Investigating the Impact of Temperature Shocks on Income Disparity

Nicolas Longuet Marx*
Columbia University

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Abstract

Most of the attention brought towards the uneven economic effects of climate change has been devoted to inequality between countries. This paper investigates how weather shocks affect inequality within a country. We measure the non-linear economic effects of weather shocks on the average level of income and the distribution of income in France combining French fiscal data with historical weather data from meteorological stations. Allowing for non-linear effects of weather, we are able to compute the marginal effect of weather shocks on income and inequality. We find that days with an average temperature above 15°C start to have a detrimental effect on average income, with most significant effects located at the top of the distribution; an additional day above 30°C reduces the average household yearly income by 0.1%. This loss is equivalent to 34% of the average daily contribution to yearly income. These weather shocks increase *between*-areas inequality as poorer municipalities are more vulnerable to temperature and and are hit more strongly than richer parts of the country. These shocks also increase *within*-area inequality by hitting more hardly the lowest income deciles. An additional day above 30°C increases the D9/D1 inter-deciles ratio by 1.4 percentage point. We then use a Regional Climate Model to predict potential effects of global warming. Under *business as usual* scenarios, these effects would be equivalent to a yearly reduction in national income by 1 percentage point over the medium run and 2 percentage points for the last decades of the century, due to additional warm days. Finally, using Randomized Inference, we are able to assess the reliability of the results, controlling for any spurious spatial correlations.

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*email: nicolas.longuetmarx@columbia.edu
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1 Introduction

Most of the attention brought towards the uneven economic effects of climate change has been devoted to inequality between countries. However, one may also wonder what effect climate change might have on the way income is distributed within a country. These divergent outcomes may result from varying exposure to climate hazards, influenced by factors such as geographic location or employment status, alongside differences in the ability to adapt and mitigate climate change effects, shaped by individual resources and public provisions. Understanding the impact of climate change on various economic groups is crucial for targeting adaptation strategies effectively. This is particularly important because many climate change mitigation policies can influence income distribution. By discerning which populations are most affected, policymakers can tailor interventions to address specific needs and vulnerabilities.

This paper investigates the average and heterogeneous income responses to weather shocks in France. We analyze historical short-term reactions to marginal weather shocks to establish a baseline for predicting the short-term economic impacts of global warming. We examine the income and inequality response to local temperature and precipitation shocks.

We combine French local fiscal data to get the average income for each of the $36,000$ French municipality from 1990 to 2015 and indicators on the distribution of income since 2000 at the *canton* level (approximately 10 municipalities) with a weather interpolation model. We are able to use deviations in local income and local inter-decile ratio 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.

We find that the response function of income to temperature starts declining for days above 15°C, with most significant losses occurring above 27°C. An additional day in the top bin, days above 30°C, is associated on average with a decrease of the yearly income by 0.1%. It is equivalent to 34% of the average daily contribution to yearly income. We show that these results are not driven by the impact on agricultural income.

We find that this effect has been much larger for low-income municipalities than richer municipalities, leading to an increase in *between*-area inequality. The average effect in the bottom 50% municipalities is twice as large as the average effect in the top 50% municipalities. In addition, poorer municipalities have been more exposed to larger temperature than richer ones, exacerbating between-municipality inequality. We then look at the impact of weather shocks on each decile of the income distribution. We show that every single income decile is significantly affected by weather shocks, with first deciles being hit more severely. Every additional day above 30°C increases the D9/D1 inter-decile ratio by 1.5 percentage points.

These results shed new light to the estimation of the impact of global warming in France and emphasize the importance of non-linear effects and studying various sub-populations. It uncovers an important inequality dimension, not only between but also within municipality.

We then test the robustness of the results through Randomized Inference. Indeed, studies that use weather 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)). In particular because of the spatial auto-correlation of the data; weather and income of two neighboring municipalities cannot be seen as independent from each other. Randomized Inference (or Permutation Tests) allows us to assess the extent of this issue in our setting. Our results are robust to the computation of Randomization Inference based p-values but show that simple two-way clustering p-values are under-estimated, leading to an over-rejection of the null hypothesis of no effect.

Using the historical estimates on the average level of income, we are able to assess potential short run impact of global warming in France using a Regional Climate Model (RCM). Under the RCP 8.5 scenario of the IPCC, French national income would be reduced by 1.1% every year in the medium term (2050-2080) and 2% every year in the long-term (2080-2100).

This paper relates and contributes to the literature aiming to assess the economic consequences of weather shocks. Specifically, it builds on articles using panel estimates exploiting year-to-year fluctuations and within-country variations. These deviations in weather conditions are assumed to be exogenous. Dell et al. (2012) uncovers a significant negative correlation between higher temperatures and economic growth, primarily observed in low-income countries. Meanwhile, Burke et al. (2015), employing a similar methodology but allowing for non-linear effects of temperature, reveal impacts on both poor and rich countries. Their findings suggest a global inverted-U shape relationship between temperature and income, with an optimal temperature for output and productivity at 13°C, a trend persisting since 1960. Notably, France emerges as an exception, exhibiting no significant impact, positive or negative, from global warming on its economy according to Burke et al. (2015). This paper aims to challenge such findings by exploring nuanced dimensions of non-linearity in the relationship and investigating potential heterogeneous and detrimental impacts on various population sub-groups, which could come from geography, occupation, housing quality, or income level.

Kalkuhl and Wenz (2020) show that larger temperatures have a substantial negative impact on income and productivity levels using region-level data across 77 countries. Deryugina and Hsiang (2017), employing a non-parametric approach based on the number of days within temperature bins, study the effects of temperature and precipitation on county income per capita in the U.S., revealing a linear decline in income beyond daily temperatures of 15°C.

These sub-national studies shed light on within-country disparities. Hsiang et al. (2017) underscore the importance of examining the redistributive impacts of climate change within the United States. They predict that climate change will exacerbate national inequality, with poorer counties, predominantly in the South and Midwest, bearing the brunt of the consequences, thus widening the gap between counties.

However, despite offering insights into within-country climate change impacts, these studies may overlook the rise in within-county inequality, focusing solely on geographical disparities rather than social ones. Burke and Tanutama (2019) and Diffenbaugh and Burke (2019) further emphasize the exacerbating effect of warming on inequality, both within and between regions and countries. Burke and Tanutama (2019) highlight regional data indicating that warming is likely to worsen inequality, while Diffenbaugh and Burke (2019) estimate a 25% increase in global inequality over the past six decades attributable to global warming.

This article contributes to the literature by employing an approach that assesses the impact of temperatures on overall income inequalities within a country, spanning both intra-regional and inter-regional disparities.

Based on all this aforementioned literature, several methodological challenges arise as crucial for an accurate estimation of weather impact on income. First, we use a panel setting rather than cross-section in order to get rid of unobservable invariant counfounders and mitigate the risk of an omitted variable bias. Second, using a non-parametric specification in temperature and precipitations in order to not constrain weather impact on income to be linear such as temperature bins or flexible restricted cubic splines. Our 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. In addition, we are able to study a differentiated effect by deciles of income and the impact of weather shocks on inter-decile ratios. This approach towards uneven within-country effects in a developed country has scarcely been explored by the literature.

The remaining of this paper is organized as follows: section 2 describes the data used and provides descriptive statistics, section 3 presents the estimation strategy, section 4 presents the 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. We describe the climate simulation models in section 6.

2.1 Climate Data

We make use of a dataset computed by the Centre National de Recherches Météorologiques (CNRM) and the Centre de géosciences de Mines ParisTech and provided by Météo France, called Safran-Isba-Moscou (SIM). It gives 9 000 points of gridded data for France (excluding overseas territories) obtained from an interpolation of the 554 weather stations and corrected by weather models. We then interpolate this data to obtain the weather of each municipality as a weighted-average of the four neighboring points.

Mean daily temperature over the period are going from -25°C to + 35°C. While the particularly cold temperature are not representative of temperature of any municipality because they occur in areas uninhabited (top of mountains), especially warm temperature occur in inhabited areas. The highest average daily temperature has been observed on the 13^{th} of August 2003 in Perpignan (near the Spanish border) at 35°C.

All municipalities have experienced days with a daily average temperature above 26°C and half of the municipalities have experienced daily average temperature above 30°C. Figure 4 shows the localization of these municipality. Those municipalities are not localized specifically in the South and do not show any significant differences in income, size or composition of labor force compared to municipality which did not experienced any days above 30°C.

2.2 Income Data

2.2.1 Average Income

We use income data at the municipal level provided by the *Direction Générale des Finances Publiques* (DGFiP) which gives the average level of income of fiscal households per municipality (approximately 36 000) for each year from 1990 to 2015.

Values before 2002 are converted from Francs to Euros and values for each year are converted into Euros of 2015.

2.2.2 Distribution of Income

To study the distribution of income, we use another dataset, also provided by the DGFiP and distributed by the French Statistical Institute (INSEE[1]) but at the *canton* level (approximately 10 municipalities). This data gives each decile of income. For statistical confidentiality reasons, deciles are not disclosed when it would reveal

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

information on less than 50 households. This pertains to less than one percent of the data, with very small population, by definition. When re-estimating the results on aggregate income while excluding these municipalities, we obtain identical point estimates.

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

We obtain the inter-decile ratio in each municipality that gives the relative disparity between the highest and lowest tax incomes, without being distorted by the most extreme incomes. For example the D9/D1 inter-decile ratio gives the ratio between the lowest income of the top 10% income earners and the highest income of the bottom 10% income earners. From the deciles, we also obtain the average income by group and the share of total income earned by this group using Pareto interpolation, following Blanchet et al. (2017).

2.3 Socio-demographic Data

As covariates we also use data provided by the French Statistics Institute (INSEE) which traces the evolution of the composition of French municipalities in terms of unemployment rates, education levels, etc. Finally, we use data from the *Recensse-ment agricole* (agricultural census) provided by the French Ministry of agriculture to obtain the share of people working in agriculture by municipality for years 1990, 1997, 2004 and 2010. We then compute for each year of our study (1990-2015) the weighted average of these values depending on the distance to the date with available information[2].

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

3 Empirical Strategy

The main equation of interest is a two-way fixed effects specification with the (log) average income per fiscal household as a function of the (log) lag income, current and previous weather, municipality time-varying observables and municipality and year fixed effects. This is summarized by equation (1) below.

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

where $Y_{i,t}$ is the (log) income per capita of municipality i in year t, $T^m_{i,t}$ the number of days of year t for which mean daily temperature have been in the interval m in municipality 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, $X_{i,t-1}$ 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 municipality fixed effects, θ_t year fixed effects, $\epsilon_{i,t}$ the error term.

The principal coefficients of interest are here β^m. 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 adding lag weather and interaction terms between temperature and precipitations.[3]

This specification has several advantages. First, it allows us to estimate non-linear impacts of temperature and precipitation on income, which is critical. 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)). To check for further non-linearities, we also estimate a flexible restricted cubic spline specification.

The two-way fixed-effects approach controls for both observable and unobserv-

[3]Note that we 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. We will rather compute the number of days inside a temperature bin with substantive rain (ie: with rain higher than 1mm).

able characteristics of each municipality that do not vary over time. We therefore compare a municipality to itself when it experienced several types of weather. For instance, we 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. We 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 municipality. In other words, the coefficients will not be biased by the fact that some years, such as 2009, may experience highest temperature than usual as well as economic recessions at the national level. In brief, the coefficients estimated are computed on local idiosyncratic deviations of each municipality compared to the usual conditions.

Following Cameron et al. (2011), we are clustering the standard-errors in two dimensions. First, within municipality across years to take into account the serial correlation. Second, within regions by year to take into account the spatial auto-correlation.

To assess the impact on inequality, we run the same specification, using inter-decile ratios as dependent variable. We also look at the impact of weather shocks on average income earnd by each decile.

4 Results

4.1 Impact on the Average Level of Income

Table 6 shows the results of Equation 1. Standard-errors are clustered by municipalities and region×year to take into account both the serial and spatial auto-correlation. Figure 5 shows the coefficients for temperature from column (4) and from flexible restricted cubic splines fitted with seven knots.

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) adds an interraction term between temperature and precipitation, column (3) controls for the weather in the previous year, column (4) adds demographic of the municipality: share of farmers in the municipality, the percentage of the population with no diploma, the percentage of the population with a diploma higher than an undergraduate degree and the percentage of unemployed as controls and lastly column (5) adds both controls, lags in temperature and interaction between temperature and precipitation. Results are weighted by the population in 1999 to get an average effect for the French metropolitan population.[4] We divided all bins 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 34.0% of the average daily contribution to yearly income (column 1). 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 coefficients are quite stable across specifications. Controlling for lag weather and the interaction with precipitation moderately attenuates the impact of extremely hot days on average income. Controlling for the demographic composition of the municipality at the last period increases the magnitude of the coefficient on extremely hot days and increases their precision. As can be seen on Figure 5, the negative impact of temperature on income seems to be linearly increasing, starting at 15°C with most dramatic effects occurring above 30°C. This is in line with previous findings of the literature in other countries (Burke et al., 2015; Deryugina and Hsiang, 2017). Results of the cubic splines and the piecewise linear functions give similar results.

In comparison with temperature, precipitations do not have a significant effect. This is in line with what has been found by Dell et al. (2014) and Deryugina and Hsiang (2017).

The magnitude of the effect is not only statistically significant but also economically. For example, any day above 30° C reduces the municipality average income by about a third of the average daily income contribution compared to a day with cooler temperature.

[4] The results can therefore be interpreted as for the average French taxpayer, unweighted results would rather be interpreted as for the average municipality.

4.2 Impact on Agricultural income

One might wonder if the entirety of the effect of temperature shocks on income happens through the impact on agriculture. In order to test this hypothesis, we run the same specification, including interaction terms between each temperature bins and the share of people working in agriculture in each municipality.

The results are displayed in Table 3. Columns (2) and (4) include an interaction term for each temperature bin and the share of farmers. Columns (1) and (3) show the initial effect without interaction terms, 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 $[30^{\circ}$ C;$+\infty[$) increases in magnitude by 4 percentage points from column (3) to column (4). The interaction term for days between 27 and 30°C and days above 30 with the share of people working in agriculture are positive and significant for most of them.

It can be interpreted as, any additional day above 30°C has an impact on municipalities with one additional percentage point of farmers in their population that is lower by 2 percentage points compared to the impact on another municipality. The median share of farmers in the municipalities is relatively low (at 5%) and the average is around 2.5%. Thus, even for a municipality that is at the median in terms of share of farmers, the coefficient is still negative and significant. The effect becomes null for a municipality that has more than 11% of farmers (less than 20% of the municipalities).

To be more precise, we can also compare the estimated coefficients between the municipalities that have more agricultural workers than the median and those that have less workers than the median. These results are presented on Figure 6.

These results are obviously counter-intuitive at first but can be explained by administrative characteristics of the French tax system. Contrary to other taxpayers, farmers are allowed to report the average of their income over the three previous years (*Moyenne triennale*) in order to smooth their taxes. They can also choose to report the income of year $n-2$ in year n instead of the one of year $n-1$ as the rest of the population does. 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. We therefore can expect farmers reported taxable income to be less representative of their actual annual income.

In addition to these tax reporting differences, most farmers subscribe to insurance policies that compensate them in case of extreme weather, notably drought. These insurance compensations are reported by farmers as income to the tax authority. Moreover, in case of drought, the Government may also decide to compensate farmers for their losses[5]. These compensations either publicly or privately funded are included in the farmers' earnings and are therefore included in the reported income.

These compensation mechanisms and tax reporting types explain why those who are *a priori* the more sensitive to weather seem to be the ones for whom the income responds less. In addition, this is in line with a report conducted by the French Senate (Sénat, 2004) which estimated the impact of the 2003 heatwave on farmers' income. They find an ambiguous impact on agriculture and 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[6] which led to an ambiguous impact on farmers' income. The same report underlines a sizable detrimental impact on industrial, transport, energy, and distribution sectors.

Nonetheless, it is important to note that observing a low impact for municipalities 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 farmers do not ultimately end up paying these costs.

Secondly, even when farmers are compensated by their insurance, this likely leads to a more expensive insurance policy for following years which can also be considered as a negative impact on the net actualized income.

[5] See, for instance, the Arrêtés interministériels d'indemnisation du 9 septembre 2003

[6] 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

Lastly, one should keep in mind that the timing of the heat waves may be very crucial as well, *i.e.,* 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 most heatwaves French has experienced until now). Climate change may lead to hot days occurring much earlier in the year which would have an impact that we under-estimate in such specifications where there is no distinction of when hot days occur. This aspect is true not only for farmers but may apply to the whole population and thus to the previous estimates as well. This will be discussed in more details in section 7.

To summarize, we do not conclude that farmers are actually less impacted by hot days in France but that institutional settings prevent to seize the impact of temperature on their current income. However, this section allows us to show that our results are not driven by the impact of temperature on farmers' income. In other words, temperature have impacts on other sectors than agriculture. Also, considering the reasons described above, our coefficients are likely an under-estimate the true impact of temperature on income.

4.3 Impact on the Distribution of Income

Weather shocks can foster inequality in two main ways, either by increasing inequality between areas or by increasing inequality within areas. Contrary to most of the literature, our framework allows us to study both phenomena. The first phenomenon has already been documented by the literature in the past and this article is able to bring further evidence. Using estimates from the previous section, we can compute what has been the total impact of the occurrence of temperature shocks on municipality's average income and compare it with municipality's demographic characteristics, in particular initial average income.

Figure 7 shows the correlation between the estimated impact of hot days on municipalities' average pre-tax income and the initial income of the municipality. The results are also reported in Table 8 in Appendix. Richer municipalities have been less impacted on average by temperature shocks. Simply put, wealthier municipalities are located in places that are often less exposed to temperature shocks, implying that temperature shocks have been fostering inequality between municipalities. More economically disadvantaged municipalities have been hit more strongly by weather shocks than richer ones. This echoes findings from Hsiang et al. (2017) who show that climate change impacts are likely to increase inequality between counties in the U.S., with poorer counties being more vulnerable to weather shocks.

Contrary to Hsiang et al. (2017), our setting allows us to also look at the impact of weather shocks on inequality within areas. As mentioned in the introduction, there are several reasons why various income groups might be differentially affected by weather shocks, even within the same city. First, jobs that are likely to be more affected by climate change are disproportionally occupied by first deciles (in particular, outdoor and physical jobs). Second, within each municipality, the bottom of the income distribution might be living mostly in areas that are more subject to weather shocks, or less resilient to weather shocks. For example, previous research has shown that urban green spaces are unequally distributed, leading more disadvantaged communities to be more at risk of climate shocks (Liotta et al., 2020). Third, income constraints themselves might lead economically disadvantaged households to be more sensitive to weather shocks.

The inequality measure we use is the inter-decile ratio which gives the relative disparity between the highest and lowest tax incomes, without being distorted by the most extreme incomes. More precisely, the inter-decile ratio (D9/D1) measures the ratio of the highest to the lowest incomes, removing the 10% of households with the most extreme incomes from each side. As mentioned above, the data is not at the same geographical scale as the one used in section 4.1 to compute the effect on average income. We now use *canton*-level (approximately 10 municipalities) income distribution. Nevertheless, running the same regression on the average income by *canton* gives the same results as the ones on the average income by municipality.

We estimate Equation 1 using the inter-decile ratio as the dependent variable. Results are shown on table 4 and plotted on figure 8. The results, though noisy, show that most extreme temperature tend to increase inequality in each municipality. The magnitude of the effect is small but not negligible; one extra day above

30°C increases the inter-decile ratio by 0.02 (from a baseline at 5.7). One should emphasize that this is only the effect on pre-tax income, not on disposable income. The true post-tax effect is therefore probably smaller since income taxes and transfers typically reduces this inter-decile ratio.

To better understand this relationship, we are looking at alternative inter-decile ratio, comparing D9/D5 and D5/D1. Figure 9 shows the impact of temperature in each bin. temperature seem to not impact the D9/D5 ratio at all while the D5/D1 ratio is impacted just as much as the D9/D1, meaning that the increase in inequality is mainly driven by a higher impact on lowest deciles compared to all other deciles rather than a lower impact on highest deciles. Table 5 shows the associated results.

Lastly, Figure 10 also shows the point estimation for each of the ten deciles average income, estimated using Pareto interpolation (Blanchet et al., 2017). Tables 6 and 7 report all the regression statistics. Estimates for the first deciles are much more noisy than for other deciles. The first decile may be subject to more income variability in general and more measurement errors (income coming more from unemployment benefits, part-time jobs, etc.).

5 Randomization 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, meaning that if one can exploit the randomness of weather across time, assuming random and independent variation across space is not a credible 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 case, 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.

We therefore 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 municipality (resp. *canton*) we randomize the "treatment" (*ie:* the weather) received and run the same regression on this "placebo" weather variable. For each permuted dataset, we can compute the t-statistic associated with each coefficient. The distribution of these t-statistics which is the distribution under the null hypothesis, should be compared with the "true" t-stat in order to test its significance. In other words, we create a distribution of t-statistics for which we know that we cannot reject the null hypothesis of an effect and we compare it to our estimated t-statistic. In other words, we break the existing structure in the dataset in order to quantify the patterns we 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 we consider that treatment is assigned to four "big weather regions" independently, we can randomize across these big regions (see Appendix Figure 14 for the delimitation). It means that two municipalities of different weather regions may be assigned weather of different years but that two municipalities of the same weather region will be assigned weather of the same year. Secondly, one could consider that no observations within France could be considered as independent from one another. We therefore also randomize at the national level; *ie:* all municipalities of the country are assigned to the weather of the same year.

Figures 11 and 12 are showing the distribution of t-statistics of the coefficients for the number of days in $[27°C; 30°C[$ and $[30° C ;+\infty [$ assuming either an independence of two municipalities in different weather regions or no independence at all. We therefore obtain new p-values under the sharp-null hypothesis of no-effect (Table 10). These p-values correspond to the number of "null" t-statistics that are larger in absolute terms than the "true" t-statistic. In other words, one can calculate the probability to obtain an estimate of such a magnitude if these days had no effect at all. From these graphs, it is clear that most regular approaches tend to under-estimate the standard errors. More than 5% of the t-statistics are located above 1.96 (in absolute value). This is true with both clustering levels. The null hypothesis is therefore falsely rejected in more than 5% of the cases. Appendix Table 10 shows the distribution of p-values for all coefficients under both alternative clustering levels. The p-values of the two main coefficients of interest (coefficients for the number of days in [27°C; 30°C[and [30° C ;$+\infty$[) also increase (up to 0.043 and 0.071 for the most demanding correlation) but remain below commonly admitted thresholds. We cannot reject the sharp null of no effect for coefficients of more moderately hot days (between 15° and 27°C) that are much lower in magnitude and have p-values above commonly admitted thresholds.

6 Simulation and climatic projections

The effects measured on the aggregate level of income, despite being quite sizable, have had only a marginal effect on the French eonomy since the occurrence of extremely hot days is quite rare (see Figure 4 for historical specific local occurrences of days above 30°C). Nevertheless, the occurrence of such days will dramatically increase in the coming years according to all climatic projection models. We therefore make some back-of-the-envelope estimation of the potential costs of the occurrence of extremely hot days. These estimates are valid under several very strong hypotheses, in particular we assume that the reaction function to long-term common shocks is similar than to the one to short-term idiosyncratic shocks. We discuss the likelihood of this hypothesis and the reliability of these estimates in the discussion section.

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", *i.e.,* no specific change of gas emissions.

Note that with global warming, French municipalities will experience temperature that have never before occurred (or very rarely). There are two possibilities to estimate the impacts of such extreme days. First, one could extrapolate the relationship found for days above 30° C. Alternatively, one can set the effect of days far above 30° C as the same as days just above 30° C. We choose to use the second option, which is more conservative.

According to the climate projections, only 24 municipalities in France will never experience any days above 30°C, all in very mountainous areas. Three quarters of the municipalities will experience a day above 30°C at least once every five years. Three quarter of the population, as it is currently distributed, will experience such temperature every three years. Finally, almost 40% of the population will experience such temperature more than once a year. At the end of the period, France will experience, on average, two days above 30°C per year for the period with some regions experiencing more than 20 days per year above 30°C with a non-negligible share of days above 36°C[7].

For each French municipality, we compute the predicted number of days in each temperature bin. We compute the 11-year moving-average for each year in order to smooth the results. We 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).

$$\hat{\delta}_{i,t} = \sum_d \beta_d (T^d_{i,t} - \bar{T}^d_{i,1970-1989}) \tag{2}$$

where $\hat{\delta}_{i,t}$: the predicted impact in municipality i and year t, $\hat{\beta}_{30}$ the estimated

[7]Let us recall that the maximum average temperature observed over the period 1990-2015 has been once 33°C in Perpignan

coefficient of an additional day above 30°C, $T_{i,t}^{d}$ the number of days in bin d in municipality i and year t, $\bar{T}_{i,1970-1989}^{d}$ the number of days in bin d in municipality i during the reference period.

We then compute the overall average effect, $\hat{\delta}_t$ weighted by the municipality population of 2012, to get a nationally representative estimate. Since most coefficients from Equation (1) are not significantly different from zero, we use only coefficients that are significant at the 5% level. We do not include lag effect of temperature.

According to the RCP 8.5 scenario, we get a national average estimated impact of -1.13% of national income each year over the medium-run (for the period 2050-2080) and -2.00% over the long-run (for 2080-2100) compared to a no global warming scenario.

These numbers should be seen in parallel with growth predictions. Furthermore, there are obviously cumulative effects of having a contracted national income in $t-1$ on the national income of t.

7 Conclusion and Discussion

This paper has assessed the impact of local temperature on income and inequality in France. Results show that income starts to decrease for days with an average temperature above 15°C with the most dramatic effect for days above 27°C. In particular, an additional day with temperature above 30°C reduces the yearly income per fiscal household by 0.1%. This is equivalent to 34% of the average daily contribution to the yearly income. This impact is not driven by weather consequences on agriculture. In addition, larger temperature increase inequality levels. First, larger temperature deepen inequality between municipalities. Poorer municipality are twice more vulnerable to temperatures and exposure is correlated with income. Second, larger temperature also exacerbate within municipality inequality, increasing the ratio of top income earner to bottom income earners. Every single income decile remains, however, negatively affected by extreme temperature. Using predictions made by Regional Climate Models, we obtained an estimate for the costs of global warming. The estimate gives a reduction of national income over the medium run on average by 1.13 %, and over the long run by 2.00% each year. Even these small effects on national income may have large consequences over time, taking into account cumulative effects. Finally, we assessed the robustness of the estimates using Randomization Inference to avoid the risk of spurious correlations. This exercise shows that many specifications that do not take into account spatial correlation in the data tend to over-reject the null hypothesis of no effect.

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

The first aspect to underline is the reliance on specific climate models which are uncertain and should be approached with cautious attention. Control for the robustness of our 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, questioning both the internal and external validity of our estimates.

Deryugina and Hsiang (2017), using the envelope theorem, argue that their estimates take into account adaptation since each counties (or municipalities in our case) would be at the production possibility frontier. This is also an argument developed in Hsiang (2016). Reaction functions to weather would therefore be optimal and represent a fair estimator of climate change future costs. One could, however, challenged this statement since several characteristics of the weather shocks used in this paper differ from actual climate shocks. In particular, this paper has focused on shocks that are idiosyncratic, mostly unexpected and non-permanent. These three properties make our 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. We discuss each of them below.

Our specification imperfectly takes into account common shocks and therefore does not allow to estimate entirely a national level impact for two main reasons. First, national shocks will be captured by year-fixed effects, whereas, some national detrimental effects exist, leading our coefficients to under-estimate the "true" costs of global warming. Second, complex interactions between municipalities, may lead the national impact to differ from the aggregated impact. One could argue that these costs would be higher if every municipality were to be affected at the same time (less geographical solidarity, less compensation and substitution mechanisms available).

Second, we have assumed that the relationship between income and the number of days in each bin is linear. However, this relation is likely to be convex with higher cumulative effects; *i.e.:* 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. With higher frequency, weather shocks could also hamper economic activity harder. For instance, two consecutive droughts on two subsequent years will likely be more detrimental.

Third, climate change and specifically global warming may lead to days with temperature above the threshold computed here (ie: temperature above 35 or 36°C that have not occurred during the period studied here). In the specification, we 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.

Fourth, historically, days above 30°C have occurred only during summer and especially in August. This is not the more critical period in terms of agriculture and a large part of the French labor force is not working at that time. If days above 30°C were to occur in other periods than during the summer, we expect a stronger detrimental effect to be observed.

Fifth, the share of municipalities to experience extremely hot temperature is to be enlarged with global warming. For instance, while only about half of French municipalities have experienced a day with average temperature above 30°C so far, all of them will experience it by 2100. One may argue that this will lead them to be more sensitive than the previously treated population thus leading again to an under-estimation of the true effect.

Sixth, as it has been shown in previous sections, the impact of temperature on farmers' income is only scarcely taken into account. Since we do not observe all the impact on farmers' income, our estimate is likely to underestimate the true costs of global warming.

Finally, a major difference between short-run response estimates and climate change future costs is adaptation. 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 these weather shocks will be permanent, agents may also develop adaptation strategies to climate change, (e.g., more air conditioned living and working environments, technological changes or factor reallocation (*e.g.*, migration)) which would reduces the magnitude of the impact.

This paper has focused on global warming and is therefore close 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. Lastly, since climate change is a global phenomenon, its impact on other countries 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 and inequality.

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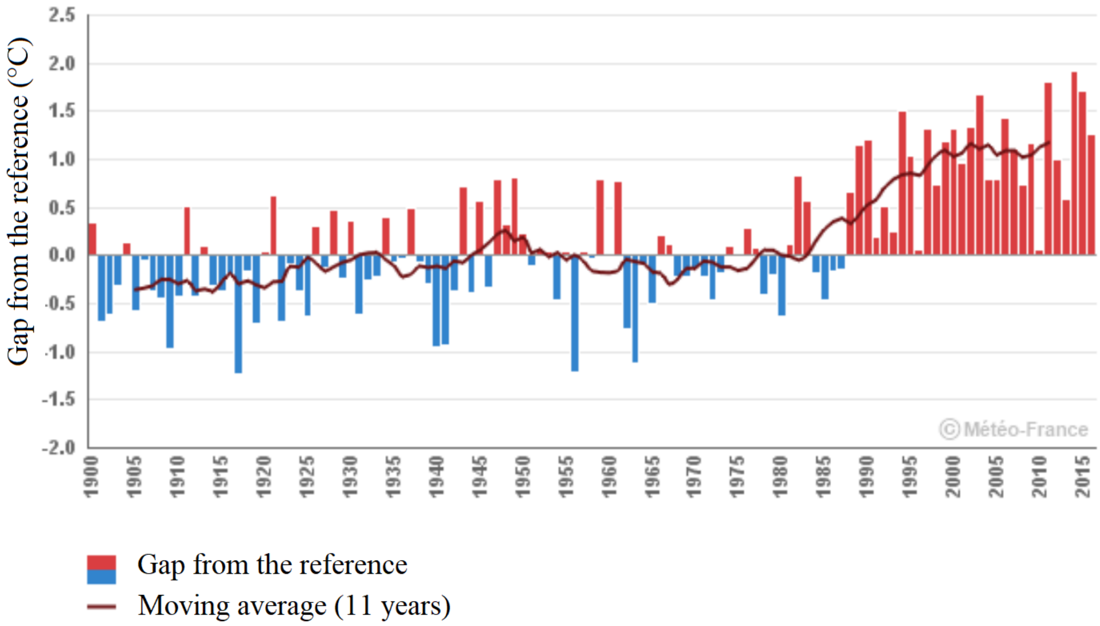


Figure 1: Evolution of the temperature between 1900 and 2015

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.

	Medium-Term (2050-2080)	Long-Term (2080-2100)
Point Estimate 95 % CI	-1.13% [-1.87; -0.38]	-2.00% [-0.70; -3.30]

Table 1: Estimated future yearly short run impact of global warming in France

Notes: Under the RCP 8.5, scenario, average income will be reduced by 1.13% each year due to additional warm days in 2050-2080 and by 2.00% in the long run (2080-2100).

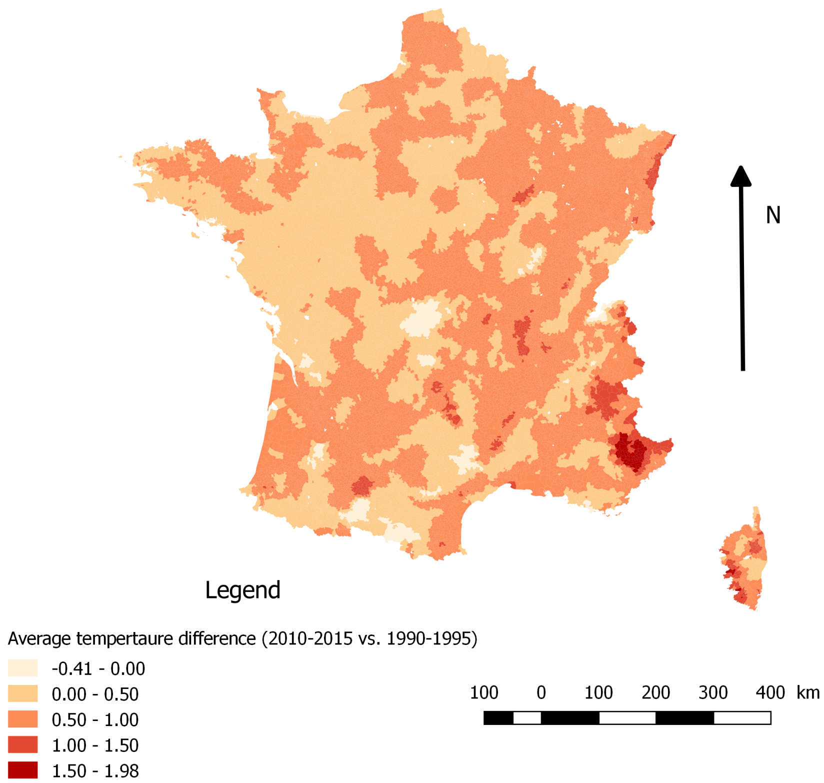


Figure 2: Evolution of the temperature between 1990-1995 and 2010-2015.

Data from Météo France

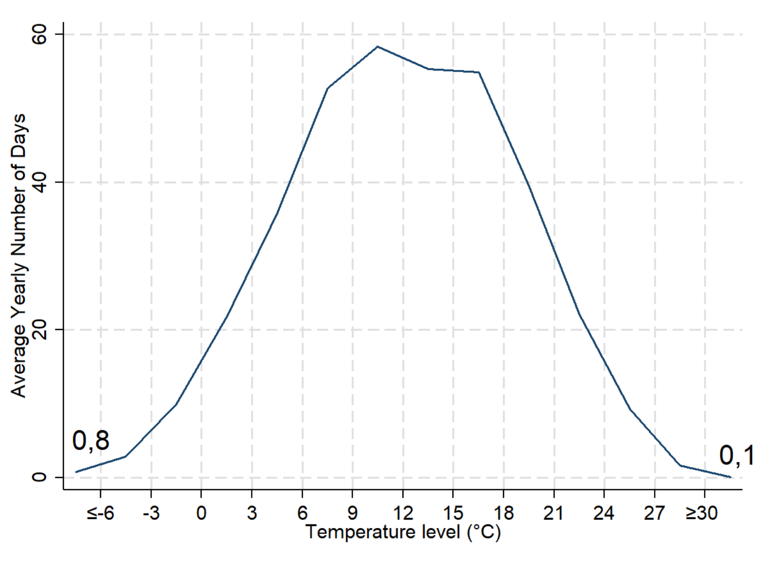


Figure 3: Average yearly number of days in each temperature bin (1990-2015).

Data from Météo France

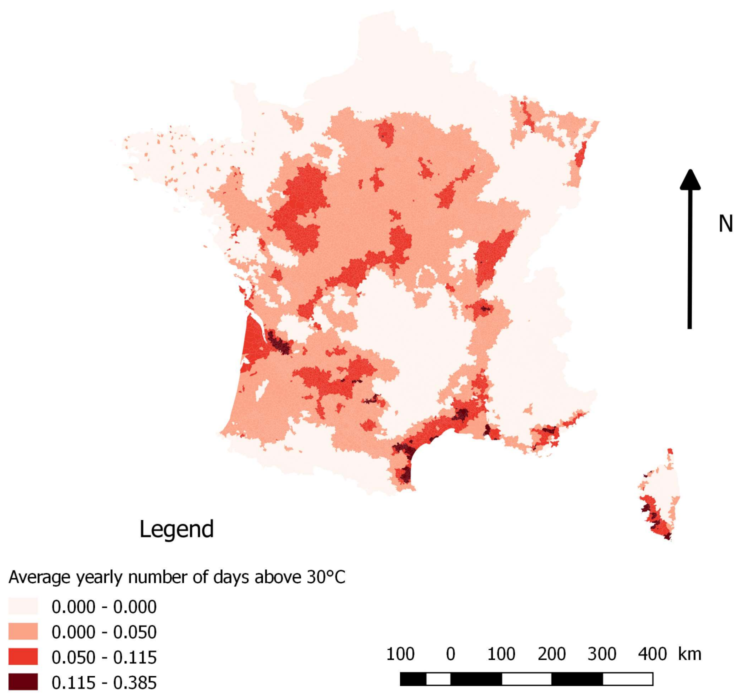


Figure 4: Average yearly number of days above 30 by municipality (1990-2015).

Data from Météo France

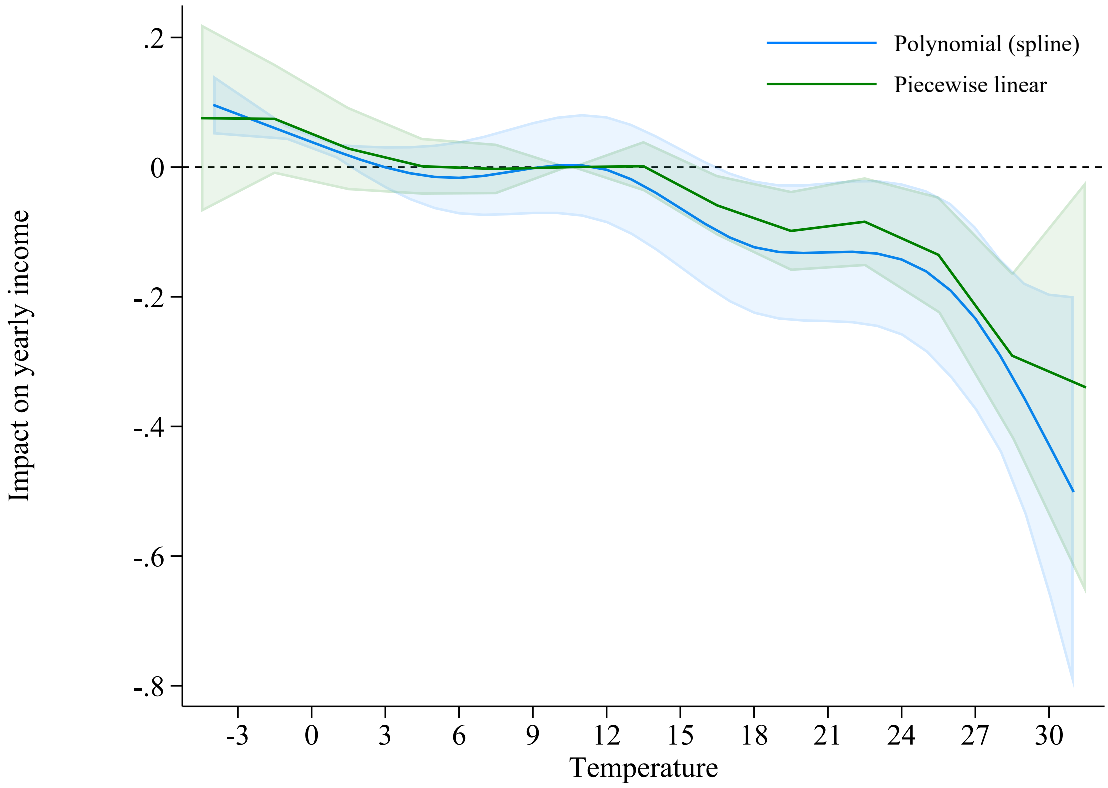


Figure 5: Marginal effect of an additional day in each temperature bin

Notes: Results of the equation 1 estimated by OLS with municipality and year fixed effects. All coefficients have been multiplied by 365 to be compared with the average daily contribution to yearly income. The blue model shows the non-linear impact of temperature on income, using restricted cubic splines in temperature with seven knots (at 0, 6, 12, 18, 24, 27, and 30°C). Standard errors are clustered by municipality and by region by year. One additional day above 30°C is associated on average with a decrease of the yearly income by 34% of average daily contribution to yearly income.

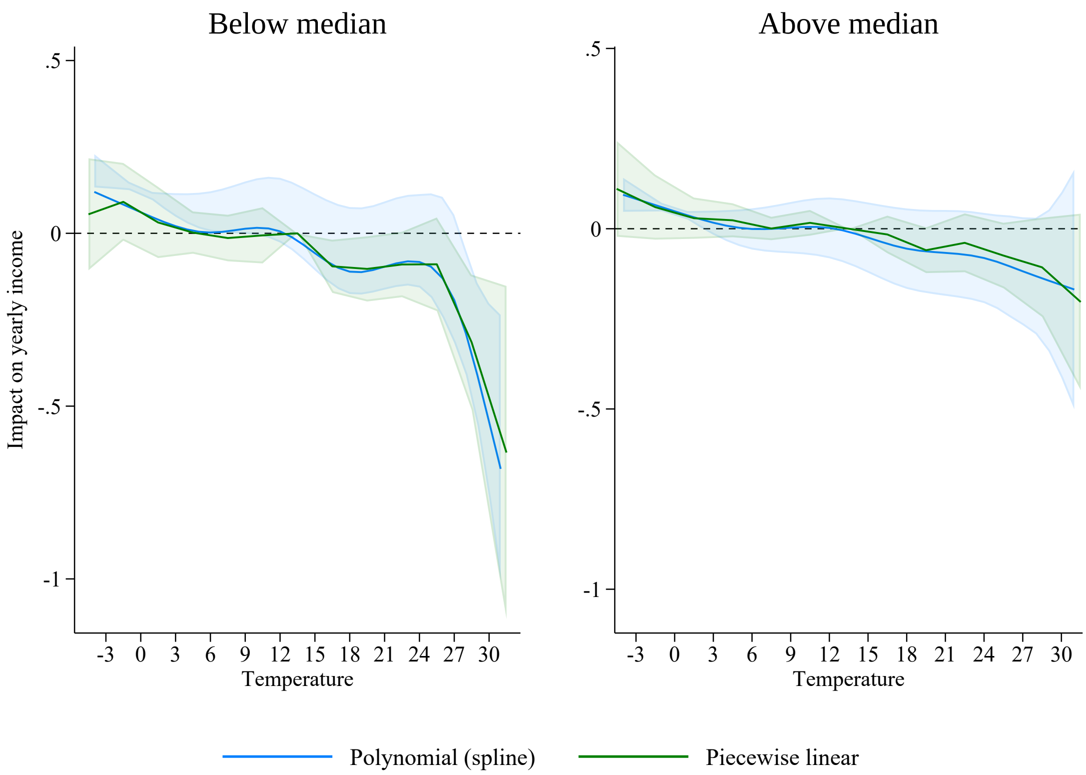
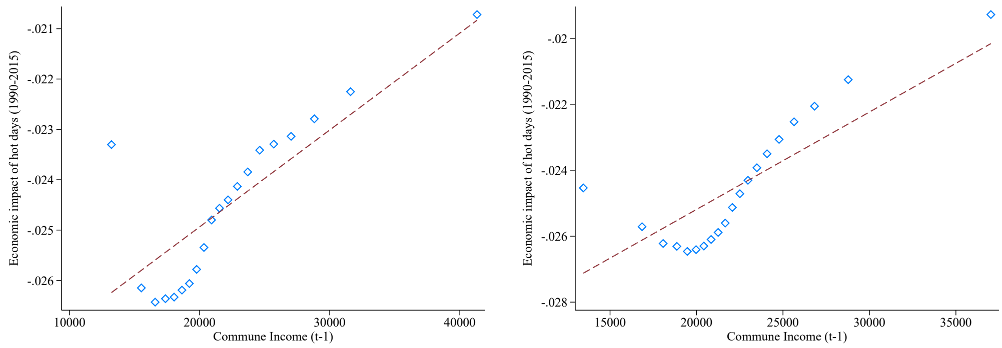


Figure 6: Marginal effect of an additional day in one temperature bin on (log) income depending on the municipalities composition.

Note: Results of the estimation by OLS of Equation 1 for municipalities below the median proportion of farmers (left) vs. municipalities 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%)



Notes: This graph shows the quantiles of the distribution of relative impact (in terms of pre-tax income) of weather shocks as a function of the initial income level of the municipality. The left panel controls only for year fixed effects while the right panel also controls for the demographic composition of the municipality (unemployment rate, educational attainment, and share of farmers). The economic impact is computed by comparing the predicted municipalities' income with and without days in the bins that have coefficients significant at the 5% level. The results are reported in Table 8 in Appendix.

Figure 7: Impact of hot days occurence (1990-2015) on municipalities' average pre-tax income

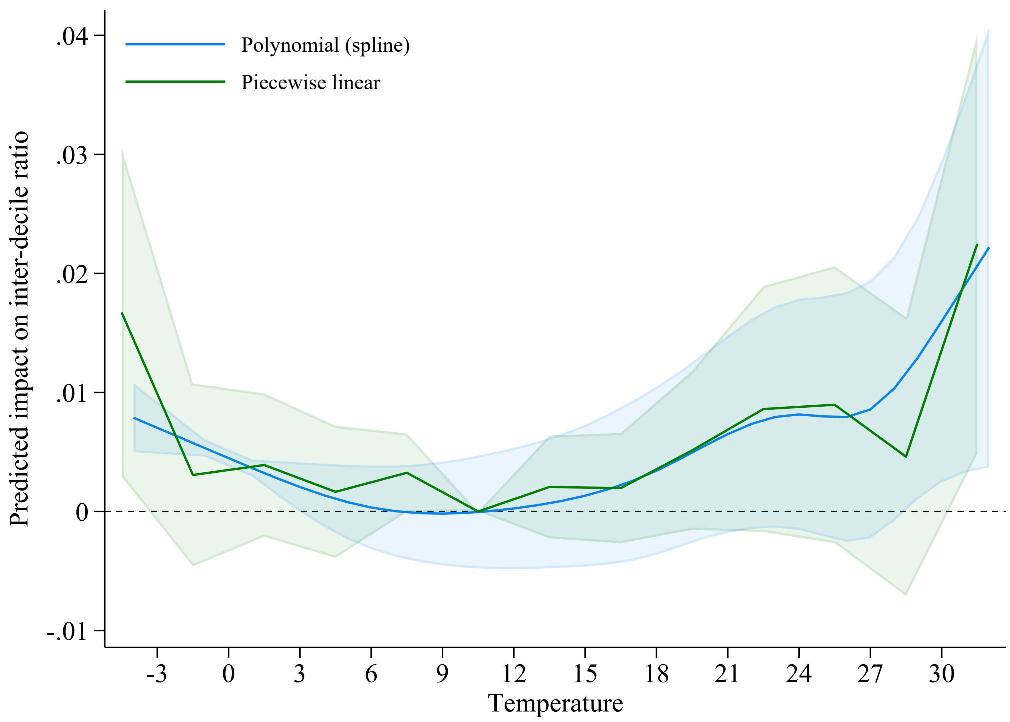
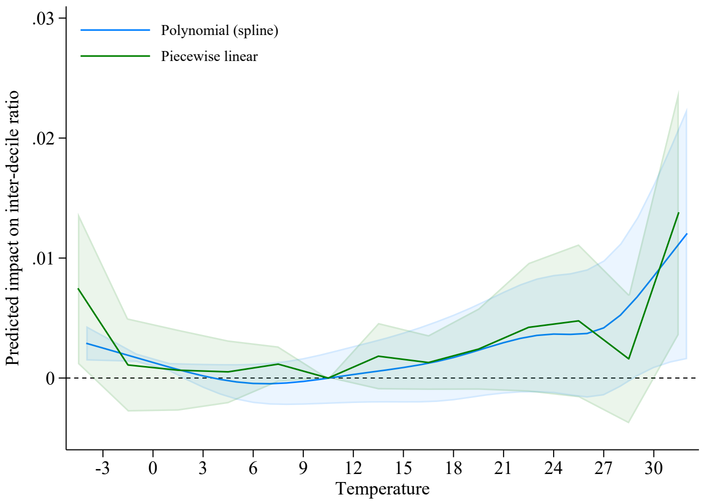
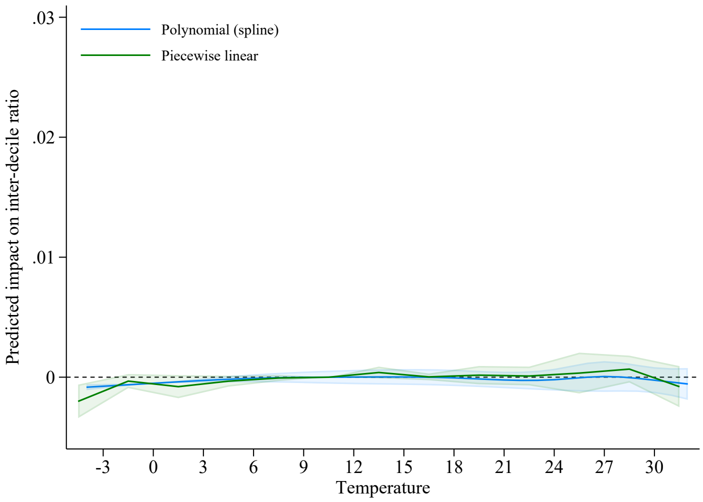


Figure 8: Impact of temperature shocks on inter-decile ratio (D9/D1)

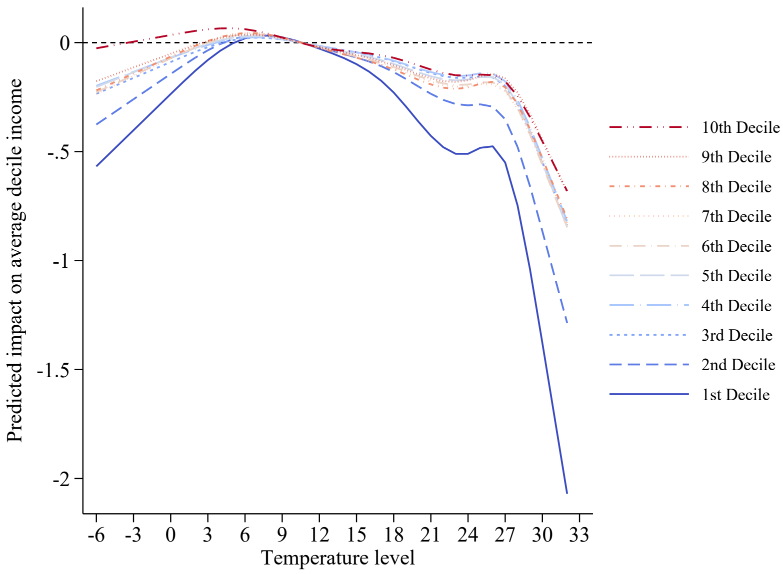


(a) D5 over D1

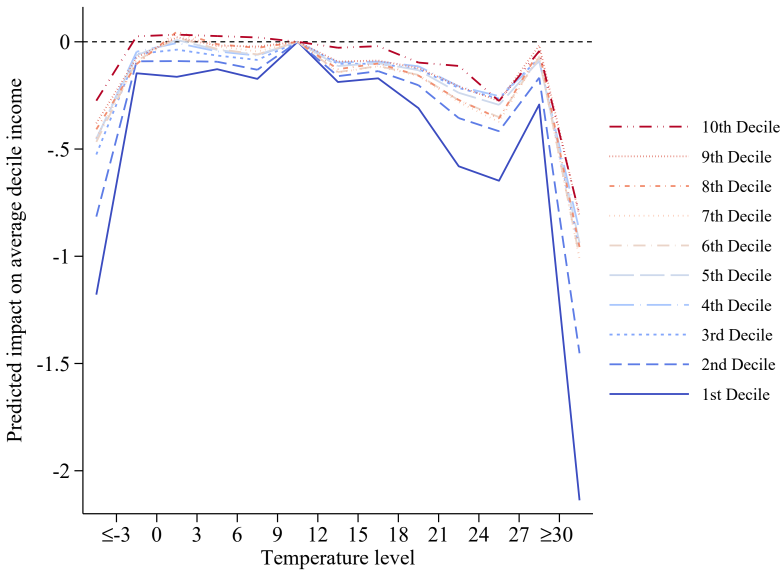


(b) D9 over D5

Figure 9: Impact of temperature on inter-decile ratio (D5/D1 and D9/D1)



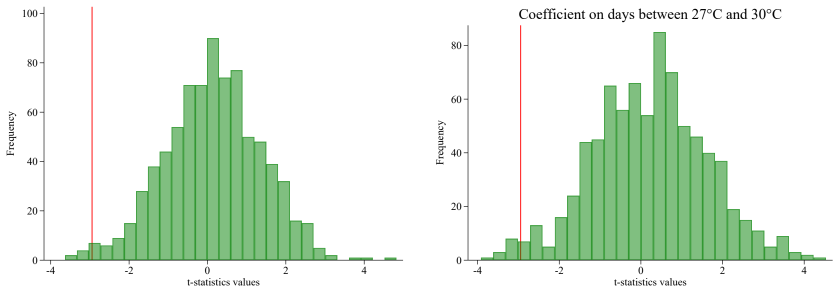
(a) Spline



(b) Piecewise linear

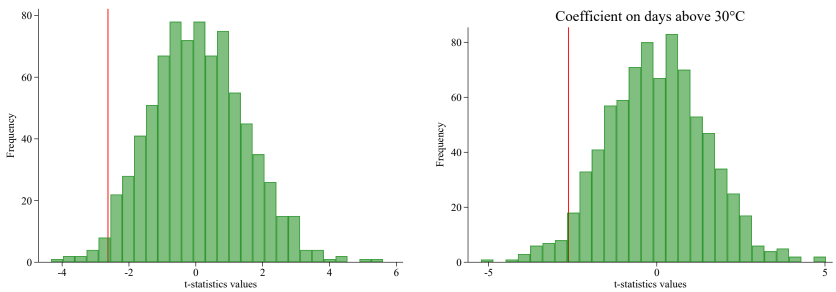
Figure 10: Marginal effect of an additional day in one temperature bin by deciles

Note: Results of the estimation by OLS of Equation 1 for each decile separately.
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 municipality 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 13).



(a) Shuffled by weather regions (b) Shuffled for the whole country

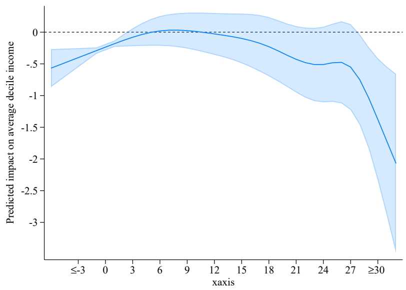
Figure 11: Distribution of t-statistics for the coefficient on days between 27°C and 30°C from randomized samples



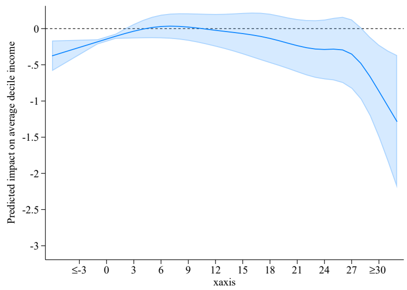
(a) Shuffled by weather regions (b) Shuffled for the whole country

Figure 12: Distribution of t-statistics for the coefficient on days above 30°C from randomized samples

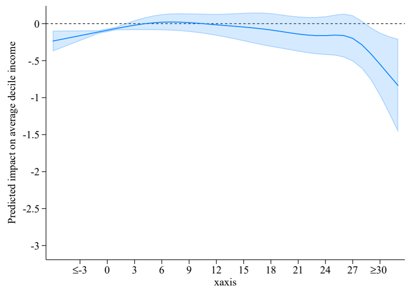
Appendix



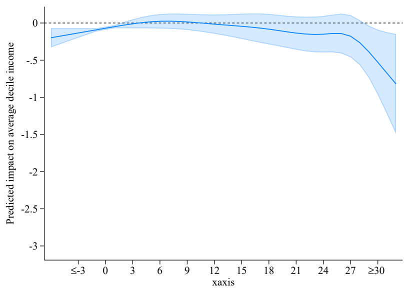
(a) 1st decile



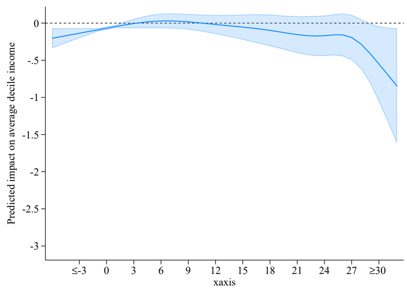
(b) 2nd decile



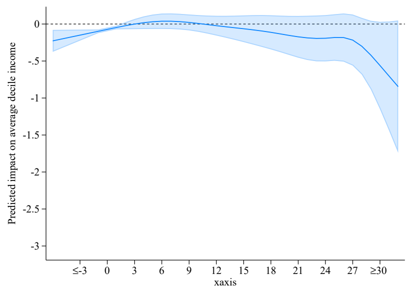
(c) 3rd decile



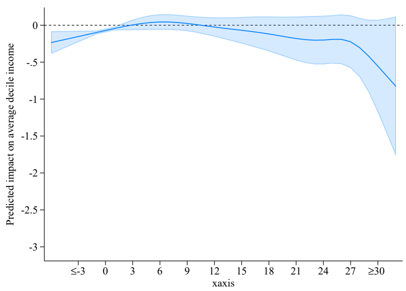
(d) 4th decile



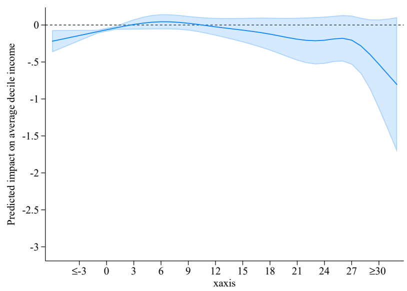
(e) 5th decile



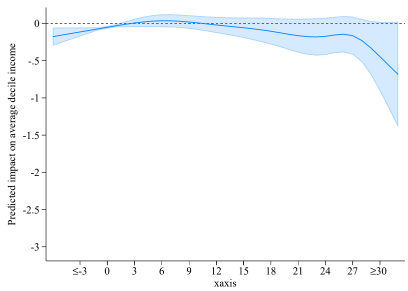
(f) 6th decile



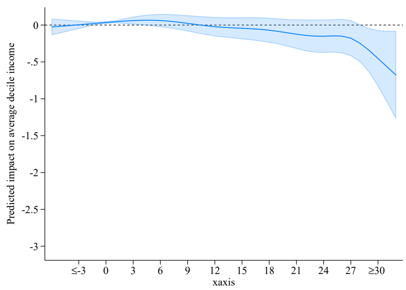
(g) 7th decile



(h) 8th decile



(i) 9th decile



(j) 10th decile

Figure 13: Marginal effect of an additional day in one temperature bin by deciles

	(log) Income				
	(1)	(2)	(3)	(4)	(5)
Lag Income	0.685***	0.703***	0.702***	0.640***	0.622***
	(0.017)	(0.015)	(0.015)	(0.016)	(0.018)
$]-\infty;-3°C[$	0.076	0.035	0.017	0.089	0.020
	(0.074)	(0.057)	(0.054)	(0.062)	(0.076)
$[-3°C;0°C[$	0.075*	0.066*	0.049	0.079**	0.047
	(0.043)	(0.037)	(0.037)	(0.037)	(0.046)
$[0°C;3°C[$	0.029	0.035	0.021	0.029	0.024
	(0.033)	(0.030)	(0.029)	(0.026)	(0.036)
$[3°C;6°C[$	0.001	0.001	-0.011	0.003	-0.024
	(0.022)	(0.023)	(0.022)	(0.020)	(0.025)
$[6°C;9°C[$	-0.003	-0.003	-0.013	-0.002	-0.016
	(0.020)	(0.019)	(0.018)	(0.016)	(0.020)
$[12°C;15°C[$	0.002	-0.002	0.005	-0.003	0.009
	(0.020)	(0.019)	(0.018)	(0.017)	(0.021)
$[15°C;18°C[$	-0.059**	-0.055**	-0.044**	-0.067***	-0.045*
	(0.024)	(0.022)	(0.022)	(0.022)	(0.026)
$[18°C;21°C[$	-0.098***	-0.086***	-0.070***	-0.113***	-0.081**
	(0.032)	(0.028)	(0.027)	(0.028)	(0.032)
$[21°C;24°C[$	-0.084**	-0.085***	-0.056*	-0.095***	-0.048
	(0.035)	(0.032)	(0.030)	(0.031)	(0.035)
$[24°C;27°C[$	-0.135***	-0.140***	-0.110***	-0.134***	-0.099**
	(0.046)	(0.041)	(0.039)	(0.039)	(0.045)
$[27°C;30°C[$	-0.291***	-0.245***	-0.185***	-0.294***	-0.202***
	(0.066)	(0.060)	(0.055)	(0.062)	(0.059)
$[30°C;+\infty[$	-0.340**	-0.321***	-0.295**	-0.463***	-0.290**
	(0.163)	(0.119)	(0.121)	(0.133)	(0.141)
Precipitations	X	X	X	X	X
Commune FE	X	X	X	X	X
Year x Region FE	X	X	X	X	X
Interaction Temp and Pcip		X	X		X
Lag weather			X		X
Controls				X	X
Observations	889,980	878,066	878,066	864,551	876,226
Number of communes	36,523	36,520	36,520	36,143	36,145
R2 (within)	0.484	0.574	0.575	0.596	0.505

Table 2: Impact of weather shocks on municipalities' income.

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	(log) Income			
	(1)	(2)	(3)	(4)
Lag Income	0.683***	0.681***	0.639***	0.637***
	(0.016)	(0.017)	(0.016)	(0.016)
$]-\infty;-3°C[$	0.099*	0.087	0.024	0.006
	(0.059)	(0.062)	(0.056)	(0.058)
$sharefarmers\times\ ]-\infty;-3°C[$		0.706***		0.756***
		(0.250)		(0.237)
$[-3°C;0°C[$	0.095**	0.115***	0.053	0.067*
	(0.037)	(0.038)	(0.038)	(0.038)
$sharefarmers\times\ [-3°C;0°C[$		-0.489**		-0.386*
		(0.200)		(0.199)
$[0°C;3°C[$	0.037	0.034	0.027	0.022
	(0.028)	(0.030)	(0.029)	(0.031)
$sharefarmers\times\ [0°C;3°C[$		0.386**		0.392***
		(0.156)		(0.148)
$[3°C;6°C[$	0.019	0.014	-0.010	-0.017
	(0.021)	(0.022)	(0.023)	(0.023)
$sharefarmers\times\ [3°C;6°C[$		0.532***		0.562***
		(0.146)		(0.146)
$[6°C;9°C[$	0.009	0.019	-0.013	-0.005
	(0.019)	(0.020)	(0.018)	(0.018)
$sharefarmers\times\ [6°C;9°C[$		-0.090		-0.040
		(0.153)		(0.143)
$[12°C;15°C[$	-0.007	-0.025	0.004	-0.015
	(0.018)	(0.019)	(0.017)	(0.018)
$sharefarmers\times\ [12°C;15°C[$		0.669***		0.681***
		(0.174)		(0.172)
$[15°C;18°C[$	-0.067***	-0.089***	-0.049**	-0.073***
	(0.022)	(0.022)	(0.023)	(0.023)
$sharefarmers\times\ [15°C;18°C[$		1.084***		1.134***
		(0.149)		(0.145)
$[18°C;21°C[$	-0.104***	-0.107***	-0.084***	-0.090***
	(0.028)	(0.028)	(0.027)	(0.028)
$sharefarmers\times\ [18°C;21°C[$		0.476***		0.520***
		(0.163)		(0.158)
$[21°C;24°C[$	-0.092***	-0.092***	-0.056*	-0.058*
	(0.032)	(0.032)	(0.030)	(0.030)
$sharefarmers\times\ [21°C;24°C[$		0.227		0.259
		(0.168)		(0.168)
$[24°C;27°C[$	-0.144***	-0.149***	-0.105***	-0.108***
	(0.042)	(0.043)	(0.039)	(0.039)
$sharefarmers\times\ [24°C;27°C[$		0.255		0.169
		(0.292)		(0.288)
$[27°C;30°C[$	-0.293***	-0.329***	-0.202***	-0.242***
	(0.064)	(0.065)	(0.055)	(0.057)
$sharefarmers\times\ [27°C;30°C[$		2.800***		2.836***
		(0.549)		(0.532)
$[30°C;+\infty[$	-0.389***	-0.392***	-0.341***	-0.363***
	(0.138)	(0.151)	(0.117)	(0.128)
$sharefarmers\times\ [30°C;+\infty[$		1.999		2.262**
		(1.372)		(1.147)
Precipitations	X	X	X	X
Commune FE	X	X	X	X
Year x Region FE	X	X	X	X
Interaction Temp and Pcip			X	X
Lag weather			X	X
Controls			X	X
Observations	864,551	864,551	864,551	864,551
Number of communes	36,143	36,143	36,143	36,143
R2 (within)	0.581	0.582	0.597	0.598

Table 3: Impact of weather shocks on municipalities' income, interacted with agricultural shares.

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	Inter-deciles ratio (D9/D1))				
	(1)	(2)	(3)	(4)	(5)
Lag inter-decile ratio	0.690***	0.693***	0.693***	0.694***	0.697***
	(0.070)	(0.070)	(0.070)	(0.067)	(0.067)
$]-\infty;-3°C[$	0.017**	0.006	0.006	0.017**	0.007
	(0.007)	(0.005)	(0.005)	(0.007)	(0.005)
$[-3°C;0°C[$	0.002	-0.003	-0.003	0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$[0°C;3°C[$	0.004	0.002	0.002	0.004	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$[3°C;6°C[$	0.002	-0.001	-0.001	0.002	-0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
$[6°C;9°C[$	0.003*	0.003*	0.003*	0.003*	0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$[12°C;15°C[$	0.002	0.002	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$[15°C;18°C[$	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$[18°C;21°C[$	0.005	0.002	0.002	0.005	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$[21°C;24°C[$	0.008	0.007	0.007	0.009	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$[24°C;27°C[$	0.008	0.007	0.007	0.009	0.008
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
$[27°C;30°C[$	0.003	0.005	0.005	0.005	0.006
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
$[30°C;+\infty[$	0.024***	0.016**	0.016**	0.022**	0.014*
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
Precipitations	X	X	X	X	X
Canton FE	X	X	X	X	X
Year x Region FE	X	X	X	X	X
Interaction Temp and Pcip		X	X		X
Lag weather			X		X
Controls				X	X
Observations	35,211	35,211	35,211	34,906	34,906
Number of cantons	3,515	3,515	3,515	3,482	3,482
R2 (within)	0.325	0.330	0.330	0.338	0.343

Table 4: Impact of weather shocks on municipalities' income.

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	D5/D1		D9/D5	
	(1)	(2)	(3)	(4)
D5/D1 lag	0.734***	0.715***		
	(0.064)	(0.065)		
D9/D1 lag			0.891***	0.812***
			(0.022)	(0.037)
$]-\infty; -3°C[$	2.730**	1.504	-0.735***	-0.564**
	(1.173)	(0.936)	(0.261)	(0.245)
$[-3°C; 0°C[$	0.397	-0.098	-0.119	-0.114
	(0.724)	(0.650)	(0.112)	(0.206)
$[0°C; 3°C[$	0.239	0.101	-0.287	-0.152
	(0.629)	(0.553)	(0.180)	(0.140)
$[3°C; 6°C[$	0.188	0.114	-0.121	-0.080
	(0.489)	(0.429)	(0.086)	(0.085)
$[6°C; 9°C[$	0.424	0.696**	-0.025	0.022
	(0.276)	(0.315)	(0.047)	(0.081)
$[12°C; 15°C[$	0.665	0.382	0.143	0.102
	(0.517)	(0.413)	(0.091)	(0.064)
$[15°C; 18°C[$	0.472	0.562	0.009	-0.060
	(0.426)	(0.387)	(0.054)	(0.102)
$[18°C; 21°C[$	0.881	0.659	0.062	-0.059
	(0.632)	(0.472)	(0.142)	(0.119)
$[21°C; 24°C[$	1.543	1.508*	0.035	-0.180
	(1.001)	(0.839)	(0.148)	(0.159)
$[24°C; 27°C[$	1.740	1.441	0.125	-0.020
	(1.188)	(0.951)	(0.317)	(0.191)
$[27°C; 30°C[$	0.584	0.964	0.246	0.297
	(1.003)	(1.149)	(0.208)	(0.232)
$[30°C; +\infty[$	5.043***	2.613*	-0.288	-0.291
	(1.901)	(1.405)	(0.321)	(0.382)
Precipitations	X	X	X	X
Canton FE	X	X	X	X
Year x Region FE	X	X	X	X
Interaction Temp and Pcip		X		X
Lag weather		X		X
Controls		X		X
Observations	35,211	34,906	35,263	34,958
Number of cantons	3,515	3,482	3,515	3,482
R2 (within)	0.338	0.367	0.507	0.533

Table 5: Impact of weather shocks on municipalities' income.

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	D1	D2	D3	D4	D5
	(1)	(2)	(3)	(4)	(5)
Lag Decile Income	0.632***	0.755***	0.827***	0.848***	0.852***
	(0.124)	(0.065)	(0.036)	(0.032)	(0.033)
$]-\infty;-3°C[$	-0.909*	-0.782**	-0.531**	-0.465**	-0.462**
	(0.528)	(0.340)	(0.206)	(0.182)	(0.179)
$[-3°C;0°C[$	-0.062	-0.109	-0.072	-0.062	-0.078
	(0.290)	(0.179)	(0.101)	(0.093)	(0.100)
$[0°C;3°C[$	-0.069	-0.070	-0.034	-0.006	0.010
	(0.214)	(0.143)	(0.090)	(0.088)	(0.102)
$[3°C;6°C[$	-0.037	-0.071	-0.059	-0.046	-0.040
	(0.199)	(0.119)	(0.066)	(0.057)	(0.060)
$[6°C;9°C[$	-0.196*	-0.142**	-0.089**	-0.070**	-0.066*
	(0.111)	(0.068)	(0.038)	(0.033)	(0.034)
$[12°C;15°C[$	-0.301*	-0.176	-0.100	-0.097	-0.115
	(0.167)	(0.116)	(0.076)	(0.078)	(0.092)
$[15°C;18°C[$	-0.174	-0.142	-0.103	-0.100	-0.106
	(0.154)	(0.109)	(0.069)	(0.065)	(0.071)
$[18°C;21°C[$	-0.281	-0.228	-0.143	-0.135	-0.150
	(0.219)	(0.154)	(0.102)	(0.101)	(0.114)
$[21°C;24°C[$	-0.481	-0.384*	-0.246*	-0.236*	-0.263
	(0.340)	(0.228)	(0.140)	(0.139)	(0.163)
$[24°C;27°C[$	-0.537	-0.449	-0.291	-0.285	-0.322
	(0.413)	(0.277)	(0.182)	(0.182)	(0.210)
$[27°C;30°C[$	-0.088	-0.133	-0.108	-0.117	-0.114
	(0.493)	(0.293)	(0.161)	(0.141)	(0.145)
$[30°C;+\infty[$	-1.985***	-1.560***	-1.006***	-0.919***	-0.965***
	(0.679)	(0.469)	(0.307)	(0.314)	(0.369)
Precipitations	X	X	X	X	X
Canton FE	X	X	X	X	X
Year x Region FE	X	X	X	X	X
Interaction Temp and Pcip					
Lag weather					
Controls					
Observations	35,209	35,263	35,263	35,263	35,263
Number of cantons	3,515	3,515	3,515	3,515	3,515
R2 (within)	0.270	0.377	0.444	0.465	0.465

Table 6: Impact of weather shocks on each decile's average income.

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	D6	D7	D8	D9	D10
	(1)	(2)	(3)	(4)	(5)
Lag Decile Income	0.851***	0.871***	0.889***	0.904***	0.723***
	(0.035)	(0.033)	(0.030)	(0.029)	(0.059)
$]-\infty;-3°C[$	-0.480***	-0.460***	-0.408**	-0.367**	-0.197
	(0.179)	(0.171)	(0.163)	(0.157)	(0.170)
$[-3°C;0°C[$	-0.112	-0.125	-0.114	-0.104	-0.008
	(0.112)	(0.115)	(0.113)	(0.114)	(0.125)
$[0°C;3°C[$	0.021	0.038	0.065	0.084	0.198
	(0.120)	(0.129)	(0.132)	(0.133)	(0.164)
$[3°C;6°C[$	-0.037	-0.024	-0.009	0.001	0.037
	(0.066)	(0.067)	(0.067)	(0.066)	(0.071)
$[6°C;9°C[$	-0.066*	-0.052	-0.038	-0.028	0.001
	(0.036)	(0.037)	(0.035)	(0.034)	(0.044)
$[12°C;15°C[$	-0.141	-0.142	-0.137	-0.132	-0.180
	(0.110)	(0.118)	(0.118)	(0.117)	(0.130)
$[15°C;18°C[$	-0.118	-0.118	-0.111	-0.106	-0.169*
	(0.079)	(0.082)	(0.081)	(0.079)	(0.100)
$[18°C;21°C[$	-0.173	-0.179	-0.180	-0.180	-0.181
	(0.131)	(0.138)	(0.137)	(0.135)	(0.140)
$[21°C;24°C[$	-0.299	-0.308	-0.302	-0.297	-0.313
	(0.194)	(0.209)	(0.211)	(0.211)	(0.221)
$[24°C;27°C[$	-0.376	-0.397	-0.399	-0.404	-0.496*
	(0.248)	(0.266)	(0.268)	(0.266)	(0.277)
$[27°C;30°C[$	-0.099	-0.091	-0.082	-0.070	-0.163
	(0.156)	(0.154)	(0.147)	(0.142)	(0.145)
$[30°C;+\infty[$	-1.042**	-1.049**	-1.009**	-0.996**	-1.169**
	(0.431)	(0.461)	(0.464)	(0.462)	(0.490)
Precipitations	X	X	X	X	X
Canton FE	X	X	X	X	X
Year x Region FE	X	X	X	X	X
Interaction Temp and Pcip					
Lag weather					
Controls					
Observations	35,263	35,263	35,263	35,263	35,263
Number of cantons	3,515	3,515	3,515	3,515	3,515
R2 (within)	0.460	0.475	0.492	0.509	0.407

Table 7: Impact of weather shocks on each decile's income (2).

Notes: This table shows the impact of the number of days in each temperature bins compared to the reference bin (11 to 14°C). Standard errors are clustered by municipality and by region by year.

	(1) Relative impact on income	(2) Relative impact on income
Average income	0.0035***	0.0059***
	(0.0007)	(0.0009)
Unemployment rate		-0.6534***
		(0.0816)
Share of farmers		0.0302
		(0.0198)
Share of college graduates		-0.6377***
		(0.0779)
Share without high-school degree		0.0760***
		(0.0254)
Constant	-0.4121***	-0.3581***
	(0.0157)	(0.0202)
Year FE	X	X
Observations	894,000	878,970
R2	0.31217	0.34050

Table 8: municipality demographics and impact of historical temperature shocks.

Notes: Income in thousand euros

	Coefficient	Initial p-value	RI Weather Region correlation	RI National correlation
$]-\infty;-3°C[$	0.110	0.158	0.218	0.236
$[-3°C;0°C[$	0.082	0.077	0.095	0.130
$[0°C;3°C[$	0.041	0.220	0.261	0.319
$[3°C;6°C[$	-0.003	0.917	0.939	0.930
$[6°C;9°C[$	-0.004	0.840	0.825	0.871
$[12°C;15°C[$	0.000	0.996	0.996	0.996
$[15°C;18°C[$	-0.068	0.009	0.140	0.185
$[18°C;21°C[$	-0.118	0.000	0.071	0.087
$[21°C;24°C[$	-0.097	0.009	0.013	0.025
$[24°C;27°C[$	-0.134	0.005	0.013	0.016
$[27°C;30°C[$	-0.319	0.000	0.000	0.001
$[30°C;+\infty[$	-0.456	0.006	0.040	0.058

Table 9: Randomization Inference-based p-values for the impact on average municipalities' income

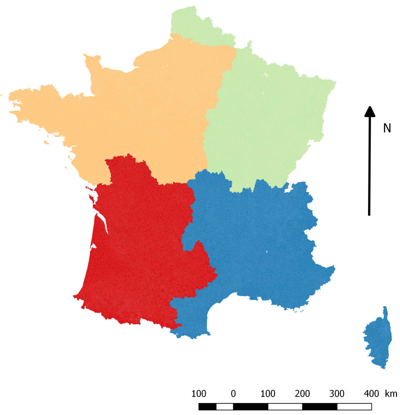


Figure 14: Separation of France in 4 Weather Regions for Randomization Inference

	Coefficient	Initial p-value	RI Weather Region correlation	RI National correlation
$]-\infty;-3°C[$	0.017	0.019	0.048	0.081
$[-3°C;0°C[$	0.002	0.580	0.671	0.671
$[0°C;3°C[$	0.004	0.208	0.363	0.416
$[3°C;6°C[$	0.002	0.576	0.719	0.734
$[6°C;9°C[$	0.003	0.084	0.154	0.385
$[12°C;15°C[$	0.002	0.270	0.384	0.521
$[15°C;18°C[$	0.002	0.447	0.600	0.583
$[18°C;21°C[$	0.005	0.141	0.249	0.389
$[21°C;24°C[$	0.008	0.132	0.258	0.304
$[24°C;27°C[$	0.008	0.148	0.270	0.303
$[27°C;30°C[$	0.003	0.565	0.688	0.666
$[30°C;+\infty[$	0.024	0.008	0.036	0.085

Table 10: Randomization Inference-based p-values for the impact on average cantons' inter-decile ratio