COLUMBIA | SIPA
Center for Environmental Economics and Policy

CEEP Working Paper Series
Working Paper Number 38

January 2026

Costs of Climate Adaptation: Evidence From French Agriculture

Tristan Emma Du Puy and Jeffrey G. Shrader

Costs of Climate Adaptation: Evidence From French Agriculture*

Tristan Emma Du Puy and Jeffrey G. Shrader

[1]Columbia University

January 5, 2026

Abstract

Climate policy requires credible estimates of the costs of adapting to warming, yet such estimates are scarce. We use a uniquely rich panel of French farms, merged with realized and forecasted weather, to provide novel, direct evidence of these costs. Holding realized weather fixed, we use forecasts as information shocks to identify the costs and benefits of ex ante responses to weather. In the year heat occurs, farmers' anticipatory responses are inexpensive but yield large benefits. Over subsequent years, however, these initial adjustments generate rising costs that eventually offset their benefits, consistent with dynamic optimization but inconsistent with static sufficient-statistic estimators of climate damages. Mechanisms are adjustments in crop timing and crop mix, which create dynamic switching costs, rather than costly input changes. Using the estimates, projected costs of adapting to climate change through more frequent use of current adaptation strategies would cost about 30% of average profit by 2100.

JEL Codes: D22, D24, Q12, Q54
Keywords: Climate Change, Adaptation, Agriculture, Forecasts

*We are grateful for comments from Sylvain Chabé-Ferret, Andrew Hultgren, Derek Lemoine, and Wolfram Schlenker as well as numerous participants in seminars at NBER EEE, ASSA annual meeting, Columbia University, the MIT/NOVA School of Business Lisbon Workshop on Climate Change Adaptation, London School of Economics, Paris School of Economics, Toulouse School of Economics, the Transatlantic Kellen Conference Series, the Big Sky Workshop on the Economics of Agriculture and the Environment and the Heartland Environmental and Resource Economics Workshop. We thank the French Ministry of Agriculture and INSEE for providing access to the data, as well as the CASD for secured data access. We gratefully acknowledge funding from the Columbia Center for Environmental Economics and Policy, the Columbia Climate School, and the Columbia Center for Political Economy. All remaining errors are ours.

1 Introduction

The potential consequences of climate change are a central concern for our century. The damages from climate change are a function of both the direct effects of climate change and the costs people bear when adapting to a changing climate.[1] And adaptation costs feed back on the direct effect: the extent to which people pay such costs determines their ultimate exposure to a changed climate. Thus, adaptation costs are fundamental to understanding all aspects of climate change damages. Despite the importance of adaptation costs, there is currently little direct evidence on them. In this paper, we provide novel evidence related to the costs of adaptation in agriculture, one of the sectors of the economy most directly affected by climate, and use them to provide a novel test of a commonly used sufficient statistics approach to estimating climate damages.

The scarcity of evidence on costs is, in part, driven by estimation challenges. First, there is simply a lack of cost data. Crop yields, profits, and farm land values are relatively commonly observed and a large literature has used them to estimate the damages from changing weather (see, e.g., Mendelsohn et al., 1994; Schlenker and Roberts, 2009). Output data have also been used to estimate the marginal benefits of adaptation which have then been used to bound adaptation costs using a revealed preference approach (Hultgren et al., 2025). But the input levels and prices needed to directly recover adaptation costs are rarely observed. This lack of cost data is not limited to the agricultural setting. For example, recent work on the effect of climate change on mortality also bounds unobserved adaptation costs using adaptation benefits (Carleton et al., 2022).

Second, there are identification challenges. Adaptation actions are endogenous and high-dimensional. A common definition of climate adaptation used, for instance, in IPCC (2007), states that adaptation is "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities."[2] One identification challenge is to separate the effect of endogenous adaptation actions from the direct effect of climate shocks—the effect that climate shocks have on the farmer holding their adaptation decisions fixed. Another identification challenge comes from the large number of potential adaptation actions. To be informative about the overall cost of adaptation, one would like to understand the costs of many potential adaptation actions.[3] A third challenges comes from using the responses to beliefs about weather variation—which we can identify directly—to say something about adaptation to persistent climate change.

To overcome the data challenge, we use a uniquely rich panel dataset on the French agriculture sector for 1994–2018. The dataset contains accounting measures for both revenue and—crucially—costs directly at the farm level. To solve the first two identification issues, we leverage variation in both realized and forecasted weather. The forecasts, in particular, allow us to isolate how farm-level

[1] In other words, adaptation costs are a form of defensive expenditure, and reducing defensive expenditures is a benefit from reducing a negative externality like greenhouse gas pollution (Freeman et al., 2014; Deschênes et al., 2017).

[2] Section 2 presents the formal definition of adaptation used in this paper. In words, that formalization says that adaptation actions are changes in farm inputs (including choices like timing of planting and harvesting) in response to changes in beliefs about the climate.

[3] Again connecting this to defensive expenditures, estimates of the willingness to pay to avoid a negative externality that come from defensive expenditures will better reflect total willingness to pay the more complete the set of defensive expenditures observed.

revenue and costs respond to information about upcoming weather events, and we can do so while holding actual weather realizations constant. We thus identify the marginal costs and benefits of ex ante responses of farmers to realizations of harmful, extreme weather events. Climate change will cause changes in the frequency of these extreme events. To use the estimates to infer the costs and benefits of *climate change*, we consider how the frequency of these events will change as the climate changes, in turn causing changes in the frequency of adaptation actions and their attendant costs and benefits. Our approach implicitly holds the mapping of forecasts to farmer actions constant while allowing farmers to change how frequently those actions are taken. In further analysis, we use historical data on farmers facing tighter constraints on weather responses to assess the plausibility of this assumption.

The motivation for our identification comes from considering the multiple ways that weather can affect a farm, some of which are due to farmer responses that we want to separately identify. Most directly, weather affects farm productivity because weather is an important input into crop production (for instance, sunny days help corn grow, but too much heat will kill corn). The farmer can also respond to weather in many ways. They can take actions after the weather occurs (for example, weeding more intensively if weather conditions have been conducive to weed growth). And because farmers can form beliefs about upcoming weather, they can act in advance to try to make the effect of weather more favorable (for example, by changing their crop mix or, for a more extreme example, apple farmers who anticipate an early season freeze sometimes hire helicopters to fly over their orchards to blow warmer air down onto the apple trees). In our empirical strategy, we regress farm outcomes on both forecasts and weather realizations. On their own, weather realizations suffer from an omitted variable bias: they cause direct effects, can induce ex post responses, and (given weather is autocorrelated) are also correlated with ex ante responses. Controlling for weather realizations, we use the conditional variation from forecasts—which is orthogonal to the direct and ex post effects captured by realizations—to identify the effect of ex ante responses on farm outcomes.

Another way to think about our empirical strategy is that forecasts help identify quasi-experimental treatment and control groups. Consider how one would estimate the effect of weather responses in an experiment. One could tell farmers they will be exposed to weather of a given type and, for one set of farmers, allow them to respond as usual while constraining the other set of farmers to take no action. The difference in costs and revenues between those two groups would be informative about the effectiveness of farmer actions. We use forecasts to approximate this experimental setup. Conditional on forecasts, weather realizations are a surprise, so farms by definition cannot respond to them ahead of time. Conditional on weather realizations, variation in forecasts around the realizations determines farmer's beliefs about upcoming weather, allowing them time to respond. Variation in these two measures, therefore, helps us identify times when farmers have and have not been able to respond, and we can compare cost and revenue outcomes for farms in these two cases. When using only realized weather in an observational setting one cannot separate the treatment group (farmers who have responded) and the control group (farmers who have not)—an identification issue that forecasts help overcome.

In a workhorse model of firm-level adaptation to climate change, we formalize the identification strategy and show how the estimates can be used to test a sufficient statistics approach that multiple previous studies employ to estimate climate change damages and bound climate adaptation costs.

In the model, farms can adapt to weather either prior to the realization using forecasts or at the time of the weather realization. In line with the static envelope theorem, farmers choose to engage in all net-beneficial adaptation actions until the marginal benefit and marginal cost of each adaptation action are equalized. Farmer optimization thus implies that the marginal effect of forecast variation on farm profits should be zero. Our empirical strategy allows us to generate estimates of the effect of forecasts on profit, a test of one of the necessary conditions of the static envelope theorem.

The model also helps clarify the set of actions for which we obtain marginal cost estimates. To think through how informative these estimates are for climate adaptation, we first consider the adaptation actions that have been highlighted in previous literature. These include changes in timing and application of on-farm inputs such as fertilizer and pest control (Reidsma et al., 2010); crop choice that necessarily happens before the growing season (Rising and Devineni, 2020; Costinot et al., 2016; Gouel and Laborde, 2021; Obolenski, 2025); labor reallocation (Rosenzweig and Udry, 2014; Colmer, 2021); irrigation decisions (Hagerty, 2022; Burlig et al., 2024); changes in land use patterns including the migration of farms and transition of farmland to other uses (Mendelsohn et al., 1994; Costinot et al., 2016; Gouel and Laborde, 2021); and technical change including the development of new seed varieties or farming techniques (Moscona and Sastry, 2022). In our empirical application, we focus on the effect of temperature forecasts issued from one to five months ahead, and use them to identify the benefits and costs of actions that a farmer can take with a few months of advance warning of upcoming weather. Changes in scale, input mix, crop choice, and the timing of key production actions such as ploughing, sowing and harvesting have all been shown to change within that time window. Fitting dynamic models, we can also estimate how these adaptation actions affect farm profits over subsequent growing seasons to better capture longer-term effects. By examining how the frequency of these actions change as the climate changes, we can provide information about an important class of adaptation costs and benefits.

Implementing this approach empirically, the second part of the paper provides estimates of the costs and benefits of farm-level responses to weather as well as evidence on mechanisms. Within the period of the weather shock, farmers are able to leverage heat forecasts to generate relatively large revenue gains at small costs. A one standard deviation increase in forecasted heating degree days leads to a 1% increase in revenue, while costs have no statistically significant response. In comparison, farms respond to more moderate temperature forecasts by increasing the scale of their production, leading to equal increases in revenue and costs. Both these results hold across alternative specifications, different aggregations of temperature variables, as well as robustness tests.

Focusing on heat forecasts, we decompose results by the sign of the forecast error (with respect to the heat realization). Relative to a forecast that turns out to be accurate, under-forecasts are harmful to farm profit, while over-forecasts have no additional positive effect. This suggests that the benefits are not monotonically increasing in actions, but rather rely on matching the expected heat (Shrader et al., 2023). Making use of additional field level data, we show that farms respond to heat shocks by changing the timing of different steps of the growing season and by switching which crops are grown. Farmers switch from heat-sensitive crops towards less sensitive ones: away from sunflower and towards colza, away from corn and towards wheat. We also observe increases in the area allocated to peas and beans in line with the results of Aragón et al. (2021).

The difference in the cost and revenue consequences of ex ante farm responses translates into net profit gains for the farm in the year of the shock. This positive profit effect of forecasts contradicts the prediction from the static envelope condition discussed above. The results also suggest that, at least in this setting, using the envelope condition to indirectly estimate marginal costs by bounding them with marginal benefits overstates costs substantially. A bounding exercise would set them to 1% of total annual costs, while the estimates imply they should be 0 in the initial year.

We discuss the potential reasons for the failure of the static envelope theorem. First, growing and heating degree days can result from either marginal or non-marginal variation in weather. Over our period of study, growing degree days are mostly represent marginal variation,[4] while heating degree days are mostly composed of non-marginal variation. This source of variation tracks with our observed, statistically indistinguishable cost and benefit responses to forecasted growing degree days (GDDs), and net-positive profit responses to forecasted heating degree days (HDDs). A second element of answer is the difference in nature of the response to forecasted growing and heating degree days. Responses to forecasted GDDs imply some timing changes, as well as input responses, while responses to forecasted HDDs are uniquely driven by significant timing and cropping changes. These changes are likely to drive discontinuous changes in farm-level profits, and are hence less suited to the assumptions of usual envelope theorem which assumes differentiability.

Focusing on the static consequences of responses does not, however, provide a complete picture. In a third part of the paper, we study responses of the profits and costs in periods following the initial shock. While the period of the forecast is marked by net profit gains, the following two periods show significant profit losses. The cost movement parallels the evolution of profit, with increases in costs in future periods. Overall, the net discounted profit consequences of ex ante adaptation have a 95% confidence interval of $[-3.7k, 1.4k]$ euros, which hence overlaps zero. This implies that while we can reject the static envelop theorem, we cannot reject that the dynamic envelope theorem holds.

Because we identify crop switching as one of the main strategies used by farmers, the presence of these future costs suggests that changes to one's crop mix entail switching costs. The presence of such costs has been central to the growing dynamic land use literature (Livingston et al., 2008; Scott, 2013; Burlig et al., 2024) but we are one of the first papers to recover evidence for them in a reduced form setting. We further show these cost increases are mostly driven by future increased fertilizer and pesticide use, as well as labor hours. These are in lines with agro-science interpretations that deviations from optimal crop-rotations will hurt field nutrient stocks and raise exposure to pests (Livingston et al., 2008).

In a last section, we use the farm responses to investigate adaptation to climate change over coming decades. This exercise first requires projections of how climate change will impact French weather, and second to understand how farm actions will shift with changes in the climate. On

[4] We code marginal variation as realizations less than 1.96 standard deviations away from the usual hour-day-month realization over the last thirty years.

the first point, we use CMIP6 climate change predictions until the end of the century. Holding the weather exposure-response function constant, we extrapolate the costs of adaptation. Under these conditions, climate change is expected to increase the yearly costs of adaptation from €2.6k currently to €21k by the end of the century, or a change from 3% to 27% of average current-day yearly profits. We finally discuss the extent to which we can expect farms to shift their adaptation behavior. For this exercise, we rely on a combination of Ricardian and panel approaches to climate change damage estimation (Auffhammer, 2018). Specifically, we look at costs of adaptation heterogeneity across hotter and colder areas of France. This approach is cross-sectional in nature, and provides suggestive evidence for decreasing returns to adaptation as average temperature increases, which implies that adaptation practices might not remain similarly successful in the future.

Related Literature: This paper is first and foremost related to the literature on climate adaptation and climate damages. This literature has long debated how to provide comprehensive estimates of the consequences of climate change on human systems. This in turn has implied accounting for the costs of adaptation, or isolating measures of direct weather damages (hence indirectly of climate damages).

To understand the effects of climate change on the economy, agriculture is a central part of the story. From the earliest analyses through to the most recent updates to the U.S. Federal Government's estimates of climate change damage, agriculture has been recognized as one of the economic sectors most affected (Schelling, 1992; EPA, 2023). Agriculture is also an ideal setting for the study of climate change, as the physical consequences of temperature are well understood, and representative spatial data tends to be more readily available. Our paper stands out by the unusual precision of the data directly measured at the farm-level, and within a repeated panel format. While studies of adaptation to climate change have previously relied on farm-level data, for example Aragón et al. (2021) with repeated cross sections of smallholder farms in Peru, our panel structure and the depth of the data collected is to the best of our knowledge unprecedented. In the context of developed economies, most research has relied on aggregated data for which yields or profits are available (Schlenker and Roberts, 2009, for example). In France, previous research has been conducted at the department-level and over a longer period of time by Gammans et al. (2017), but has focused on yields specifically, while research that has been done at the establishment-level has focused on a small subset of farms (Bareille and Chakir, 2023). Global analyses have shown that climate affects agriculture all around the world (Hultgren et al., 2025). We build on these papers by explicitly estimating cost and revenue adaptive responses, and relating those to climate adaptation costs and benefits. These estimates reveal a surprising results: in France farms face low costs of adaptation in the period of exposure, and large costs over subsequent periods, highlighting the inherent nature of adaptation. The granularity of our data also implies that we can explore farm-level mechanisms to explain the results we find.

Our paper also relates to a broad literature on sufficient statistics approaches (Chetty, 2009; Kleven, 2021). Most directly, recent papers use such an approach to estimate climate adaptation costs by bounding those costs with estimates of adaptation benefits (Carleton et al., 2022; Hultgren et al., 2025). We complement these papers in two ways. First, by directly estimating marginal costs and benefits of adaptation, we are able to test the central implication of this approach, which is that individuals undertake adaptation actions until the marginal benefits and costs of those adaptation are equal. We find support for this implication, with one nuance: marginal costs come to equal marginal benefits over time.[5] Second, we use an alternative identification strategy that has pros and cons relative to other approaches. By using seasonal forecasts, we are able to include fixed effects and other controls that eliminate potential omitted variable bias, along the lines of Deschênes and Greenstone (2007), while still allowing for the estimation of adaptation costs and benefits, though only for a subset of possible adaptation actions as discussed above. Previous literature relies on comparisons across locations with hotter or colder average weather to estimate adaptation benefits, potentially capturing a broader set of adaptation actions at the cost of cross-sectional identification.[6]

Another approach to study adaptation costs and benefits is to construct a structural model that explicitly specifies the possible adaptation mechanisms to be studied. Bareille and Chakir (2023) pursue such an approach in the context of French agriculture. Again, this approach is complementary to our own. We can estimate adaptation benefits and costs without enumerating each possible mechanism while they can quantify the role of each mechanism included in the model.

Finally, our paper also builds on the subset of the literature which has approached adaptation with a focus on the definition of farmers' climate beliefs. Such papers have highlighted how the nature of beliefs about the climate process structures what can be interpreted as adaptive behavior in response to changes in climate. For example, Kelly et al. (2005) shows that steady state differences in equilibria do not fully characterize climate damages. Instead, transition dynamics between steady states play an important role. Building on this, Downey et al. (2023) show that even dynamics around steady states can be important to understand climate damages, as agents repeatedly adjust to climate shocks. Both of these results imply that beliefs are an important compenent to the response of agents to the climate. Burke and Emerick (2016) illustrate how the definition of beliefs drives our understanding of adaptation. Kala (2019) extends these approaches by comparing different learning models for the timing of the monsoon in India. She makes the point that recovering farmers' learning behavior can depend on our modeling of the objective that they maximize. What we measure as the extent of their adaption to changing climate patterns relies on the behavioral model and the objective function assigned to them. Shrader (2023) offers a way to use weather forecasts to disentangle adaptation effects from direct climate damages. Our paper builds on the arguments from this paper. Lemoine (2024) extends this argument to a richer dynamic setting and, relevant to our results, shows that adaptation can have first-order consequences for an agent's static profits even if adaptation has no net effect dynamically. This is consistent with our empirical findings. Related to this literature, we also show that here, not controlling for weather forecasts induces an upward bias in the measurement of the profit impact of extreme heat—extreme heat seems less damaging that it really is. We run a distributed lag model that includes all the forecasts available during the growing season (at all the possible lead values), and hence attempts to capture as much as possible of the agents' beliefs formation and adaptive behavior, and their consequences on farm profit. Running such a regression significantly increases the negative impact

[5] Theoretical analysis of the agricultural sector has previously pointed to the applicability of the dynamic envelope theorem in this context (Scheinkman and Schechtman, 1983).

[6] Other papers which use comparisons between high and low frequency weather, or use lower frequency variation to estimate adaptation benefits include Butler and Huybers (2013); Burke and Emerick (2016); Auffhammer (2022).

of extreme heat on French farm profits. This is suggestive evidence that as we better control for the indirect consequences of adaptation on profit, we can better isolate the negative consequences of marginal variation in extreme heat. Finally Burlig et al. (2025) use a randomized control trial to study the effect of seasonal forecasts on agricultural decision making in India. Their paper shows that farmers update their beliefs based on forecasts, and use them to meaningfully change their production practices.

The rest of the paper proceeds as follows. Section 2 describes the central challenge of identifying adaptation costs and describes the sufficient statistic approach used either to justify ignoring or to bound adaptation costs in the literature. In section 3, we describe our data sources, and in section 4 we link our production model to the estimating equations used in our empirical strategy. In section 5, we present the main results on the marginal benefits and costs of responses to weather shocks, and the channels through which they operate. Section 6 examines the effects over time. Section 7 discusses how our estimates inform costs of adaptation to climate change. Finally, section 8 concludes the paper.

2 Model

This model section serves a dual purpose. First, it formalizes the way agents respond to both variation in weather realizations and their beliefs about upcoming weather, providing the rationale for our identification strategy and precisely defining the costs we estimate. Second, it demonstrates how our empirical framework can be used to test the empirical applicability of the envelope theorem, which is a central tool of the climate economics literature. We generally keep a structure close to models used in the literature to discuss adaptation to climate change (e.g. Ortiz-Bobea and Just, 2013; Hsiang, 2016).

We model a static, price-taking, profit-maximizing agricultural firm that makes decisions in a two-stage production process under uncertainty. In a later part of the paper, we will provide evidence that a dynamic envelope theorem is likely more appropriate to discuss adaptation. A production season runs from time t to $t+1$. At the beginning of the season, time t, the firm receives a forecast f_t about the weather that will be realized later in the season. Based on this forecast, the firm chooses an initial vector of inputs, which we denote the ex ante actions x_t^1. Later in the season, at time $t+b$, with $b \in (0,1)$ denoting forecast lead, the weather shock w_{t+b} is realized. We assume forecasts are unbiased, such that $f_t = w_{t+b} + \varepsilon_{t+b}$, with $\varepsilon_{t+b} \sim \mathcal{N}(0, \sigma^2)$. After observing the realized weather w_{t+b}, the firm can take a second set of actions, the ex post actions, x_{t+b}^2. Production then occurs and profits are realized, conditional on all actions and the realized weather.

The firm's realized profit is given by $\pi_{t+b} = p_{t+b} q_{t+b}(x_t^1, x_{t+b}^2, w_{t+b}) - c(x_t^1, x_{t+b}^2, w_{t+b})$. The firm chooses its actions sequentially. The ex post action x_{t+b}^2 is chosen to maximize profit with full knowledge of w_{t+b} and conditional on the chosen x_t^1. The ex ante action x_t^1 is itself chosen to maximize expected profit conditional on the forecast f_t, anticipating the future optimal choice of x_{t+b}^2. Throughout the analysis, we assume that these functions are continuously differentiable and satisfy the necessary regularity conditions for the dominated convergence theorem to apply.

The firm's initial problem can be written as solving for the ex ante static value function, $\overline{v}(f_t)$:

$$\begin{aligned}\overline{v}(f_t) &= \max_{x_t^1} \mathbb{E}\big[\max_{x_{t+b}^2} \pi_{t+b}(x_t^1, x_{t+b}^2, w_{t+b})|f_t\big] \\ &= \mathbb{E}\big[\pi_{t+b}(x_t^{1,\star}, x_{t+b}^{2,\star}, w_{t+b})|f_t\big],\end{aligned}$$

with $x_t^\star = \{x_t^{1,\star}, x_{t+b}^{2,\star}\}$ denoting the set of expected profit-maximizing actions.

We are interested in the marginal cost of responses to a change in the weather forecast. In order to isolate this cost, we start by decomposing the effect of a change in forecasts on expected costs:

$$\begin{aligned}\frac{d\mathbb{E}[c_{t+b}|f_t]}{df_t} =& \underbrace{\mathbb{E}\left[\frac{\partial c_{t+b}}{\partial w_{t+b}}\bigg| f_t\right]\frac{dw_{t+b}}{df_t}}_{\text{Price Effect}} + \\ & \underbrace{\mathbb{E}\left[\frac{\partial c_{t+b}}{\partial x_t^1} + \frac{\partial c_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial x_t^1}\bigg| f_t\right]\frac{dx_t^1}{df_t}}_{\text{Effect of Ex Ante Actions}} + \\ & \underbrace{\mathbb{E}\left[\frac{\partial c_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial w_{t+b}}\bigg| f_t\right]\frac{dw_{t+b}}{df_t}}_{\text{Effect of Ex Post Actions}}.\end{aligned} \tag{1}$$

The first term is the effect on input prices. This term captures how expected costs change because the forecast is correlated with realized weather, which itself can affect prices even holding actions constant (e.g., by increasing wages to compensate for occupational disamenities). The second term is the effect of ex ante actions or how the forecast directly alters the firm's optimal ex ante action, which in turn changes expected costs. This term accounts for the fact that ex ante actions can constrain future ex post actions. The third term reflects ex post responses. A change in the forecast will empirically be correlated with a change in the realized weather, which prompts a change in the optimal ex post action. This is the cost of responding to the new information learned from the weather realization itself.

Rationale for Using Forecasts: Forecasts conditional on weather solve an identification challenge that arises when using only variation in weather. Conditional on weather, equation (1) identifies the ex ante cost response, which we write as:

$$\frac{d\mathbb{E}[c_{t+b}|f_t]}{df_t}|_{dw_{t+b}=0} = \mathbb{E}\left[\frac{\partial c_{t+b}}{\partial x_t^1} + \frac{\partial c_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial x_t^1}\bigg| f_t\right]\frac{dx_t^1}{df_t}. \tag{2}$$

A natural alternative to our strategy would be to estimate the effect of weather on costs, which identifies the following total derivative:

$$
\begin{aligned}
\frac{dc_{t+b}}{dw_{t+b}} =& \frac{\partial c_{t+b}}{\partial w_{t+b}}\frac{dw_{t+b}}{dw_{t+b}} + \\
& \left(\frac{\partial c_{t+b}}{\partial x_t^1} + \frac{\partial c_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial x_t^1}\right)\frac{\partial x_t^1}{\partial f_t}\frac{df_t}{dw_{t+b}} + \\
& \frac{\partial c_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial w_{t+b}}\frac{dw_{t+b}}{dw_{t+b}}
\end{aligned} \tag{3}
$$

However, this approach faces two fundamental challenges. First is an identification problem: weather variation affects costs in three ways (the three terms in equation (3)), and these different channels cannot be separated using weather variation alone. Second, and perhaps more importantly, even though weather variation affects more than just direct cost effects, it also does not fully capture the cost of responses. Looking at the second term of equation (3), one can see that weather identifies ex ante responses only in so far as it affects agents' beliefs about the weather ($\frac{df_t}{dw_{t+b}}$). This means that weather is at best an imperfect proxy, or at worst has no impact on beliefs because it arrives after the agents has already formed their beliefs. If the agent faces adjustment costs, then ex post actions (third term) will in depend on actions taken earlier (x_t^1). Thus, agents might not take much ex post actions, making the third term small and relatively unimportant.

In effect, our strategy isolates the costs of ex ante responses by using the variation in farmer beliefs generated by forecast errors, holding realized weather constant. This approach is analogous to a reduced form instrumental variable (IV) strategy that simultaneously addresses the two challenges outlined above. It resolves the endogeneity problem by design, as it nets out any direct effects of realized weather on costs. Furthermore, it mitigates measurement error by using forecasts as a more relevant belief shifter for ex ante decisions than the imperfectly observed, contemporaneous weather shock (Shrader, 2023). Consequently, our estimate has a Local Average Treatment Effect (LATE) interpretation: it captures the marginal costs for the subset of actions that are responsive to forecast information.

Testing the Envelope Theorem: A second objective of this model is to provide a framework for testing the applicability of the envelope theorem, a central tool in the climate economics literature. To fix ideas, we first outline the theorem in the context of our model. To see how a change in forecasts affects the maximized expected value of profit, we take the total derivative of the value function with respect to f_t:

$$
\begin{aligned}
\frac{d\bar{v}(f_t)}{df_t} =& \mathbb{E}\left[\frac{\partial \pi_{t+b}}{\partial w_{t+b}}|_{x_t=x_t^\star}|f_t\right]\frac{dw_{t+b}}{df_{t+b}} + \\
& \mathbb{E}\left[\left(\frac{\partial \pi_{t+b}}{\partial x_t^1}|_{x_t=x_t^\star} + \frac{\partial \pi_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial x_t^1}|_{x_t=x_t^\star}\right)|f_t\right]\frac{dx_t^1}{df_t}|_{x_t=x_t^\star} + \\
& \mathbb{E}\left[\left(\frac{\partial \pi_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial w_{t+b}}|_{x_t=x_t^\star}\right)|f_t\right]\frac{dw_{t+b}}{df_t}
\end{aligned}
$$

This expression states that a change in forecasts affects expected profit directly (the first line), and indirectly by inducing the firm to change its optimal actions (second and third terms). The envelope theorem states that these second and third terms are equal to zero. The economic intuition is that the marginal costs and benefits of re-optimizing are already in perfect balance, so small changes have no first-order effect on the maximized value of ex ante profit.

The envelope theorem provides the theoretical foundation for two common empirical exercises in climate economics. The first application allows researchers to infer unobservable costs of adaptation from observable adaptation benefits (Carleton et al., 2022). The theorem's result stems from the firm's first-order condition, which in words says that individuals take actions until the marginal benefits equal the marginal costs. This implies that in an optimized system, if one can estimate the marginal benefits of an action (e.g., increased revenue), those benefits can serve as a proxy for the marginal costs of that action, even if those costs are not directly observable or hard to define. Some studies then use this principle to extrapolate total costs responses to non-marginal changes in climate from these marginal estimates (Schlenker et al., 2013; Hsiang, 2016).

The second, and more widespread, application is to justify the use of short-run weather variation to estimate the damages from long-run climate change (Merel et al., 2022). As outlined by Auffhammer (2018), this approach has been central to the empirical literature that estimates the economic consequences of climate change. The argument rests on the envelope theorem's core result: the effect of a change in an environmental parameter on an agent's welfare is equal to its direct impact, as the first-order effects of re-optimization are zero. This implies that the marginal damages of both weather and climate variation reduce to their respective direct effects, and that the effects of adaptation drop out and therefore can be ignored. Under the assumption that this direct damage function is the same for both types of shocks, the observable marginal damages from weather can serve as a measure of the unobservable marginal damages from climate change.

Our framework provides a direct method for testing the applicability of the envelope theorem in a climate economics context. To see this, consider how a change in the forecast affects the firm's expected value function, holding realized weather constant. Drawing from our previous derivation:

$$\frac{d\overline{v}(f_t)}{df_t}|_{dw_{t+b}=0} = \mathbb{E}\left[\left(\frac{\partial \pi_{t+b}}{\partial x_t^1}|_{x_t=x_t^\star} + \frac{\partial \pi_{t+b}}{\partial x_{t+b}^2}\frac{\partial x_{t+b}^2}{\partial x_t^1}|_{x_t=x_t^\star}\right)\Big| f_t\right]\frac{dx_t^1}{df_t}|_{x_t=x_t^\star} = 0.$$

This expression isolates the change in value resulting only from ex ante re-optimization in response to forecasts. This expression is zero in the model, exactly because of the usual implication of agent optimization, which is that the marginal benefits and costs of changes in actions are equal. This central prediction of the envelope theorem stems from the premise that each action is individually optimized, including the specific ones driven by forecasts. This provides a testable hypothesis: that the effect of forecasts on profit is zero.

3 Empirical Context and Data

3.1 Exposure to Weather in French Agriculture

We test our model using data from French agriculture, a setting that offers several distinct advantages for identifying the costs of ex ante adaptation. We focus on cereal, oil, and protein crops, which are sensitive to weather variation and major contributors to France's agricultural output. As the largest grain producer in the European Union, and one of the world's largest cereal exporters, understanding adaptation in France has direct implications for food security.

Importantly for our identification strategy, this sector has very low exposure to irrigation; only 6% of agricultural land was irrigated in 2015 (Colas-Belcour et al., 2015). This general absence of irrigation minimizes concerns that unobserved irrigation decisions could endogenously bias our estimates of weather impacts, a challenge noted by Braun and Schlenker (2023). It also aligns with recommendations to study weather shocks in areas where irrigation is not heavily subsidized (Schlenker et al., 2005). The adoption rate of commodity futures trading by farmers is also very low in Europe (Michels et al., 2019). This implies that farmers face the full consequences of unexpected weather shocks, and further motivates the use of forecasts by farmers in order to reduce such damages.

French climate features significant weather variability, providing the necessary shocks for our analysis (Canal, 2015), and significant heterogeneity with a Mediterranean region more heavily exposed to heat and water stress over the summer. Figure A23 shows splines describing the evolution over time of unconditional and conditional growing season mean temperature realizations at the department level. These are helpful to characterize the average climate in France. On average, temperatures remain around 10°C, with little change over our period of study. On average, below 0°C temperature are not very negative, and on average extreme heat temperature remains around 30°C. Figure A6 in the annex further shows that while there is more dispersion across French department in extreme heat events, the general dispersion of average conditional temperatures remains moderate. We also provide maps showing the geographic dispersion in growing and heating degree days in France over our time period.

To characterize weather sensitivity in our sample, we present two sets of descriptive evidence. First, Table 1 shows the land allocation for the four main crops in our sample, which account for over 85% of the agricultural area in the data. We associate each crop with its mean growing season temperature, and with a critical temperature threshold above which growth in impaired, which we take from the literature.[7] Wheat is the dominant crop, and it is relatively more heat tolerant than corn or colza. This suggests the average farm in our sample has a baseline resilience to some heat shocks.

[7]We note that the thresholds used for crop-specific tolerance are only indicative. Tolerance to heat varies across the growing stages of each crop, and also relate among else to drought conditions. We take these as only indicative that wheat is more heat tolerant than other crops, and is likely to be less responsive to extreme heat events observed for France in our sample. References are Gammans et al. (2017), Schlenker and Roberts (2009), Elferjani and Soolanayakanahally (2018).

Table 1: Crop mix composition

	Share	Mean Temperature	Threshold	Reference
Wheat	47.89	10.2	33C	Gammans et al, 2017
Corn	15.29	10.5	29C	Schlenker and Roberts, 2009
Barley (Winter)	11.38	10.0	33C	Gammans et al, 2017
Colza (Rapeseed)	11.26	10.2	29C	Elferjani et al, 2018

Notes: We compute the shares of cropland allocated to each crop in our dataset, and show the four largest ones. None of the remaining crops account for more than 5% each of the total land considered. We show the associated average temperature, among farms growing the crop, and a threshold for heat damages taken from the literature.

Second, to confirm the impact of temperature on farm output, we estimate a flexible regression model following Schlenker and Roberts (2009). We use a restricted cubic spline to model the non-linear relation between exposure to temperature and outcomes, and include farm fixed effects and region-specific quadratic time trends. Figure 1 shows the crop-specific effect of temperature, while subsubsection A.1.4 looks at the aggregate effect at the farm level. These results show that crop yields have heterogeneous responses to heat. Corn and sunflower yields decline sharply at temperatures above 25°C, whereas wheat and colza exhibit flatter damage functions in this range. These heterogeneous sensitivities highlight the importance of ex ante crop choice as a key adaptation margin.

Our strategy relies on farmers responding to weather forecasts. High-quality coupled atmosphere-ocean models started to be used for seasonal forecasts by Météo-France in the mid-to-late 1990s, allowing forecasts to move past the four months ahead lead (Canal, 2015). For our analysis, we use hindcasts produced by the European Center for Medium-Range Weather Forecasts (ECMWF), which are available from 1994 onwards. While our data includes forecast leads of up to four months, our main analysis focuses on one-month-ahead forecasts, which represent a credible and widely available information source for farmers' in-season decisions during our study period. Today, different companies offer an access to month-ahead forecasts throughout the season, and the EU's Joint Research Center has been providing real-time cereal yield predictions based on the Crop Yield Forecasting System with its MARS bulletin since 2007. Meteo France, the French weather agency, also provide three-month ahead weather bulletins which are made public on its website.

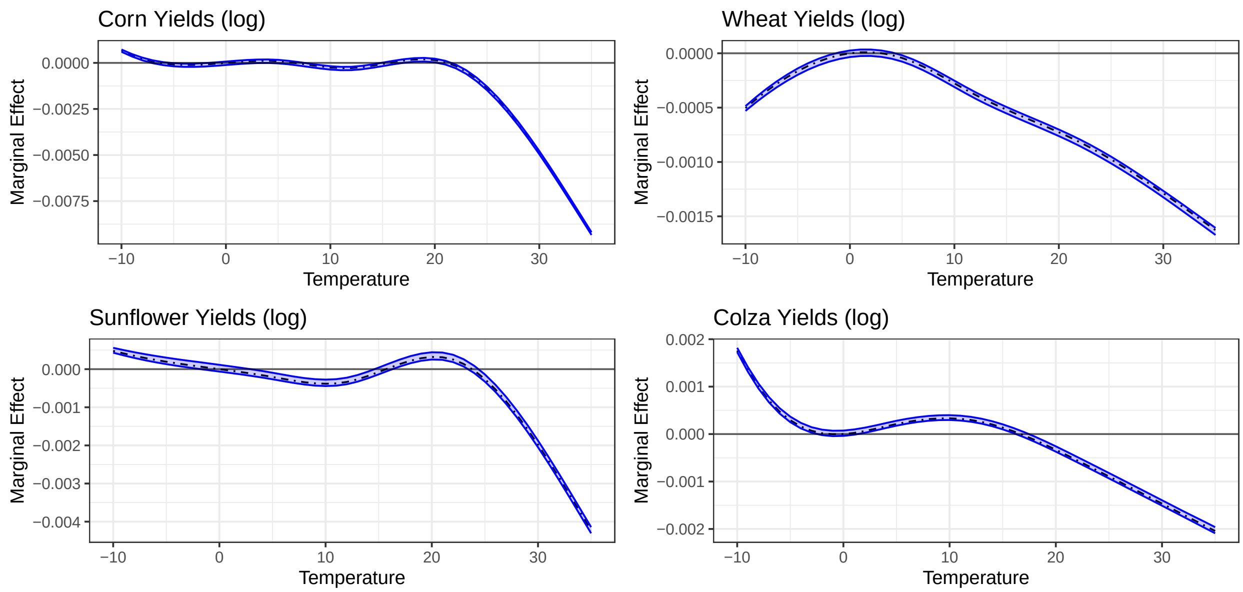


Figure 1: Temperature Effects on Crop-Specific Yields

Notes: This figure shows restricted cubic splines describing the non-linear relation between exposure to temperature during the growing season and crop yields. The regressions are farm-level versions of the specification from Schlenker and Roberts (2009). In addition to cubic splines in temperature, the regressions include farm fixed effects and region-specific quadratic time trends as controls. Standard errors are computed by bootstrapping at the farm level. Temperature effects are normalized relative to the impact at 0°C.

Finally, we address two key institutional features of French agriculture that could influence profit-based measures of adaptation: subsidies from the Common Agricultural Policy (CAP) and the national crop insurance scheme. During our period of interest, CAP subsidies were primarily distributed per hectare and thus should be largely insensitive to the weather forecast shocks we study. Agricultural insurance, while available, has a low uptake rate, with only 17% of total agricultural area being insured as of 2023.[8]

To formally account for the potential influence of these programs, we will compare results using different profit measures. The first is value added, capturing profits from production before subsidies or insurance transfers. The second is a broader measure, which includes these transfers. Comparing the results across these two measures allows us to test whether our estimates are driven by production decisions rather than by the institutional environment. We provide precise definitions for all variables in appendix B.1.

[8]In France, the main insurance scheme is one of harvest coverage, where extreme weather events leading to substantial losses in harvest lead to compensation. See https://agriculture.gouv.fr/animation-la-reforme-de-lassurance-recolte.

3.2 Agricultural Data

3.2.1 Farm Data

Our analysis relies on farm-level panel data from the French section of the Farm Accountancy Data Network (FADN), an annual survey of approximately 7,000 farms. The FADN is designed to be statistically representative of French commercial agriculture, which accounts for the vast majority (95% in 2000) of the country's total agricultural production.[9] From this dataset, we select a subsample of farms specializing in cereal and oil crops, defined as those for whom these products constitute at least 50% of total annual sales. This focus is justified as these crops dominate large-scale field farming in France, and excludes distinct agricultural sectors like viticulture or animal husbandry.

The richness of the FADN is crucial for our analysis. For the selected farms, it collects data on farm profit, costs and revenue, which are crucial for our analysis of adaptation. The panel further contains data on input-specific expenses and crop-specific production, prices and land use, enabling us to explore specific adaptation margins.

We geocode the farms at the department level, and match them with department-level weather data.[10] While farms locations at the commune-level are available from 2000 onward, the forecast data is too coarse for such granularity. We choose to measure realized and forecasted weather at a similar level. We perform a robustness analysis over the 2000-2018 period, where realized weather is computed at the commune-level and forecasts kept at the department-one.

3.2.2 Input Price Data

To properly measure the costs of adaptation, our model requires accurate, location-specific prices for key agricultural inputs. We construct these measures using two official French data sources. Prices for land are derived from the Land Market Value survey (Valeur Venale des Terres).[11] Prices for seeds, fertilizers, and pesticides are sourced from the EPCIA survey, which is the official survey mandated by the European Commission to construct price indices for French agricultural goods.[12] We localise the sale points at the department level, and match them with department-level weather data.

[9] The definition of a commercial farm changed in 2010. This change only affected rules for replacing farms leaving the panel and did not alter the composition of the existing sample, ensuring continuity for our analysis. Before 2010, a commercial farm was defined as a farm with a unique manager, selling more than half of their production, and whose manager's working hours correspond to at least 75% of their total annual work hours. Finally, farms with less than 5ha of land were removed from the targeted population if they were not specialized. In 2000, there were 380,000 such farms recorded in the Agricultural Census out of 663,800, but together they accounted for 95% of the country's total agricultural production. From 2010 onward, the working hours requirement was removed, and the 5ha threshold was replaced by a requirement that farms have a production capacity of at least €25,000.

[10] There are 101 departments in France, which make for slightly larger entities than US counties.

[11] The survey is fielded every year by the statistical services of the French departmental administration for agriculture and forestry. These are based on data provided by the public company in charge of land management (SAFER), which authorizes agricultural land purchases and consolidations when transactions surpass a given threshold. It is then complemented by data provided by local notaries, and several local administrations. The data was digitized from scanned data magazines for the first years of the series.

[12] The EPCIA ensures representativeness by sampling goods in proportion to their category's sales and by sampling prices from firms in proportion to their market share for each good.

We also use the Laspeyres price indices derived by the INSEE from the EPCIA in order to deflate the FADN farm-level input bills for seeds, fertilizers and pesticides. Specifically we use the Ipampa price index series, from 1994 to 2020. Figure A16 compares input price indices from Ipampa with a time series for nitrogen-based fertilizers producers prices from the Federal Reserve Economic Data, and shows the strong correlations in fluctuations. This confirms that the indices properly track variations in prices. Due to lack of data on water prices, we deflate irrigation expenses using a regular CPI index.

Finally, agricultural wages are taken from the continuous labor survey "Enquête Emploi."

3.2.3 Plot Level Data

While our main analysis uses farm-level panel data to estimate the overall costs of adaptation, this approach cannot reveal adjustments in terms of timing, i.e. when specific actions are undertaken within the season. To investigate this channel, we leverage the "Pratiques Cultures sur les Grandes Cultures" (Agricultural Practices for Field Crops) survey, a plot-level dataset. We use the survey waves from 1994, 2001, and 2006.[13] It is important to note that this dataset is a repeated cross-section, not a panel. Consequently, our analysis of this data will not include farm or plot fixed effects and will rely on regional characteristics to control for confounding factors.

3.3 Climate Data

3.3.1 Weather Data

Our weather data is sourced from the European Centre for Medium-Range Weather Forecasts' (ECMWF) ERA5 reanalysis product, which provides hourly estimates of key climate variables on a 0.25° x 0.25° grid. We use hourly temperature and precipitation, aggregating the gridded data to the French department level by calculating an area-weighted average.

Using the time separability assumption common in the literature on agricultural climate impacts, we measure temperature exposure using growing degree days (GDD) and heating degree days (HDD). GDDs capture moderate temperature exposure beneficial for growth, while HDDs capture exposure to extreme heat. Crucially, to ensure consistency between our realized weather data and the forecast data used in our model, we construct these variables using only the four daily temperature measurements available in the forecast dataset (midnight, 6:00, 12:00, and 18:00). The resulting daily integrals are scaled to be equivalent to degree days calculated from 24-hourly data.[14]

We define a single, expansive growing season from October of the previous year to July of the current year. This choice is driven by two factors. First, as shown in figure A15 and table A1,

[13] Plots surveyed are selected among the farms that benefit from the European Union's Common Agricultural Policy. The survey focuses on land plots defined as the set of contiguous land for which the same crop is cultivated, with homogeneous agricultural practices (fertilizer and pesticide use for example). For each crop, the survey selects the minimum number of regions covering at least 95% of that crop's production, and within each region the minimum set of departments accounting for at least 90% of the region's production. Within departments, the survey selects farms with at least .1 hectare cultivated, and less than 200ha. A unique plot is selected within each farm. For the waves that we study, around 20,000 plots are sampled each time.

[14] As a robustness check, we replicate our analysis using realized degree days computed from the full set of 24-hourly ERA5 data.

farms in our sample are predominantly multi-product operations, often growing multiple crops with different sensitivity to heat. A broad temporal window is necessary to capture all potentially relevant weather shocks that affect a farm's decisions and profit. Second, this October-to-July window aligns perfectly with the growing season for winter wheat, the dominant crop in our sample (Gammans et al., 2017). We show in figure A9 and figure A10 the cross-sectional and cross-temporal variations in growing seasons for resp. wheat and corn in France.

We set our extreme heat threshold for HDDs at 30°C. This threshold is chosen to balance the heterogeneous heat tolerances of the dominant crops in our sample. While winter wheat suffers significant yield losses primarily at temperatures above 33°C (Gammans et al., 2017), corn—which accounts for 15% of the agricultural area we study—is known to be damaged by temperatures above 29°C (Schlenker and Roberts, 2009). Our 30°C threshold captures the onset of heat stress for a significant portion of the crops grown by farms in our data. We confirm the robustness of our results to this choice by testing an alternative 28°C threshold. GDDs are computed over the $[4°, 30°]$ degree interval.[15]

3.3.2 Seasonal Weather Forecasts

Our identification strategy requires measures of the farmer's information set at various points before the weather is realized. We aim to construct growing-season weather forecasts for different lead times (e.g., one-month ahead, two-months ahead). The raw forecast data, however, presents a structural challenge: new forecasts are issued only on the first day of each calendar month. This means that a forecast with a true, constant one-month lead (e.g., exactly 30 days) is not available for every day of the growing season.

We address this by defining our forecast variables based on their issuance month. We define a "one-month-ahead" forecast for any given day as the forecast that was issued on the first day of the prior month. Consequently, this variable represents the complete forecast information available to a farmer at a horizon of approximately one to two months. For example, the "one-month-ahead" forecast for both May 5th and May 25th is the one issued on April 1st. Similarly, a "two-month-ahead" forecast bundles all predictions issued between two and three months in advance. All one-month ahead forecasts are then aggregated across the growing season, to produce the forecast equivalent to the observed GDD and HDD measures, and the same procedure is applied to other leads. This approach ensures that we are using a consistent information set for each lead-time category.

The underlying forecast data comes from ECMWF's SEAS5 seasonal forecasting system (System 8, from Météo France). On the first of each month, an ensemble of 25 forecasts is produced for the subsequent seven months, which we average to create a single measure. The temporal granularity of this raw data—four temperature readings and one precipitation total per day—is used to construct the seasonal department-level values within our forecast aggregates, ensuring consistency with our realized weather variables.

In this paper, we will also investigate the role of forecasts received when farmers are mak-

[15] A robustness check includes freezing degree day to our analysis, in order to obtain a more comprehensive measure of realized weather over the season.

ing planting decisions, for different crops, e.g. what farmers know about incoming weather on October 1st when they are supposed to sow wheat, or on May 1st when they should sow corn. In appendix A.1.5, we use a specification in every point similar to the main regression equation used throughout this paper, and presented in equation (4). We plot in these figures the marginal impact of a higher seasonal HDD forecast on short run month-specific forecasts about expected cold weather. Conditional on all our baseline controls and fixed effects, these show that our seasonal HDD forecasts correlate strongly with short-term temperature forecasts received by farmers throughout the year: specifically with forecasts emitted on the first day of every month—for the next 30 days—predicting how cold the weather is expected to be.[16] As such our seasonal forecast for HDDs correlates well with short run forecasts received by farmers throughout the year, and will be able to track farmers' responses taken not only in the spring before the onset of the hot summer, but also in the fall in preparation for upcoming heat. These results confirm that farmers can predict a hot summer from observations of abnormally hot winters, and preemptively change their production decisions. In appendix A.1.5 we also document some heterogeneity in this response. For most of our sample, the bottom 90% of the distribution in terms of average forecasted HDD realizations, a higher seasonal HDD forecasts is significantly associated with hotter predicted weather in October through December, as well as in May and June. For the top 10% of the sample, where forecasted HDDs are much more frequent, a higher seasonal HDD forecast will only correlate with hotter predicted weather in the summer. While being in keeping with the seasonal aggregations used throughout the agricultural climate change literature, our seasonal heat forecasts will hence be able to track the cost and benefits of actions taken by farms throughout the year, in expectation of extreme heat.

3.3.3 Forecast Accuracy

A necessary condition for our empirical strategy is that the seasonal forecasts contain meaningful information that can influence farmers' decisions. We confirm this in two ways. First, as shown in the calibration plots in figure A4 and figure A5, forecasted GDDs and HDDs are highly correlated with their realized values. For GDDs, the relationship is strong at both one- and two-month horizons, with observations clustering tightly around the 45-degree line, indicating that the forecasts are well-calibrated. While forecasted HDDs are also highly correlated with realizations, the plots show a tendency to underestimate the most extreme heat events.

Having established that the forecasts are informative, we now characterize their error distributions. As shown in figure A1 and figure A2, the distributions are generally centered around zero. For GDDs, we observe a slight negative bias and a long left tail, both corresponding to over-predictions. To ensure our estimates are not driven by tail outliers, we trim 120 observations where the forecast error is less than -500 GDDs.[17] The error distribution for HDDs exhibits a slight

[16] French farmers receive repackaged forecasts from Météo France throughout the year, which predict the probability that the upcoming months will be more or less hot than average. These are the main type of longer-run forecasts we expect them to use when making crop choice decisions. Here we proxy the likelihood that weather will be colder with a measure which computes the forecasted number of degree hours spent below resp. 1.64, 1.96 and 2.58 standard deviations below the average department-specific hour-of the day-of the month temperature. See https://meteofrance.fr/actualite/publications/les-tendances-climatiques-trois-mois

[17] Our main results are robust to the choice of trimming strategy, including trimming based on absolute error values.

skew, consistent with the calibration plots showing that forecasts tend to under-predict extreme heat. Splitting our sample between high and low average HDD quqntiles reveals that forecast errors are slightly larger in departments where HDD realizations are more frequent. The bottom half of our sample has an average error of 1.21, meaning that on average forecasts under-predict HDDs by 1.21 units (standard deviation of 2.14). In the top half, that error is of 2.72 (standard deviation of 3.73). However, this difference is not statistically significant, and the gap in forecast errors between these groups is smaller than the gap in average HDD realizations (1.41 vs 3.43), which means that forecasts do track to some extent this spatial heterogeneity in realized heat.

Rainfall forecasts show a slight upward bias but are otherwise largely symmetric around zero. Overall, this analysis confirms that the forecasts provide meaningful information about future weather.

4 Empirical Strategy

To estimate the costs and revenue effects of ex ante adaptation, as well as test for the empirical validity of the envelope theorem, we use an estimating equation that regresses profits, total costs, or total revenue on both realizations and forecasts of weather. In particular, we use the following estimating equation.

$$\begin{aligned} y_{jt} =& \beta_1^w \text{GDD}_{d(j)t} + \beta_2^w \text{HDD}_{d(j)t} + \beta_1^f \text{FGDD}_{d(j)t} + \beta_2^f \text{FHDD}_{d(j)t} + \\ & g(P_{d(j)t}) + g_2(FP_{d(j)t}) + \gamma_j + \eta_t + \zeta_{r(j)}^1 t + \zeta_{r(j)}^2 t^2 + \varepsilon_{jt} \end{aligned} \tag{4}$$

The outcome variable is either profit, costs or revenues for farm j in growing season t. In later results, we also explore effects with different outcomes including farm inputs, planting decisions, and crop-specific land use. The main right-hand-side variables are realizations of temperature (GDD and HDD) and forecasts of temperature (FGDD and FHDD) experienced by farms located in department d during the growing season. Given that weather and forecasts vary at the department and year level, we use two-way standard errors at the department and year level.[18]

We focus on the marginal effects of forecasts, and do so for two reasons. First, conditional on weather realizations, variation in forecasts should cleanly identify changes in information available to farmers, and through that the consequences of their actions. When looking at outcomes such as revenue, rather than farm decisions, coefficients recovered off weather realizations will not only capture the effect of farmer action, but also of weather realization. Controlling for realizations, and using forecast variation isolates farmer decisions.

Second, forecasts can also better capture the information available to farmers regarding weather, and more cleanly isolate the one relevant for their decisions. Forecasts are a way to avoid the attenuation bias caused by recovering cost and revenue effects off weather realizations—which, to a minimum, will contain both predicted and unpredicted weather (farmers knowing and responding only to the known part of the realization). Additionally, if the farmer faces adjustment costs when choosing actions, then they have an incentive to choose actions prior to the arrival of

These results are available upon request.

[18]We later also show results with weather realizations measured at the municipality level.

weather. In such a case, forecasts provide more powerful identification of the effect of temperature on farmer actions than looking at realizations of temperature. In a farm setting, adjustment costs are likely high given that many actions need to be taken prior to the growing season (e.g., the choice of which crops to plant, total cropped area) or prior to weather arrival during the growing season (e.g., fertilizer application, defense of crops against freezing).

We focus, in the initial results, on one-month-ahead forecasts. In cases with convex adjustment costs, marginal value of information falls as forecast horizon increases. Thus, short-horizon forecasts should again improve power to detect effects. In additional results, we examine forecasts with longer horizons.

The estimating equation also includes controls for the level and square of realized and forecasted precipitation over the growing season to account for effects of precipitation on farm outcomes. We write these as $g(P_{d(j)t}) + g_2(FP_{d(j)t})$. We include region specific time trends in the form of $\zeta^1_{r(j)}t$ and $\zeta^2_{r(j)}t^2$. These account for potential sub-national trends that would correlate with weather and our outcomes of interest.[19] Finally, farm fixed effects, γ_j, and year fixed effects, η_t, mean that effects are identified from within-farm variation in weather over time, while accounting for national time series patterns in both weather and agricultural costs or revenues, as well as region-level quadratic trends. The identification assumption is that the remaining error term, ε_{jt} is uncorrelated with the temperature forecast variables. The control set is similar to prior work on the effects of climate on agriculture, with one important difference: we are able to use farm fixed effects rather than geographic area fixed effects (e.g., many studies in the U.S. include county fixed effects). This more granular cross-sectional control should alleviate concerns about confounding farm-level characteristics like geographic features that determine crop suitability and weather patterns.

5 Results: Effects on Revenues, Costs, Profits, and Adaptation Mechanisms

In this section, we present evidence of costless, revenue-increasing ex ante actions by farms in response to forecasted heat shocks in the period when shocks arrive. We first document the farm-level consequences of these actions on costs, revenues, and profits, and highlight a heterogeneous response to forecasts depending on the sign of the forecast error. We finally analyze evidence on the actions themselves to shed light on mechanisms, and we highlight the consequences our results for the implementation of the static envelope theorem.

[19] Recent work has highlighted the endogeneity of agricultural technical change to the heterogeneous exposure of crops to heat, with crops more exposed being a relatively higher focus of innovation. See Moscona and Sastry (2022). We also run regressions without the department-specific trends, and find very similar results. This structure of time trends follows from Schlenker and Roberts (2009), albeit we also include year fixed effects to account for potentially non-linear France-level shocks. Year fixed effects seem particularly relevant in the European context, with an integrated agricultural market and likely spatially correlated heat shocks across countries which will impact overall demand.

5.1 Farm-level Consequences of Forecasted Temperature

Table 2: Farm-Level Profit, Revenue, and Cost Responses to Forecasts (1 month lead)

Dependent Variables:	Profit	Revenue	Costs
Model:	(1)	(2)	(3)
Variables			
GDD	-8.32	5.10	1.21
	(13.16)	(11.84)	(7.81)
GDD (F)	3.26	37.4	30.8**
	(43.1)	(34.7)	(14.5)
HDD	185	-158	-192
	(277)	(332)	(157)
HDD (F)	2,067***	1,192***	-56.7
	(708)	(403)	(178.5)
Mean	86,695	155,386	123,249
Unique Farms	2,603	2,603	2,603
Fixed-effects			
Farm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	18,917	18,917	18,917
R^2	0.84	0.89	0.94

Notes: Estimates are based on equation (4), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

5.1.1 Revenue, Cost, and Profit Effects

We first show the effect of forecasted moderate and extreme temperature on farm profits, revenues and costs, controlling for realizations of temperature. Table 2 displays the results. The outcomes are profits, revenues (measured by total sales) and a measure of the costs of production. The measure of costs is broad and includes the cost for intermediate inputs, social contributions to workers, personnel expenses, taxes, and insurance. This broad measure is less likely to miss potential cost responses. The profit variable corresponds to the farm's gross operating income, and includes value added, subsidies, expenses for insurance, and insurance indemnities.[20]

[20] We perform a test and run the regressions using only expenses for intermediate inputs, as a check for potential mismeasurement, and find similar results. Results are available upon request. See subsection B.1 for the definition of

GDDs, as the name implies, help crops grow and can thus be interpreted as positive productivity shocks. HDDs, in contrast, are temperatures so extreme that they cause crop losses. We expect that forecasts of GDDs are useful for taking advantage of better growing conditions, while forecasts of extreme heat are useful to either cut production costs, to increase input usage to compensate for adverse conditions, to better target input usage, or to modify decisions such as the timing of harvest or one's crop mix composition. In a simple model where farms optimize profit, local, idiosyncratic, adverse weather (either lower GDD or higher HDD) corresponds to a negative TFP shock, and we would expect forecasts of worse conditions to lead to a reduction in the scale of production, leading in turn to reduced revenues and costs. On the other hand, changes in the timing of harvest could allow for a positive revenue response without substantial changes in costs.

Table 2 shows that profit and revenues respond positively to forecasted GDDs and HDDs. In contrast, costs respond positively to forecasted GDDs but exhibit an insignificant, negative response to forecasted HDDs. And, most importantly, in comparison to the forecasted HDD effect on revenues, the response is quantitatively small. The point estimates of the effects of realized GDDs and HDDs are generally in keeping with our assumptions that higher GDDs are productivity improving while higher HDDs are generally productivity reducing. The interpretation of these coefficients, however, is not straightforward. They mix direct effects of realized weather with the effect of ex post actions. In our sample, these effects are also not statistically significant. Given that the central goal of the paper is to identify and quantify cost responses to forecasts, we do not give further attention to these coefficients.

Looking first at the effect of forecasted GDDs, one can see that the effects on profits are near zero, and that costs and revenue have coefficients of similar magnitude. This result suggests that for moderate temperatures, farmers are taking costly actions to arrive at an increase in revenue, resulting in little net effect on profit. The effects on both revenues and costs are substantial: the standard deviation of forecasted GDDs is about 240, so a typical change in GDDs will lead to a roughly 6% change in sales and costs. This is in line with the known sensitivity of the agricultural sector to weather.

The effect of forecasted HDDs shows a different pattern. Profits and sales increase while costs do not. An increase in the HDD forecast by one degree-day one month in advance leads to an increase in profit by €2k, and an increase in revenue of €1k. Given typical revenue per farm of about €150k and a standard deviation of forecasted HDD of just over 1 (see table A2), this coefficient indicates that a typical change in forecasted HDD causes revenues to change by about 1%, on average. Similarly, given an average yearly profit of €87k, a typical change in forecasted HDD leads to an increase in profits of 2%. In contrast, forecasts of extreme heat have no substantial or significant effect on production costs.

intermediary inputs. We also consider a measure of value added as an alternative to profit, defined as the difference between sales and costs of production. Results are shown in table A9.

5.1.2 Non-Linear Response to Forecast Error

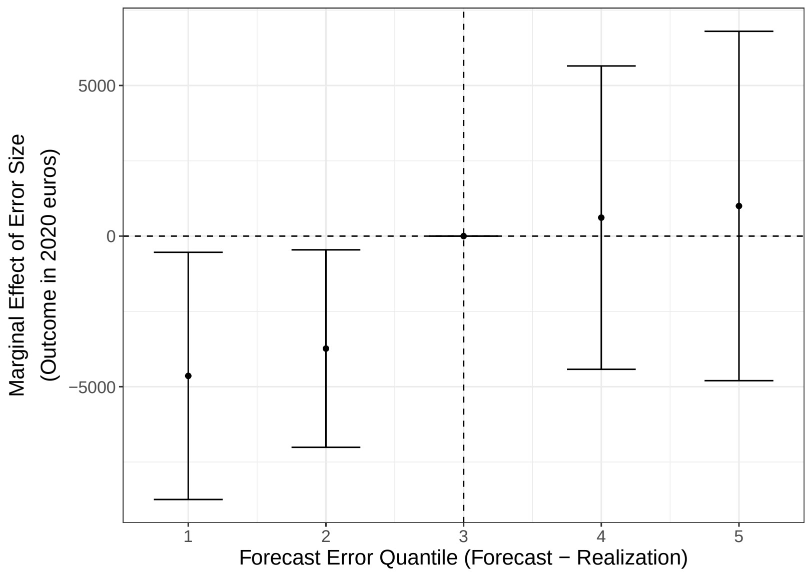


Figure 2: Profit and Sign of the Forecast Error

Notes: Estimates display the non-linear response of farm profit to forecast errors. Errors are labeled from 1 to 5, increasing in forecast error from the largest negative error where the realization is largest compared to the forecast, up to the largest positive error, where the forecast is largest compared to the realization. The omitted error category contains errors between -0.1 and 0.1. The regression is otherwise based on equation (4), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

It is useful to decompose the forecast effects by the sign and magnitude of the forecast error. To do so, we run a specification that is the same in all respects to the one used for table 2, but where we break down the the forecasted HDD variable into conditional quantiles. Focusing first on positive forecast errors (realized HDD is smaller than the forecast) with values of 0.1 or greater, we construct two bins based on whether the error is above or below median among that set of positive errors. We do the same for negative errors (-0.1 or below). Errors between -0.1 and 0.1 around the realized HDD shock are our central bin, which we use as the omitted category. These errors are labeled in figure 2 from 1 to 5 by increasing forecast error.[21]

The figure shows the marginal profit effects of one extra forecasted HDD in each specific bin. Complete cost, revenue and profit responses are shown in table A30, and the cost and revenue figure in figure A20.

The pattern of results indicates that negative forecast errors have a statistically significant, negative effect on profit, while positive errors have a small and not significant effect. This results is intuitive: negative forecast errors likely lead farmers to under-forecast future heat shocks, rendering

[21] HDD forecasts tend to under-predict HDD realizations, and the median negative forecast error is of -1.5, and the median positive one is 0.5. This skewness explains that coefficients for negative errors are slightly better identified.

them under-prepared for the impact of heat. On the contrary, over-forecasts could induce farmers to take protective actions which limit the negative consequences of realized heat on production. Actions in excess of the realized heat then matter little for the realized profit. This pattern helps one interpret the main results in table 2. An increase in forecasted heat—holding realized heat constant—will reduce the risk of a negative forecast error and allow farmers to take the necessary protective actions to shield their profit from potential negative shocks.[22]

5.1.3 Information Timing

To help understand the mechanisms underlying the results above, we start by looking at a distributed lag model which includes both weather realizations and the entire set of forecasts with a lead from one through five months ahead. That is, we run the following regression on our outcome measures:

$$
\begin{aligned}
y_{jt} = & \beta_1^w \text{GDD}_{d(j)t} + \beta_2^w \text{HDD}_{d(j)t} + \sum_{\ell=1}^{5} \left(\beta_{1,\ell}^f \text{FGDD}_{d(j)t}^{\ell} + \beta_{2,\ell}^f \text{FHDD}_{d(j)t}^{\ell} + g_{2,\ell}(FP_{d(j)t}^{\ell}) \right) + \\
& g(P_{d(j)t}) + \zeta_{r(j)}^1 t + \zeta_{r(j)}^2 t^2 + \gamma_j + \eta_t + \varepsilon_{jt}
\end{aligned}
\tag{5}
$$

where all variables are the same as in equation (4) except we have added forecasts for each horizon, as indicated by the variables FGDD^{ℓ}, FHDD^{ℓ} and $FP_{d(j)t}^{\ell}$.

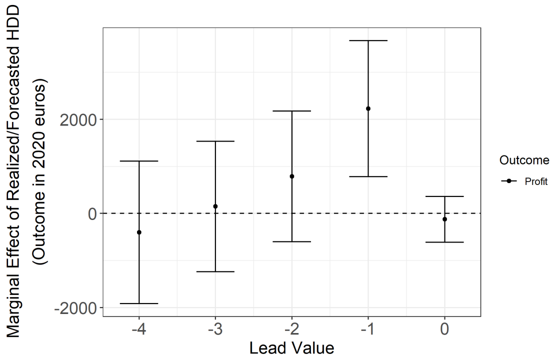
This regression serves two main purposes. First, it identifies the precise timing of information arrival, and is thus useful for understanding what type of action our analysis is recovering if different farm responses face different magnitudes of adjustment costs or need to occur at different times. When running regressions with a set of forecasts, variation in one forecast, conditional on all others, will capture the information received at that lead time. Second, and relatedly, it allows us to assess responses from a larger set of actions that might require longer lead time.

Equation (5) essentially decomposes the effect we show using a single forecast horizon in section 5. Not including all the leads available creates a form of omitted variable bias where the included forecast captures a composite of the effects of all forecast horizons, with the composite effect being determined by the autocorrelation of forecasts across horizons. As long as we control for realized weather, this omitted variable will not be an issue for identification, because the interpretation of the forecast coefficients is still that it causes changes in the agent's belief, and through it, action. However, it is useful to include all the possible forecast leads in order to understand which one is most useful to farmers (in the sense that it generates the largest response).[23] It also puts the forecast and realization effects on similar footing in the sense that both are then identified by shocks: surprising realizations in the case of the realized temperature and news shocks in the

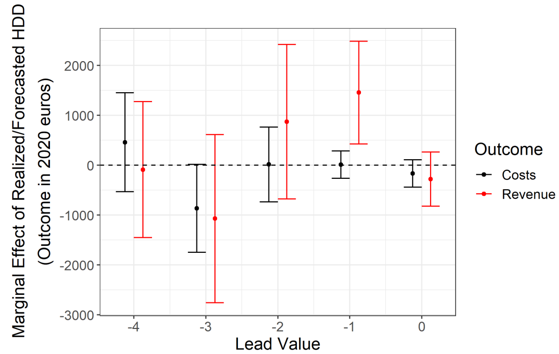
[22]We similarly decompose the profit effect of GDD forecast errors in figure A21, and recover a flat response. Neither positive nor negative GDD forecast errors generate significant profit effects, relative to the on-point forecast. These results confirm that there is a specific role of forecasts in predicting incoming heat shocks sufficiently well, in order to allow for farms to prepare and shield their production.

[23]In a model with non-convex adjustment costs, a specific forecast lead might generate a larger response at a given horizon because the optimal timing of a particular responses matches that lead value the most. Changes in forecast accuracy by lead could also cause different responses to different leads. Figure A1 shows that forecast errors do not change significantly across lead values, at least when aggregated into our growing season variables. As such, we can expect that here, differences across lead values are mainly driven by questions of timing.

case of all forecasts for horizons less than five months ahead.



(a) Profits



(b) Cost and Revenue

Figure 3: Timing of Forecasts on Farm Profit, Cost and Revenue

Notes: Estimates display the response of resp. farm profit, costs and revenue to forecasts of heating degree days received at different lead times from one to four months ahead, as well as the effect of realized heating degree days. The regressions are based on equation (5), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

Figure 3 plots the coefficients associated with heating degree days from estimating two different versions of equation (5). In particular, the figure shows β_ℓ^f for $\ell \in [1, 4]$ and shows β^w for the lead value of 0 for regressions with costs and revenues on the left hand side. We exclude the coefficients for lead 5, given that these are less cleanly identified, accounting for all the information received more than four months in advance.[24]

We see that the the effect on revenues associated with a one-month-ahead forecast is statistically significant and of a similar magnitude to the effect found in table 2. The cost effect of a one-month-ahead forecast of HDDs remains centered around zero. Revenue responses are not statistically significant at the 5% level for horizons longer than one month, but the point estimates indicate that information close to the shock allows for revenue-enhancing responses while information farther from the shock leads to, if anything, a decrease in revenues. Costs are near zero for all horizons aside from three months ahead. The fact that cost effects do not consistently get stronger as the forecast horizon increases suggests that convex adjustment costs are not a major factor driving the results that we find (Downey et al., 2023). The three-month-ahead forecast effect could indicate that there are adjustments that are uniquely available at a quarterly frequency. Each month, the French meteorological agency also delivers a publicly available document with forecasts up to three month ahead, so the three months ahead forecast is the first forecast easily observable by farmers, which could explain why farmers do not respond to four-month-ahead forecasts.[25] The same regression looking at profits shows a clear pattern: news arrive one month ahead has a

[24]And as discussed in Canal (2015), forecasts were only available up to four months in advance in the 1990s in France, and our five-month ahead hindcast is hence less likely to correspond to information available to farmers at the time.

[25]For an example of these publicly available and processed forecasts, see https://meteofrance.fr/actualite/publications/les-tendances-climatiques-trois-mois.

significant effect on profit while all other leads exhibit smaller and insignificant effects.

5.2 What is Driving Cost, Revenue, and Profit Responses?

The large effect on revenues and small effect on costs naturally raises a question: how are farmers achieving an improvement in revenues with little to no change in costs? Below, we explore farm-level behavior that does and does not respond to forecasts to shed light on this question. We also test for—and rule out—a variety of measurement and identification arguments that could explain the results.

5.2.1 Ruling Out Explanations Due to Offsetting Effects, Measurement Error, Specification Choices, Identification of News, or Adjustment Costs

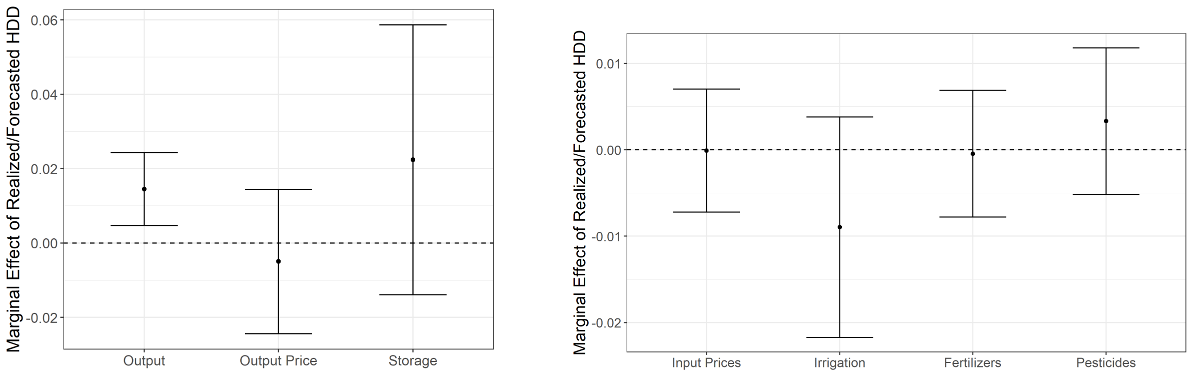
Before investigating the mechanisms by which firms might be adapting to temperature, we first rule out some alternative explanations of the results. We investigate these in figure 4.[26]

Offsetting Prices and Quantities: We examine the revenue effect in more detail asking whether the response comes from agent reoptimization or equilibrium effects. To do so, we estimate versions of the equation (4) where the outcome variables are physical output (simply the sum of all produced quantities), the output price index, or storage (sum of all stored quantities).[27]

The results are shown in figure 4 (see table A7 for the table version). One can see that output rises in response to a change in HDD forecasts, consistent with the results shown above in table 2. Output prices, in contrast, do not change on average (though the effect is imprecisely estimated). Flat prices and increased quantities confirm that farmers are individually responding to forecasts, and that gains in farm profit and revenues are not a result of general equilibrium forces. Storage finally shows a relatively large, though insignificant, response, indicating that farm actions might have dynamic consequences—a point we return to below—and suggests that our revenue results in table 2 are an underestimate of the consequences of farm responses.

[26] The table corresponding to the figure is in table A7.

[27] We show in table A12 the crop-specific responses of output quantity to temperature realizations and forecasts. The output price index used in this regression corresponds to a weighted average of crop-farm level output prices as observed in the data, using relative land shares as weights. subsection B.1 gives a formal definition of the different variables.



(a) Revenue Decomposition

(b) Cost Decomposition

Figure 4: Prices and Quantities for (log) Outputs and Inputs

Notes: Estimates display the response to one month ahead forecasted heating degree days of resp. farm output, output price, storage levels, irrigation, fertilizers and pesticides expenses. We also show the response of input prices as observed in an agricultural input price survey at the store-year-input level. The regressions are based on equation (4), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

In table A12, we decompose output effects at the crop level. These show that the gains are positive and significant for both wheat (one forecasted HDD increases output by 1.6%) and beets (0.7%), while also positive but not significant for colza (1.4%). On the contrary, increases in forecasted HDDs decrease the amount produced in corn and sunflower, albeit in a non-significant way.[28] We discuss later how crop choices are impacted by forecasts.

On the right hand side of figure 4, we look at the cost side and rule out potential agent re-optimization that would produce no net effect on costs: differentiating between equilibrium effects where input price movement would offset varying input use, and individual behavior where changes in the input mix would leave total costs flat. First, we show a separate regression focusing on input prices, where prices are observed at the store-year-product level, and the regression includes store and product fixed effects in addition to year fixed effects. The regression shows a relatively precise zero effect of forecasted HDDs on input prices, ruling out offsetting price and quantity movements

[28] In our context, wheat shows no statistically significant relation with heat. In comparison, and using department-level time series of yields, Gammans et al. (2017) find that an additional one-day exposure to temperature above 32°C will decrease wheat production by about 2.5ppt. The comparison between these two results is not directly straightforward. Our analysis is done at the farm level, while theirs is at the department one, and it is not guaranteed that the elasticities of production to heat would be the same at the two levels. Our heating degree day cut-off is also at 30°C, in order to account for the impacts such temperature can already have on corn. We also account for weather realizations and forecasts over the entire possible growing season, allowing for farmers to both switch their crop mix composition (and hence the relative density of their land exposed to summer or winter growing seasons), and switch their growing season at the crop level (moving their wheat or corn specific growing seasons earlier or later for example). We also note that they focus on weather accrued during the warm part of the wheat growing season–although warm weather accrued over the total growing season, and the warm months should be comparable quantities in the French context. As such, it makes sense that they find a larger effect for unavoidable hotter weather, while we find that farmers face lower consequences form their endowed weather which might not necessarily be the effective weather they end up facing.

on the cost side. We give price responses per input category in table A11, confirming that none of the input prices respond to forecasts.

We then decompose the total farm input bill into input-specific ones. We consider the inputs easiest to adapt to one-month ahead information shocks: irrigation, fertilizers and pesticides.[29] None of these inputs respond to forecasts, ruling out offsetting input-specific responses.[30]

Measurement Error in Costs: A second issue is that the total costs variable could be subject to measurement error, leading to attenuation of the effect of forecasted HDDs. To address this, we decompose land and labor, the two inputs for which we observe sub-categories, and analyze the response of these sub-categories directly measured in levels rather than expenses (resp. hectares and hours). Decomposing land responses in figure A18, we see that the zero land effect does not seem to be driven by an aggregation of different land categories with heterogeneous adjustment costs. Both the response of rented land with short rental contracts, and of owned and used land are non-statistically significant. Additionally, fallow land does not respond as well, whereas we could have considered it as a potential source of extensive margin response.

When decomposing labor responses in figure A19, most categories remain unresponsive, while we note that the two most flexible types of labor respond negatively to expected hot weather. Non-regular salaried workers dropping in a statistically significant way by about 2.83 hours per additional forecasted HDD. This response remains small, given that labor is measured in total hours of work per year, and that the standard deviation in forecasted HDD is of one.

Further Robustness: Finally, we examine the robustness of the results to changes in the specification of the estimating equation including the addition of lags of realized weather or removing region-specific time trends. We vary the cutoffs used to define a GDD versus an HDD and add a measure of freezing degree days. We also use a disaggregated measure of realized weather, measured at the municipality level, combined with the same department-level measure of forecasts. In this case, realized weather is also computed using the entire range of hourly realizations, and not only four observations per day. And we investigate heterogeneity in the response to forecasts across farms. In all cases, we find results that are in line with the baseline estimates. These robustness checks are reported in appendix D.

5.2.2 What Is Driving the Results? Heterogeneous Weather Variability, Endogenous Exposure to Weather, and Crop Switching

What explains the revenue and cost patterns we find? In this section, we argue that the answer lies in two related mechanisms.

First, we show that the statistical properties of GDD and HDD shocks differ. GDDs typically represent marginal variation in temperature, while HDDs represent non-marginal, tail-risk events.

[29] Fertilizers and phytosanitary products are measured as deflated input bills, using France-level input-specific Laspeyres price indices which translate the deflated input bills into 2020 euros. See subsection B.1 for detailed definitions of the different variables.

[30] We show in table A10 results for a larger set of inputs, including land and labor. None of land, labor, fertilizers, phytosanitary products, seeds, or irrigation respond to forecasted HDDs. Labor does respond to forecasted GDDs.

We posit that this distinction drives different types of adaptive behavior. In response to marginal GDD changes, farmers appear to make continuous adjustments to inputs, leading to effects on both costs and revenues. In contrast, the threat of a non-marginal HDD shock prompts "lumpy" strategic responses—such as shifting the timing of harvest or crop switching—which primarily involve opportunity costs or dynamic costs rather than direct input costs, explaining the muted effect on our measured cost variable at time t.

Second, we provide direct evidence that farmers use forecasts to endogenously manage their exposure to forecasted HDDs through shifts in the timing of key agricultural activities within the growing season, and changes in crop choice to alter the farm's fundamental sensitivity to heat.

Heterogeneous Variability Along the Temperature Distribution: To test the hypothesis that the nature of the shock drives the nature of the response, we first decompose all temperature variations into "marginal" and "non-marginal" events. We define for this a non-marginal shock as any hourly temperature realization that deviates by more than 1.96 standard deviations from its historical (1963–1993) hour-day-month mean. Applying this definition to our data reveals a fundamental difference between our two temperature variables. As shown in table A18, HDDs are overwhelmingly non-marginal events (85% of occurrences), while GDDs are overwhelmingly marginal (only 13% of GDD variation is classified as non-marginal).

This decomposition helps to understanding our main results. We re-estimate our baseline specification, separating both forecasts and realizations into their marginal and non-marginal components. The results, shown in table A13, reveal a distinction for forecasted extreme heat. The profitable adaptation response is driven entirely by non-marginal HDD forecasts. In contrast, marginal HDD forecasts lead to a statistically significant reduction in sales. This is precisely the pattern our hypothesis predicts: lumpy adaptations are only triggered by the threat of a significant, non-marginal shock. When the forecasted shock is marginal, firms engage in the more standard response of scaling back production. Given that the support for marginal HDD is small, our average effect for forecasted HDDs is mostly driven by the response to non-marginal changes in forecasted HDDs.

In contrast to the sharp distinction we find for HDDs, the decomposition for GDDs is less conclusive. Costs go up similarly for both marginal and non-marginal GDD forecasts. Marginal GDD forecasts increase revenue but non-marginal GDD forecasts do not, on average, substantially increase revenue, though the difference in coefficients is not significant.

Within-Season Timing Decisions: Next, we investigate whether farmers change the timing of within-season production actions in response to the forecasts. Such adjustments could explain the positive revenue and profit effects we find, as they can improve crop outcomes without large changes in input expenditures. To test this, we use plot-level data on the dates of ploughing, sowing, and harvest for our main crops in the PKGC survey. As this is a repeated cross-section and involves coarser sampling than our main analysis dataset, we cannot include farm fixed effects and instead use department fixed effects. We cluster the standard errors at the department level, rather than department-by-year in order to account for our shorter panel, with only three years of data. Our specification is otherwise identical to the baseline in equation (4).

The results, shown in figure 5, confirm that farmers adjust their production schedule in response to heat forecasts, and responses vary across crops. While wheat timing decisions show little response to heat forecast, crops that are more heat sensitive do show changes in timing decisions. Some crops are plowed and sowed earlier, and some later, to either insulate crops from heat shocks or take advantage of a hotter growing season (table A14 through table A16 give the corresponding results in a table format).

The effect of these timing changes on weather exposure is an empirical question. We quantify it using a simple simulation, for the specific case of wheat. First, we compute the baseline distribution of temperatures experienced by farms over a fixed October–July growing season. We then use the coefficients for wheat to predict how the start and end dates of the season shift in response to each department-year's specific HDD forecast. Finally, we compute a new "endogenous" temperature distribution based on these adjusted season boundaries. Figure A22 compares the cumulative distribution functions of the endogenous and baseline seasons. The results show that the timing adjustments, while small, systematically shift the distribution in the expected direction. Farmers alter their effective growing season to increase exposure to cooler temperatures and reduce exposure to the hottest temperatures.

Overall, these timing responses represent a plausible channel for the "no-cost" revenue improvements we observe. They allow farmers to protect their revenues from heat without significantly increasing input costs. However, the modest size of these shifts suggests they are unlikely to be the main explanation for the large profit effects.

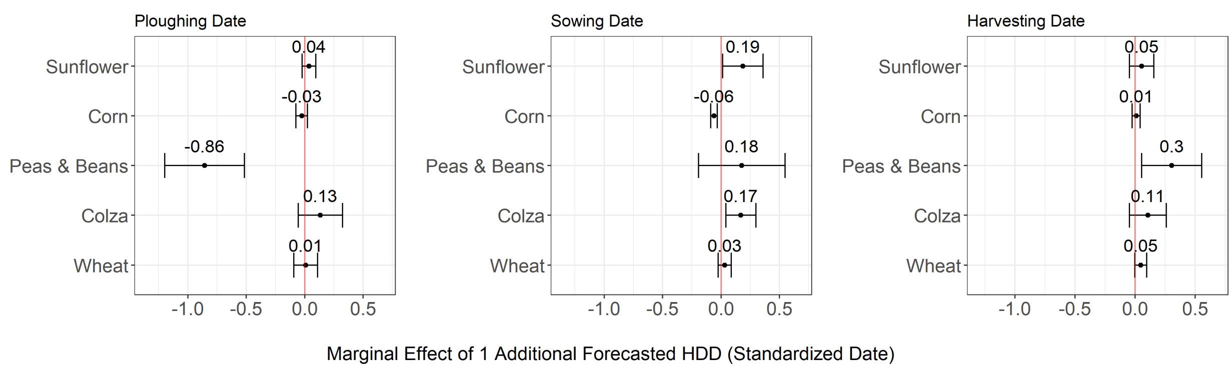


Figure 5: Crop-Specific Timing Responses

Notes: Estimates display the response to one month ahead forecasted heating degree days of crop-specific timing decisions at the plot level, using the PKGC repeated cross-sectional data. The regressions are based on equation (4), but replace farm fixed effects with department level ones. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the PKGC. Standard errors are clustered at the department level to account for the very small number of time periods, and confidence bands display the 95% confidence interval.

Crop Switching: We finally explore crop switching as a potential adaptive strategy. Crop switching has been identified as crucial to reduce the damages from heat exposure and climate change in agriculture (Rising and Devineni, 2020). Like timing, crop switching can also play along the sensitivity and exposure margins. On sensitivity, one can switch towards heat resilient crops when expecting hotter weather, hence reducing the losses faced when actually encountering bad weather.

Corn and wheat, colza and sunflower have different heat tolerance, as highlighted by the specifications in figure 1—and moving from corn to wheat and sunflower to colza might reduce one's sensitivity to heat shocks. Switching crops can also change one's exposure to weather. We show in figure A9 and figure A10 that typically, wheat is sown around November, and harvested before August in France, while corn is sown around May and harvested around October. Sowing wheat when a hot summer is expected can allow you to avoid August heat shocks, hereby reducing the effective amount of HDDs faced. Finally, we have shown in subsection 3.3 that farmers receive short term forecasts throughout the year which they can use to make inference about summer heat shocks, and to modify their exposure through crop switching.

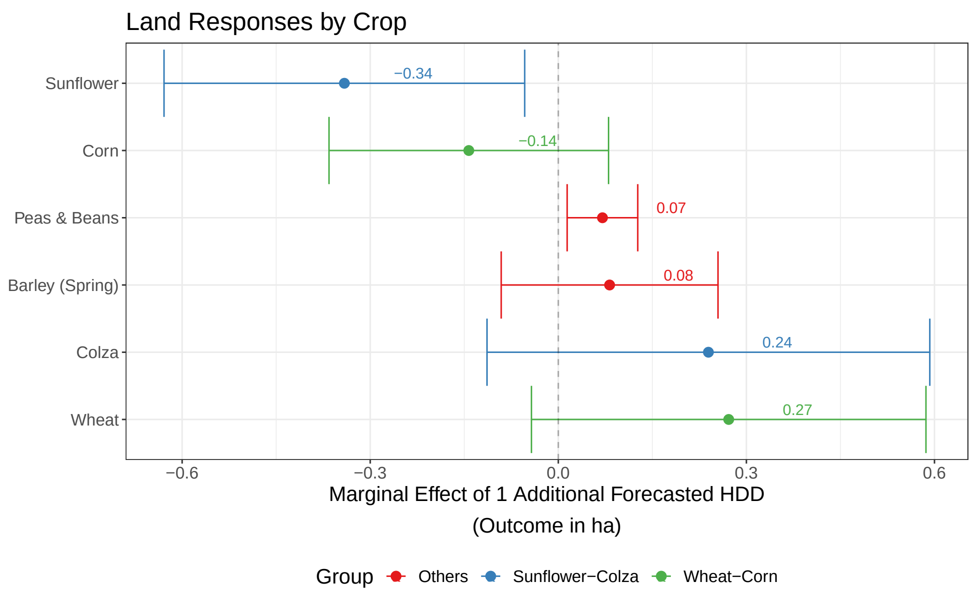


Figure 6: Decomposition of Cropland Responses

Notes: Estimates display the response to one month ahead forecasted heating degree days of crop-specific land allocations at the farm level. The regressions are based on equation (4), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

To test for this channel, we estimate our baseline model using the land area dedicated to specific crops as the outcome variable. Figure 6 plots the coefficients for one-month-ahead HDD forecasts. The results show a clear pattern consistent with adaptation: in response to forecasted heat, land allocated to heat-sensitive crops like corn and sunflower decreases, while land allocated to more heat-resilient crops like wheat, colza, barley, and legumes increases. Land use patterns are in line with heat sensitivity observed in the output results we discussed earlier (table A12). The increase in land dedicated to peas and beans matches cropping patterns observed by Aragón et al. (2021).

To formally test these substitution patterns, we use a system of OLS regressions and perform Wald tests on the coefficients for key pairs. The results, shown in table A21, provide clear evidence of switching between oilseed crops: we can reject the null of an equal response for colza and sunflower at the 5% level (p=0.048). For cereals, the pattern is suggestive but less precise. While the point estimates in figure 6 show a clear reallocation away from corn and towards wheat, a formal test fails to reject the null that their responses are equal (p=0.29). This suggests that while farmers are actively reallocating land away from heat-sensitive crops in response to forecasts, the substitution between winter wheat and summer corn is either less pronounced or measured with more noise in our data than the substitution between colza and sunflower.

5.3 Implications for the Static Envelope Theorem

5.3.1 Framework and Implications

Our results have direct and significant implications for the application of the static envelope theorem in climate economics. As shown in table 2, forecasts of extreme heat (HDDs) have a significant positive effect on farm profit (confidence interval of [680, 3500]), while forecasts for moderate heat (GDDs) have a null effect (confidence interval of [-81, 88]). This finding—that adaptation to forecasted extreme weather has a non-zero, positive effect on profits—is a direct rejection of the theorem's prediction in this context. The results are robust to using value added as an alternative profit measure (table A9).

The implication is that methods for estimating climate damages based on the static envelope condition may be biased. Regressions of profits on realized weather implicitly assume that any adaptive responses have, at the margin, a zero effect. Our findings show this is not the case for extreme heat. Instead, the coefficient on realized heat in a standard regression will capture the sum of the true, direct damage and the offsetting profit gain from adaptation. This omitted variable bias will lead to a significant underestimation of the true damages from extreme heat. We demonstrate this bias in table A9, where the coefficient on realized HDDs decreases when forecast variables are included in the specification. These results also imply that, in our context, methods relying on the envelope conditions to recover costs of adaptation will overstate the static costs. These methods assume that marginal costs and benefits of adaptation are equal, while here, static adaptation has little or no cost and large benefits.

5.3.2 Why Does the Static Envelope Theorem Fail Here?

The theorem's validity rests on three key assumptions: (1) the firm's optimization problem is differentiable, implying smooth, continuous adjustments; (2) the shocks are marginal, (3) firm optimization is static and optimality implies equating static rather than dynamic costs and benefits of adaptation. Our previous results suggest that neither of the first two assumptions are met, and we address the third assumption in the following section, finding that it fails as well.

First, the adaptation mechanisms we identify are "lumpy." As shown in subsubsection 5.2.2, farmers respond to heat forecasts by making some discrete decisions about timing and crop choice. For instance, farmers need to determine what crop to plant on each field. These actions involve opportunity costs but do not necessarily appear as continuous changes in input expenditures, violating the differentiability assumption.

Second, the shocks themselves are not marginal. Our decomposition analysis in subsubsection 5.2.2 reveals that HDDs are overwhelmingly non-marginal. The envelope theorem is not guaranteed to hold for large shocks. Decomposing weather variation into its marginal and non-marginal components could be a useful robustness check for studies in this literature, as a divergence in the estimated effects could signal a failure of the theorem's underlying assumptions.

A third possibility is that the costs and benefits of adaptation are distributed unevenly over time, meaning the theorem may hold dynamically but not statically. We explore this possibility in the next section.

6 Dynamic Effects of Farm Responses

Statically, the previous results show that farms respond to forecasted heat in a way that affects revenue but not costs. In this section, we investigate the dynamic trade-off stemming from these farm decisions. To do so, we examine how future profits and costs are also affected by the initial shock. We find evidence that the profit gains in the initial period are eroded in subsequent periods by significant profit losses driven by increases in production costs in subsequent periods. The net effect on the present discounted value of profit over four periods is statistically indistinguishable from zero, consistent with the implications of a dynamic envelope theorem. We further explore the mechanisms giving rise to these future cost increases.

6.1 Empirical Framework

To test for the dynamic effects of heat forecasts, we estimate the impact of a weather forecast issued in year t on farm outcomes in the years before, during, and after the forecast, from $t-2$ to $t+3$. Our empirical design, based on local projections (Jordà, 2005; Jordà and Taylor, 2025), implements this strategy. The estimating equation is the same as equation (4), except that we now look at outcome y for farm j in year $t+h$, where $h \in [-2, 3]$, and include additional controls for past weather. Our estimating equation is:

$$\begin{aligned} y_{j,t+h} = \sum_{k=-2}^{0} \Big(& \beta^{w}_{1,h,k} GDD_{d(j),t+k} + \beta^{w}_{2,h,k} HDD_{d(j),t+k} + g^{h,k}\big(P_{d(j),t+k}\big)\Big) + \\ & \beta^{f}_{1,h} FGDD_{d(j),t} + \beta^{f}_{2,h} FHDD_{d(j),t} + g^{h}\big(FP_{d(j),t}\big) + \\ & \zeta^{1}_{r(j)} t + \zeta^{2}_{r(j)} t^2 + \gamma_j + \eta_t + \varepsilon_{jt}, \end{aligned} \tag{6}$$

where $GDD_{d(j),t+k}$ is period $t+k$ growing degree days for department d in which j is located, $HDD_{d(j),t+k}$ the heating degree days, the function $g^{h,k}(.)$ is a second order polynomial in realized rainfall for the period $t+k$. $FGDD$ denotes a forecast, and we follow the same notation for the other weather variables.

The addition of past weather controls is motivated by the new threats of endogeneity caused by the dynamic framework, specifically for the [t-2,t-1] results where w_{t-h} is both directly related to y_{t-h}, and can relate dynamically to $FHDD_t$. To isolate the causal effect of the forecast at time t on outcomes at time $t+h$ requires that the forecast is not correlated with other factors that determine outcomes in the surrounding years. Under the assumption that the forecast is unbiased and informationally redundant once the realized weather at time t is known, controlling for current weather will remove the correlation between the time t forecast and both future weather or forecast values. However, controlling for realized weather at time t is not sufficient to remove the potential correlation between the time t forecast and past weather events, which could in turn bias our estimates. Therefore, to isolate the effect of the new information arriving at time t, we must explicitly control for past weather realizations.

We provide evidence to support our identification strategy with a falsification test. If our controls are sufficient to absorb confounding information from other periods, then the HDD forecast at time t should not predict forecasts for other years. We test this by regressing lead and lagged forecasts on the time t forecast, conditional on our full set of controls from equation (6). The results in table A19 show that the coefficient on the time t forecast is statistically indistinguishable from zero in all cases. This demonstrates that, conditional on our controls, the forecasts are not serially correlated, alleviating concerns that our estimates of $\{\beta^f_{2,h}\}_h$ are biased by unobserved weather information from other periods.

6.2 Profits

We now present the main results of our dynamic analysis, focusing on the effect of farm responses to forecasted heat on the stream of profits over subsequent growing seasons. Figure 7 plots the dynamic response of profits to a forecasted HDD shock at time t (the table of results is available in table A20). The coefficients reveal a clear pattern of intertemporal trade-offs. We find a positive and significant contemporaneous profit effect of $+1.9k$ euros. This initial gain, however, is followed by statistically significant profit losses in the subsequent two periods, with effects of $-1.8k$ euros in year t+1 and $-1.4k$ euros in year $t+2$. The effect in year $t+3$ is small and not statistically significant.

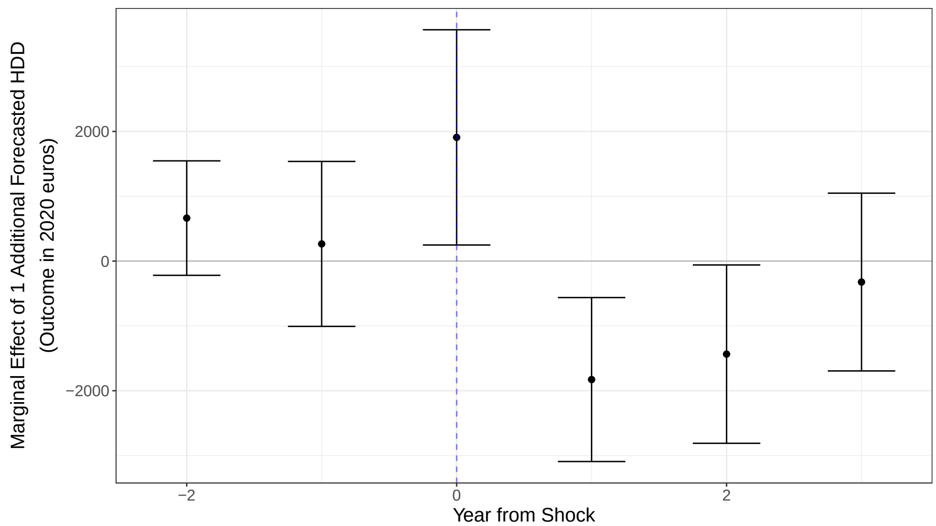


Figure 7: Dynamic Effects of Ex Ante Responses on Profit

Notes: Estimates display the dynamic response of farm profit to forecasted heating degree days at time t. The regressions are based on equation (6), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

These estimates allow for a direct test of the dynamic envelope theorem. We calculate the net present value (NPV) of the profit stream over the $[t, t+3]$ horizon, using a 10% discount factor. The resulting point estimate for the total effect of ex ante responses is $-1.1k$ euros, and its 95% confidence interval of $[-3.7k, 1.4k]$ includes zero. Relative to the average discounted profit over this period (€$298k$), this represents a negligible change. Therefore, we cannot reject the null hypothesis that the dynamic envelope theorem holds. While ex ante responses are profitable within a single period, their net effect on the discounted present value of profits is near zero.

6.3 Evidence for Costs in Subsequent Growing Seasons

We next examine the pattern of production costs to understand the source of the intertemporal profit trade-offs. The results are shown graphically in figure 8 and in table form in table A22.

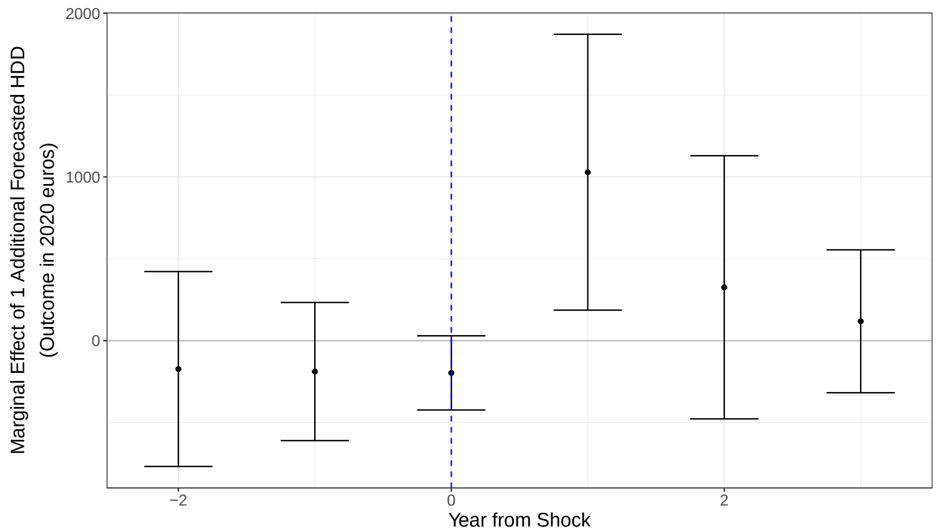


Figure 8: Dynamic Effects of Ex Ante Responses on Production Costs

Notes: Estimates display the dynamic response of farm costs to forecasted heating degree days at time t. The regressions are based on equation (6), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

The cost results closely mirror the profit findings. Consistent with our static results, there is no significant change in production costs in the year of the forecast (denoted by 0 on the x-axis). However, this is followed by a statistically significant cost increase of €$1k$ in year $t+1$, and an NPV of €1.1. This pattern of delayed cost increases suggests that strategies like crop switching, while profitable upfront, have future financial consequences. The benefits (avoided heat damage) and costs (disrupted production patterns) are realized at different times.

Consistent with the profit results, costs do arise, but they arise in future periods rather than at the time of the shock. In our context, the net welfare consequences of a forecasted heat shock come not from direct, un-adapted damages, but almost entirely from the future costs of the actions taken to avoid those damages.

This interpretation—that crop switching incurs delayed costs—is well-supported by the literature on dynamic land use. Results from Livingston et al. (2008) and Scott (2013) show that deviating from an optimal crop rotation can have future productivity consequences. More specifically, such disruptions can decrease soil nutrients and increase exposure to pests (Vanino et al., 2019). This suggests a clear, testable hypothesis: the aggregate cost increases we observe should be driven by future increases in specific inputs like fertilizers, pesticides, and the labor required to apply them. We test this directly in our final analysis by decomposing the dynamic response by input type, using the same specification as in equation (6).

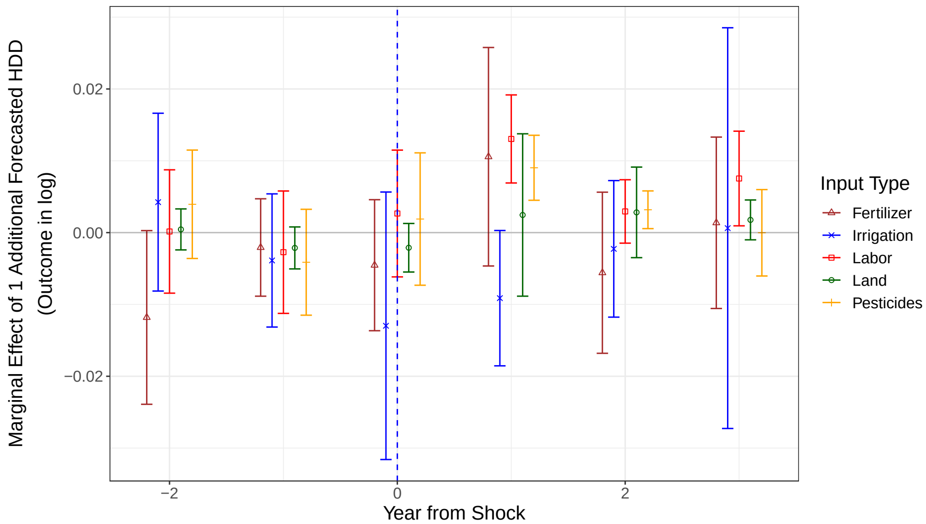


Figure 9: Dynamic Effects of Ex Ante Responses on (Log) Input Use

Notes: Estimates display the dynamic response of different (log) farm input bills to forecasted heating degree days at time t. The regressions are based on equation (6), using the baseline sample. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls in addition to the indicated fixed effects. Observations are weighted using the sample weights provided in the FADN. Standard errors are clustered two-way department-by-year, and confidence bands display the 95% confidence interval.

The results, shown in figure 9, corroborate this hypothesis and reveal a clear pattern of delayed input intensification. We find no significant change in input use in the year of the forecast. However, in year $t+1$, we observe statistically significant increases in expenditures on both labor and pesticides. The effect on pesticide use persists into year $t+2$, and the increase in labor re-emerges in year $t+3$. We also find a positive, though not statistically significant, increase in fertilizer use at $t+1$.

These findings provide direct evidence for the mechanisms highlighted in the dynamic land-use literature. The crop switching that is profitable in the short run appears to be associated with a future decrease in land productivity. Farms then compensate for this deviation from their optimal cropping pattern by increasing their use of pesticides, fertilizers, and the labor required to apply them in subsequent years.

7 Implications for Climate Change

So far we have analyzed the response of farms to forecasts about one-off, seasonal variation in weather. We now focus on the implications these results have for the cost of adapting to repeated shocks from climate change.

Our first exercise assumes that actions in response to forecasts will scale with the frequency of those weather conditions. This exercise calculates the future costs of adaptation under the assumption that the way farmers respond to variation in heat, and the cost of that response, remains the same as it is today.

Of course, it is unlikely that adaptation costs, or the set of available adaptation actions will remain constant as climate changes. Our second exercise works to relax that assumption by using spatial variation in local climates as a proxy for temporal change in climate, following the Ricardian cross-sectional tradition (Auffhammer, 2018; Carleton et al., 2022).

7.1 Costs of Adaptation to Heat under Climate Change and Constant Costs

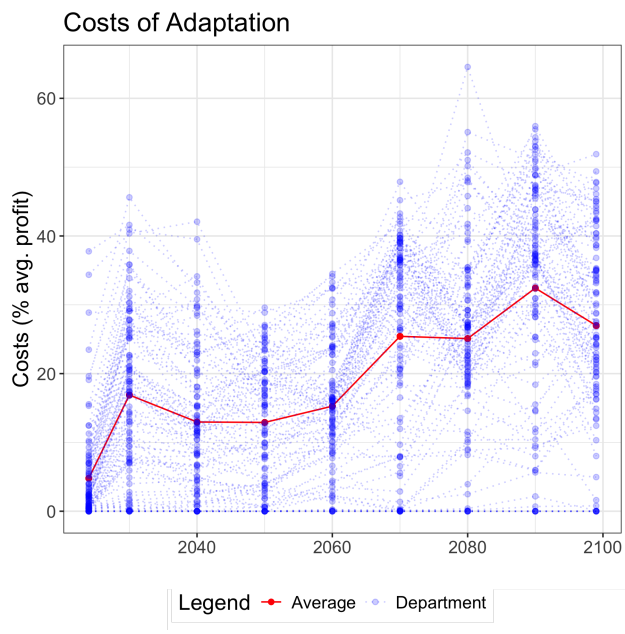


Figure 10: Costs of Adaptation Under Climate Change

Notes: The figure displays on the projected evolution of the costs of adaptation, using our estimate for the costs of responding to HDDs in figure 8. The projections are based on yearly HDD realizations in France according to the ECMWF CMIP6 model under the SSP3-7.0 scenario. The red line traces the average value, while the blue dots indicate department-specific realizations.

In section 6, we estimated the average, farm-level cost of responding to a one-off, forecasted, one-HDD increase to be €1.1k. Given a baseline average of 2.4 HDDs per year in our sample period, if we assume that realized HDDs are well forecasted, this implies that current responses to extreme heat cost farms approximately €2.6k annually, or 2.9% of their yearly profit. We now use this empirically-estimated marginal cost to project the future costs of adaptation under a climate change scenario, holding the cost function itself constant.

Our methodology involves several steps. First, we use climate projections from the ECMWF CMIP6 model under the SSP3-7.0 scenario, a middle-range pathway. Second, we correct these projections for systematic biases by comparing them to ERA5 historical data on their 2015-2024 overlapping period (Fisher et al., 2012).[31] The distribution of these biases is shown in figure A14. Finally, we use the method of Snyder (1985) to interpolate daily minimum and maximum projection values into hourly realizations, from which we calculate our projected HDD variable.

[31]See the discussion on debiasing in https://climate.copernicus.eu/sites/default/files/2021-01/infosheet7.pdf. Here we compute the average bias at the minimum and maximum day-of-the-month level.

The left panel of figure 10 plots the projected decadal evolution of average HDDs in France. The number of HDDs is projected to rise from a baseline of 2.4 to approximately 22 by the end of the century. To calculate the cost of adapting to this change, we multiply the projected increase in HDDs (19.6) by our constant marginal cost of €1.1k. This implies that by the end of the century, the annual cost of adapting to extreme heat will increase by approximately €21.6k per farm. This projection says that under our assumption of a stable response to heat, climate-induced warming would cause a substantial financial burden on the French agricultural sector.

7.2 Suggestive Evidence for Long-Term Adaptation

A central limitation to the exercise conducted in the previous section is that costs of adaptation are unlikely to remain constant as climate change keeps unfolding. We could expect both that current adaptation channels will become inaccessible to farmers in the future—for example a farmer only growing wheat and colza cannot further switch its crop mix composition. On the contrary, one can also imagine that costs of adaptation to changes in climate will be lower than the costs of adaptation to weather variation today. The presence of learning-by-doing could reduce costs in the future—an example being improvements in irrigation techniques.

Here we use a cross-sectional analysis frequently used in the climate change literature to test the sensitivity of costs of adaptation to variations in climate.[32] Specifically, we compute the department-level average temperature over 1994–2018. We then run a specification similar to the one in equation (4), to which we add the interaction of all temperature-related variables with this average temperature. We are specifically interested by the coefficient for the interaction between forecasted HDDs and average temperature, or how the marginal response rate of farm profit, revenue and costs, changes along with the average climate faced by these farms, This analysis is correlational in nature, but suggestive of how farms might change their adaptation strategies with climate.

Results are shown in table A23. Including these interactions has two consequences. The first one is that the coefficients associated with forecasted HDDs in levels become much larger in value for both the profit and the revenue regressions. Second, the coefficients associated with the interacted terms (average temperature) is negative and also statistically significant. These suggest that there are potentially decreasing returns to adaptation as the average temperature increases, or that the current adaptation strategies implemented in French farming are mostly relevant in moderate climate conditions. For example, it might be the case that farms in hot regions of France already grow little corn and colza, and have little room for adapting their crop mix to expected heat variations.

8 Conclusion

Climate change is expected to have significant and wide ranging impacts on human and non-human systems. Human impacts range from migration, to human health consequences, to productivity effects across multiple sectors (see Hsiang, 2025; Lemoine et al., 2025, for recent reviews). Recovering

[32]See a discussion of this method described as a combination of the Ricardian and panel approaches in Auffhammer (2018).

precise estimates of the impacts of climate change in all these areas is important to understand the scope of climate change, and to design policies that could mitigate its effects. Costs of adaptation are a central element for this exercise: the effects of climate change are composed first of the damages stemming from the direct exposure to climate change, and second of the costs incurred by agents when they adapt to these changes. The relative size of these costs will also determine the extent to which agents will adapt, and their degree of exposure to direct effects.

Here, we propose an analysis of the costs of ex ante responses to heat shocks in French agriculture, a relevant context given the centrality of agriculture for climate change policies, and the relative size of France as an exporter of agricultural goods. We leverage precise, farm-level accounting data over 1994–2018, which allows us to track the differential responses of farmers to routine and extreme temperatures. We rely on forecasts, conditional on realized weather, to identify the cost and benefits of the farms' ex ante responses to expected shocks. Our identification strategy is novel in that it allows us to recover cost estimates without having to rely on a revealed preference sufficient statistics approach where cost are bounded by estimates of benefits. This strategy further allows us to test the applicability of this approach in a climate economics setting.

In our context, agents respond to expected shocks until the marginal costs and benefits of their responses are equal. However, this equalization only happens over time, as benefits are realized at the time of the shock, while costs arise only in following years. In this context, our estimates of delayed costs can be understood as costs of crop switching which realize over time.

The costs we uncover are substantial, amounting to roughly 5% of average profit currently and projected to rise by the end of the century if farmers continue to employ current strategies—just at greater frequency—as the climate warms. These costs would not be detected by a static analysis, highlighting the importance of attending to dynamics when analyzing climate impacts on agriculture.

References

Aragón, F. M., F. Oteiza, and J. P. Rud (2021): "Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat," *American Journal of Economics: Economic Policy.*

Auffhammer, M. (2018): "Quantifying Economic Damages from Climate Change," *Journal of Economic Perspectives*, 32, 33–52.

——— (2022): "Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption," *Journal of Environmental Economics and Management.*

Bareille, F. and R. Chakir (2023): "Structural Identification of Weather Impacts on Crop Yields: Disentangling Agronomic from Adaptation Effects," *American Journal of Agricultural Economics.*

Braun, T. and W. Schlenker (2023): "Cooling Externality of Large-Scale Irrigation," *NBER Working Paper.*

Burke, M. and K. Emerick (2016): "Adaptation to Climate Change: Evidence From U.S. Agriculture," *American Economic Journal: Economic Policy*, 8, 106–140.

Burlig, F., A. Jina, E. M. Kelley, G. Lane, and H. Sahai (2025): "The Value of Forecasts: Experimental Evidence from India," *Working Paper.*

Burlig, F., L. Preonas, and M. Woerman (2024): "Groundwater and Crop Choice in the Short and Long Run," *Working Paper.*

Butler, E. E. and P. Huybers (2013): "Adaptation of US maize to temperature variations," *Nature Climate Change.*

Canal, N. (2015): "Application a l'agriculture de la prevision saisonniere: evaluation a l'echelle de la France," *PhD Thesis, Universite Paul Sabatier Toulouse III.*

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022): "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits," *Quarterly Journal of Economics*, 137, 2037–2105.

Chetty, R. (2009): "Sufficient Statistics for Welfare Analysis: a Bridge between Structural and Reduced Form Methods," *Annual Review of Economics.*

Colas-Belcour, F., R. Renoult, and M. Vallance (2015): "Synthèse Eau et Agriculture," *Rapport de synthèse de missions d'expertise n°14061 CGAAER.*

Colmer, J. (2021): "Temperature, Labor Reallocation, and Industrial Production: Evidence From India," *American Economic Journal: Applied Economics*, 13, 101–124.

Costinot, A., D. Donaldson, and C. Smith (2016): "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World," *Journal of Political Economy*, 124, 205–248, publisher: University of Chicago Press-Chicago, IL.

Deschênes, O. and M. Greenstone (2007): "The Economic Impacts of Climate Change: Evidence From Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 97, 354–385.

Deschênes, O., M. Greenstone, and J. S. Shapiro (2017): "Defensive investments and the demand for air quality: Evidence from the NOx budget program," *American Economic Review*, 107, 2958–2989.

Downey, M., N. Lind, and J. G. Shrader (2023): "Adjusting to Rain Before It Falls," *Management Science*.

Elferjani, R. and R. Soolanayakanahally (2018): "Canola Responses to Drought, Heat, and Combined Stress: Shared and Specific Effects on Carbon Assimilation, Seed Yield, and Oil Composition," *Frontiers in Plant Science*.

EPA (2023): "Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review"'; EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances," Tech. rep., Environmental Protection Agency, docket ID No. EPA-HQ-OAR-2021-0317.

Fisher, A. C., W. M. Hanemann, M. J. Roberts, and W. Schlenker (2012): "The Economic Impacts of Climate Change: Evidence From Agricultural Output and Random Fluctuations in Weather: Comment," *American Economic Review*, 102, 3749–3760.

Freeman, A. M., J. A. Herriges, and C. L. Kling (2014): *The Measurement of Environmental and Resource Values: Theory and Methods*, New York: Routledge, 3 ed.

Gammans, M., P. Merel, and A. Ortiz-Bobea (2017): "The Impact of Climate Change on Cereal Yields: Statistical Evidence from France," *Environmental Research Letters*.

Gouel, C. and D. Laborde (2021): "The Crucial Role of Domestic and International Market-Mediated Adaptation to Climate Change," *Journal of Environmental Economics and Management*.

Hagerty, N. (2022): "Adaptation to surface water scarcity in irrigated agriculture," *Unpublished, Working Paper*.

Hsiang, S. (2025): "The Global Economic Impact of Climate Change: An Empirical Perspective," Tech. Rep. w34357, National Bureau of Economic Research.

Hsiang, S. M. (2016): "Climate Econometrics," *Annual Review of Resource Economics*, 8, 43–75.

Hultgren, A., T. Carleton, M. Delgado, D. R. Gergel, M. Greenstone, T. Houser, S. Hsiang, A. Jina, R. E. Kopp, S. B. Malevich, et al. (2025): "Impacts of climate change on global agriculture accounting for adaptation," *Nature*, 642, 644–652.

IPCC (2007): *Climate change 2007: impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC*, vol. 4, Cambridge University Press.

Jordà, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Jordà, O. and A. M. Taylor (2025): "Local Projections," *Journal of Economic Literature*, 63, 59–110.

Kala, N. (2019): "Learning, Adaptation, and Climate Uncertainty: Evidence from Indian Agriculture," *Working Paper*.

Kelly, D. L., C. D. Kolstad, and G. T. Mitchell (2005): "Adjustment Costs fro Environmental Change," *Journal of Environmental Economics and Management*.

Kleven, H. J. (2021): "Sufficient Statistics Revisited," *Annual Review of Economics*, 13, 515–538, publisher: Annual Reviews.

Lemoine, D. (2024): "Estimating the consequences of climate change from variation in weather," *NBER Working Paper*, 25008, 41.

Lemoine, D., C. Hausman, and J. G. Shrader (2025): "A Guide to Climate Damages," Tech. Rep. w34348, National Bureau of Economic Research.

Livingston, M., M. Roberts, and J. Rust (2008): "Optimal Corn and Soybean Rotations," *Working Paper*.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw (1994): "The Impact of Global Warming on Agriculture: A Ricardian analysis," *American Economic Review*, 84, 753–771.

Merel, P., E. Paroissien, and M. Gammans (2022): "Sufficient Statistics for Climate Change Counterfactuals," *Working Paper*.

Michels, M., J. Mollman, and O. Musshoff (2019): "Understanding the Intention to Use Commodity Fugures Contracts," *Agricultural Finance Review*.

Moscona, J. and K. A. Sastry (2022): "Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture," *Quarterly Journal of Economics*.

Obolenski, M. (2025): "Protect or Prepare? Crop Insurance and Adaptation in a Changing Climate," *Working Paper*.

Ortiz-Bobea, A. and R. Just (2013): "Modeling the Structure of Adaptation in Climate Change Impact Assessment," *American Journal of Agricultural Economics*.

Reidsma, P., F. Ewert, A. O. Lansink, and R. Leemans (2010): "Adaptation to climate change and climate variability in European agriculture: the importance of farm level responses," *European journal of agronomy*, 32, 91–102.

Rising, J. and N. Devineni (2020): "Crop Switching Reduces Agricultural Losses from Climate Change in the United States by Half under RCP 8.5," *Nature Communications*.

Rosenzweig, M. R. and C. Udry (2014): "Rainfall Forecasts, Weather, and Wages Over the Agricultural Production Cycle," *American Economic Review Papers & Proceedings*, 104, 278–283.

Scheinkman, J. A. and J. Schechtman (1983): "A Single Competitive Model with Production and Storage," *The Review of Economic Studies*.

Schelling, T. C. (1992): "Some Economics of Global Warming," *American Economic Review*, 82, 1–17.

Schlenker, W., M. Hanemann, and A. C. Fisher (2005): "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach," *American Economic Review*, 95, 395–406.

Schlenker, W. and M. J. Roberts (2009): "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change," *Proceedings of the National Academy of Sciences*, 106, 15594–8.

Schlenker, W., M. J. Roberts, and D. B. Lobell (2013): "US Maize Adaptability," *Nature Climate Change*.

Scott, P. (2013): "Dynamic Discrete Choice Estimation of Agricultural Land Use," *Working Paper*.

Shrader, J. G. (2023): "Improving Climate Damage Estimates by Accounting for Adaptation," *Working Paper*.

Shrader, J. G., L. Bakkensen, and D. Lemoine (2023): "Fatal Errors: The Mortality Value of Accurate Weather Forecasts," *NBER Working Paper*.

Snyder, R. (1985): "Hand Calculating Degree Days," *Agricultural and Forest Meteorology*.

Vanino, S., R. Farina, R. Hüppi, B. Pennelli, and J. Six (2019): "A Toolkit of Indicators for Characterising Productivity and Sustainability," *Report*.

Appendix for online publication:
Costs of Climate Adaptation: Evidence from French Agriculture

A Additional Figures and Tables

A.1 Figures

A.1.1 Precision of Forecasts

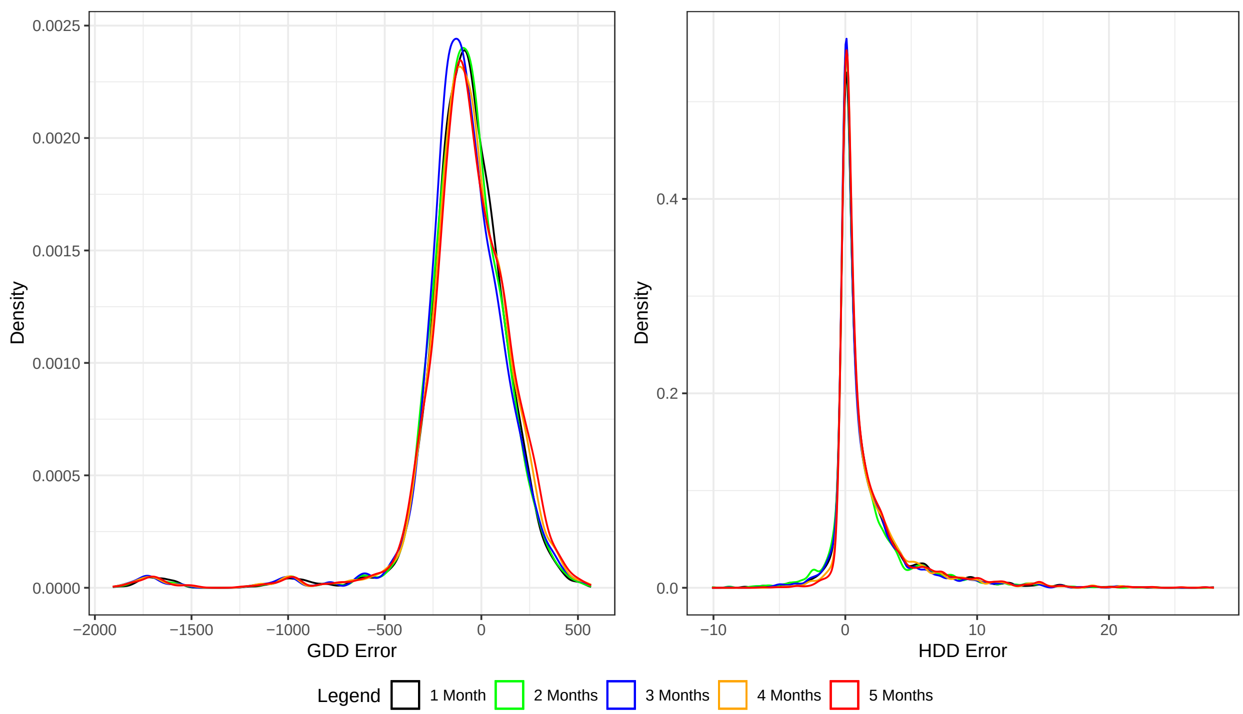


Figure A1: Distribution of Temperature Forecast Error

Notes: These estimated kernel densities show the empirical distribution of the forecast errors (realized minus forecasted), for both growing and heating degree days (aggregated over the growing season) in France over the 1994-2018 period. We later cut our sample so GDD errors are above -500, cutting the left tail of the GDD error distribution. As expected, HDDs correspond to extreme events which are harder to predict, and are under predicted in France.

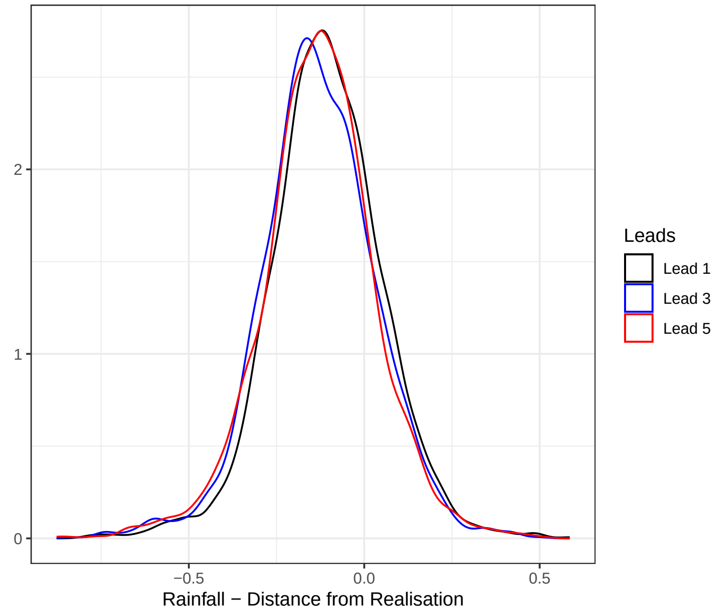


Figure A2: Distribution of Rainfall Forecast Error

Notes: These estimated kernel densities show the empirical distribution of the forecast errors for rainfall (aggregated over the growing season) in France over the 1994-2018 period.

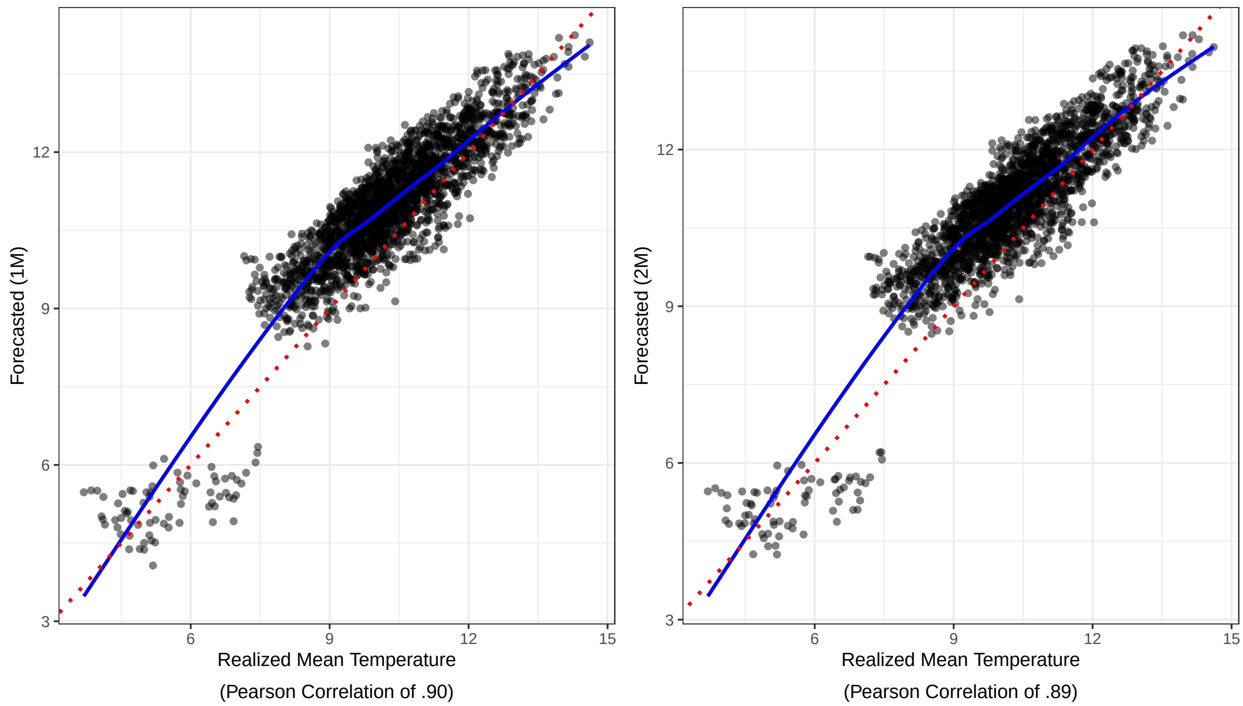


Figure A3: Correlation Realized and Forecasted Mean Temperature

Notes: We show the correlation between forecasted mean temperatures and realized ones over 1994-2018 in France. We show the correlation for the sample used for estimation, that is for the set of observations with one month ahead forecasted GDD errors above -500. The red line corresponds to the 45°line, and the blue line to a smoothed estimator matching the distribution of points.

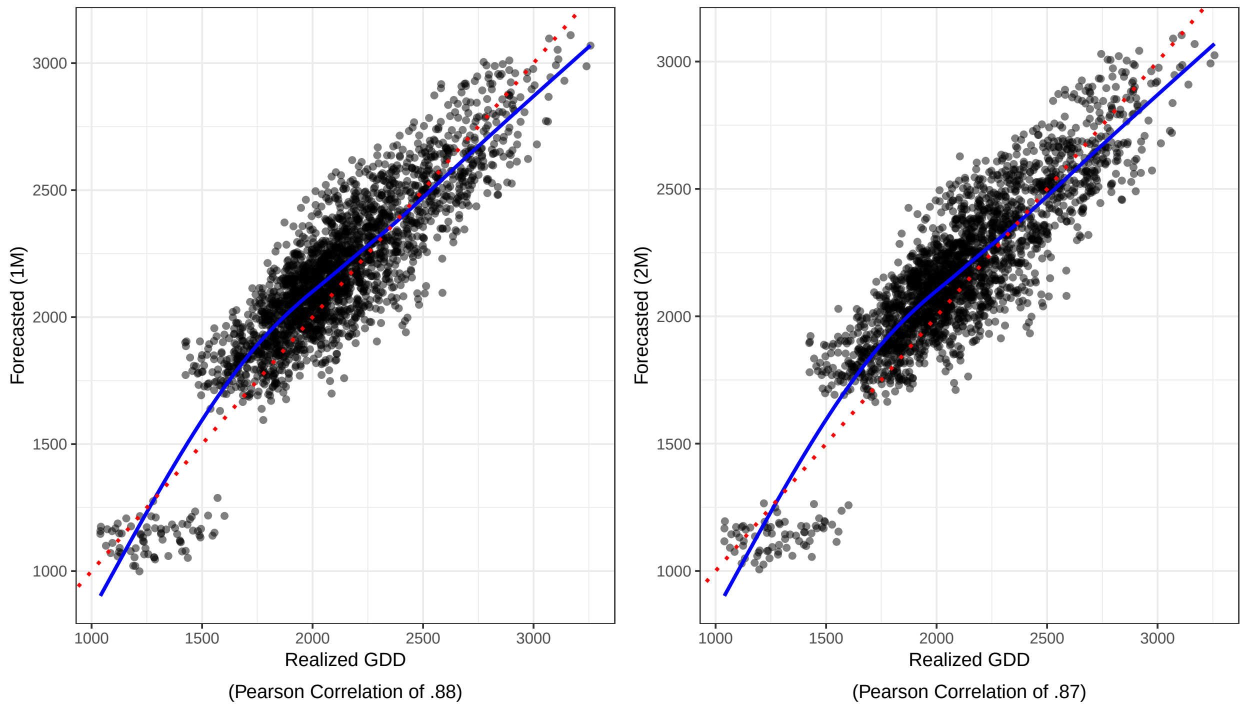


Figure A4: Correlation Realized and Forecasted GDDs

Notes: We show the correlation between forecasted GDDs and realized ones over 1994-2018 in France. We show the correlation for the sample used for estimation, that is for the set of observations with one month ahead forecasted GDD errors above -500. The red line corresponds to the 45°line, and the blue line to a smoothed estimator matching the distribution of points.

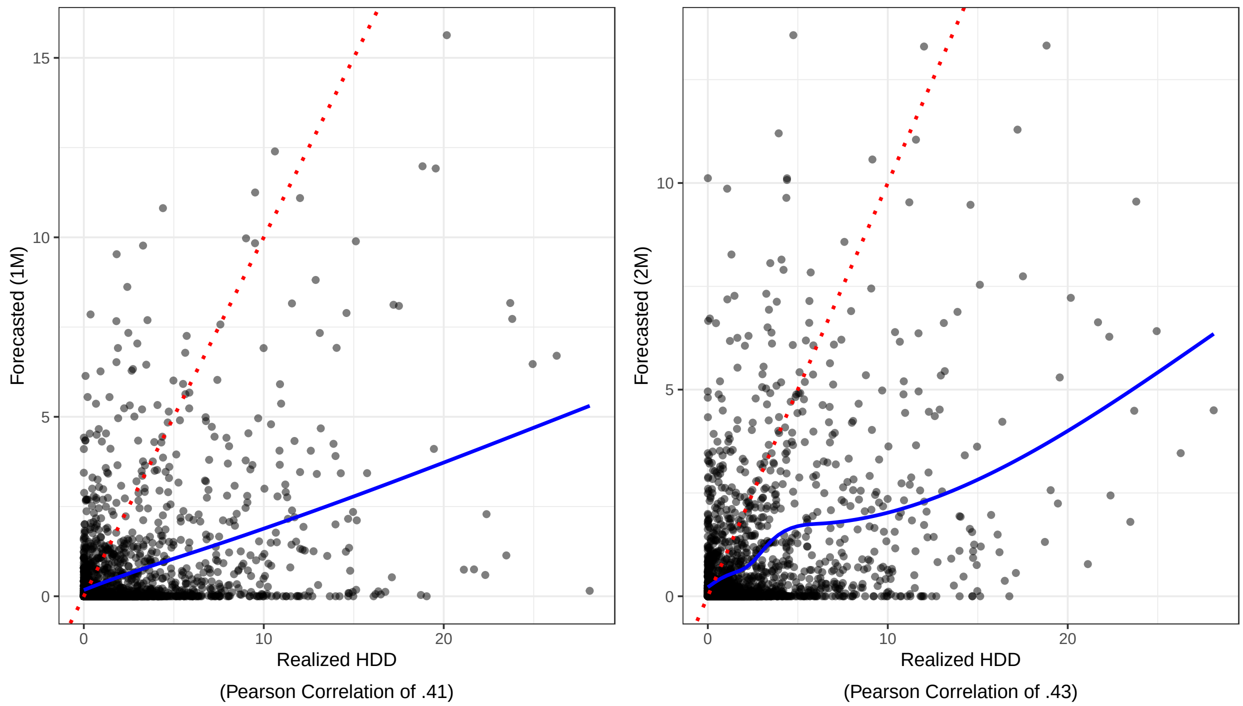


Figure A5: Correlation Realized and Forecasted HDDs

Notes: We show the correlation between forecasted HDDs and realized ones over 1994-2018 in France. We show the correlation for the sample used for estimation, that is for the set of observations with one month ahead forecasted GDD errors above -500. The red line corresponds to the 45°line, and the blue line to a smoothed estimator matching the distribution of points.

A.1.2 Climate in France

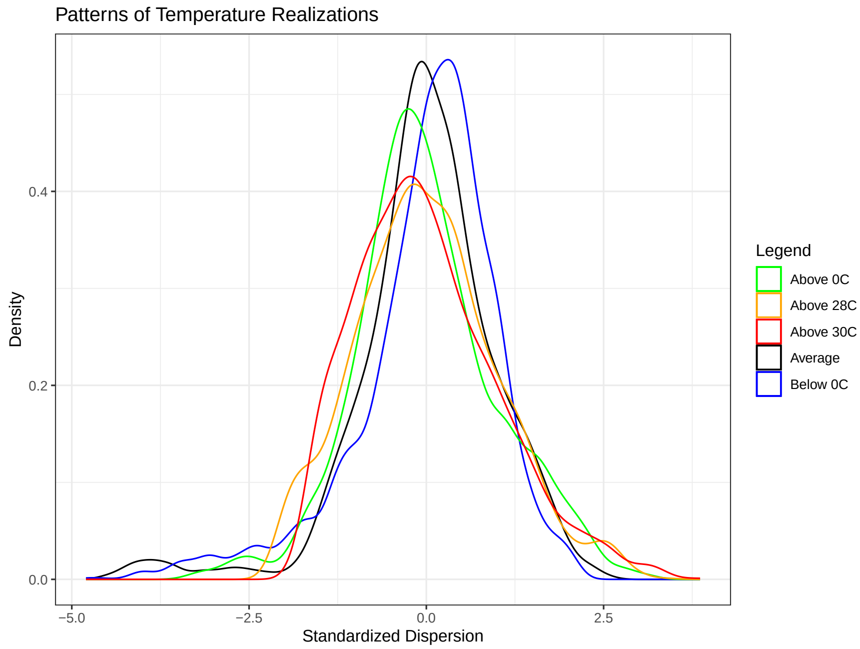


Figure A6: Distribution of the Standardized Conditional and Unconditional Mean Temperature

Notes: We show kernel density estimators giving the distribution of conditional standardized temperature realizations in France, at the department level, over 1994-2018. As expected, higher realizations have distributions with a larger spread. On average, however, realizations are quite homogeneous across the country.

These graphs are useful to highlight the spatial variation in exposure to heat in France. We first observe the divide between the South of the country more exposed to heating degree days than the center and North. Second, we see how mountainous regions in the center, around the Massif Central, the Alpes and the Pyrénées have lower growing degree days values.

The main cereal region of the country situated in the large plains below Paris up to the Massif Central have overall large growint degree day values, and low heating degree day values for the 1994-2018 period.

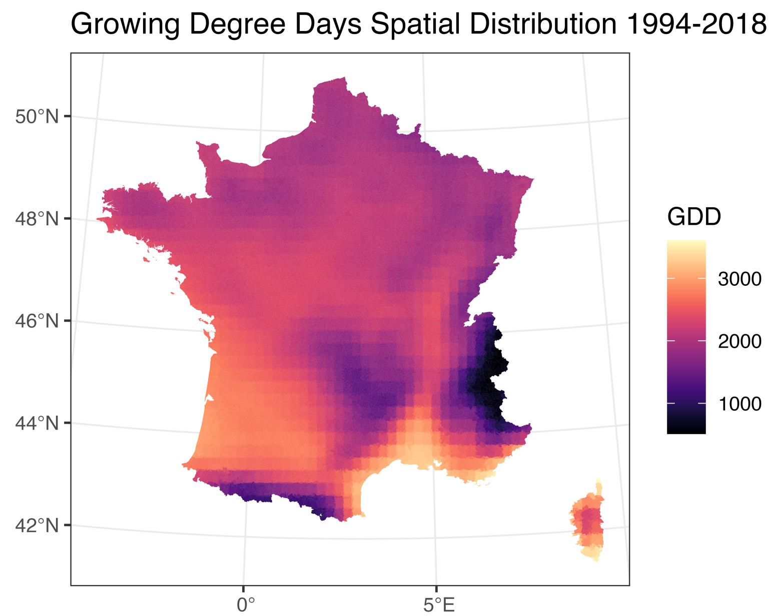


Figure A7: Distribution of Growing Degree Days

Notes: We show a map of average GDD realizations in France over 1994-2018 at the department level. The large geographical patterns are that temperature is on average higher in the South along the Mediterranean coast, and lower in mountain regions (Massif Central in the center, Pyrenees in the South at the border with Spain, and the Alpes at the border with Switzerland and Italy).

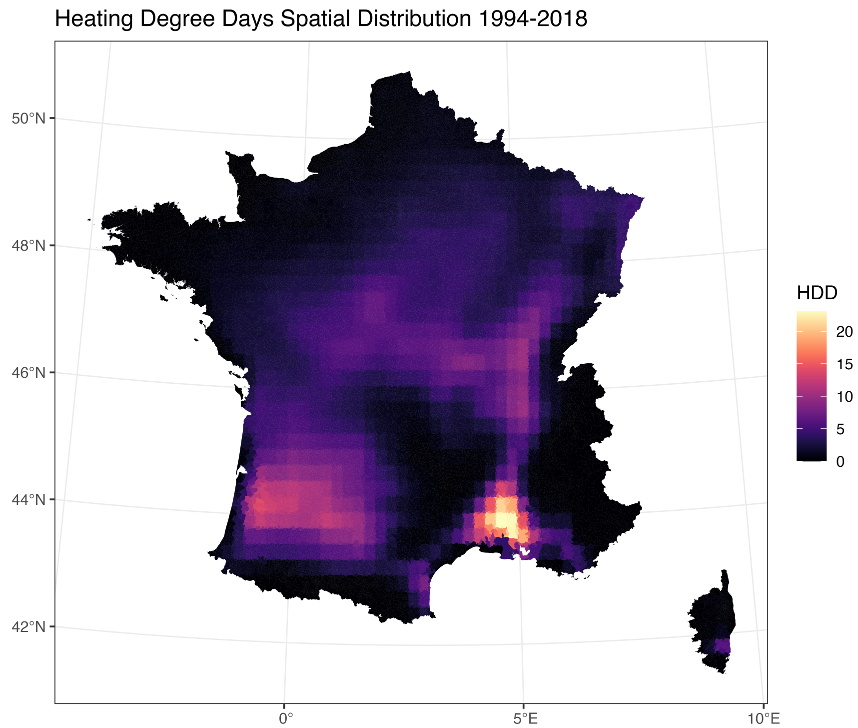


Figure A8: Distribution of Heating Degree Days

Notes: We show a map of average HDD realizations in France over 1994-2018 at the department level. HDDs are on average close to zero, with positive values in the South both around Marseilles, and in the agricultural region stretching between Toulouse and Bordeaux.

A.1.3 Growing Seasons

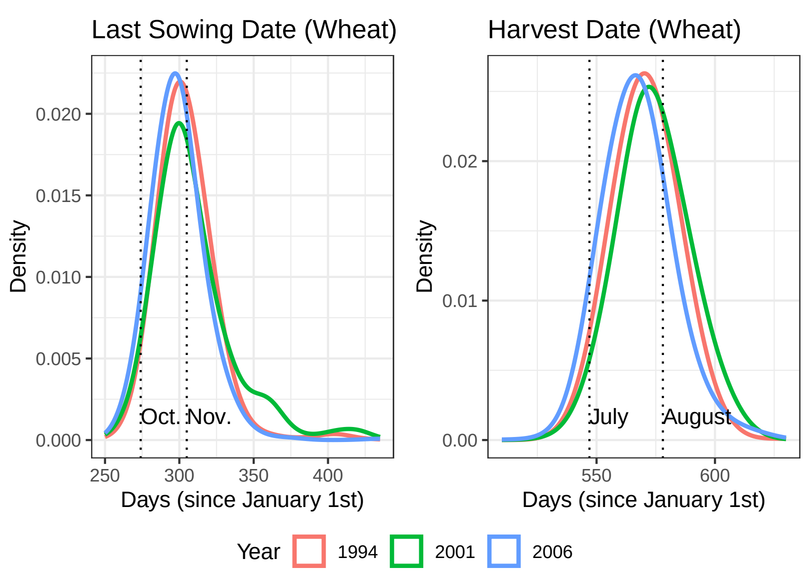


Figure A9: Wheat Growing Season in France

Notes: This figure shows the distribution of a proxy for the start and end of the wheat growing season as observed at the plot level in three cross-sectional surveys of growing practices. A unique kernel density describes spatial and cross-farm heterogeneity within a same year, while the variation across kernels shows variation across growing seasons. The x-axis shows the number of days since January 1st of the first of two calendar years overlapped within a unique agricultural season.

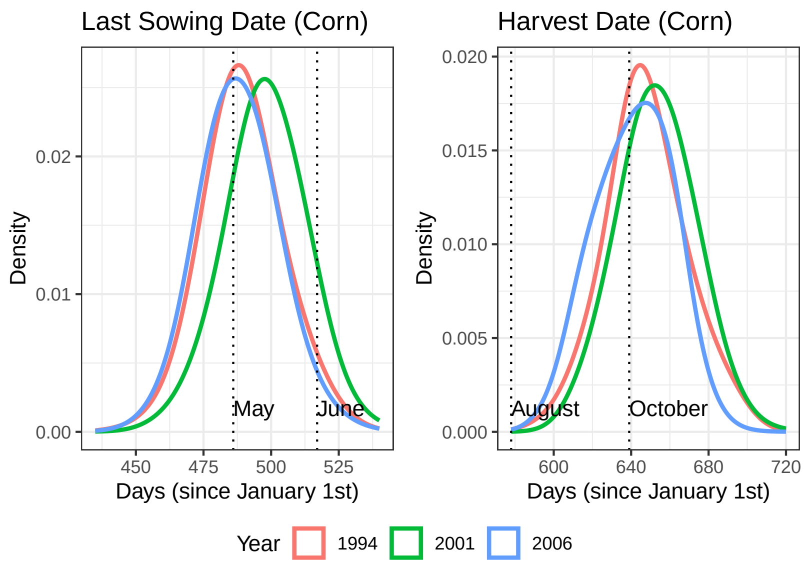


Figure A10: Corn Growing Season in France

Notes: This figure shows the distribution of a proxy for the start and end of the corn growing season as observed at the plot level in three cross-sectional surveys of growing practices. A unique kernel density describes spatial and cross-farm heterogeneity within a same year, while the variation across kernels shows variation across growing seasons. The x-axis shows the number of days since January 1st of the first of two calendar years overlapped within a unique agricultural season.

A.1.4 Yield and Output Effects of Weather Variation

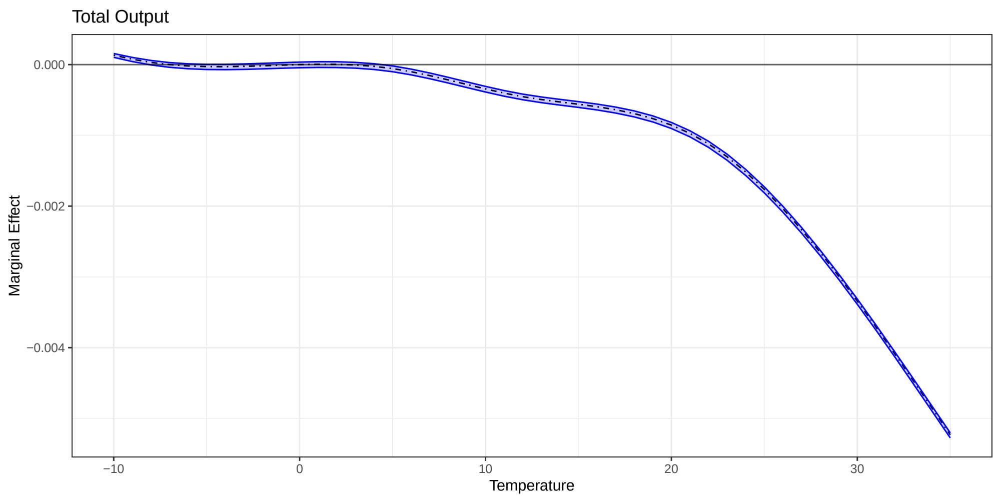


Figure A11: Temperature Effects on Farm Total Output

Notes: This figure shows restricted cubic splines describing the non-linear relation between exposure to temperature during the growing season and farm output. Output is measured as the sum of output for wheat, durum, oats, corn, sorghum, barley, rye, triticale, sunflower, colza, soy, peas and fava. Our regressions are similar to that of Schlenker and Roberts (2009).The regressions are farm-level versions of the specification from Schlenker and Roberts (2009). In addition to cubic splines in temperature, the regressions include farm fixed effects and region-specific quadratic time trends as controls. Standard errors are computed by bootstrapping at the farm level. Temperature effects are normalized relative to the impact at 0°C.

A.1.5 Forecasted Heat & Other Signals

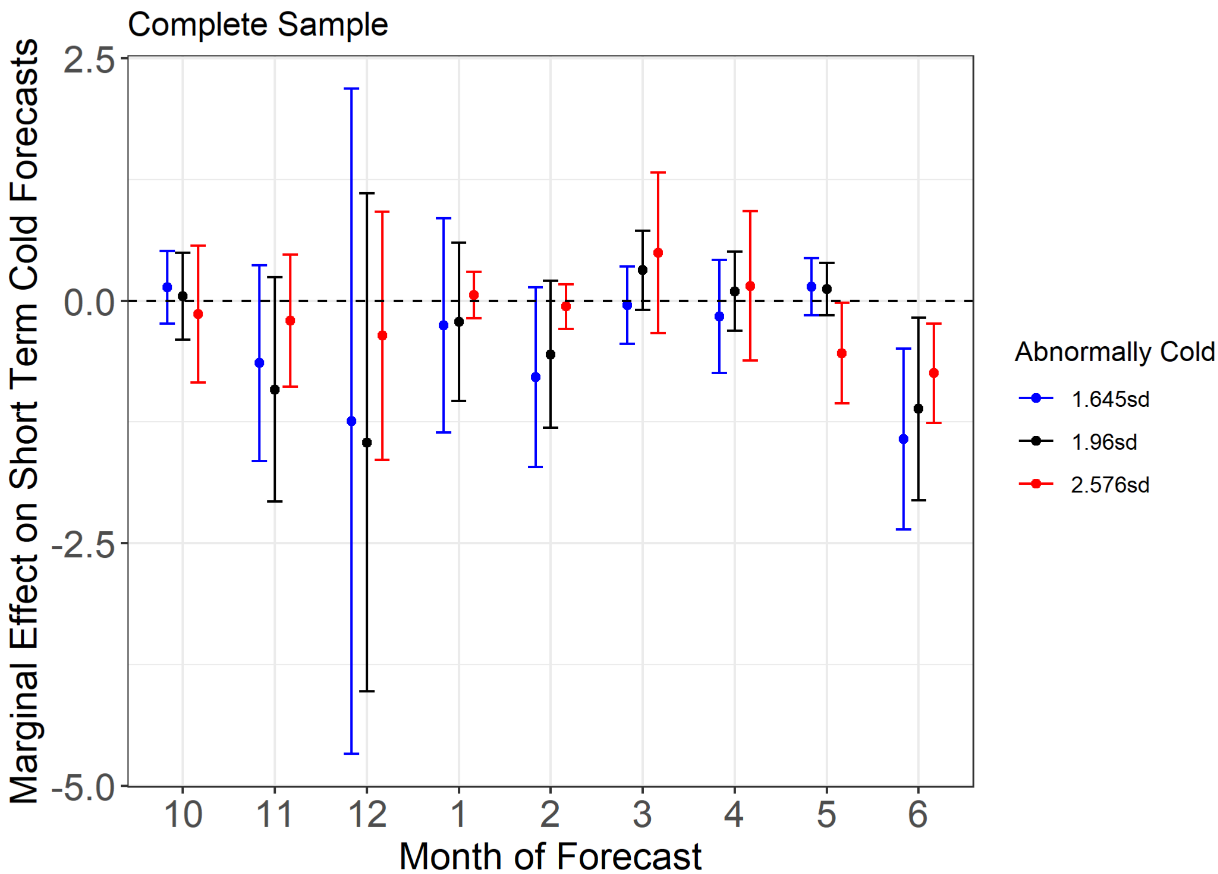
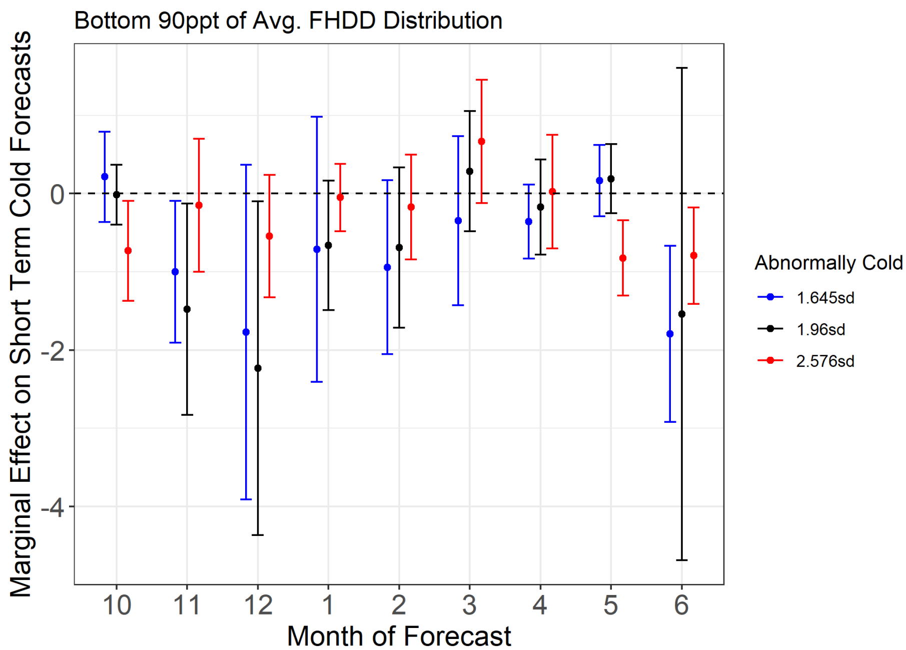
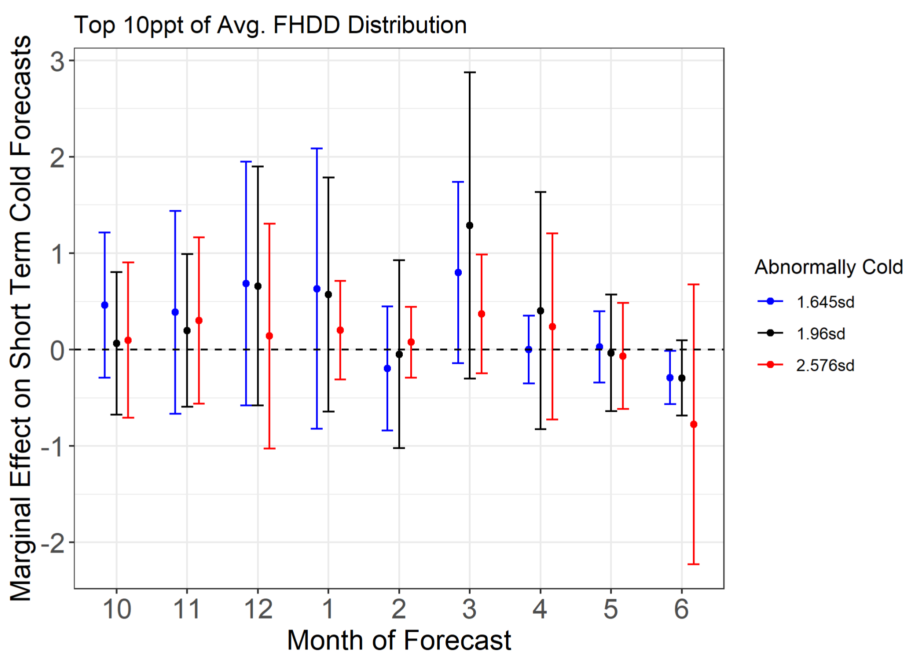


Figure A12: Relation Between Growing Season Forecasted HDD & Short Term Cold Forecasts

Notes: This figure shows effect of a growing-season forecast of HDDs on month-specific forecasts of days which are colder than usual. These short term forecasts correspond to the forecast received by farmers on the first day of the month, for the rest of the month. Outcome variables are cold days, corresponding to the integral of cold weather realizations below a threshold corresponding resp. to 1.96 standard deviations from the historical department-month-day-hour average, 1.645 deviations and 2.576 deviations. In this sense, the forecasts correspond to predicted temperature significantly colder than the average. Forecasts that are 2.576 deviations away from the average hence correspond to the coldest realizations.



(a) Results for Departments with Small FHDD Values



(b) Results for Departments with Large FHDD Values

Figure A13: Relation Between Growing Season Forecasted HDD & Short Term Cold Forecasts (Heterogeneity)

Notes: This figure shows effect of a growing-season forecast of HDDs on month-specific forecasts of days which are colder than usual. These short term forecasts correspond to the forecast received by farmers on the first day of the month, for the rest of the month. Outcome variables are cold days, corresponding to the integral of cold weather realizations below a threshold corresponding resp. to 1.96 standard deviations from the historical department-month-day-hour average, 1.645 deviations and 2.576 deviations. In this sense, the forecasts correspond to predicted temperature significantly colder than the average. Forecasts that are 2.576 deviations away from the average hence correspond to the coldest realizations. The top figure corresponds to the results on the part of our sample where FHDDs are less frequent and smaller, while the second corresponds to the tail of the sample where they are large and more frequent. The first sample corresponds to the bottom 90 percent of the distribution of average department-level FHDD values, and the second to the top 10 percent of that distribution.

A.1.6 Bias of Climate Projections

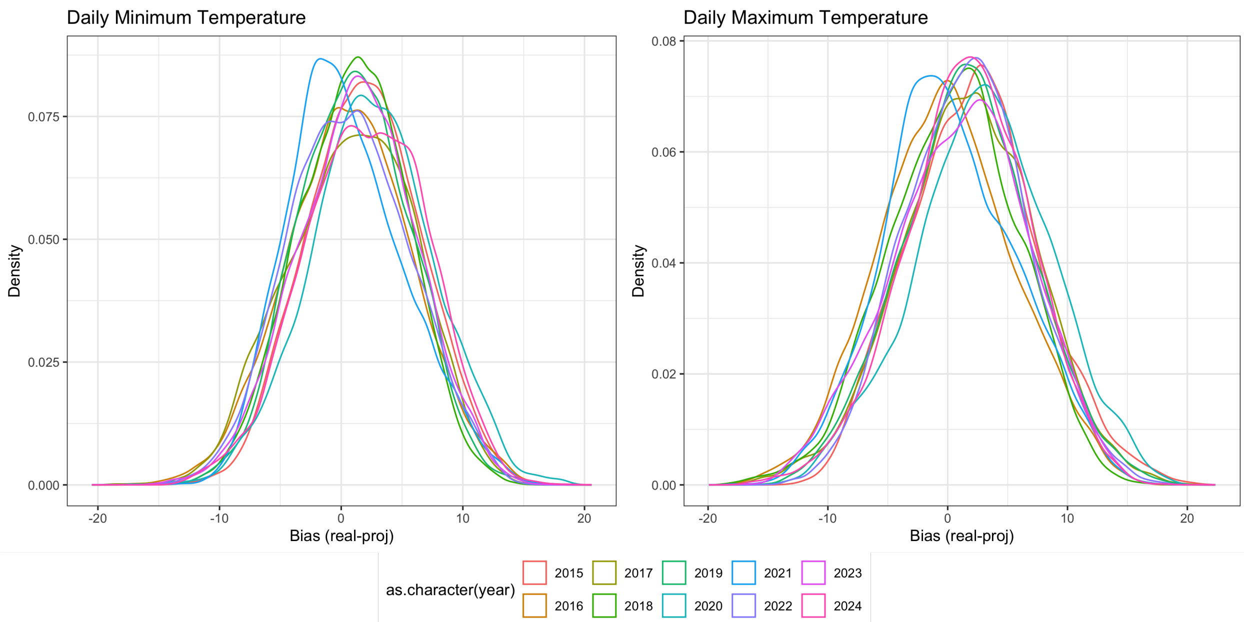


Figure A14: Distribution of Biases between CMIP6 and ERA5

Notes: This figure shows the distribution of the projection bias relative to observed temperature realizations. Observations are at the department-year-month-day level. This data is used to debias the climate temperature projections.

A.1.7 Multi-Product Farms

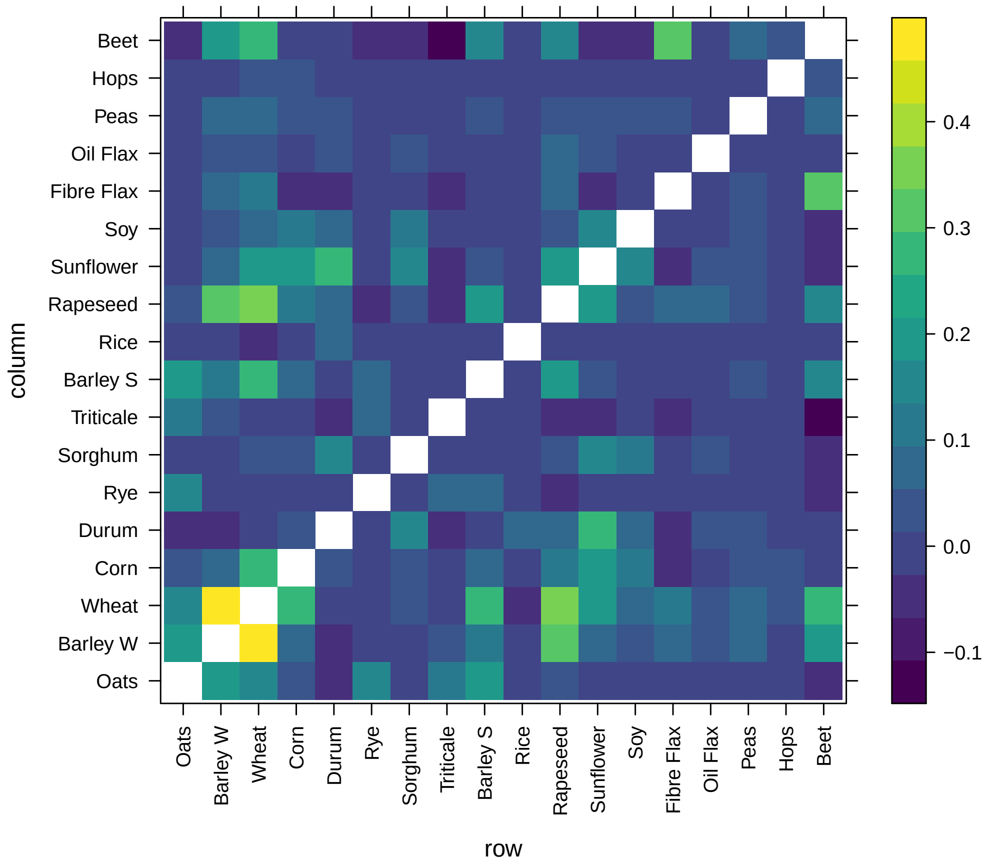


Figure A15: Conditional Probabilities to Grow Crop Pairs

Notes: This figure shows the probability that a farm in the FADN grows a given crop, conditional on growing the row-specified one.

Table A1: Descriptive Statistics - Farm-Level Crop Mix

	Cereals	Oil-Protein	Industrial
Cereals	1	0.33	0.09
Oil-Protein	0.99	1	0.13
Industrial	0.99	0.44	1

A.1.8 Input Price Indices

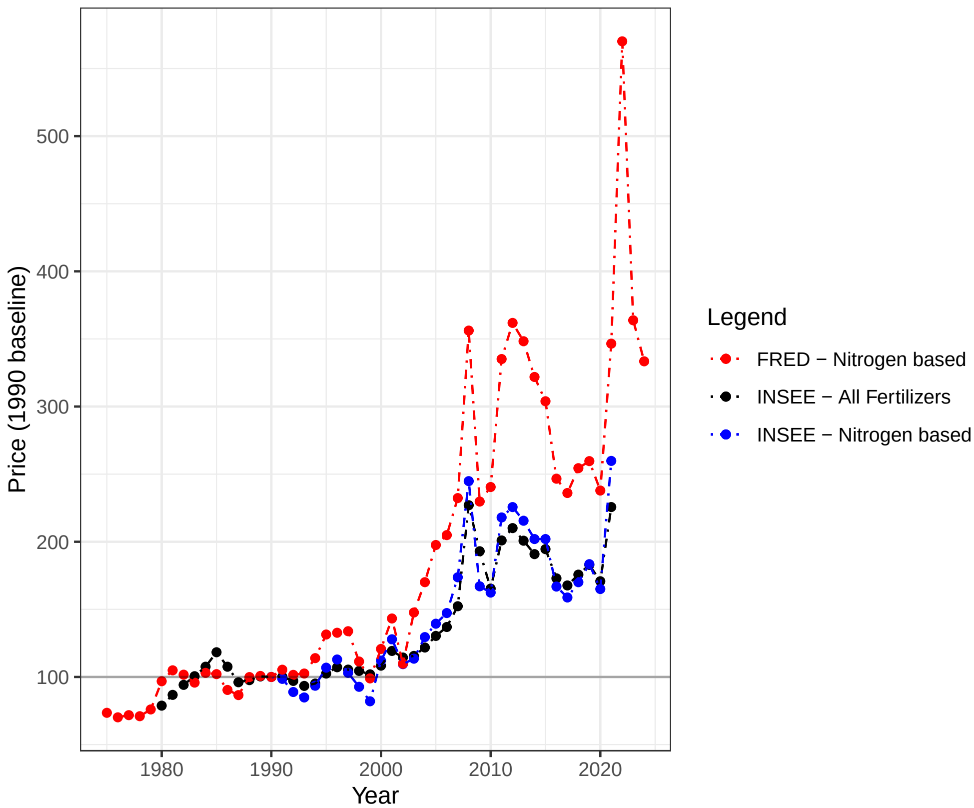


Figure A16: Comparison of Input Price Indices Series

Notes: This figure shows the input price index used for fertilizers used in the paper, and coming from the French statistical agency (INSEE), and compares this index, and its subset specific to nitrogen-based fertilizers to the Producer price index for fertilizer-based fertilizers from FRED for the USA.

A.1.9 Additional Results

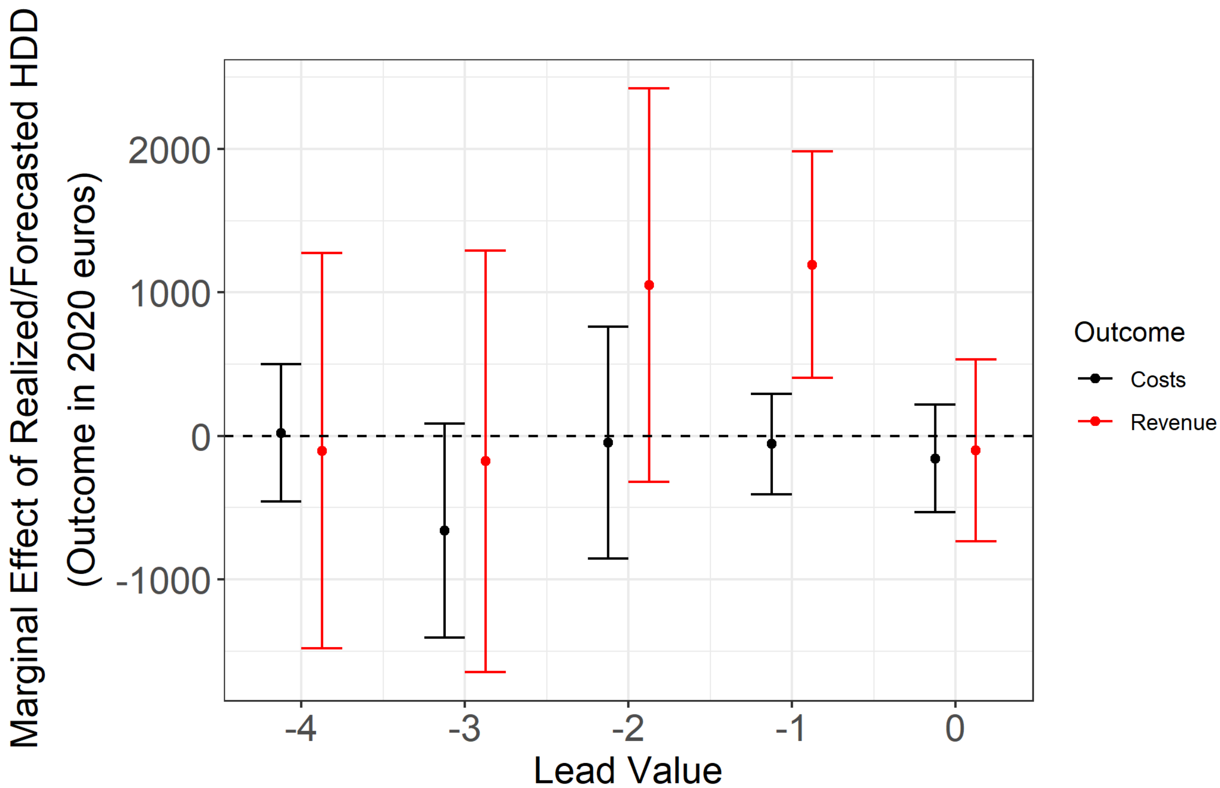


Figure A17: Effect of Forecated HDDs

Notes: We show the results of our main specification, varying the forecast lead value used in the regression. For the forecast of lead 0, we only include the realization of the weather shocks. As such, the graph compares the effect of expected HDD shocks across independent regressions, and serves as a robustness test of our results.

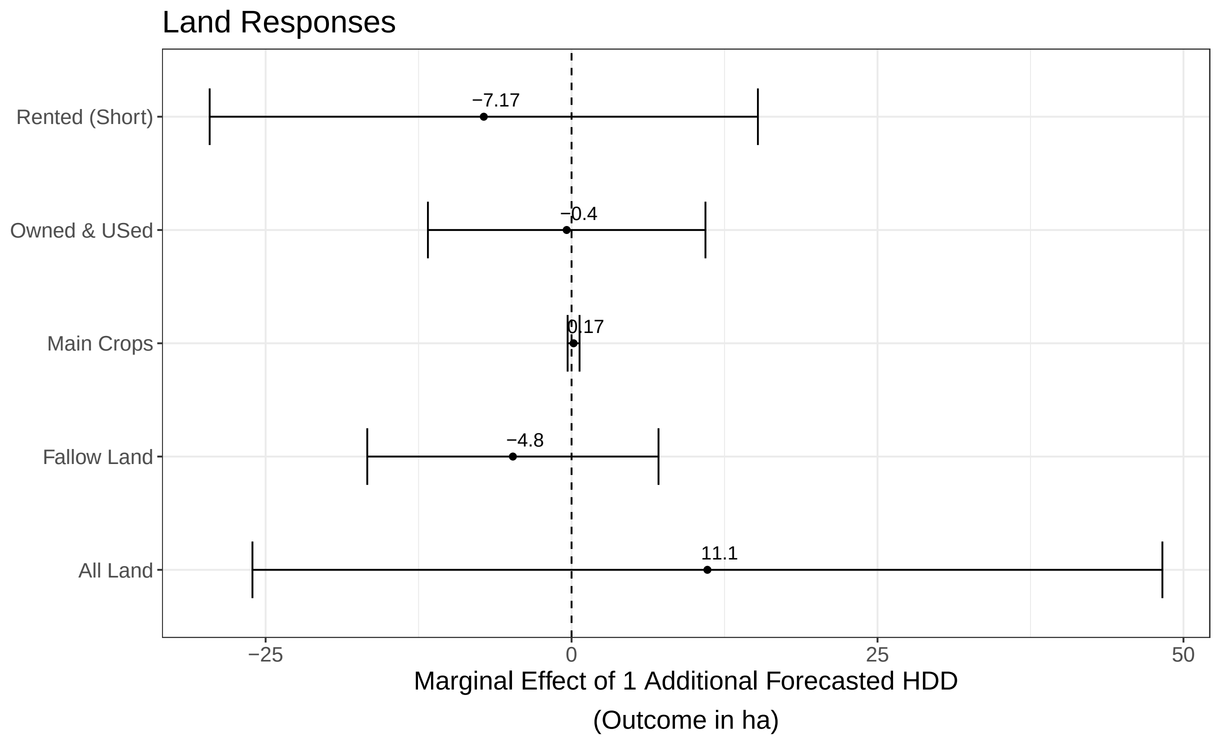


Figure A18: Decomposition of the Land responses: Ownership and Use

Notes: We show the results of our main specification, showing the reaction of different land area margins. Each regression contains realized and forecasts weather outcomes (rainfall and temperature), as well as region-specific quadratic time trends, farm and year fixed effects. Standard errors are clustered at the department-by-year level.

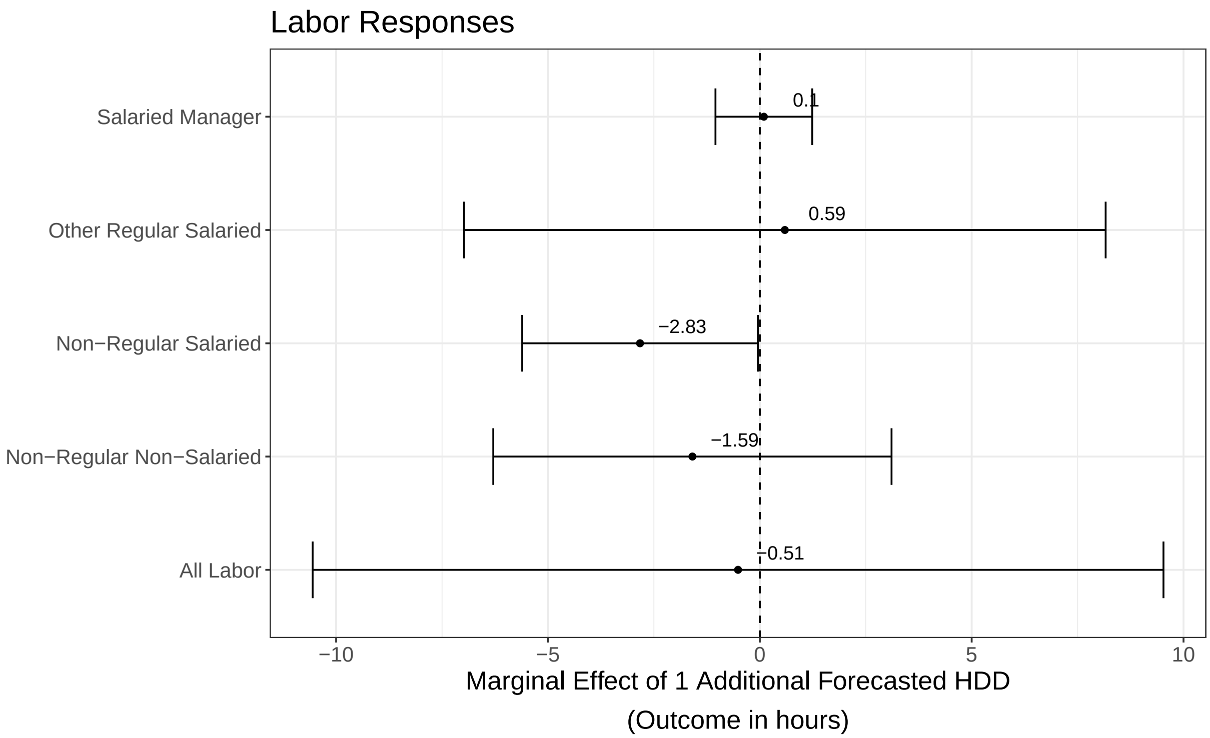


Figure A19: Decomposition of Labor Responses

Notes: We show the results of our main specification, showing the reaction of different labor margins. Each regression contains realized and forecasts weather outcomes (rainfall and temperature), as well as region-specific quadratic time trends, farm and year fixed effects. Standard errors are clustered at the department-by-year level.

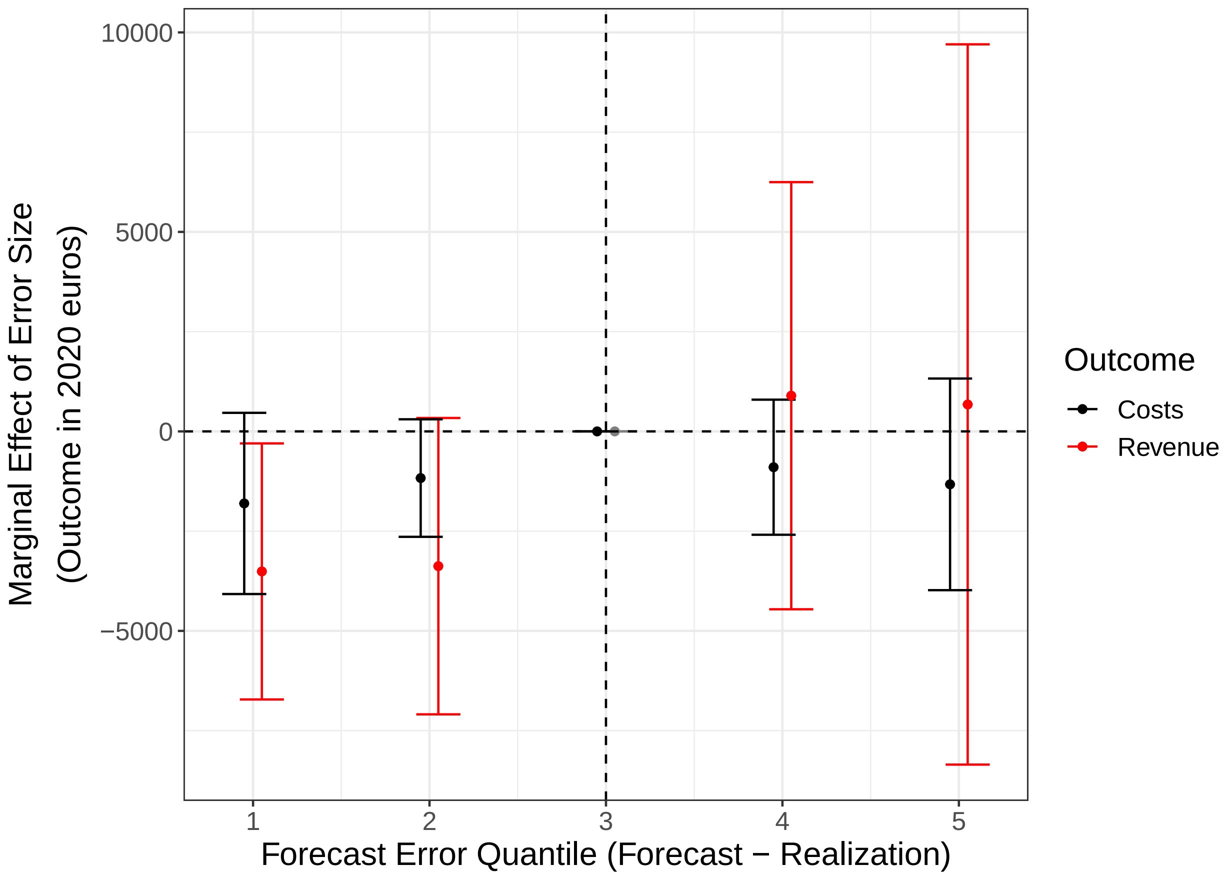


Figure A20: Cost and Revenue & Sign of the Forecast Error

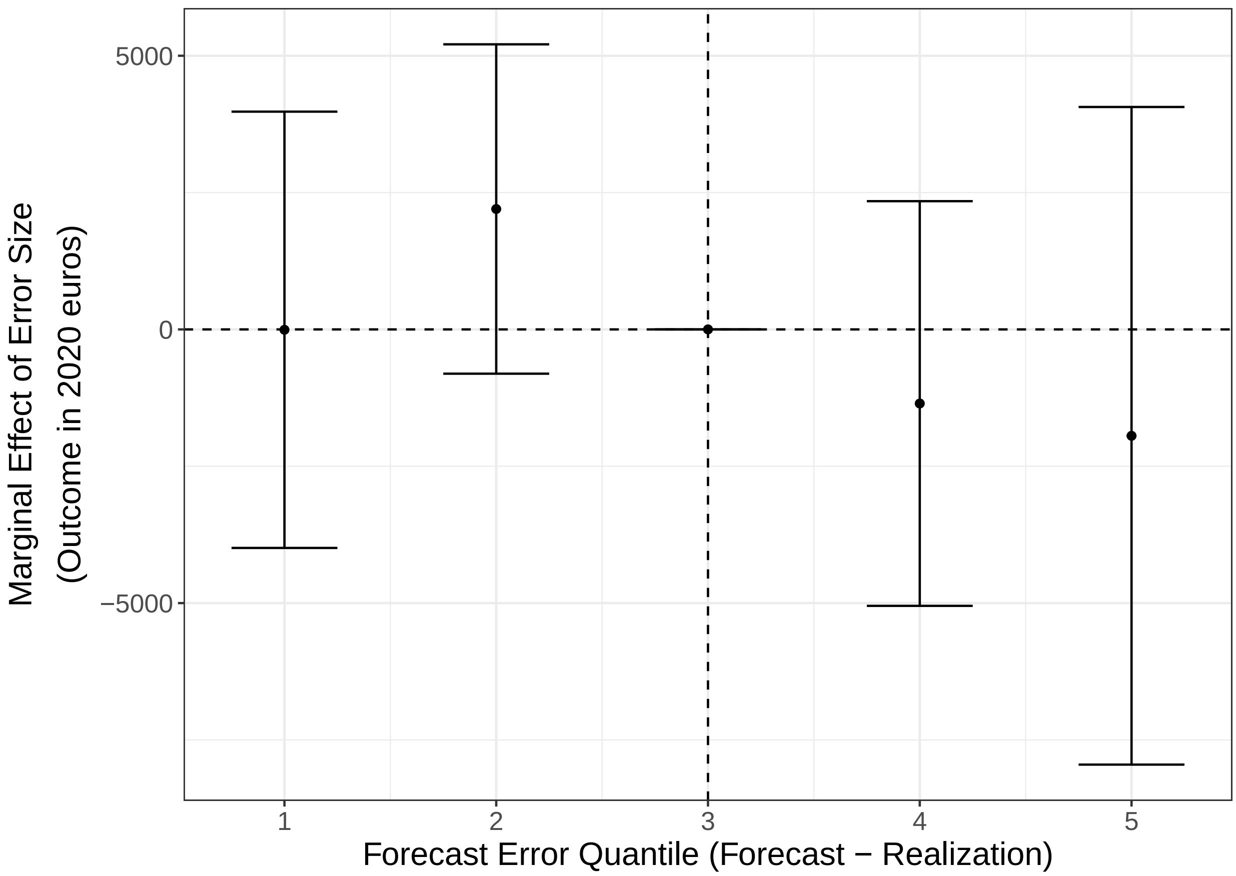


Figure A21: Profit & Sign of the GDD Forecast Error

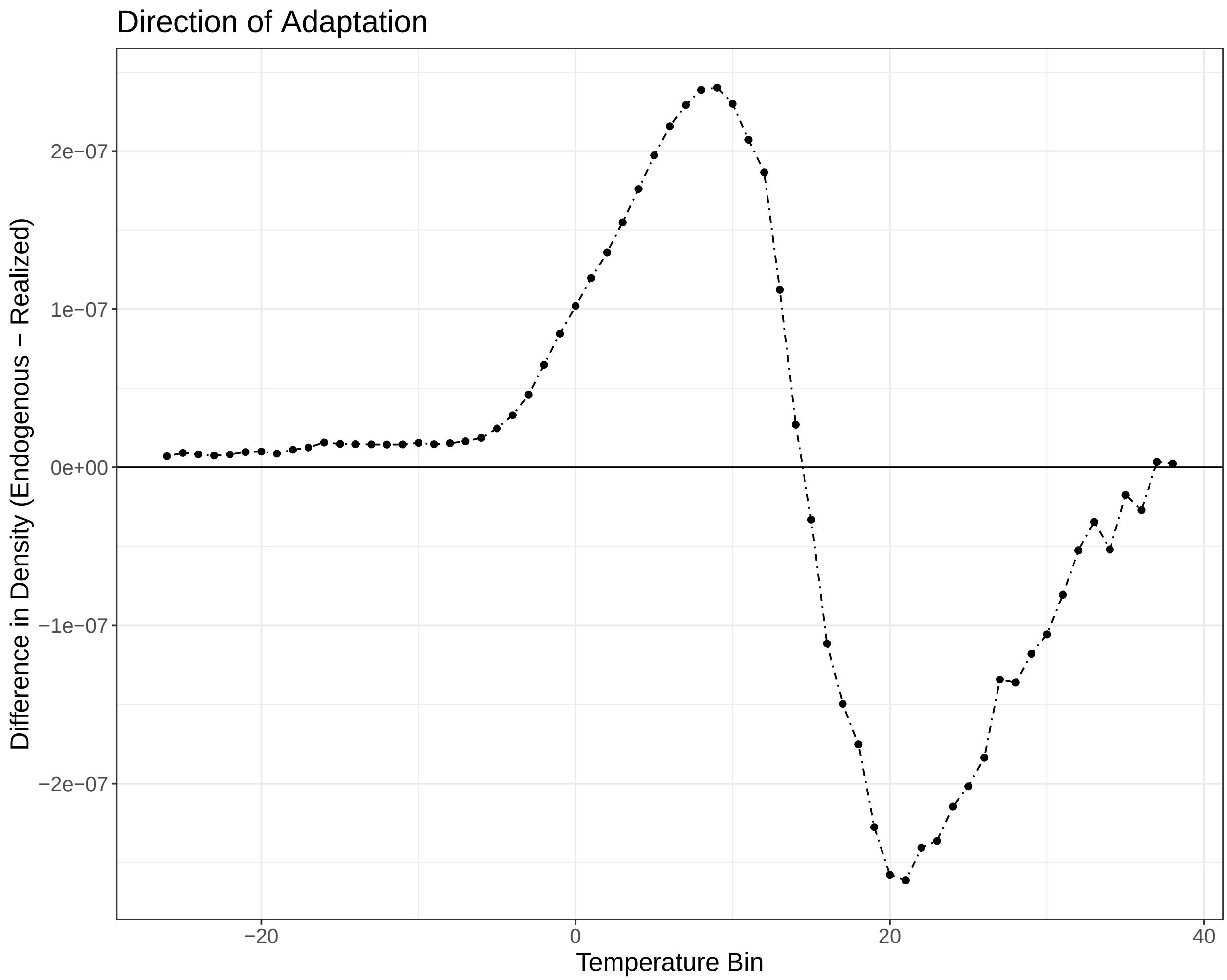


Figure A22: Difference in Temperature Distributions

A.2 Tables

Table A2: Descriptive Statistics - Farm-Level Dataset

Statistic	N	Mean	St. Dev.	Pctl(25)	Pctl(75)
Rainfall	18,917	0.75	0.17	0.63	0.85
Rainfall (F1)	18,917	0.85	0.13	0.76	0.92
GDD	18,917	2,140	264	1,957	2,292
GDD (F1)	18,917	2,182	238	2,022	2,305
HDD	18,917	2.36	3.2	0.24	3.13
HDD (F1)	18,917	0.44	1.12	0	0.4
Sales (€)	18,917	155,386	113,740	78,739	199,717
Total Costs (€)	18,917	123,249	85,427	66,903	156,468
Intermediate Inputs (€)	18,917	103,749	67,149	59,074	132,589
Value Added (€)	18,917	58,357	62,858	18,306	80,436
Profit (€)	18,917	86,695	70,268	40,066	114,771
Price Index (€/t)	18,917	263	296.4	140.5	230.6
Storage (sum, 0.1 t)	18,917	88.7	1,877	-280	500
Storage (index, 0.1 t)	16,075	65.4	983.7	-67.9	176
Output (sum, 0.1 t)	18,917	7,793	5,033	4,252	10,170
Output (index, 0.1 t)	18,917	2,401	2,926	769	2,847
Production (corn, 0.1 t)	10,346	3,464	4,046	877	4,682
Price (corn) (€/t)	9,958	150	39.1	122.9	172.8
Sales (corn) (€)	10,346	53,508	69,739	11,163	68,978
Quantity Sold (corn, 0.1 t)	10,346	3,437	4,133	817	4,617
Production (wheat, 0.1 t)	17,336	3,840	3,005	1,665	5,248
Price (wheat) (€/t)	17,181	163.1	37.95	136.4	184
Sales (wheat) (€)	17,336	61,538	53,986	24,345	82,922
Quantity Sold (wheat, 0.1 t)	17,336	3,799	3,162	1,560	5,166
Irrigation (€)	18,917	683.1	2,665	0	0
Labor (€)	18,917	2,684	1,330	1,600	3,200
Phytosanitary (€)	18,917	23,072	16,499	11,388	30,872
Fertilizer (€)	18,917	31,777	20,727	17,456	41,061
Land (ha)	18,917	145.04	86.19	8.379	18.7
Seeds (€)	18,917	12,231	9,686	5,847	15,882

Table A3: Descriptive Statistics - Store-Level Dataset

Statistic	N	Mean	St. Dev.	Pctl(25)	Pctl(75)
Pesticide Prices	2,126	615.5	718.3	258	697
Fertilizer Prices	3,098	3,254	2,959	2,450	3,783
Seed Prices	1,831	343.7	1,777	95.7	171.8

Table A4: Descriptive Statistics - Plot-Level Data

Statistic	N	Mean	St. Dev.	Min	Max
Ploughing	32,263	337.4	83.5	15	570
Sowing	39,988	378.6	99.2	15	570
Irrigation	3,775	532.1	24.3	170	630
Harvest	38,818	594.3	41.5	510	720

Table A5: Descriptive Statistics - Land Price Data

Statistic	N	Mean	St. Dev.	Pctl(25)	Pctl(75)
Land Prices	3,405	5,754	3,085	3,717	6,834

Table A6: Descriptive Statistics - Weather Outcomes within Samples

Statistic	N	Mean	St. Dev.	Pctl(25)	Pctl(75)
Panel A	Entire Sample				
Rainfall	18,926	0.76	0.17	0.63	0.85
Rainfall (F1)	18,926	0.85	0.13	0.76	0.92
GDD	18,926	2,140	264	1,957	2,292
GDD (F1)	18,926	2,182	237.7	2,022	2,306
HDD	18,926	2.361	3.2	0.24	3.13
HDD (F1)	18,926	0.44	1.12	0	0.4
Panel B	Worst Region-Years				
Rainfall	1,425	0.68	0.14	0.56	0.75
Rainfall (F1)	1,425	0.88	0.11	0.79	0.95
GDD	1,425	2,418	255.7	2,196	2,587
GDD (F1)	1,425	2,356	276.1	2,136	2,548
HDD	1,425	10.4	3.51	7.35	12
HDD (F1)	1,425	1.41	2.07	0.02	2.1

Table A7: Prices and Quantities for Outputs and Inputs (1 month lead)

Dependent Variables:	Output Price	Output (log)	Storage (log)	Input Price	Irrigation	Fertilizer	Phytosanitary
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
GDD	-0.0275	1.58×10^{-5}	-0.0018**	-0.1264	0.4377	-2.648	-1.297
	(0.0291)	(0.0001)	(0.0007)	(0.2577)	(0.2677)	(2.659)	(1.256)
GDD (F)	0.0771	0.0002	-0.0002	0.5127	-0.4981	7.640	-0.6958
	(0.0595)	(0.0004)	(0.0015)	(1.061)	(0.6717)	(8.721)	(2.423)
HDD	-0.2299	-0.0045*	-0.0021	-15.64	7.506	-86.74	-16.09
	(0.3170)	(0.0022)	(0.0153)	(10.31)	(6.729)	(63.42)	(36.68)
HDD (F)	0.2609	0.0089*	0.0248	-0.2832	-23.88	-9.140	54.64
	(1.561)	(0.0046)	(0.0213)	(11.63)	(17.36)	(77.49)	(71.49)
Mean	205.2	7,793.0	88.65	1,899.6	683.1	31,777.2	23,072.2
Unique Farms	2,603	2,603	2,183		2,603	2,603	2,603
Fixed-effects							
Farm	Yes	Yes	Yes		Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company				Yes			
Product				Yes			
Fit statistics							
Observations	18,917	18,917	9,602	33,174	18,917	18,917	18,917
R^2	0.73239	0.94659	0.66516	0.35144	0.86328	0.89547	0.92414

Notes: Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^*p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares, as well as quadratic region-specific time trends, are included as controls. The input price variable corresponds to prices observed at the store level in an agricultural input price survey run across France in order to build input price indices.

Table A8: Cost and Revenue Reactions to HDD—Comparison

Dependent Variables:	Revenue		Costs	
Model:	(1)	(2)	(3)	(4)
Variables				
GDD	5.1	9.88	1.21	2.48
	(11.8)	(11.7)	(7.81)	(8.44)
GDD (F)	37.4		30.8**	
	(34.7)		(14.5)	
HDD	-158	-100	-192	-158
	(332)	(324)	(157)	(191)
HDD (F)	1,192***		-56.7	
	(401)		(170)	
Mean	155,386	155,386	123,249	123,249
Unique Farms	2,603	2,603	2,603	2,603
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,917	18,917	18,917	18,917
R^2	0.89	0.89	0.94	0.94

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends. Sales correspond to total sales at the farm levels, and costs to total costs.

Table A9: Profit and Value Added Reaction to HDD—Comparison

Dependent Variables:	Value Added		Profit	
Model:	(1)	(2)	(3)	(4)
Variables				
GDD	2.59	7.93	-8.32	-3.99
	(12.7)	(14.5)	(13.2)	(14.2)
GDD (F)	16.3		3.257	
	(43.1)		(43.1)	
HDD	53.4	118	185	232
	(292)	(273)	(277)	(253)
HDD (F)	2,429***		2,067***	
	(809)		(708)	
Mean	58,357	58,357	86,695	86,695
Unique Farms	2,603	2,603	2,603	2,603
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,917	18,917	18,917	18,917
R^2	0.81	0.8	0.84	0.84

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: *$p < .10$, **$p < .05$, ***$p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A10: Input Reactions to Forecasts (1 month lead)

Dependent Variables:	Land	Labor	Fertilizer	Phytosanitary	Seeds	Irrigation
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GDD	-0.15	0.066	-2.65	-1.29	0.39	0.44
	(0.23)	(0.14)	(2.66)	(1.26)	(1.18)	(0.27)
GDD (F)	0.096	0.39**	7.64	-0.69	-0.25	-0.49
	(0.74)	(0.18)	(8.72)	(2.42)	(2.27)	(0.67)
HDD	5.88	-0.53	-86.7	-16.1	-17.9	7.51
	(6.06)	(4.22)	(63.4)	(36.7)	(25.7)	(6.73)
HDD (F)	11.1	-0.51	-9.14	54.6	-32.9	-23.9
	(18.9)	(5.12)	(77.5)	(71.5)	(52.6)	(17.4)
Mean	14,504	2,684	31,777	23,072	12,231	683
Unique Farms	2,603	2,603	2,603	2,603	2,603	2,603
Fixed-effects						
Farm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	18,917	18,917	18,917	18,917	18,917	18,917
R^2	0.98	0.86	0.89	0.92	0.88	0.86

Notes: Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^*p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A11: Input Prices Reactions to Forecasts (1 month lead)

Dependent Variables:	All Store Prices	Fertilizers	Pesticides	Seeds	Land
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDD	-0.13	-0.12	-0.33	-0.0022	-0.92**
	(0.26)	(0.11)	(0.36)	(0.71)	(0.38)
GDD (F)	-0.51	0.29*	-1.02	-0.54	0.38
	(1.06)	(0.17)	(1.34)	(2.56)	(0.74)
HDD	-15.6	-0.9	-17.4	-15.2	5.28
	(10.3)	(1.97)	(14.1)	(26.5)	(7.41)
HDD (F)	-0.28	-2.03	3.34	3.64	-1.19
	(11.6)	(3.21)	(21.1)	(20.9)	(12.7)
Mean	1,899	517	3,151	311	4,848
Unique Farms	298	203	283	195	2,428
Fixed-effects					
Company	Yes	Yes	Yes	Yes	Year
Product	Yes	Yes	Yes	Yes	
Year	Yes	Yes	Yes	Yes	Yes
Farm					Yes
Fit statistics					
Observations	33,174	9,258	17,883	6,033	17,003
R^2	0.35	0.62	0.22	0.38	0.96

Notes: Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A12: Output Quantities Reactions to Forecasts (1 months lead)

Dependent Variables:	Wheat	Corn	Sunflower	Colza	Beets
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDD	-0.53	0.39	0.13	-0.41**	1.84
	(0.64)	(0.36)	(0.1)	(0.19)	(2.87)
GDD (F)	0.49	0.95	-0.19	0.51	-6.31
	(1.09)	(1.26)	(0.24)	(0.56)	(4.83)
HDD	1.23	-27.7*	-2.15	9.31**	-24
	(8.99)	(14.6)	(2.61)	(3.57)	(58.4)
HDD (F)	61.7***	-6.59	-1.01	13.3	66.4**
	(19.6)	(9.32)	(5.21)	(12.4)	(29.8)
Mean	3,840	3,464	509	915	9,128
Unique Farms	2,448	1,607	1,357	1,940	346
Fixed-effects					
Farm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	17,336	10,346	7,203	12,394	2,267
R^2	0.9	0.93	0.79	0.81	0.93

Notes: Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A13: Responses with Decomposed Weather

Dependent Variables:	Revenue	Costs
Model:	(1)	(2)
Variables		
GDD (m)	10.2	14.7
	(11.4)	(11.2)
GDD (nm)	6.28	3.59
	(11.5)	(9.02)
GDD (m) (F)	21.8	24.5
	(34.1)	(16.9)
GDD (nm) (F)	1.87	31.3*
	(49.8)	(15.8)
HDD (m)	-281	-226
	(326)	(145)
HDD (nm)	-484	168
	(1,735)	(809)
HDD (m) (F)	-1,687**	-78.9
	(735)	(934)
HDD (nm) (F)	1,713***	-79.3
	(438)	(363)
Mean	155,396	123,265
Unique Farms	2,523	2,523
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	17,581	17,581
R^2	0.89	0.94

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^*p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends. Here (m) indicates marginal weather, (nm) stands for non-marginal, and the F indicates one month ahead seasonal forecasts.

Table A14: Timing Response to Forecasts: Ploughing

Dependent Variable:	Standardized Ploughing Date				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDD	-0.0012	0.0010	-0.0053	-0.0021	-0.0149**
	(0.0018)	(0.0010)	(0.0040)	(0.0022)	(0.0057)
GDD (F)	0.0010	-0.0004	-0.0155**	-0.0048	-0.0136*
	(0.0030)	(0.0016)	(0.0062)	(0.0053)	(0.0071)
HDD	-0.0046	-0.0025	0.0344	-0.0714**	0.2189*
	(0.0175)	(0.0135)	(0.0249)	(0.0335)	(0.1149)
HDD (F)	0.0085	-0.0253	0.1344	0.0372	-0.8561***
	(0.0520)	(0.0254)	(0.0968)	(0.0295)	(0.1743)
Crop	Wheat	Corn	Colza	Sunflower	Peas & Beans
Mean Date	290.7	420.3	234.4	368.0	365.4
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	7,313	8,562	3,069	3,016	2,015
R^2	0.37	0.46	0.22	0.28	0.34

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Outcomes are standardized at the crop level, to make comparisons of effects across crops more straightforward. The mean ploughing dates are also shown in the table. These dates run from 0 (the first day of the calendar year) to 730, the last day of the following year. As such ploughing for wheat happens in the fall, and for corn in the winter. One-way department standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A15: Timing Response to Forecasts: Sowing

Dependent Variable:	Standardized Sowing Date				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDD	-0.0017	0.0020	-0.0051	0.0066	0.0104***
	(0.0015)	(0.0014)	(0.0036)	(0.0044)	(0.0035)
GDD (F)	0.0047**	-0.0048**	-0.0126**	-0.0095	0.0348***
	(0.0023)	(0.0019)	(0.0047)	(0.0093)	(0.0124)
HDD	-0.0109	0.0194	0.0131	-0.2667***	-0.1907
	(0.0172)	(0.0181)	(0.0246)	(0.0813)	(0.1434)
HDD (F)	0.0317	-0.0599***	0.1703**	0.1861**	0.1777
	(0.0281)	(0.0142)	(0.0653)	(0.0880)	(0.1885)
Crop	Wheat	Corn	Colza	Sunflower	Peas & Beans
Mean Date	301.5	490.5	247.8	484.1	449.8
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	9,987	9,307	4,436	3,430	2,143
R^2	0.25	0.27	0.16	0.23	0.31

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Outcomes are standardized at the crop level, to make comparisons of effects across crops more straightforward. The mean sowing dates are also shown in the table. These dates run from 0 (the first day of the calendar year) to 730, the last day of the following year. One-way department standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A16: Timing Response to Forecasts: Harvesting

Dependent Variable:	Standardized Harvesting Date				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDD	-0.0005	-0.0004	-0.0009	-0.0036	0.0018
	(0.0014)	(0.0013)	(0.0031)	(0.0024)	(0.0076)
GDD (F)	0.0044*	-0.0046*	-0.0017	0.0079	0.0195
	(0.0025)	(0.0024)	(0.0047)	(0.0069)	(0.0118)
HDD	-0.0069	-0.0179	-0.0029	-0.0542	-0.0568
	(0.0143)	(0.0200)	(0.0326)	(0.0492)	(0.0690)
HDD (F)	0.0470*	0.0083	0.1063	0.0532	0.3040**
	(0.0255)	(0.0168)	(0.0784)	(0.0519)	(0.1277)
Crop	Wheat	Corn	Colza	Sunflower	Peas & Beans
Mean Date	569.2	648.7	561.0	627.8	574.4
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	9,974	9,186	4,419	3,409	2,138
R^2	0.54	0.22	0.38	0.23	0.49

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Outcomes are standardized at the crop level, to make comparisons of effects across crops more straightforward. The mean harvesting dates are also shown in the table. These dates run from 0 (the first day of the calendar year) to 730, the last day of the following year. One-way department standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A17: Cost and Revenue Reactions to Alternative Weather

Dependent Variables:	Revenue	Costs
Model:	(1)	(2)
Variables		
GDD	2.73	-1.26
	(10.6)	(8)
GDD (F)	21.3	35.9**
	(37.1)	(14.8)
HDD	-534	-106
	(178)	(90.8)
HDD (F)	628**	-13.6
	(261)	(128)
FDD	22.7	-2.68
	(30)	(12.4)
FDD (F)	-23.4	-96
	(107)	(84.3)
Mean	155,638	123,304
Unique Farms	2,625	2,625
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	18,428	18,428
R^2	0.89	0.94

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A18: Weather Decomposition

	Mean
GDD	2066
GDD marginal	1803
GDD non-marginal	263
GDD - ratio	0.13
HDD	2
HDD marginal	0.25
HDD non-marginal	1.78
HDD - ratio	0.85

Notes. We specify the ratio of marginal to total GDD and HDD realization along with their respective average over all French departments for 1994-2018.

Table A19: Persistence in Heating Degree Days Forecasts

Dependent Variables:	FHDD (lag 2)	FHDD (lag 1)	FHDD	FHDD (lead 1)	FHDD (lead 2)	FHDD (lead 3)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GDD	-0.0024	-0.0018	1.56×10^{-17}	-1.61×10^{-5}	0.0016	-0.0005
	(0.0018)	(0.0022)	(4.29×10^{-10})	(0.00)	(0.0025)	(0.0025)
GDD (F)	-0.0007	-0.0019	2.26×10^{-17}	0.0008	0.0058	0.002
	(0.0045)	(0.0035)	(1.17×10^{-9})	(0.0052)	(0.0067)	(0.0035)
GDD (lag)	-0.0022	0.0009	-3.73×10^{-17}	0.0001	0.0001	-0.0002
	(0.0014)	(0.0016)	(2.1×10^{-10})	(0.0013)	(0.0012)	(0.0015)
GDD (lag 2)	0.0008	-0.0001	-4.94×10^{-17}	0.0004	-0.0006	0.0017
	(0.0015)	(0.0009)	(6.3×10^{-11})	(0.0011)	(0.0010)	(0.0021)
HDD	-0.029	-0.0033	-1.27×10^{-15}	0.049	0.0014	0.053
	(0.053)	(0.026)	(1.5×10^{-8})	(0.068)	(0.046)	(0.09)
HDD (F)	-0.11	-0.11	1^{***}	-0.14	-0.19	-0.23
	(0.14)	(0.13)	(1.75×10^{-8})	(0.14)	(0.11)	(0.33)
HDD (lag)	-0.0014	0.013	-9.05×10^{-16}	0.022	0.03	0.0085
	(0.038)	(0.049)	(1.71×10^{-8})	(0.037)	(0.084)	(0.045)
HDD (lag 2)	-0.006	0.027	5.2×10^{-16}	0.022	0.003	-0.033
	(0.052)	(0.032)	(1.87×10^{-8})	(0.086)	(0.042)	(0.056)
Fixed-effects						
Farm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	14,097	14,097	14,097	12,193	10,504	9,019
R^2	0.69	0.73	1	0.71	0.69	0.70

Clustered (Department & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as the one-period and two-period lag values for rainfall in squares and levels. We finally include quadratic region-specific time trends.

Table A20: Dynamic Effects on Profit

Dependent Variables:	Profit (lag 2)	Profit (lag)	Profit	Profit (lead)	Profit (lead 2)	Profit (lead 3)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GDD	-37.5	3.04	0.86	1.67	6.46	-12.1
	(26.4)	(18.6)	(15.6)	(21.2)	(28.9)	(15.2)
GDD (F)	-28.5	19.2	22.6	35.8	-23	74.2
	(44.2)	(41.4)	(51.6)	(31.8)	(65.7)	(68.7)
GDD (lag)	-20.2	23.1	-8.89	-11.2	24.5	-19.4
	(13.5)	(20)	(10.8)	(12.8)	(15.5)	(23.4)
GDD (lag 2)	33.1	-1.88	-19.3*	17.5	7.01	-4.01
	(20)	(10.6)	(10.9)	(11.4)	(22.9)	(23.4)
HDD	85.8	-646	110	344	295	-271
	(351)	(399)	(339)	(272)	(539)	(537)
HDD (F)	663	265	1,908**	-1,828***	-1,435*	-324
	(450)	(649)	(847)	(645)	(702)	(699)
HDD (lag)	-628	-383	523**	747**	-301	1,425*
	(388)	(500)	(234)	(313)	(533)	(703)
HDD (lag 2)	-810	546**	709**	-239	1,350*	196
	(528)	(225)	(255)	(408)	(774)	(732)
Mean	89,684	87,948	86,695	86,836	86,756	86,848
Unique Farms	1,904	1,904	1,904	1,689	1,485	1,308
Fixed-effects						
Farm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	14,097	14,097	14,097	12,193	10,504	9,019
R^2	0.84	0.84	0.84	0.84	0.83	0.83

Clustered (Department & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares for period t are included a controls, as well as lag realized rainfall for periods $t-1$ and $t-2$, in both levels and squares, and finally quadratic region specific time trends.

Table A21: Crop-Specific Land Movement

Dependent Variable:	Land	
Model:	(1)	(2)
Variables		
HDD (corn)	0.0017	
	(0.093)	
HDD F (corn)	-0.14	
	(0.17)	
HDD (wheat)	-0.051	
	(0.087)	
HDD F (wheat)	0.27	
	(0.32)	
HDD (colza)		0.07
		(0.075)
HDD F (colza)		0.24
		(0.19)
HDD (sunflower)		-0.016
		(0.067)
HDD F (sunflower)		-0.34**
		(0.15)
Unique Farms	2,604	2,604
Wald	1.13	3.89
Fixed-effects		
Farm	Yes	
Year		Yes
Fit statistics		
Observations	37,834	37,834
R^2	0.94	0.84

Clustered (CDEPT & year_num) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Two-way department-by-year standard-errors in parentheses. Regressions are run using system OLS, in order to compute the coefficient equivalence Wald tests. Stars indicate estimate is significantly different from zero: *$p < .10$, **$p < .05$, ***$p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends. We also include GDD realization and forecasts, but only show the HDD specific coefficients as they are the focus of the tests.

Table A22: Dynamic Effects on Costs

Dependent Variables:	Costs (lag 2)	Costs (lag)	Costs	Costs (lead)	Costs (lead 2)	Costs (lead 3)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GDD	-3.58	-6.16	-1.82	9.01	-1.59	-0.63
	(2.94)	(7.39)	(6.77)	(7.43)	(6.44)	(15.3)
GDD (F)	4.23	10.8	25.2	1.03	19.5	0.15
	(12.4)	(15.8)	(16.9)	(15.5)	(13.9)	(13.4)
GDD (lag)	-2.73	-1.79	8.35**	-1.98	-7.64	7.86
	(5.28)	(5.15)	(3.89)	(3.21)	(5.51)	(8.93)
GDD (lag 2)	-7.52	1.59	-1.1	-6.29*	3.88	-1.25
	(5.38)	(3.26)	(3.04)	(3.29)	(7.43)	(10.7)
HDD	156	85	-284	-213	-20	164
	(103)	(93.5)	(176)	(223)	(178)	(228)
HDD (F)	-173	-189	-197	1,028**	326	118
	(304)	(215)	(116)	(429)	(409)	(223)
	(127)	(116)	(118)	(145)	(301)	(186)
HDD (lag)	1.88	-243	-88.2	124	218	-152
	(114)	(157)	(175)	(144)	(222)	(314)
HDD (lag 2)	-177	-61.7	56	172	-117	212
Unique Farms	1,904	1,904	1,904	1,689	1,485	1,308
Fixed-effects						
Farm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	14,097	14,097	14,097	12,193	10,504	9,019
R^2	0.94	0.94	0.94	0.94	0.94	0.95

Clustered (Department & Year) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^*p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares for period t are included as controls, as well as lag realized rainfall for periods $t-1$ and $t-2$, in both levels and squares, and finally quadratic region-specific time trends.

Table A23: Heterogeneity of Farm-Level Results

Dependent Variables:	Profit	Revenue	Costs
Model:	(1)	(2)	(3)
Variables			
GDD	-64.7	-46.6	-22.2*
	(55.9)	(54.5)	(12.5)
GDD (F)	146	39.2	-53.8
	(87.1)	(82.1)	(84.7)
HDD	-1,233	-2,694	-1,106
	(1,311)	(1,998)	(677)
HDD (F)	13,143***	16,512**	4,357
	(4,326)	(6,247)	(3,303)
GDD × Mean Temperature	6.04	5.39	2.16***
	(5.09)	(4.97)	(0.76)
GDD (F) × Mean Temperature	-12.8**	-1.33	6.49
	(6.16)	(6.94)	(7.31)
HDD × Mean Temperature	124	224	80.2
	(130)	(183)	(62.5)
HDD (F) × Mean Temperature	-968**	-1,350**	-394
	(379)	(536)	(289)
Mean	86,695	155,386	123,249
Unique Farms	2,603	2,603	2,603
Fixed-effects			
Farm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	18,917	18,917	18,917
R^2	0.84	0.89	0.94

Clustered (Department & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $*p < .10$, $**p < .05$, $***p < .01$. Realized and forecasted rainfall in levels and squares for period t are included as controls, and finally quadratic region-specific time trends.

B Data Details

B.1 Definition of Variables

Definitions for the main variables used:

- **Crop Prices.** They are measured by dividing the total value of sales of that given crop, by the total quantity sold.

- **Output Price Index.** For l_{jct} the land area allocated to crop c by farm j in period t, $\mathbb{C}_{jt}$ the crop mix of farm j in period t, and p_{jct} the output price of that same crop for that same farm, we build:

$$p_{jt} = \sum_{c \in \mathbb{C}_{jt}} \frac{l_{jct}}{\sum_{c \in \mathbb{C}_{jt}} l_{jct}} p_{jct} \tag{7}$$

  We consider the following crops for that purpose: wheat, durum wheat, oats, corn, corn (seeds), sorghum, spring barley, winter barley, rye, triticale, summer cereals, other cereals, sunflower, colza, soy, dry peas, feverole beans, protein peas.

- **Output/Storage Quantity Index.** This index is used as an aggregate measure of farm output/storage, and is intended to represent the average level of output/storage across the farm rather than a total quantity. It is built for the same set of crops as the one used for the output price index. We use the analogous formula: with q_{jct} the output/storage quantity for crop c in farm j in year t:

$$q_{jt} = \sum_{c \in \mathbb{C}_{jt}} \frac{l_{jct}}{\sum_{c \in \mathbb{C}_{jt}} l_{jct}} q_{jct} \tag{8}$$

- **Storage.** We define the variation in storage at period t - the net storage flow - as the difference between the quantity produced and the quantity sold for a specific crop.

- **Land prices.** are defined as the total value of land divided by the total quantity of land.

- **Fertilizer, pesticide and seed.** They are observed at the farm-level, correspond to deflated bills, and are defined as the difference between purchases plus beginning-of-period stocks, minus end-of-period stocks.

- **Labor.** Defined as the total number of paid hours worked over the season. By definition, this does not account for non-wage work, which are not collected.

- **Intermediary Inputs.** Defined as a deflated bill. The sum of expenses for: fertilizer, seeds, pesticides, animal food, veterinary products, products for animal reproduction, packaging, fuel, maintenance products, supplies, food for workers, raw materials, purchases of services for cultivation, breeding or others, water, gas, electricity, irrigation water, lease installments, material rental, animal rental, maintenance for buildings, lands and material, studies and research, veterinary services, communication and commercials, transportation costs, travel costs, postal services, banking services, other services and costs.

- **Total Costs.** Defined as a deflated bill. Corresponds to the sum of intermediary inputs, social contributions for workers, personnel expenses, taxes, insurance.

- **Value Added.** Defined as the difference between total production value minus animal purchases, minus intermediary inputs. Total production itself corresponds to total production sold, self-consumed production, immobilised production, stored production, gains from animal boarding, land rentals, other rentals, agricultural tourism.

- **Profit** Defined as the gross operating income of the farm. Our profit variable encompasses value added, and among else also includes subsidies, expenses for insurance, and insurance indemnities.

All variables measured in euros are converted into 2020 euros using the INSEE consumer price index.

B.2 Weather Data

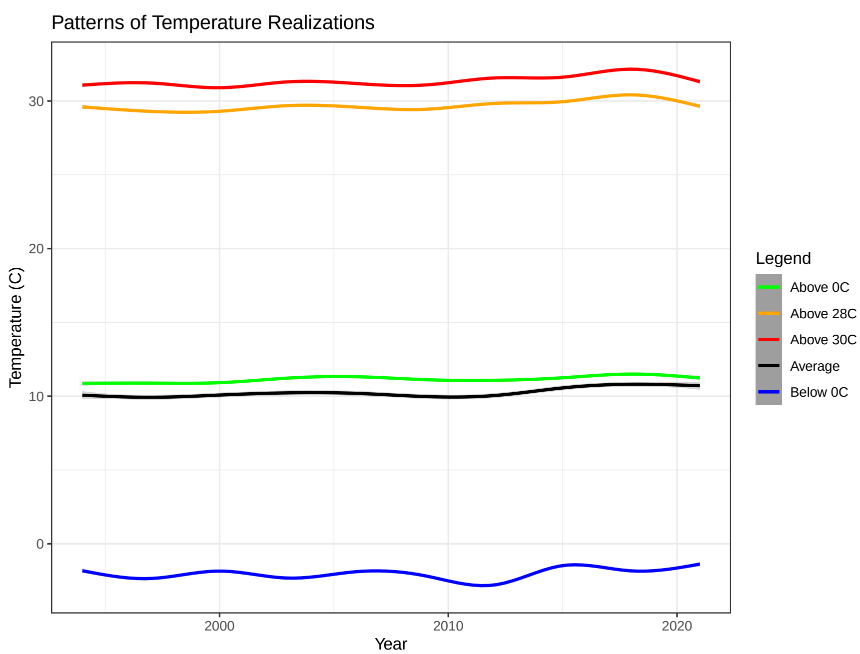


Figure A23: Unconditional and Conditional Average Temperature Realizations

C Validation of Results

Table A24: Corn-Specific Outcomes

Dependent Variables:	Output	Price	Revenue	Quantity Sold
Model:	(1)	(2)	(3)	(4)
Variables				
GDD	0.47	-0.0041	8.82	0.66
	(0.37)	(0.0094)	(8.33)	(0.52)
HDD	-30.7*	0.73**	-134	-13.7
	(15.2)	(0.29)	(186)	(11.4)
Mean	3,464	150	53,508	3,437
Unique Farms	1,607	1,581	1,607	1,607
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	10,346	9,958	10,346	10,346
R^2	0.94	0.73	0.88	0.88

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: *$p < .10$, **$p < .05$, ***$p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Table A25: Farm-Level Outcomes

Dependent Variables:	Revenue	Costs	Intermediary Inputs	Value Added	Profit	Output Price Index
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
GDD	9.88	2.48	-3.79	7.93	-3.99	-0.16
	(11.7)	(8.44)	(5.61)	(14.5)	(14.2)	(0.12)
HDD	-100	-158	-127	118	232	0.28
	(324)	(191)	(161)	(273)	(253)	(1.72)
Mean	155,386	123,249	103,749	58,357	86,695	263
Unique Farms	2,603	2,603	2,603	2,603	2,603	2,603
Fixed-effects						
Farm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	18,917	18,917	18,917	18,917	18,917	18,917
R^2	0.89	0.94	0.93	0.80	0.84	0.70

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: *$p < .10$, **$p < .05$, ***$p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

D Robustness

D.1 Heterogeneous Response to Forecasts

We show that there is little heterogeneity in farms' response to forecasted HDDs, looking at two potential important margins. First, we show that farms of different size do not seem to respond in very different ways to forecasts, then that farmers from different generations seem to have also a similar response to forecasts.

In the following graph we show the coefficient associated to the one month ahead HDD forecast when regressing farm log profit on realized and forecasted weather, and including year and farm fixed effects. We measure farm size using their gross operating income deflated to 2020 euros. While the graph shows some variation across quantiles and showcases a form of U-shape, there are no large differences in coefficient values across these quantiles. Farms are able to save the same percentage of their profit by using forecasted HDDs. This implies however that larger farmers are able to save a larger value whe using forecasts, hinting that heat shocks act as a negative multiplier to production rather than an additive shock.

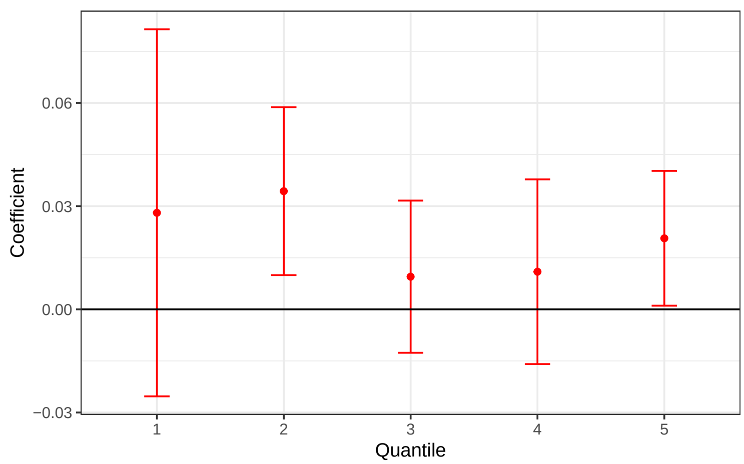


Figure A24: Varying Response to Fixed Lead of HDD

Next we rank farms by the date of birth of their manager. This analysis relies on the fact that forecasts are a relatively new technology, dating to the 1990s, and might be more easily adopted by farmers who went through their education when these were already available.

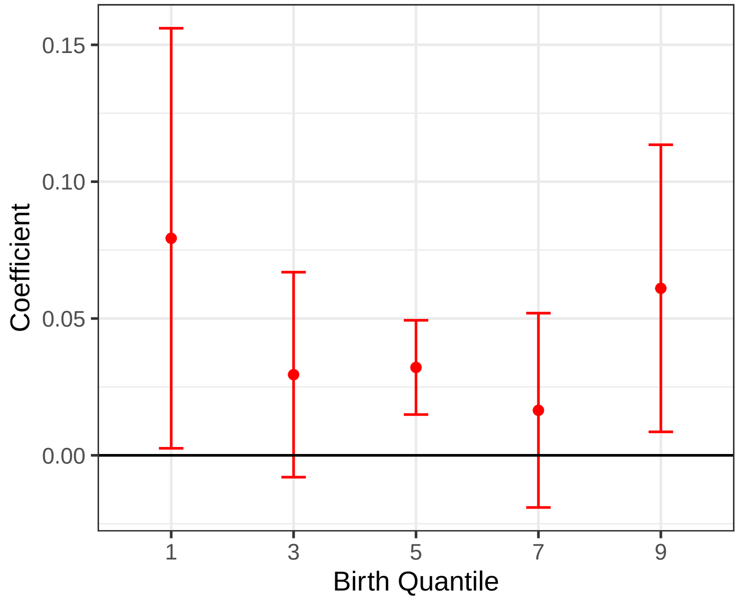


Figure A25: Profit Response to Forecasts across Manager's Age

We see a small increase in the reaction to forecasts for the youngest group of farmers, but again the difference is not stark. This is indicative that the timing of the farmers' education is not a strong predictor for their adoption of forecasts.

D.2 Including Lags

As a robustness check, we run the same regression as before but including lagged values of weather realization (rainfall in levels and squared, GDD and HDD). Again, the regressions also include farm and year fixed effects, and we cluster standard errors at the department level. Lagged realizations might matter, first because of auto-correlation in weather, for example due to the role of large weather patterns such as the North Atlantic Oscillation. Second, lags might also play a role in the setting of farmers' beliefs about the upcoming weather, as modeled and discussed by Burke and Emerick (2016). In this case, including both lags and forecasts might better account for farmers' beliefs.

As we see however, lagged realizations of growing and heating degree days play a non-significant role in driving farm profit once we control for forecasts. Forecasts of heating degree days, on the other hand, still have a large positive and significant impact on farm profit.

Table A26: Farm-Level Profit - Lead 1 with Lags

Dependent Variables:	Value Added	Profit
Model:	(1)	(2)
Variables		
GDD	7.83	-2.9
	(14.8)	(14.4)
GDD (lag)	-3.25	-7.94
	(9.94)	(9.86)
GDD (F)	24.8	9.61
	(47.1)	(45.9)
HDD	-22.8	134
	(333)	(331)
HDD (lag)	353*	429*
	(201)	(219)
HDD (F)	2,202**	1,781**
	(849)	(762)
Mean	58,357	86,695
Unique Farms	2,217	2,217
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes s
Fit statistics		
Observations	16,314	16,314
R^2	0.81	0.84

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

Compared to our main results in Table A9, we see a slight decrease in the coefficients associated to forecasted HDDs: the coefficient for value added moves from 2,430 to 2,199, and the one for profit moves from 2,005 to 1,712. As such, results are stable to the inclusion or exclusion of lags.

D.3 Alternative Weather Aggregation

We perform another robustness check, and recompute our growing and heating degree days. This time, we use 28°C as a cutoff for the classification of hourly temperature realizations as GDD or

HDD. The hours spent below are now counted towards growing degree days, while those above count towards the heating degree days. We also create a measure of freezing degree days, which counts the degree-hours spent below 0°C in absolute value. This might be useful, first to identify whether we can observe interesting responses to freeze, and see whether we also observe non-marginal profit responses to their forecast. Second, low growing degree day values might correlate with abnormally low temperature, and without including freezing degree days, might capture in part the impact of freeze on agriculture. Including them will then purge GDD from its correlation with very cold events.

Table A27: Farm-Level Profit - Alternative Weather

Dependent Variables:	Value Added	Profit
Model:	(1)	(2)
Variables		
GDD	6.97	-4.1
	(11.2)	(11.3)
GDD (F)	-12.4	-20.3
	(44.7)	(44.6)
HDD	61.3	129
	(177)	(171)
HDD (F)	943***	797***
	(296)	(269)
FDD	68.2*	64.4
	(39.1)	(37.7)
FDD (F)	189	142
	(158)	(156)
Mean	58,332	87,330
Unique Farms	2,625	2,625
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	18,428	18,428
R^2	0.81	0.84

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: *$p < .10$, **$p < .05$, ***$p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

The results are similar to the ones from our main specification. Forecasted HDDs have a positive impact of profit, albeit a smaller one than previously. A one unit increase in forecasted HDD corresponds here to a smaller increase in temperature over the growing season, and it should be expected that it implies a smaller response. Forecasted freezing days also imply a positive profit response. As such, it seems that farmers adapt both to extremely hot and cold events, in a way that leads to non-marginal changes in their optimal profit.

In Table A17 we show the costs and revenue responses to these alternative weather calculations.

D.4 Removing Time Trends

Here we run the same regressions as in the main part of the paper, using our initial measures of weather, but removing the quadratic department-specific time trends. Results are very close to those in Table 2.

Table A28: Farm-Level Profit - No Time Trend

Dependent Variables:	Revenue	Costs
Model:	(1)	(2)
Variables		
GDD	3.47	-1.27
	(10.7)	(7.36)
GDD (F)	47.8	37.7**
	(34.4)	(14.4)
HDD	-212	-184
	(303)	(149)
HDD (F)	1,342***	39.3
	(455)	(270)
Mean	155,386	123,249
Unique Farms	2,603	2,603
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	18,917	18,917
R^2	0.89	0.94

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.

D.5 Disaggregated Realized Weather

Below we run our main specification using village-level realized weather and department-level forecasted weather, which is the least coarse geographic unit that can match the forecasts' grid. We note there are about 36,000 villages in France, and hence this disaggregation corresponds to a significant gain in precision. This analysis is performed on a subset of our main sample from 2002 onwards, as we cannot locate farms at a finer level than the department prior to 2002.

Table A29: Cost and Revenue Reactions to Disaggregated Realized Weather

Dependent Variables:	Revenue	Costs
Model:	(1)	(2)
Variables		
GDD	1.51	-2.43
	(16.7)	(5.36)
GDD (F)	42.9	52.7**
	(45.7)	(22.5)
HDD	43.1	39.9
	(328)	(114)
HDD (F)	1,289***	52.9
	(256)	(37.9)
Mean	164,532	131,969
Unique Farms	1,890	1,890
Fixed-effects		
Farm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	12,754	12,754
R^2	0.89	0.94

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends. Realized weather is measure at the village level, while forecasts remain measured at the department one.

D.6 Decomposing along the Forecast Error Sign

Table A30: Cost and Revenue Responses - Heterogeneity along the sign of Forecasts Errors: Forecasts - Realization (1 month forecasts)

Dependent Variables:	Revenue	Costs	Profit	Value Added
Model:	(1)	(2)	(3)	(4)
Variables				
GDD	7.59	2.33	-3.98	6.73
	(10.5)	(7.56)	(13.2)	(12.8)
GDD (F)	37.1	28.6**	3.8	18.3
	(33.9)	(12.8)	(45.1)	(45.1)
HDD	-84.5	-185	322	179
	(392)	(193)	(291)	(298)
Forecast Bin 1	-3,509**	-1,806	-4,642**	-4,291*
	(1,637)	(1,159)	(2,094)	(2,209)
Forecast Bin 2	-3,378*	-1,169	-3,735**	-3,962**
	(1,895)	(752)	(1,673)	(1,722)
Forecast Bin 4	895	-898	613	340
	(2,731)	(864)	(2,569)	(2,601)
Forecast Bin 5	675	-1,327	999	1,755
	(4,605)	(1,353)	(2,959)	(3,184)
Mean	155,386	123,249	86,695	58,357
Unique Farms	2,603	2,603	2,603	2,603
Fixed-effects				
Farm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,917	18,917	18,917	18,917
R^2	0.89	0.94	0.84	0.80

Notes. Two-way department-by-year standard-errors in parentheses. Stars indicate estimate is significantly different from zero: $^*p < .10$, $^{**}p < .05$, $^{***}p < .01$. Realized and forecasted rainfall in levels and squares are included as controls, as well as quadratic region-specific time trends.