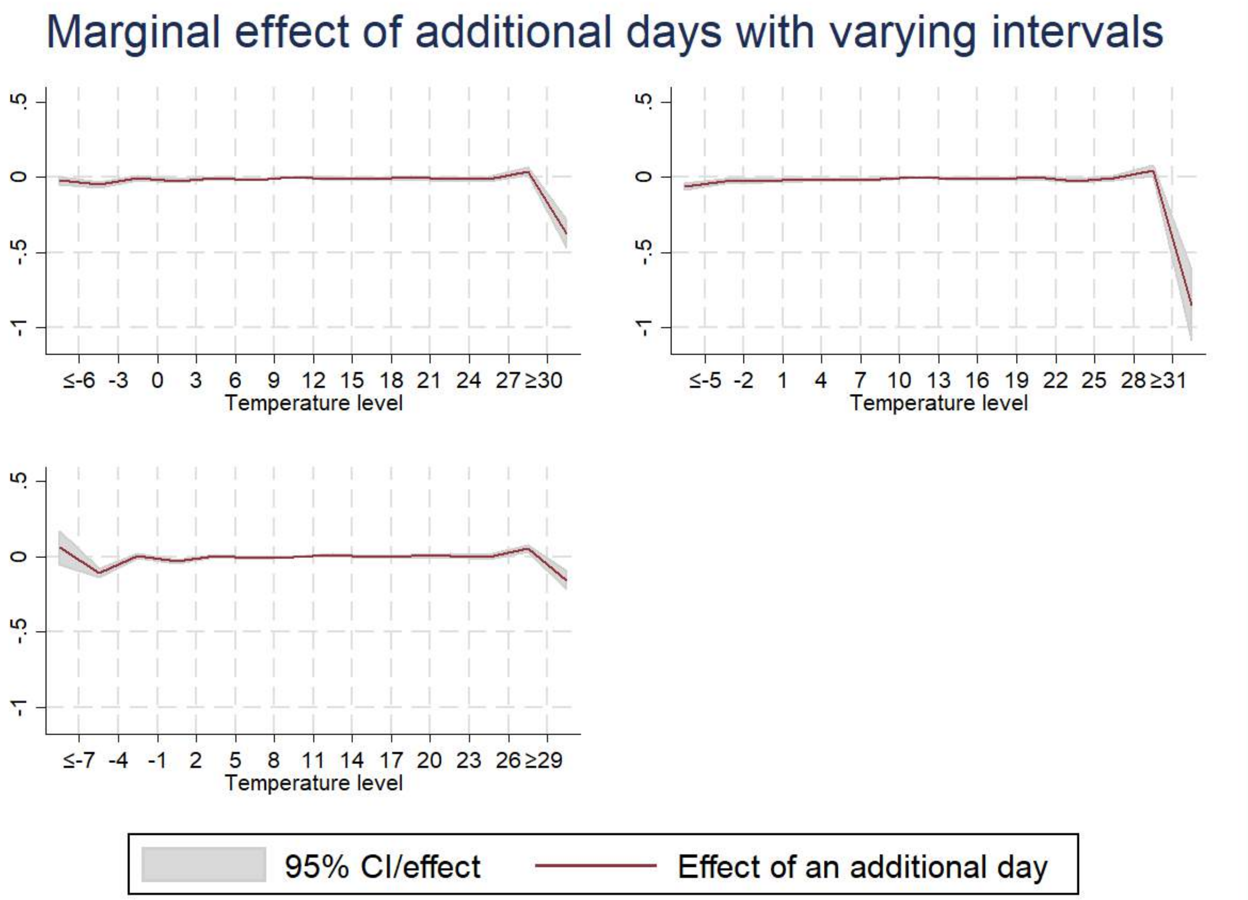

Figure 13: Effects of additional days with various intervals

Note: Results from the estimation by OLS of equation 1 with various temperature intervals: top-left=initial bins (from −6 to +30); top-right= from −5 to +31 ; bottom-left=from −7 to +29.
Lecture: (top-left): One additional day above 30°C is associated on average with a decrease of the yearly income by 36% of the average daily income contribution.

Testing for the two other interval distributions gives the same insights, ie: negative effect of an additional day in a temperature bin higher than either 29, 30 or 31° C. This nevertheless allows me to precise my estimation. Indeed, I find that the negative effect begins for days above 29 ° C, this effect also seems to increase with temperature. The coefficient for the impact above 31 ° C is indeed at -0.7% though much more noisy (because there are very few cases of an average daily temperature above 31°C). Such a high coefficient would suggest that extremely hot days do not only impact the income of the given day but also the income of following days. Indeed, it is difficult to assume that on average a day above 31°C decreases the income of one day by 70%. The elements described above, confirm my hypothesis of strong non-linear effects of temperature on income.

One could also argue that the effect is significant because of the choice of the interval of reference ([9; 12° C]). This interval has been chosen because the national average temperature lies in this interval. Moreover, because coefficients for neighbouring intervals are precisely estimated at zero (or very close to zero), the coefficient for days above 30 °C would be significant and of the same magnitude whatever the reference interval.

5.2 Randomized Inference

One major concern of statistical studies using weather, either as an explanatory variable or as an instrument, is to take into account the spatial auto-correlation of the data. Indeed, weather, and to a lesser extent income, are strongly geographically correlated. It means that if one can exploit the randomness of weather across time, assuming random and independent variation across space would be a harsh assumption. Unless one takes that structure of the data into account, one would obtain (downward) biased standard-errors.

This element may also be reinforced by the interpolated characteristics of my weather dataset. Two-way clustering has been a common tool for controlling for spatial correlation. Nevertheless, as has been emphasized by Lind (2015) or Cooperman (2017), it may not be enough and may still lead to spurious correlations. Some solutions exist such as models of spatial dependence or a correction of the standard-errors by the method proposed by Conley (1999). In both cases it nevertheless it brings about assumptions on the spatial dimension of the data. This may still lead to over-rejection of the null hypothesis of no average effect. Because weather boundaries do not correspond to any political boundaries, it may be not restrictive enough to chose to cluster by region for instance.

I therefore here chose to use Randomized Inference as proposed by Gerber and Green. (2012) or Cooperman (2017) to test the robustness of the results. The idea of Randomized Inference is to permute (with replacement) the weather for each year; *ie:* for each *commune* (resp. *canton*)

I randomize the "treatment" (*ie:* the weather) received and run the same regression on this "placebo" weather variable. For each permuted dataset, I can compute the t-statistic associated with each coefficient. The distribution of these t-statistics which is the distribution under the null hypothesis, should after be compared with the "true" t-stat in order to test its significance. To be clearer, I create a distribution of t-statistics for which I know that I cannot reject the null hypothesis of an effect and I compare it to my estimated t-statistic. In other words, I break the structure present in the dataset to try in order to quantify the patterns I could have observed only "by chance".

The "treatment" can be randomized at several levels. The question is here to know at what level the true treatment (weather) is assigned. Firstly, if I consider that treatment is assigned to four "big weather regions" independently, I can randomize across these big regions (see Figure 14 for the delimitation). It means that two *communes* of different weather regions may be assigned to the weather of different years but that two *communes* of the same weather region will be assigned to the weather of the same year. Secondly, one could consider that no observations within France could be considered as independent from one another. I therefore also randomize at the national level; *ie:* all *communes* (resp. *cantons*) of the country are assigned to the weather of the same year.

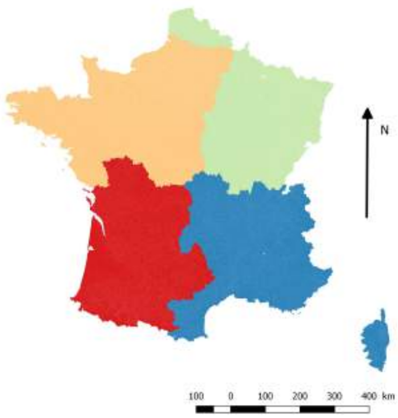

Figure 14: Separation of France in 4 big Weather Regions

Once all these test statistics have been computed, I can calculate a p-value by computing the proportion of the null distribution that is larger than my "true" observed test-statistic. The new p-values (p^*_m) associated with all coefficients β^m for the temperature bin m are therefore:

$$p^*_m \quad = \quad \frac{\sum_j^J \mathbb{1}(|t^j_m| \geq |t^*_m||\beta^m_j = 0)}{J}$$

with t^*_m the t-statistic observed for the "true" estimator, J the number of permutations (1 000 in my present case) and β_j^m the coefficient of the interval m computed in permutation j and t_m^j its associated test-statistic.

I can therefore test the robustness for each of the coefficients of Equation 1 estimated in the previous section by Randomization Inference.

Figures 15 and 17 are presenting the distribution of t-statistics of the coefficients for the number of days in [30° C ;+∞ [assuming either an independence of two *communes* in different weather regions (15) or no independence at all (17). I therefore obtain new p-values under the sharp-null hypothesis of no-effect (Table 2). These p-values correspond to the number of "null" t-statistics that are larger in absolute terms than my "true" t-statistic. In other words, one can calculate the probability to obtain an estimate of such a magnitude if days above 30° C have no effect at all. Figure 17 gives two insights:

- Looking only at usual p-values would tend to over-reject the null hypothesis of no association between temperature and income. Increasing the number of potential correlations between observations in the space dimension leads to higher estimated t-statistics in absolute term. In all clustering levels, despite having a distribution of t-statistics centered at zero, the null hypothesis is rejected in more than 5% of cases. Indeed, more than 5% of the estimated t-statistics have an absolute value above 1.96 [23]. This is very likely due to the spatial correlation that subsists in the dataset despite having used as a dependent variable the gap from a moving-average and having clustered in two dimensions (by *commune* (resp. *canton*) for the serial correlation and by region $\times$ year for the spatial auto-correlation). To be more precise, because observations are not independent in the N dimension, the central limit theorem cannot be applied.

- The "true" estimator for days above 30°C has a t-statistic (red line) that is far enough from the distribution of the t-statistics under the null hypothesis (the computed p-value has a value of 4% in the worst case). That is why, I am able to reject the null hypothesis of no-association between temperature and income.

Note that the null hypothesis tested in the framework of Randomization Inference is a sharp null hypothesis. In other words, I test if the correlation between temperature and income is null for all the treated elements (*ie:* all years). Rejecting the sharp null hypothesis thus means that there is at least one year for which the "treatment" had an effect on the outcome of interest. Assuming, as before, a constant treatment effect (ie: β not indexed neither by t nor by i) implies

[23]Because weather of previous years may impact income of given year, these correlations may not be spurious for every permuted dataset. Nonetheless, the null hypothesis of no-association is here rejected in 50% of the permutations which is far above common threshold.

the rejection of the null hypothesis of no average effect (ie: coefficients for different years cannot cancel out).

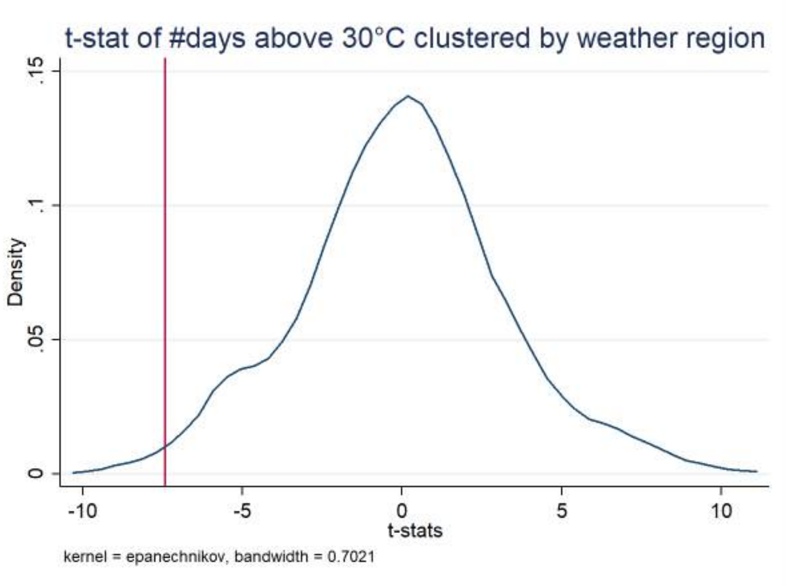

Figure 15: Distribution of the coefficients of the regressions of (log) income on the # days above 30°C clustered by weather regions.

Computed with 1 000 iterations.
The true "t-stat" (red line) is at -7.46

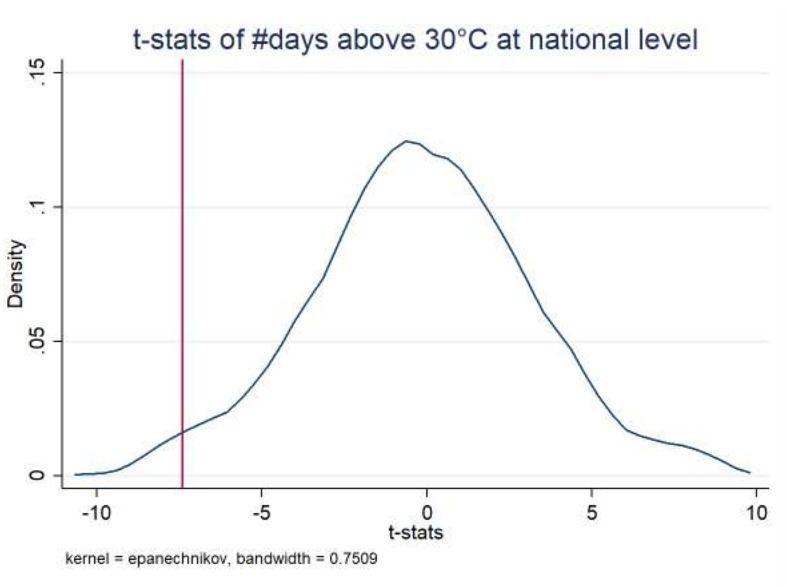

Figure 16: Distribution of the coefficients of the regressions of (log) income on the # days above 30°C for no independence

Computed with 1 000 iterations.
The true "t-stat" (red line) is at -7.46

If one applies the same strategy of Randomization Inference on the coefficient for days

Correlation level	# days > 30
Initial regression	0.000
Weather Region	0.028
Country	0.040

Table 2: New p-values obtained through RI

between 27°C and 30°C, it gives the distribution of t-statistics presented on Figure 17 without assuming independence between two *communes* of the same year (clustering at the national level). One cannot reject the null hypothesis of no association between temperatures and income (computed p-value=58%). This confirms the insights from the previous parts.

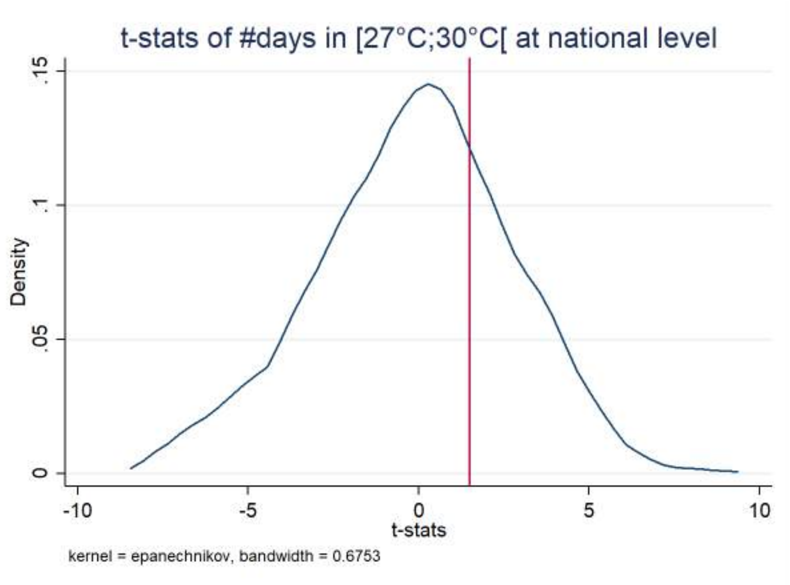

Figure 17: Distribution of the coefficients of the regressions of (log) income on the # days between 27°C and 30°C for no independence

Computed with 1 000 iterations.

6 Simulation and climatic projections

The effects measured on the aggregate level of income, despite being quite sizable and surprising, remain marginal because the occurrence of days above 30° C is quite rare (see Figure 6 for historical specific local occurrences of days above 30°C). The impact on the economy is therefore limited though non-negligible. Nevertheless, the occurrence of days above 30°C is likely to increase in the following years according to several climatic projection models. It therefore seems interesting to estimate the potential costs of the occurrence of days above 30°C.

6.1 Needed assumptions

To go from estimates computed using historical weather deviations to future climate impact, I have to advance (at least) two hypothesis:

1. As said above, the estimated coefficients have been computed on a specific sample (because not all the *communes* experienced days above 30°C and not all in the same proportion). Therefore, using these coefficients as inputs with climate simulations to estimate potential future costs of global warming requires strong assumptions. Notably, that the effect computed on a specific set of *communes* is valid for other *communes* as well. Because these *communes* are not specifically located in one part of the country but rather almost in every region (except mountainous northern regions) and because their average income per capita and their labour force compositions are similar, the assumption seems legitimate.

   Nevertheless, it may be likely that *communes* that did not experience any days above 30°C will suffer more from this new warm climate than those which have already experienced it. Thus, it would mean that out estimates for predicted negative impact would underestimate the true impact.

2. My coefficients have been computed using historical short-term, marginal and non-lasting weather variations. To infer on future costs of global warming, one therefore needs to assume that the response function will be the same, notably that adaptation will not change this reaction function. In the discussion part (section 7) I will question the relevance of this hypothesis and the differences between global warming and historical shocks to assess the pertinence of my projections.

6.2 Projection Model

The various climate scenarios intend to represent various possible future weather situations based on different greenhouse gas concentrations. The EURO-CORDEX ensemble uses Representative Concentration Pathways scenario (RCP) provided by the Intergovernmental Panel on Climate Change (IPCC). These RCPs determine greenhouse gas concentration scenarios and deduct temperature rises. From these RCPs, General Circulation Models (GCM) that study the interactions between components of the Earth system are computed. These models give projections of weather and are downscaled to get predictions at a local scale. Data is provided by the Drias. The scenario RCP 8.5 corresponds to a "business as usual", ie: no specific change of gas emissions. It is nevertheless the scenario that seems today the more likely (or even optimistic), in comparison with scenarios like RCP 4.5 would be unrealistic.

Figure 18 presents the projection of average temperatures until 2100. One can observe an increase of approximately 4° C compared to the pre-global warming situation (pre-1990).

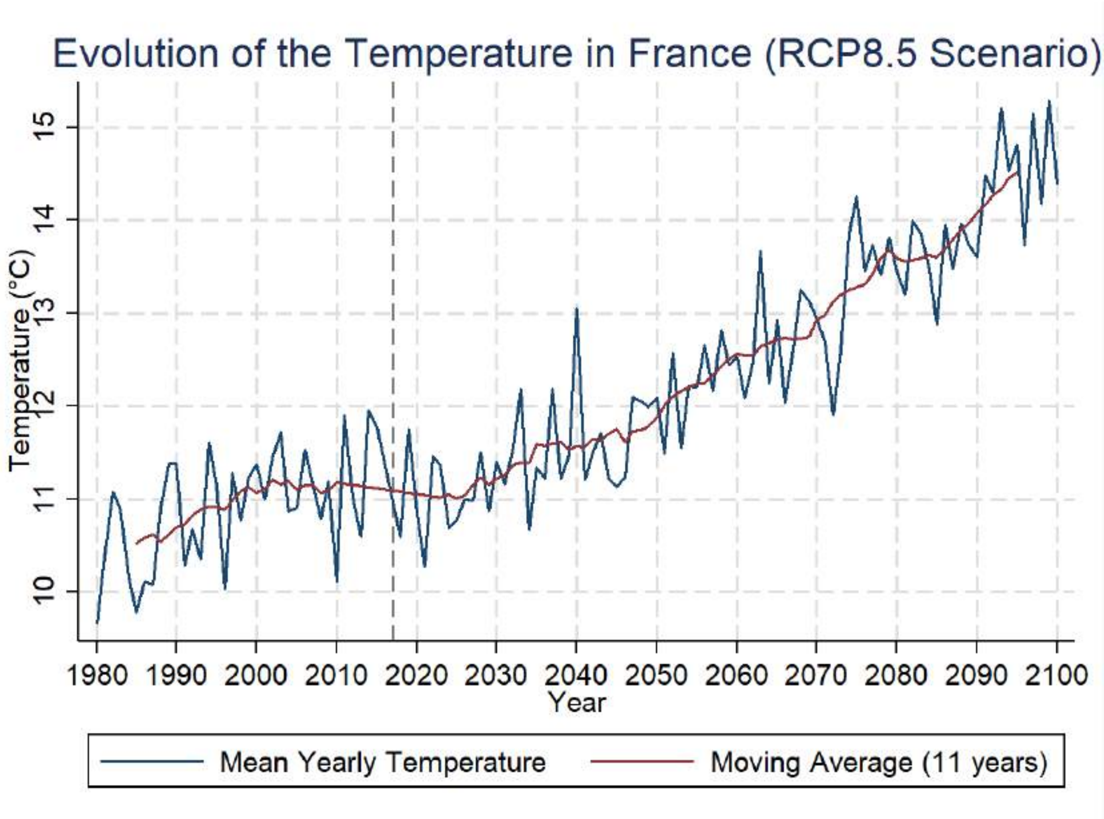

Figure 18: Evolution of average yearly temperatures according to the RCP8.5 Scenario in France.

Note: Data from Météo France and the Drias. Historical temperatures for the period 1980-2017 and forecasts for 2018-2100.

Note that with global warming, French *communes* will experience temperatures that have never before occurred (or very rarely). There is therefore two choices to estimate the impacts of such extreme days: (1) extrapolate the relationship found for days above 30° C or (2) set the effect of days far above 30° C as the same as days just above 30° C. I choose to use the second option, which is more conservative. My estimate of the projected effect is thus likely to under-estimate the true effect (under the two hypothesis stipulated above) and has to be taken as a lower bound.

According to the projections until 2100, only 24 *communes* in France will not experience any days above 30°C, all in very mountainous areas. Three quarters of the *communes* will experience a day above 30°C at least once every five years. Three quarter of the population[24] will experience such temperatures every three years. Finally, almost 40% of the population will experience such temperatures more than once a year. At the end of the period it is even more dramatic with on average a day above 30 °C every three years out of four for the period 2050-2070 and on average two days above 30 ° C per year for the period 2080-2100 with some regions experiencing more than 20 days per year above 30 ° C with a non-negligible share of days above 36 °C[25]. Figure 19 displays the additional number of days above 30 ° for each French *commune* for the end of the century compared to the reference period.

My strategy to estimate the impact is to compute for each French *commune*, the predicted number of days above 30°C. I compute the 11-year moving-average for each year in order to not have years with a huge impact and others with almost no impact at all. This would not have much sense because the models do not forecast a given year's exact temperatures with precision but rather gives an idea of the tendency over the long-run. I then multiply the difference between the number of days and the number of days from the average 1970-1989 (considered as pre-global warming) by the coefficients estimated by equation (1).

$$\hat{\delta}_{i,t} \quad = \quad \beta_{30}(T^{30}_{i,t} - \bar{T}^{30}_{i,1970-1989}) \qquad (2)$$

with:

- $\hat{\delta}_{i,t}$: the predicted impact in commune i and year t;
- $\hat{\beta}_{30}$ the estimated coefficient of an additional day above 30°C;
- $T^{30}_{i,t}$ the number of days above 30°C in commune i and year t ;

[24] If the distribution of population remains the same than in 2012.

[25] Let me recall that the maximum observed over the period 1990-2015 has been once 33 ° in Perpignan

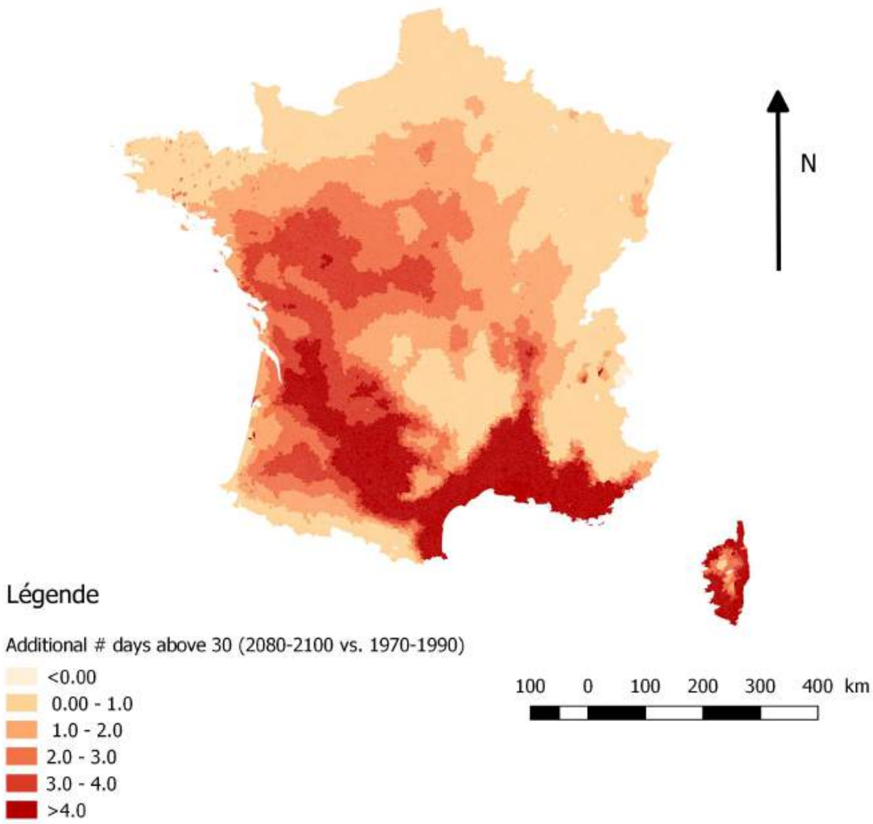

Figure 19: Additional yearly number of days above 30° C in 2080-2100 compared to the pre-global warming period.

Data from the Drias and Météo France

- $\bar{T}^{30}_{i,1970-1989}$ the number of days above 30°C in commune i during the reference period.

I then compute the average of all $\hat{\delta}_{i,t}$ weighted by the commune population of 2012 to get a nationally representative estimate.

Note that this impact is in relative terms (*ie:* decrease the future GDP of period t by $x\%$).

According to the RCP 8.5 scenario, I get a national average estimated impact of -0.08% of GDP each year over the medium-run (for the period 2050-2080) and -0.3% over the long-run (for 2080-2100) compared to a no global warming scenario.

These figures may seem small but have to be seen in parallel with growth predictions. If growth does not exceed 1 or 1.5 % each year, it represents a reduction of a fifth to a quarter of growth for the end of the period. Furthermore, there are cumulative effects of having a contracted GDP in $t-1$ on the GDP of t.

	Medium-Term (2050-2080)	Long-Term (2080-2100)
Point Estimate	-0.08%	-0.29%
95 % CI	[-0.10; -0.06]	[-0.36; -0.21]

Table 3: Estimated future yearly impact of global warming in France

Lecture: Under the RCP 8.5, scenario, GDP will be reduced by 0.08% each year due to additional warm days in 2050-2080 and by 0.29% in the long run (2080-2100).

6.3 Reliability of the Estimation

There are mainly four types of uncertainty in the above estimation: scenario incertitude, model incertitude, statistical incertitude and economical incertitude[26]. The first two are more of the prerogative of climatologists than economists. Statistical uncertainty of the estimates computed in Section 4 is taken into account through confidence intervals for the projected impact. Economical uncertainty (ie: will the economy continue to respond in the same manner to global warming than it has done historically) will be assessed in the discussion part.

[26]The EURO-CORDEX advisory document also states internal climate variability as a source of incertitude, ie: incertitude about the initialization of each model component but this may be understood as a type of model incertitude.

7 Conclusion and Discussion

This paper has assessed the impact of local temperatures on income in France. Results show that an additional day with temperatures above 30° C reduces the yearly income per fiscal household by 0.1%. This is equivalent to 37% of the average daily contribution to the yearly income. Quite surprisingly, this phenomenon has been found to not impact farmers' income. This, in reality, may be explained by compensation mechanisms and the French tax system aimed towards farmers' fiscal income and should not be kept as an insight of this paper. Despite different point estimates by deciles with bigger negative impacts of days above 30° C for first deciles, I lack statistical power to precisely conclude that global warming may foster national income inequalities in France. I can nevertheless infer that all deciles of income are affected by the occurrence of extremely hot days. Using predictions made by Regional Climate Models (RCM), I obtained an estimate for the costs of global warming. My estimate gives a reduction of GDP over the medium run on average by 0.1 %, and over the long run by 0.3% each year.

Even these small effects on GDP may have large consequences over time, taking into account cumulative effects. These figures should also to be red in light of growth prospects which may not exceed 1 or 1.5%. Finally, I assessed the robustness of my estimates using Randomization Inference to avoid the risk of spurious correlations.

I discuss below several issues related to my predictions in terms of global warming costs. I also present further interesting axes of research.

The first aspect to underline is that the results presented in this paper rely on specific climate models which are uncertain. I have focused on the statistical incertitude rather than on climatic incertitude because the former is an economist's lever for action. However, cautious attention should also be given to climatic projections. Control for the robustness of my results using more diverse models would therefore be interesting.

There are also several challenges that arise when using historical estimates to infer future global warming costs. This rises question both the internal and external validity of my estimates.

Deryugina and Hsiang (2017) argue that their estimates take into account adaptation (using the envelope theorem and arguing that counties are at the production possibility frontier). Reaction functions to weather would therefore be optimal and represent a fair estimator of climate change future costs (*ie:* costs of adaptation are already taken into account). I think this statement can nevertheless be challenged because reaction functions to idiosyncratic, unexpected and non-permanent weather shocks were computed in this study. These three properties make my coefficients very likely to estimate the costs of global warming with a bias. Depending on the assumptions made, each of these differences between global warming and the idiosyncratic, unexpected and short term weather shocks may lead to either an over- or an under-estimation of the true effect.

Firstly, as it has been shown in previous sections, the impact of temperatures on farmers' income is only scarcely taken into account. My estimation is therefore likely to underestimate the true costs of global warming.

Secondly, my specification imperfectly takes into account common shocks and therefore does not allow to estimate entirely a national level impact. This, for two reasons: (1) National shocks will be captured by year-fixed effects but it is likely that some national detrimental effects exist, leading my coefficients to under-estimate the "true" costs of global warming. (2) Complex interactions between *communes*, may lead the national impact to differ from the aggregated impact. One could argue that these costs would be higher if every *commune* were to be affected at the same time (less geographical solidarity, less compensation and substitution mechanisms available).

Thirdly, I have assumed in my estimation a linear relationship[27] between income and the number of days above 30°C. However, this relation is likely to be convex with higher cumulative effects; *ie:* three consecutive days above 30 °C may have a higher negative impact on income than three times the impact of one day above 30° C. Not taking into account this cumulative effect would therefore tend to under-estimate the true costs of global warming.

Fourthly, climate change and specifically global warming may lead to days with temperatures above the threshold computed here (ie: temperature above 35 or 36 ° C that have not occurred during the period studied here). In my specification, I have imputed the same coefficients for all days above 30° C but these days are very likely to have stronger detrimental impacts on income thus leading the historical response function to under-estimate the true impacts of global warming.

Fifthly, historically, days above have occured only in summer and notably in August. This is not the more critical period in terms of agriculture and a large part of the French labour force is not working at that time. If days above 30°C occur in other periods than summer, a stronger detrimental effect can be observed.

Sixthly, the share of "treated" people in the population (*ie:* those who have experienced days with a higher temperature than 30° C) is very likely to be enlarged. The people who are traditionally not used to experience such weather effects will be affected as well. One may argue that this will lead them to be more sensitive that the previously treated population thus leading

[27] Note that the non-linearity property that I estimated is in the effect of the temperature *level*, not in the number of days in each temperature bin

again to an under-estimation of the true effect.

Table 4 tries to summarize these six "internal" biases of my estimates and their sign. This list is nevertheless not exhaustive. All these internal biases seem to lead to an under-estimation of the "true" global warming costs. My estimator should in that sense be considered as a lower bound of the true global warming effect.

	Difference	Sign
1	Effect on farmers	-
2	Common Shocks	-
3	Cumulative and Consecutive Effect	-
4	Days far above 30°C	-
5	Warm days in other time periods	-
6	Untreated communes	-
Total		-

Table 4: Internal Differences between the Estimates and "true" Global Warming Costs.

Finally, a big difference between short-run response estimates and climate change future costs is the adaptation and anticipation. These aspects are not specific to my study. If future weather shocks (notably heat waves) are better anticipated than in the past, economic agents may prepare themselves better and change their optimal response to such events. Moreover, because it will be a permanent shock, agents may also develop adaptation strategies to climate change, for instance more air conditioned living and working environments, technological changes or factor reallocation (*e.g.* migration) which would reduces the magnitude of the impact. One should also keep in mind that these adaptation strategies also have costs. Historical estimates computed on short-term shocks by not taking adaptation and anticipation into account would therefore over-estimate the costs of global warming.

The several limits to my work are not insoluble and several enlightening answers could be brought by future research to complete this study. Notably, it would be interesting to apply the same strategy to minimum and maximum temperatures rather than only the 24h mean,. This may reveal other non-linear impacts as well.

Secondly, a question that remains (almost) entirely open at the conclusion of this paper is to know which of the four channels dominates between (1) Land and capital productivity; (2) Human productivity; (3) Labour supply response and (4) market and general equilibrium effect. It would therefore be very interesting to further explore the channels through which the effect estimated here plays. This could be done with more precise and specific data. For instance on housing, land productivity, firm daily income, local GDP decomposition by sector, amount of time worked by days and vacations, sick leaves, etc. This would also be very useful to conduct a qualitative study to understand more precisely the phenomenon estimated in this paper. One aspect that has not been mentioned yet is to know if it is more an indoor or an outdoor effect (in that case, adaptation may be easier).

Thirdly, in continuation of the question of channels, it would be interesting to know if the effect is limited to the given day or if it is spread over the following days or months.

Lastly, I would like to recall that this paper has focused on one specific aspect of climate change: which is global warming. My reasoning is therefore closed to a partial equilibrium study taking all other aspects than global warming as constant. Nonetheless, temperature rises can hardly be disentangled from other climate change aspects such as sea rise, natural disasters (notably storms) and biodiversity changes that are likely to affect income as well. Moreover, because global warming is occuring abroad as well, it will probably have indirect impact on the French economy (*e.g.* climatic migration). In light of the aforementioned elements, these results do not aim to predict precisely the future impacts of climate change impact but rather aim to highlight what temperature rises independently of other variables could imply in terms of income.

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Appendix

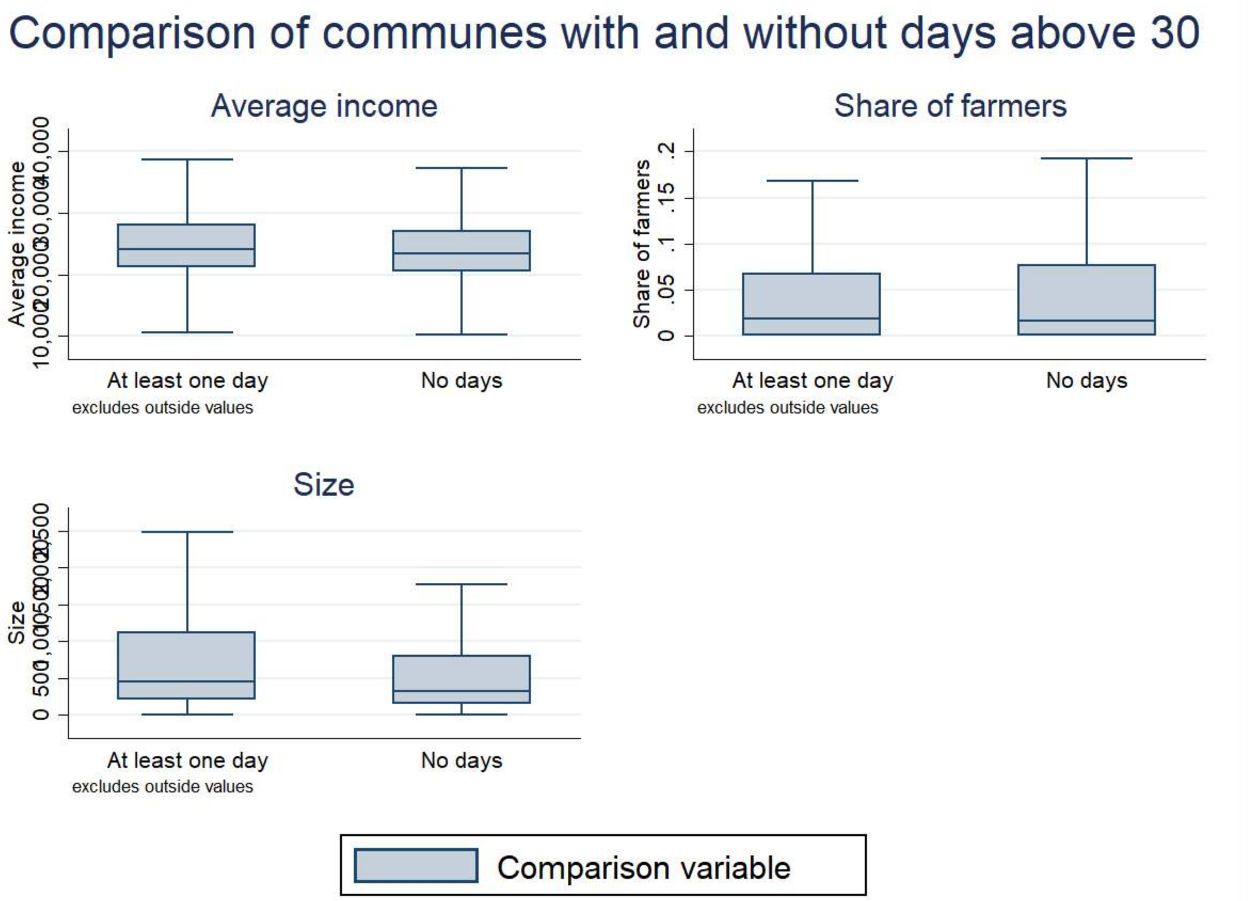

Figure 20: Differences between communes that experienced days above 30°C and those that did not

Note: Data from the DGFiP and the INSEE.

	Outliers	Whole sample
Number of observations	35 134	952 994
Size of the *commune*	205	1 523
(sd)	(568)	(6 975)
Average income	19 513	22 274
(sd)	(22 757)	(7 416)
Share of farmers	0.10	0.02
(sd)	(0.17)	(0.06)

Table 5: Comparison in and out of sample

VARIABLES	(1) (log) Income	(2) Gap (log) Income	(3) Gap in MA (log) Income
Lag	0.647***	0.433***	-0.0175***
	(0.00343)	(0.00367)	(0.00230)
#days in]-∞; -6° C[	0.181***	0.133***	0.0116
	(0.0248)	(0.0219)	(0.0165)
#days in [-6° C;-3° C[	-0.0558***	-0.0113	-0.0332***
	(0.0158)	(0.0136)	(0.0102)
#days in [-3° C; 0° C[	0.0361***	0.0204**	-0.0108
	(0.0103)	(0.00928)	(0.00700)
#days in [0° C;3° C[	-0.00740	-0.0317***	-0.0361***
	(0.00815)	(0.00731)	(0.00546)
#days in [3° C;6° C[	0.0271***	0.00662	0.000682
	(0.00659)	(0.00599)	(0.00457)
#days in [6° C;9° C[	0.0174***	0.00830	-0.0102**
	(0.00609)	(0.00559)	(0.00421)
#days in [12° C;15° C[	0.0104	-0.0401***	-0.0268***
	(0.00651)	(0.00572)	(0.00436)
#days in [15° C;18° C[	-0.0234***	-0.0313***	-0.0232***
	(0.00681)	(0.00625)	(0.00470)
#days in [18° C;21° C[	-0.0210**	-0.0285***	-0.0211***
	(0.00823)	(0.00743)	(0.00547)
#days in [21° C;24° C[	0.0170*	0.00745	-0.0252***
	(0.00899)	(0.00838)	(0.00608)
#days in [24° C;27° C[	0.0151	-0.0161	-0.0184**
	(0.0121)	(0.0113)	(0.00796)
#days in [27° C;30° C[	0.0985***	0.130***	0.0200
	(0.0203)	(0.0189)	(0.0133)
#days in [30° C;+ ∞[	-0.343***	-0.325***	-0.370***
	(0.0620)	(0.0647)	(0.0498)
Observations	1360837885	1356999398	1360837885
R-squared	0.854	0.627	0.247

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression of income on intervals of temperatures and precipitations with 2-way clustering

Note: All temperature bins have been divided by 365. To obtain a coefficient on the yearly income they should therefore be divided by 365.
Details: Estimation by OLS of Equation 1. Column (1) uses the (log) income as a dependent variable, column (2) the gap from a constant trend over the period of the (log) income, column (3) the gap from the 7-year moving-average of (log) income. Observations are weighted by *commune* population in 2000. All columns are clustered both by *commune* and by Region × Year. All columns include Precipitation, an interaction term between precipitation and temperature and a lag of the weather. Four controls are included: the share of farmers, the share of people with a higher diploma than an undergraduate, the share of people with no diploma and the unemployment rate.
Lecture: One additional day above 30°C is associated on average with a decrease by 37% of the average daily contribution to yearly income (Column (3)).

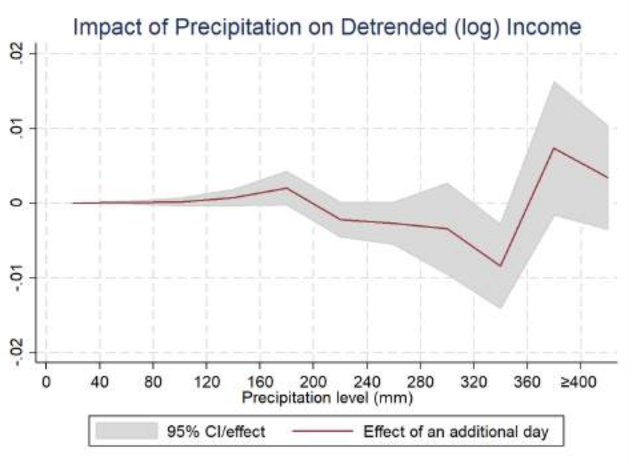

Figure 21: Average impact of an additional day in the precipitation bin on the gap from (log) moving average

Coefficients obtained with the estimation of Equation 1 by OLS with the gap from the 7-year Moving Average (Column (3)) of Table ??

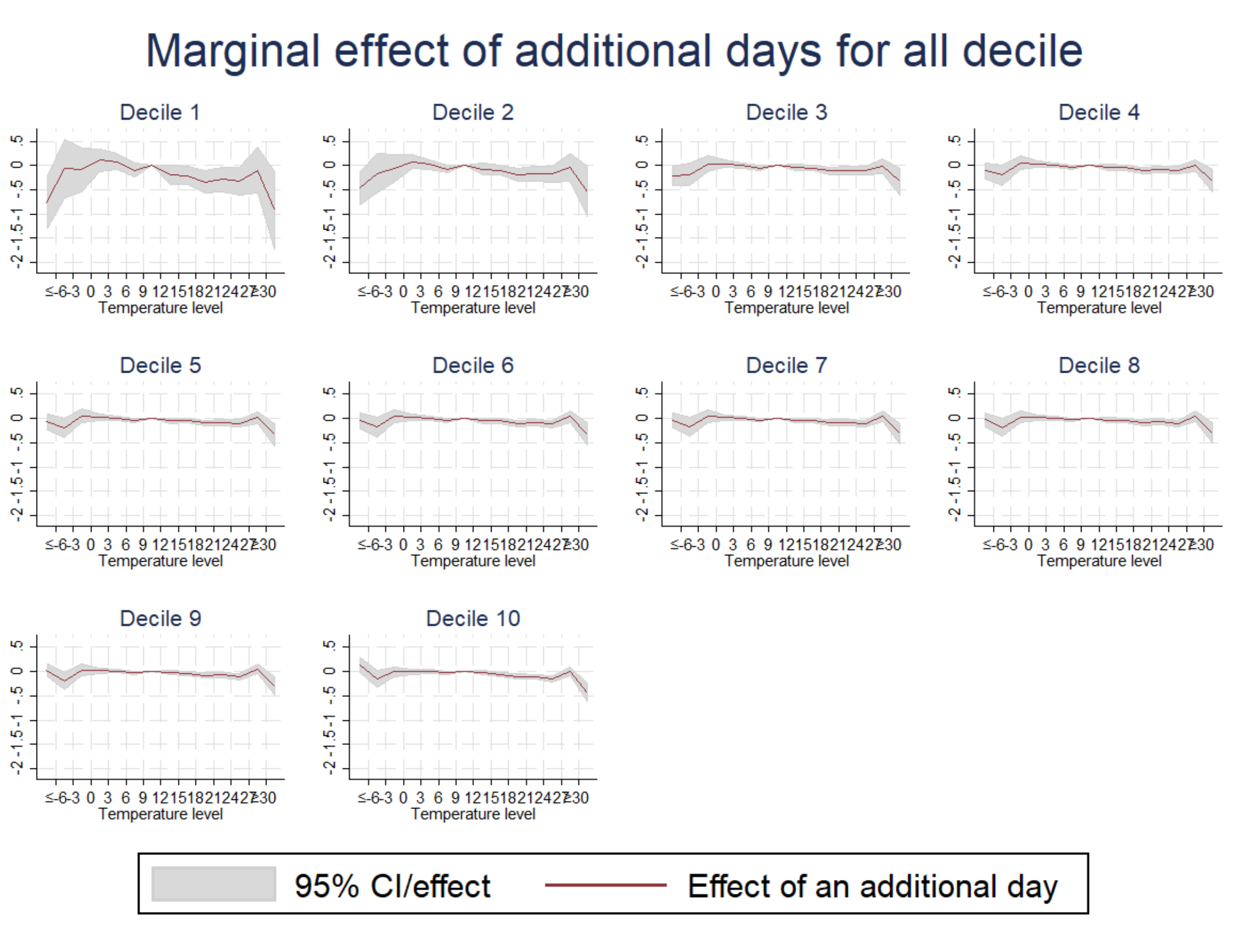

Figure 22: Effect of additional days in temperature bins for each decile

Results of the estimation by OLS of Equation 1 on each decile separately

VARIABLES	(1) Gap in MA (log) Income	(2) Gap in MA (log) Income
Lag	-0.0174***	-0.0175***
	(0.00230)	(0.00230)
#days in]-∞; -6° C[	-0.00385	0.0116
	(0.0173)	(0.0165)
$share_{farmers}\times$ #days in]-∞; -6° C[	0.559***	
	(0.0866)	
#days in [-6° C;-3° C[	-0.0359***	-0.0332***
	(0.0109)	(0.0102)
$share_{farmers}\times$ #days in [-6° C;-3° C[	0.208***	
	(0.0665)	
#days in [-3° C; 0° C[	0.00184	-0.0108
	(0.00754)	(0.00700)
$share_{farmers}\times$ #days in [-3° C; 0° C[	-0.493***	
	(0.0437)	
#days in [0° C;3° C[	-0.0318***	-0.0361***
	(0.00580)	(0.00546)
$share_{farmers}\times$ #days in [0° C;3° C[	-0.0584*	
	(0.0334)	
#days in [3° C;6° C[	0.00110	0.000682
	(0.00491)	(0.00457)
$share_{farmers}\times$ #days in [3° C;6° C[	0.0550*	
	(0.0292)	
#days in [6° C;9° C[	-0.00523	-0.0102**
	(0.00462)	(0.00421)
$share_{farmers}\times$ #days in [6° C;9° C[	-0.137***	
	(0.0330)	
#days in [12° C;15° C[	-0.0278***	-0.0268***
	(0.00479)	(0.00436)
$share_{farmers}\times$ #days in [12° C;15° C[	0.0611*	
	(0.0342)	
#days in [15° C;18° C[	-0.0214***	-0.0232***
	(0.00505)	(0.00470)
$share_{farmers}\times$ #days in [15° C;18° C[	-0.0362	
	(0.0304)	
#days in [18° C;21° C[	-0.0141**	-0.0211***
	(0.00577)	(0.00547)
$share_{farmers}\times$ #days in [18° C;21° C[	-0.265***	
	(0.0327)	

Table 7: Comparison of coefficients with and without interaction terms with the share of farmers per *commune* (Part 1)

#days in [21° C;24° C[	-0.0250***	-0.0252***
	(0.00635)	(0.00608)
$share_{farmers} \times$ #days in [21° C;24° C[	-0.0206	
	(0.0369)	
#days in [24° C;27° C[	-0.0156*	-0.0184**
	(0.00839)	(0.00796)
$share_{farmers} \times$ #days in [24° C;27° C[	-0.226***	
	(0.0622)	
#days in [27° C;30° C[	0.00422	0.0200
	(0.0143)	(0.0133)
$share_{farmers} \times$ #days in [27° C;30° C[	0.704***	
	(0.145)	
#days in [30° C;+ ∞[	-0.429***	-0.370***
	(0.0545)	(0.0498)
$share_{farmers} \times$ #days in [30° C;+ ∞[	4.583***	
	(0.525)	
Constant	0.00642	0.00995*
	(0.00522)	(0.00511)
Observations	1360837885	1360837885
R-squared	0.248	0.247
Number of communes	36,096	36,096
Commune FE	YES	YES
Year FE	YES	YES
Lag included	YES	YES
Interaction included	YES	YES
Cluster	Commune & Region× Year	

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Comparison of coefficients with interaction terms with the share of farmers per *commune* (Part 2)