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Decomposing Weather Impacts on Crop Profits: the Role of Agrochemical Input Adjustments

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Abstract

The costs of climate change borne by agriculture are critically dependent on farmers' adaptation. In this paper, we investigate how farmers adjust their input mix in response to weather fluctuations during the growing season using individual panel data from *Meuse* (France) between 2006 and 2012. Specifically, we consider weather and price information to estimate structural models of profit-maximizing farmers with crop-specific yields and input-crop-specific demand functions, conditionally on farm and annual fixed effects. The results show that weather fluctuations affect crop yields but that farmers adapt their fertilizer and pesticide applications. We use our estimates to simulate the impacts of a climate change scenario: we show that farmers in *Meuse* would increase fertilizer applications by 2.60% but reduce pesticide applications by 6.92% under an RCP 4.5 scenario in 2050. These adjustments limit the negative direct impacts of climate change on plant growth, though heterogeneously among crops. In total, the added value of the agricultural sector is likely to reduce by 3.02%. Society could benefit from adaptation as the reduction in damage due to agrochemicals' negative externalities represents twice the market costs borne by the agricultural sector.

Keywords: Climate change, Chemical inputs, Global warming, Growing-season adjustments, Short-term adaptation, Structural econometrics, Variable inputs, Weather fluctuations.

JEL Codes: Q12, Q53, Q54

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1 Introduction

Climate change is already affecting agricultural profitability in many regions of the world (Mendelsohn et al., 1994; Van Passel et al., 2017). Temperatures and precipitation impact the yields of crops and pastures through their direct effects on crop growth (e.g. photosynthesis) and their indirect effects on production conditions (e.g. pest pressure). Many studies used crop simulation models to assess the consequences of climate change on crop yields through the modification of the biophysical processes involved (e.g. Asseng et al., 2015; Roberts et al., 2017). Although these impacts are likely to be large, farmers are suspected to react to new climatic conditions by adapting their practices (Challinor et al., 2014). In this paper, we investigate how farmers adapt their applications of fertilizers and pesticides to cope with fluctuating weather conditions and how these input adjustments ultimately affect profits and yields.

The economic literature has paid considerable attention to measuring the impacts of climate change on agricultural production (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). The common methodology consists of regressing one dimension of the agricultural rent – such as yields, profits or land values – on observed climate/weather variables. Typically, the hedonic approach proposed by Mendelsohn et al. (1994) regresses land values on climate conditions, making it possible to account for the consequences of climate change once all potential switches in production decisions (e.g. switches in crop allocation) have been undertaken . The hedonic approach claims to capture long-term adaptation to climate change, but without explicitly describing the mechanisms at stake. A more recent approach, called hereafter the "*weather approach*", regresses agricultural profit or yield deviations on weather fluctuations (Deschênes and Greenstone, 2007; Lobell et al., 2011) conditionally on individual and temporal fixed effects (FE).[1] These FE are assumed to purge the estimates of all the unobserved time-invariant variables that might be correlated with both climate and agricultural production (e.g. soil quality) and, *in fine*, provide more precise and robust estimates. The disadvantage is that the weather approach can only capture – implicitly – short-term adaptations such as adjustments in cropping practices.

Though useful, all these approaches rely on reduced-form estimations where adaptation is not explicitly described and remains as a black box. Consequently, it is difficult to identify through which mechanisms weather affects agricultural profitability and productivity (Roberts et al., 2017).

[1] The difference between *climate* and *weather* lies in the distinction between a statistical distribution and a particular point drawn from that distribution: *climate* stands for the distribution while *weather* describes a realization from that distribution (Dell et al., 2014). Because a sufficiently large number of repeated random draws should reproduce the law governing the distribution, weather fluctuations should reproduce climate conditions (Deschênes and Greenstone, 2007).

Is it due to the direct effects of temperatures and precipitation on crop growth? Is it due to the increased productivity of existing inputs? Is it due to chemical input-savings, to reduction in labor needs? Unfortunately, the answer to such questions is impossible when using reduced-form estimations of yields or profits as their simplified structure prevents formal specification of the adaptation mechanisms at stake (Ortiz-Bobea and Just, 2013; Sesmero et al., 2018). An additional problem is that the use of different dependent variables implies that results are hardly comparable between studies. For example, regressing yields on weather provides information about the production consequences of weather once short-term adaptations have been made but does not isolate the effects of adaptation from the direct effects of weather on plant growth (as captured by former crop simulation models – see, e.g. Roberts et al., 2017).[2] It does not provide information about adaptation costs either, while regressing profits on weather does account for them (Mendelsohn and Massetti, 2017).

To the best of our knowledge, studies using the weather approach have only very recently tried to formally measure farmers' short-term adaptation (Aragón et al., 2021; Cui and Xie, 2021; Jagnani et al., 2021). For example, Cui and Xie (2021) estimated how Chinese farmers adapted their planting date to changes in weather and Jagnani et al. (2021) estimated how Kenyan farmers change their fertilizer and pesticide applications in response to weather fluctuations. However, neither Aragón et al. (2021), Cui and Xie (2021) nor Jagnani et al. (2021) statistically identified the induced impacts of these changes in cropping practices on crop yields (but only recalculated them using back-of-the-envelope computations). Indeed, the structure of the reduced-form models prevented simultaneous measurement of farmers' adaptation strategies and their productive consequences.

In the light of these challenges, we propose to explicitly analyse – in a structural framework – farmers' adaptation to weather fluctuations during the growing season, using pesticide and fertilizer application during the growing season as an illustrative example. Our approach disentangles the profit variation in response to weather changes into (i) fertilizer and pesticide applications, (ii) fertilizer and pesticide productivity and (iii) crop yields, both independently of the farmers' control (as captured by crop simulation models) and through the induced impacts from input adjustments. We estimate the underlying structural model using a panel of crop farms from the French region

[2]Early studies using crop simulation models focused on the relationship between climate and plant growth assuming constant cropping practices (Asseng et al., 2015). However, some recent studies using crop simulation models account for some incremental adaptations – e.g. changing varieties or planting dates – in their simulations. Running a meta-analysis of these studies, Challinor et al. (2014) found that incremental adaptation can increase crop yields by 7-15% compared to the situation without adaptation. Challinor et al. (2014) acknowledged that the benefits of adaptation could actually be overestimated in these models as adaptation is only simulated (and not observed). Also, although incremental adaptation is sometimes considered in crop simulation models, the underlying objective function remains the maximizing of crop yields, which differs from what economists consider to be a rational behavior.

of *Meuse*. This database has the unique advantage of detailing fertilizer and pesticide purchases by crop, information that is never – to our knowledge – available on commonly used economic databases. This allows us to decompose the farmers' profits on three crop-specific systems (wheat, barley and rapeseed), each consisting of one yield equation, one fertilizer demand equation and one pesticide demand equation. The different equations share the structural parameters of the quadratic production function, which are jointly estimated using input and output price fluctuations together with temperature and precipitation variations (conditionally on individual and annual FE).

The idea of explicitly specifying the farmers' adaptation mechanisms is not new. In a theoretical framework, Ortiz-Bobea and Just (2013) decomposed the effects of a marginal change in weather on profit through (i) the direct impacts on crop yields, (ii) impacts on the costs of crop practices and (iii) induced impacts on crop allocation. They then used estimates from Schlenker and Roberts (2009) to simulate how adjustments in seed applications impact corn yields. Kaminski et al. (2013) estimated a similar structural model for Israeli regions and found that farmers responded to weather by changing their aggregated input applications and crop allocation. These authors, however, departed from the standard weather approach by considering the weather conditions during the *whole year* and by using pooled data. In contrast, the weather approach has usually assumed fixed crop allocation to benefit from the panel dimension (i.e. the use of individual and annual FE), with the justification that farmers choose their crop allocation *before* the growing season.

Our contributions to this literature are threefold. First, taking the example of agrochemical input adjustments, our structural decomposition of the farmers' profits allows us to identify and estimate the different mechanisms taken into account by the various weather approach studies. Indeed, our decomposition identifies four mechanisms through which weather affects yields: (i) the direct weather effects, as measured in former crop simulation models, (ii) average yield effects, (iii) input productivity effects and (iv) input demand effects, the combination of the last three mechanisms determining the farmers' adaptation effects on crop yields and profits. Our decomposition thus allows for isolating the effects of farmers' adaptation on crop yields from the direct weather impacts, which are usually combined in the weather approach (as in, e.g., Schlenker and Roberts, 2009). Second, we contribute to the emerging literature on the measurement of short-term adaptation (Aragón et al., 2021; Cui and Xie, 2021; Jagnani et al., 2021) by formally measuring, for each crop, the impacts of weather fluctuations on fertilizer and pesticide applications. Our structural estimates provide evidence that farmers do adapt to weather fluctuations by adjusting their variable input applications. We find that an RCP 4.5 scenario in 2050 will lead farmers to increase fertilizer applications by 2.60% but to reduce pesticide applications by 6.92%, *ceteris paribus*. In addition to what is shown by the rest of the literature, we are able to statistically identify how these adjustments impact crop yields and profits. For example, we find that these input adjustments should reduce future rapeseed yield losses by two thirds. Finally, we use our estimates to value the *market* and *non-market* costs of climate change. Our central estimates suggest that the agricultural sector from *Meuse* will lose €3.04 million under the RCP 4.5 scenario in 2050, while society will benefit by an extra €6.14 million from the reduction in agrochemical input applciations. To our knowledge, this is the first evaluation of the costs of climate change through its impact on pollution induced by farmers' short-term adaptation.

The paper is organized as follows. Section 2 presents the conceptual framework and details the main assumptions of our approach. Section 3 details the empirical models, the econometric strategy and the summary statistics. Section 4 describes the estimation results. Section 5 assesses the impacts of an RCP 4.5 scenario in *Meuse* based on our estimates. Section 6 discusses and concludes.

2 Conceptual Framework

Our approach consists of explaining the impacts of weather on agrochemical input applications and how they translate into crop yields and profits. In other words, it consists of desegregating the weather approach proposed by Deschênes and Greenstone (2007) to explicitly describe the short-term adaptation mechanisms. We present the formal description of our model in the following subsections.

2.1 Farmers' profits and expectations in the growing season

Consider a risk-neutral farmer i maximizing their annual profit Π_{it} (in €/ha) according to the vector of their meteorological conditions $\mathbf{w}_{it}$ during the growing season in agricultural campaign t. The farmer's program in t can be split into two periods: (i) the growing season during which the farmer's decision variables are the applications of variable inputs $\mathbf{x}_{ijt}$ (in quantity/ha) for each of their J crops ($x_{ijkt} \geq 0$ for each input k) and (ii) the period before the growing season during which farmers decide their crop allocation $\mathbf{s}_{it}$ anticipating the outcomes in the growing season (Chambers and Just, 1989; Carpentier and Letort, 2012). The farmer's maximization of Π_{it} is thus a two-stage optimization process where they first choose their crop allocation based on their vector of expected profits $E(\boldsymbol{\pi}_{it})$ and, in the second stage, the farmer optimizes the crop-specific profit π_{ijt} on $\mathbf{x}_{ijt}$ based on the weather realizations (the crop allocations being considered as fixed) and anticipated prices. We note p^y_{ijt} the price of crop j for farmer i in agricultural campaign t and $\mathbf{p}^{\mathbf{x}}_{it}$ the corresponding vector of input prices.[3]

Because farmers are typically unaware of both weather conditions and prices in the first stage, they allocate crops by making anticipations about these elements. There have been long discussions about the form of price expectations in the agricultural economics literature (e.g. Chavas, 2000; Nerlove and Fornari, 1998). Given that farmers sow their land ca. 3-6 months before the growing season and ca. 9-12 months before harvest, the common practice is to assume that farmers have naive price expectations. The anticipation of weather conditions in the first stage has been less well-studied (Ji and Cobourn, 2020). However, because weather conditions in one location typically fluctuate around their average long-term values $\bar{\mathbf{w}}_i$, one can assume that $E(\mathbf{w}_{it}) = \bar{\mathbf{w}}_i$. With this form of anticipation, weather realizations during the growing season typically act as surprises for farmers. We can thus assume that crop allocation is not affected by weather in the growing season, and is thus considered as fixed in the remainder of this paper. This assumption – usual in the weather approach (e.g Deschênes and Greenstone, 2007) – is empirically supported by Ji and Cobourn (2020).[4]

The anticipations are different in the second stage. Indeed, if farmers still need to anticipate crop prices at this stage, they observe the input prices. In line with the agricultural economics literature, we thus assume naive expectations for crop prices $E(p^y_{ijt}) = p^y_{ijt-1}$ but rational expectations for input prices $E(\mathbf{p}^{\mathbf{x}}_{it}) = \mathbf{p}^{\mathbf{x}}_{it}$ (Carpentier and Letort, 2012).[5] Similarly, because farmers observe weather realizations in the second stage, we assume $E(\mathbf{w}_{it}) = \mathbf{w}_{it}$. As a result, the second stage of the profit maximization can be rewritten, for each crop j, as:

$$\pi_{ijt} = \max_{\mathbf{x}_{ijt}} \{p^y_{ijt-1} y_{ijt} - \mathbf{p}^{\mathbf{x}\prime}_{it} \mathbf{x}_{ijt}; y_{ijt} = f_j(\mathbf{x}_{ijt}; \mathbf{w}_{it})\}. \tag{1}$$

[3]We consider that input and output prices vary according to year (along with global markets) but also according to farmer. Prices vary among farmers as they reflect quality, volume and distance to the downstream or upstream markets.

[4]Another argument consists of remarking that the weather approach – that supposes the use of individual and temporal FE – would determine the correlation between $E(\mathbf{w}_{it}) - \bar{\mathbf{w}}_i$ and $\mathbf{s}^*_{it} - \bar{\mathbf{s}}^*_i$ (i.e., the difference between the optimal solution of the first stage given these anticipations and the optimal crop allocation under *average* weather conditions). Given our assumption on the form of the anticipations for the weather in the growing season, the first difference is null in the first stage, which prevents identification. Note however that this assumption is not valid for the whole year as Kaminski et al. (2013) and Miao et al. (2016) showed that weather conditions *outside* the growing season – i.e. during autumn and winter – are important drivers of crop allocation. By contrast with the rest of the literature, Aragón et al. (2021) showed that Peruvian farmers adapt to high temperatures during the growing season by changing their crop allocation. A possible explanation is that planting date occurs *outside* the growing season in north American and European countries but *during* the growing season in Peru (Aragón et al., 2021).

[5]An alternative assumption regarding crop price anticipation would be to use future market prices during the growing season. However, future market prices are common to all farmers: their effects would be captured by the annual FE used in the weather approach.

where y_{ijt} is the yield of crop j for i in t that depends on the weather conditions and variable input applications following the production function $f_j(\mathbf{x}_{ijt}; \mathbf{w}_{it})$. The production function respects the usual non-negative, non-decreasing, linearly homogeneous and concave relationship with $\mathbf{x}_{ijt}$. We assume that the production functions are non-negative and linearly homogeneous with $\mathbf{w}_{it}$. The production functions do not depend on the crop allocation $\mathbf{s}_{it}$, i.e. we assume constant-return to area and non-jointness for the different crop-specific technologies.[6] The solution of program (1) is $\mathbf{x}^*_{ijt}$, i.e. the optimal input applications under $\mathbf{w}_{it}$ given the anticipated prices in the second stage. We note y^*_{ijt} the corresponding crop yield.

Program (1) specifies the farmers' profit maximization in the very short-term, when crop allocation and other allocatable inputs are assumed to be fixed. It underlines that, in the growing season, the farmers' single decision variable – and thus adaptation strategy – is the application of variable inputs $\mathbf{x}^*_{ijt}$. It also highlights the fact that profits actually depend on both weather realizations and input applications such that regressing profits (or yields) directly on weather using reduced-form equations prevents one from separating the direct effects of weather on plant growth (as captured by crop simulation models – e.g. Asseng et al., 2015) from the effects from farmers' adaptation. We present the identification of these different effects in Section 3 but, first, the following subsection presents how changes in weather during the growing season affect crop profits.

2.2 Marginal impacts of weather changes on profits

The weather approach typically measures the effects of the weather in the growing season on farmers' profits by accounting *only* for the adaptations described in program (1). These effects can typically be decomposed into two main categories: the effects on quantities (output y_{ijt} and input $\mathbf{x}_{ijt}$) and those on input and output prices. Because previous studies worked on small administrative areas (e.g. at "county" level), the authors have usually assumed that the price effects were small enough to be ignored (Deschênes and Greenstone, 2007; Ortiz-Bobea and Just, 2013).[7] As we work on *individual* farmers, we here assume that farmers are price-takers such that prices remain unaffected by weather fluctuations. Like previous studies, we thus decompose the effects of weather on crop-specific profit π_{ijt} in program (1) by assuming the absence of effects on prices. As such,

[6] This is a common assumption in the climate economics literature (e.g. Deschênes and Greenstone, 2007), or more generally in the agricultural economics literature (Carpentier and Letort, 2012). This allows us to consider that farmers separately maximize their input applications on each crop in the second stage.

[7] Representative farmers at the county level are usually assumed to be price-takers. As a result, a change in crop production and input applications due to weather variations is unlikely to impact prices. Indeed, in general equilibrium, any large impacts induced by a specifically-located weather shock should be attenuated by market reorganization (Ortiz-Bobea and Just, 2013).

the changes of π_{ijt} in response to a change in the z^{th} element of the weather vector $\mathbf{w}_{it}$ during the growing season (noted hereafter $\mathbf{w}_{it}^{(z)}$) can be decomposed as:

$$\frac{\mathrm{d}\pi_{ijt}}{\mathrm{d}\mathbf{w}_{it}^{(z)}} = p_{ijt-1}^{y}(\underbrace{\frac{\partial f_j(\bar{\mathbf{x}}_{ijt}^{*}(\bar{\mathbf{w}}_i);\mathbf{w}_{it})}{\partial \mathbf{w}_{it}^{(z)}}}_{\text{Direct weather effects}} + \underbrace{\frac{\partial \mathbf{x}_{ijt}^{*}(\mathbf{w}_{it})}{\partial \mathbf{w}_{it}^{(z)}}' \frac{\partial f_j(\mathbf{x}_{ijt}^{*}(\mathbf{w}_{it});\mathbf{w}_{it})}{\partial \mathbf{x}_{ijt}}) - \mathbf{p}_{it}^{\mathbf{x}}{}' \frac{\partial \mathbf{x}_{ijt}^{*}(\mathbf{w}_{it})}{\partial \mathbf{w}_{it}^{(z)}}}_{\text{Farmers' adaptation effects}}. \tag{2}$$

where $\bar{\mathbf{x}}_{ijt}^{*}$ is the vector of the input applications that maximizes program (1) under average weather conditions $\bar{\mathbf{w}}_i$ given the anticipated prices in the second stage.

Equation (2) describes the effects of a marginal change in weather on profit of each crop through its impacts on output and input quantities. It differs from the decomposition in Deschênes and Greenstone (2007) by considering the effects of weather on variable input applications.[8] In detail, weather fluctuations affect quantities through two main mechanisms: the *direct weather effects* and *farmers' adaptation effects*. We theoretically disaggregate these two effects on yields in Figure 1, where point A is the equilibrium under average weather conditions $\bar{w}$ while point D is the equilibrium under weather realizations w_1.[9]

The direct effects show how weather affects yields directly through its effect on plant growth, independently from farmers' adaptation. This corresponds to moving from point A to point B in Figure 1. Such effects are similar to those captured by former crop simulation models that measure the biophysical processes at stake (e.g. the effect of temperature on photosynthesis). The direct effect of weather on crop yields can be positive or negative depending on the crops. Asseng et al. (2015) showed for example that, *ceteris paribus*, global warming should reduce wheat yields.

The farmers' adaptation effects capture all the impacts on profit of a marginal change in variable input applications in response to a marginal change in weather during the growing season. They account for the consequences of variable input adjustments in term of yields and input purchases. However, because $\mathbf{x}_{ijt}^{*}$ is the (optimized) solution, the adaptation effects are null at the margin (due to the envelope theorem – see e.g. Hsiang, 2016). Indeed, the optimal adaptation strategy is reached for $\mathbf{x}_{ijt}^{*}(\mathbf{w}_{it})$, i.e. the cost of adaptation equals its benefits (Hsiang, 2016; Kolstad and Moore, 2020). Formally:

[8] In Deschênes and Greenstone (2007), the change in profit consecutive to a marginal change in weather is equal to $\frac{\partial \pi_{ijt}}{\partial \mathbf{w}_{it}} = (p - \frac{\partial c_{ijt}}{\partial y_{ijt}})\frac{\partial y_{ijt}}{\partial \mathbf{w}_{it}}$, where c_{ijt} is the cost function that depends only on yields. This derivation is adapted from equation n°2 in Deschênes and Greenstone (2007), with null price effects as assumed by the authors.

[9] Note that the derivatives in points A and D are identical in Figure 1 as the marginal productivity at the optimum is equal to the ratio of input price to expected output price (which are independent of weather).

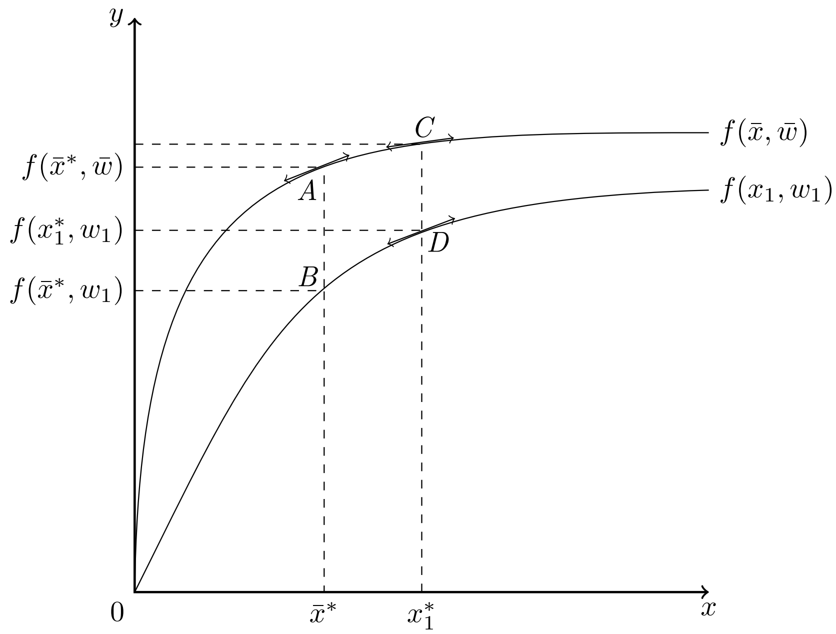


Figure 1: Decomposition of the productive effects of weather from average weather conditions $\bar{w}$ to weather realizations w_1. *Point **A** is the optimum under $\bar{w}$. Point **B** refers to the equilibrium under w_1 in the case of no adaptation. Point **C** indicates the production that would have occurred in average weather conditions $\bar{w}$ once farmers have adapted to weather realizations w_1. Point **D** is the optimum under w_1. $\bar{\boldsymbol{x}}^*$ is the optimal input application under average weather conditions $\bar{\mathbf{w}}$ given the anticipated prices.*

$$p^y_{ijt-1}\frac{\partial \mathbf{x}^*_{ijt}(\mathbf{w}_{it})'}{\partial \mathbf{w}^{(z)}_{it}}\frac{\partial f_j(\mathbf{x}^*_{ijt}(\mathbf{w}_{it});\mathbf{w}_{it})}{\partial \mathbf{x}_{ijt}} = \mathbf{p}^{\mathbf{x}\,\prime}_{it}\frac{\partial \mathbf{x}^*_{ijt}(\mathbf{w}_{it})}{\partial \mathbf{w}^{(z)}_{it}}. \tag{3}$$

The left-hand side of relation (3) defines the expected benefits of adaptation in terms of induced impacts on yields (which could be positive or negative). The corresponding differential equates to a move from point B to point D in Figure 1. Instead of suffering from a yield loss equal to the difference along the ordinate between A and B, farmers only suffer from a yield loss corresponding to the difference along the ordinate between A and D. In other words, farmers' adaptation reduces the negative direct impacts of a change in weather by half in our illustrative example (Figure 1). The expected benefits of adaptation on yields depend on (i) the properties of the production function, (ii) the weather conditions in the growing season and (iii) the anticipated prices in the second stage. The right-hand side of relation (3) defines the costs of adaptation, i.e. the costs of input adjustment in response to a weather change. Our decomposition thus allows us to isolate both the benefits and costs of farmers' short-term adaptation strategies from the direct effects of weather on plant growth. We detail here the three mechanisms driving farmers' adaptation.

The *average yield* effects are the productive consequences of farmers' variable input applications under *average* weather conditions $\bar{\mathbf{w}}_i$, multiplied by the marginal adjustment in input applications in response to $\mathbf{w}_{it}$. These effects can be positive or negative according to the considered inputs and crops depending on whether adaptation is motivated by maintenance of crop yields or input-savings. The *average yield* effects correspond to a move from point A to point C in Figure 1.

The *input productivity* effects are the impacts of the weather conditions on the productivity of variable inputs. Indeed, variable input productivity is expected to interact with the weather conditions via crop growth mechanisms, e.g. the assimilation of nutrients from fertilizers by the crop roots depends on soil humidity and temperature. In particular, the weather conditions could affect the complementarity/substitution relationship between different variable inputs, ultimately affecting the farmers' adaptation decision. These effects can be positive or negative according to the considered inputs and crops. The *input productivity* effects correspond to the difference in derivatives between point D and point C multiplied by the chemical input adaptations from $\bar{x}^*$ to x_1^* in Figure 1.

The *input demand* effects capture the consequences of weather on variable input demand. This corresponds to the change in expenditure following a move from $\bar{x}^*$ to x_1^* in Figure 1. The sign of such an effect can be either positive or negative depending on the inputs and crops, leading ultimately to (beneficial) input-savings or (costly) input-spendings. As underlined in relation (3), *input demand* effects depend on *average yield* and *input productivity* effects (i.e. on the properties of the production function under the whole weather distribution). For example, if one input becomes more productive under new weather conditions, farmers are expected to increase its use *ceteris paribus* such that farmers' expenses would increase accordingly.

The multiplication of the *average yield* and *input productivity* effects by the changes in input quantity consecutive on the *input demand* effect corresponds to the *total farmers' adaptation* effect on crop yields. The overall effect of weather fluctuations on farmers' profits thus depends on the combined effect of these three mechanisms and the direct weather effects (which remain independent of farmers' adaptation). Taking all these together, the effect of a change in weather on crop-specific profit can be approximated by the following second-order Taylor extension:

$$\Delta_{\bar{\mathbf{w}}_i^{(z)}}^{\mathbf{w}_{it}^{(z)}} \pi_{ijt} \approx (\mathbf{w}_{it}^{(z)} - \bar{\mathbf{w}}_i^{(z)}) p_{ijt-1}^y (\underbrace{\frac{\partial f_j(\bar{\mathbf{x}}_{ijt}^*(\bar{\mathbf{w}}_i); \mathbf{w}_{it})}{\partial \mathbf{w}_{it}^{(z)}} + \frac{(\mathbf{w}_{it}^{(z)} - \bar{\mathbf{w}}_i^{(z)})}{2} \frac{\partial^2 f_j(\bar{\mathbf{x}}_{ijt}^*(\bar{\mathbf{w}}_i); \mathbf{w}_{it})}{\partial (\mathbf{w}_{it}^{(z)})^2}}_{\text{Direct weather effects}}) +$$

$$(\mathbf{w}_{it}^{(z)} - \bar{\mathbf{w}}_i^{(z)}) [p_{ijt-1}^y \frac{\partial \mathbf{x}_{ijt}^*(\mathbf{w}_{it})'}{\partial \mathbf{w}_{it}^{(z)}} (\underbrace{\frac{\partial f_j(\mathbf{x}_{ijt}^*(\mathbf{w}_{it}); \bar{\mathbf{w}}_i)}{\partial \mathbf{x}_{ijt}}}_{\text{Average yield effects}} + \frac{(\mathbf{w}_{it}^{(z)} - \bar{\mathbf{w}}_i^{(z)})}{2} \underbrace{\frac{\partial^2 f_j(\mathbf{x}_{ijt}^*(\mathbf{w}_{it}); \mathbf{w}_{it})}{\partial \mathbf{x}_{ijt} \partial \mathbf{w}_{it}^{(z)}}}_{\text{Input productivity effects}}) \underbrace{- \mathbf{p}_{it}^{\mathbf{x}\prime} \frac{\partial \mathbf{x}_{ijt}^*(\mathbf{w}_{it})}{\partial \mathbf{w}_{it}^{(z)}}}_{\text{Input demand effects}}].$$

In Section 3.1 we propose a strategy to estimate a structural model compatible with the identification of the mechanisms in relation (4).

2.3 Interpretation of the estimates in previous approaches

The decomposition in relations (2) and (4) allows us to identify which mechanisms are accounted for by the various studies from the weather approach using reduced-form estimations. Table 1 summarizes the interpretations of the estimates from previous prominent studies. The studies regressing yields y_{ijt}^* on weather conditions during the growing season (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011) typically account for the first three mechanisms in $\beta_{\mathbf{w}}^y$ (namely the direct effects, average yield effects and input productivity effects) but are unable to distinguish one from another. In contrast, the studies regressing input demand $\mathbf{x}_{ijt}^*$ (or rather $\mathbf{x}_{it}^*$ since, to our knowledge, no study has ever distinguished variable input applications by crop) on weather conditions during the growing season (Jagnani et al., 2021) account only for the fourth mechanism, i.e. input demand effects. This approach typically ignores the induced consequences of input adjustments on crop yields, despite the fact that they determine farmers' optimal adaptation strategies. In fact, only studies that regress π_{ijt} on weather conditions during the growing season (Deschênes and Greenstone, 2007) account for all the four different mechanisms in $\beta_{\mathbf{w}}^{\pi}$, but without decomposing them as we do in this paper. They are thus unable to distinguish one mechanism from another. This could be particularly problematic if one mechanism drives the overall estimates (in particular if all the effects are driven by the direct effects on plant growth). Finally, crop simulation models account only for the direct effects and ignore all the adaptation mechanisms.

Table 1: Interpretations of previous estimates from weather approach studies

Dependent variable	Studies	Mechanisms captured in equation (2)
y^*_{ijt}	Schlenker and Roberts (2009) Lobell et al. (2011, 2013) Gammans et al. (2017)	$\beta^y_{\mathbf{w}} \mathrm{d}\mathbf{w}^{(z)}_{it} = \frac{\partial \mathbf{x}^*_{ijt}}{\partial \mathbf{w}^{(z)}_{it}}{}' (\frac{\partial f_j(\bar{\mathbf{x}}^*_{ijt};\mathbf{w}_{it})}{\partial \mathbf{w}^{(z)}_{it}} + \frac{\partial f_j(\mathbf{x}^*_{ijt};\mathbf{w}_{it})}{\partial \mathbf{x}^*_{ijt}}) \mathrm{d}\mathbf{w}^{(z)}_{it}$
$\mathbf{x}^*_{it}$	Jagnani et al. (2021)	$\beta^x_{\mathbf{w}} \mathrm{d}\mathbf{w}^{(z)}_{it} = \sum_{j=1}^J \frac{\partial \mathbf{x}^*_{ijt}}{\partial \mathbf{w}^{(z)}_{it}} \mathrm{d}\mathbf{w}^{(z)}_{it}$
π_{ijt}	Deschênes and Greenstone (2007)	$\beta^\pi_{\mathbf{w}} \mathrm{d}\mathbf{w}^{(z)}_{it} = p^y_{ijt-1}(\frac{\partial f_j(\bar{\mathbf{x}}^*_{ijt};\mathbf{w}_{it})}{\partial \mathbf{w}^{(z)}_{it}} + \frac{\partial \mathbf{x}^*_{ijt}}{\partial \mathbf{w}^{(z)}_{it}}{}' \frac{\partial f_j(\mathbf{x}^*_{ijt};\mathbf{w}_{it})}{\partial \mathbf{x}^*_{ijt}}) \mathrm{d}\mathbf{w}^{(z)}_{it}$ - $\mathbf{p}^{\mathbf{x}}_{it}{}' \frac{\partial \mathbf{x}^*_{ijt}}{\partial \mathbf{w}^{(z)}_{it}} \mathrm{d}\mathbf{w}^{(z)}_{it}$

3 Empirical Models, Econometric Strategy and Data

3.1 Empirical Models

We presented our conceptual framework in Section 2 using generic functions. For the following, we assume that the yields of the different crops are quadratic functions of fertilizer ($k = 1$) and pesticide ($k = 2$) applications such that:

$$y_{ijt} = \boldsymbol{\alpha}_j(\mathbf{w}_{it}) - \frac{1}{2} \sum_{k=1}^{2} \sum_{l=1}^{2} \boldsymbol{\gamma}^{-1}_{jkl}(\mathbf{w}_{it})[\boldsymbol{\beta}_{jk}(\mathbf{w}_{it}) - x_{ijkt}][\boldsymbol{\beta}_{jl}(\mathbf{w}_{it}) - x_{ijlt}]. \tag{5}$$

Femenia and Letort (2016) proposed this specification to facilitate agronomic interpretations. The term $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$ can be interpreted as the maximum yield of crop j in the sample. Similarly, $\boldsymbol{\beta}_{jk}(\mathbf{w}_{it})$ represents the quantity of input k required to achieve this maximum yield. Matrix $\Gamma_j(\mathbf{w}_{it}) \equiv [\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it})]$ is a symmetric matrix representing crop j's yield responses to variable input applications. Its elements correspond to the crop-specific productivity of pesticides and fertilizers. Specifically, $\boldsymbol{\gamma}_{j11}(\mathbf{w}_{it})$ is the – first-order – marginal productivity of fertilizers on crop j (assuming no productive interaction between fertilizers and pesticides), while $\boldsymbol{\gamma}_{j22}(\mathbf{w}_{it})$ is the marginal productivity of pesticides on j. The interaction term $\boldsymbol{\gamma}_{j12}(\mathbf{w}_{it})$ captures the relations of substitution or complementarity between fertilizers and pesticides. A positive $\boldsymbol{\gamma}_{j12}(\mathbf{w}_{it})$ implies a substitution between the two inputs, while a negative $\boldsymbol{\gamma}_{j12}(\mathbf{w}_{it})$ implies cooperation. The production function is strictly concave since the matrix $\Gamma_j(\mathbf{w}_{it})$ is positive definite.[10] Our specification of the production function differs from Femenia and Letort (2016) by allowing the parameters to depend on weather

[10]With two variable inputs, the concavity of the production function is verified since $\boldsymbol{\gamma}^{-1}_{j11}(\mathbf{w}_{it})\boldsymbol{\gamma}^{-1}_{j22}(\mathbf{w}_{it}) - \boldsymbol{\gamma}^{-2}_{j12}(\mathbf{w}_{it})) > 0$.

conditions (Kaminski et al., 2013). The sets of parameters $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$, $\boldsymbol{\beta}_{jk}(\mathbf{w}_{it})$ and $\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it})$ are the structural parameters in our model. They are assumed to be known from the farmers for each crop and variable input.

The resolution of equation (1) with (5) leads to the optimal demand function for input k on crop j:

$$x^*_{ijkt} = \boldsymbol{\beta}_{jk}(\mathbf{w}_{it}) - \frac{p^x_{ikt}\boldsymbol{\gamma}^{-1}_{jk}(\mathbf{w}_{it}) - p^x_{ilt}\boldsymbol{\gamma}^{-1}_{j12}(\mathbf{w}_{it})}{p^y_{ijt-1}(\boldsymbol{\gamma}^{-1}_{j11}(\mathbf{w}_{it})\boldsymbol{\gamma}^{-1}_{j22}(\mathbf{w}_{it}) - \boldsymbol{\gamma}^{-2}_{j12}(\mathbf{w}_{it}))}, \tag{6}$$

with $k \neq l$. Plugging back the optimal input applications (6) into (5) leads to the optimal yield for crop j:

$$y^*_{ijt} = \boldsymbol{\alpha}_j(\mathbf{w}_{it}) - \frac{1}{2}\frac{(p^x_{1t})^2\boldsymbol{\gamma}^{-1}_{j11}(\mathbf{w}_{it}) + (p^x_{2t})^2\boldsymbol{\gamma}^{-1}_{j22}(\mathbf{w}_{it}) - 2p^x_{1t}p^x_{2t}\boldsymbol{\gamma}^{-1}_{j12}(\mathbf{w}_{it})}{(p^y_{ijt-1})^2(\boldsymbol{\gamma}^{-1}_{j11}(\mathbf{w}_{it})\boldsymbol{\gamma}^{-1}_{j22}(\mathbf{w}_{it}) - \boldsymbol{\gamma}^{-2}_{j12}(\mathbf{w}_{it}))}. \tag{7}$$

The optimal yield is a function of weather through parameters $\boldsymbol{\alpha}_{jk}(\mathbf{w}_{it})$ and $\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it})$. Parameters $\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it})$ are shared between the yield and input demand functions of the structural model composed of equations (6) and (7). This model is both primal and dual. The use of duality theory here allows us to determine the impacts of weather on input productivity (through $\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it})$) while still capturing the direct impact of weather on input demand in the *primal* part of the model (through $\boldsymbol{\beta}_{jk}(\mathbf{w}_{it})$) and on yields (through $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$). To our knowledge, the addition of price variations (multiplied by weather variations) is an original feature of our framework that ultimately allows for separating the direct effects of weather on plant growth from farmers' adaptation effects.

The defined terms in relations (5), (6) and (7) are functions of the weather during the growing season. As in Deschênes and Greenstone (2007), we specify a quadratic relationship between yields and both growing degree-days (GDD) and growing total precipitation (GTP) such that:

$$\boldsymbol{\alpha}_j(\mathbf{w}_{it}) = \alpha^0_j + \alpha^{GDD}_j GDD_{ijt} + \alpha^{GDD^2}_j GDD^2_{ijt} + \alpha^{GTP}_j GTP_{it} + \alpha^{GTP^2}_j GTP^2_{it}. \tag{8}$$

We extend this specification to variable input requirements and productivity:

$$\boldsymbol{\beta}_{jk}(\mathbf{w}_{it}) = \beta^0_{jk} + \beta^{GDD}_{jk} GDD_{ijt} + \beta^{GDD^2}_{jk} GDD^2_{ijt} + \beta^{GTP}_{jk} GTP_{it} + \beta^{GTP^2}_{jk} GTP^2_{it}, \tag{9}$$

$$\boldsymbol{\gamma}_{jkl}(\mathbf{w}_{it}) = \gamma^0_{jkl} + \gamma^{GDD}_{jkl} GDD_{ijt} + \gamma^{GDD^2}_{jkl} GDD^2_{ijt} + \gamma^{GTP}_{jkl} GTP_{it} + \gamma^{GTP^2}_{jkl} GTP^2_{it}. \tag{10}$$

This decomposition of the structural parameters allows us to specifically capture the different channels through which climate affects crop profits.

3.2 Econometric Strategy

Ultimately, our empirical approach consists of estimating the structural models composed of equations (6) and (7) for the different crops and comparing the estimates with reduced-form models that are used in the weather approach literature (e.g Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007). These reduced-form models are presented in Appendix 7.1. In both cases, we use abnormal variations in weather conditions as independent variables. One difference between our structural approach and the reduced-form models from the weather approach is that we also use (individual) crop-specific price variations to distinguish farmers' adaptation effects from direct weather effects.[11]

Specifically, we estimate the structural model composed of equations (6) and (7) for wheat ($j = 1$), barley ($j = 2$) and rapeseed ($j = 3$). Indeed, because each crop has a specific production function $f_j(\mathbf{x}_{ijt}; \mathbf{w}_{it})$, they are likely to react differently to similar weather fluctuations. We estimate for crop j:

$$y_{ijt} = \boldsymbol{\alpha}_j(\mathbf{w}_{it}) - \boldsymbol{\delta}_{j11}(\mathbf{w}_{it})\frac{(p^x_{1t})^2}{2(p^y_{ijt-1})^2} - \boldsymbol{\delta}_{j22}(\mathbf{w}_{it})\frac{(p^x_{2t})^2}{2(p^y_{ijt-1})^2} + \boldsymbol{\delta}_{j12}(\mathbf{w}_{it})\frac{p^x_{1t}p^x_{2t}}{(p^y_{ijt-1})^2} + \omega^y_{ij} + \vartheta^y_{jt} + \mu^y_{ijt}, \quad (11)$$

and

$$x_{ijkt} = \boldsymbol{\beta}_{jk}(\mathbf{w}_{it}) - \boldsymbol{\delta}_{jkk}(\mathbf{w}_{it})\frac{p^x_{kt}}{p^y_{ijt-1}} + \boldsymbol{\delta}_{jkl}(\mathbf{w}_{it})\frac{p^x_{lt}}{p^y_{ijt-1}} + \omega^x_{ijk} + \vartheta^x_{jkt} + \mu^x_{ijkt}, \quad (12)$$

with $\boldsymbol{\delta}_{jkl}(\mathbf{w}_{it}) = \frac{\gamma^{-1}_{jkl}(\mathbf{w}_{it})}{\gamma^{-1}_{j11}(\mathbf{w}_{it})\gamma^{-1}_{j22}(\mathbf{w}_{it}) - \gamma^{-2}_{j12}(\mathbf{w}_{it})}$, which are shared between equations (11) and (12).[12] In this case, a smaller $\boldsymbol{\delta}_{jkk}(\mathbf{w}_{it})$ implies that farmers use more input k when the input-output price ratio increases, which means that input k becomes more productive with $\mathbf{w}_{it}$ (i.e. $\boldsymbol{\gamma}_{jkk}(\mathbf{w}_{it})$ increases). A positive $\boldsymbol{\delta}_{jkl}(\mathbf{w}_{it})$ implies that fertilizers and pesticides are substitute inputs. We decompose $\boldsymbol{\delta}_{jkl}(\mathbf{w}_{it})$ as $\delta^0_{jkl} + \delta^{GDD}_{jkl}GDD_{ijt} + \delta^{GDD^2}_{jkl}GDD^2_{ijt} + \delta^{GTP}_{jkl}GTP_{it} + \delta^{GTP^2}_{jkl}GTP^2_{it}$. We split the error terms such that (i) ω^y_{ij} and ω^x_{ijk} are the farm FE (capturing time-invariant heterogeneity such as soil quality), (ii) ϑ^x_{jkt} and ϑ^y_{jt} represent the temporal FE (capturing common annual shocks

[11] Appendix 7.2 provides the coefficients of variation of individual prices in the whole sample as well as per year (with or without centring the price variables on the individual means), confirming substantial heterogeneity of crop prices among farmers. Indeed, the coefficients of variation per year represent on average 44.7%, 51.8% and 54.3% of the coefficients of variation for the whole sample. Thus, only the half of the variations can be attributed to temporal (contextual) effects, which will be captured hereafter by temporal FE. The remaining variations can be attributed to individual heterogeneity in prices. This interpretation is also supported by the coefficients of variation for the centered variables: about half of the coefficients are greater than one (which indicates higher variation between farms than between years in our unbalanced panel).

[12] The concavity of the production function is then verified since $\boldsymbol{\delta}_{j11}(\mathbf{w}_{it})\boldsymbol{\delta}_{j22}(\mathbf{w}_{it}) - \boldsymbol{\delta}^2_{j12}(\mathbf{w}_{it})) > 0$.

such as changes in public policies and market contexts) and (iii) μ^x_{ijkt} and μ^y_{ijt} are the remaining error assumed to have white noise properties. Given the potential correlation between the error terms of these equations, we estimate these structural models using estimators from seemingly unrelated equations (SUR).[13]

3.3 Data Sources and Summary Statistics

We use an unbalanced panel of farms located in the French region of *Meuse* observed between 2006 and 2012. *Meuse* is a rainfed agricultural NUTS3 region located in north east France and specialized in crop production. The agriculture in *Meuse* is representative of the agriculture in north east France (and the *Paris Basin* in general), which is mainly orientated towards cereals and industrial crops and where farmers use rather intensive cropping practices. The database originates from the Meuse Management Center local accounting agency (*Centre de Gestion de la Meuse*).[14] This database gives information about output yields and prices and, contrary to most other economic databases, provides variable input expenditure per crop. The sample is composed of 296 crop farms remaining in the database for an average of 3.73 years. Together, these farms occupy about 31.09% of the whole useful agricultural area of *Meuse*. Although some farms cultivate peas, corn and sunflower, these are fairly marginal crops in our sample. By contrast, all the farms grow wheat ($j = 1$), barley ($j = 2$), and rapeseed ($j = 3$). We compute the variable input quantities applied by crop in constant €/ha dividing the variable input expenses per hectare by the regional input index provided by the French Department of Agriculture (*Agricultural Means of Production Purchasing Price Index*). We provide the summary statistics on prices (deflated by the national consumption price index), yields and inputs uses for these three crops in Table 2. On average, the highest yields are achieved for wheat, the highest prices are paid for rapeseed and barley requires fewer inputs than wheat or rapeseed. Wheat and rapeseed are perceptibly more profitable than barley, which is rather used as an intermediary crop in the usual crop rotation found in *Meuse*.[15] The aggregated profit per hectare ranges from €230.90 to €1672.20, while the profits of specific crops are sometimes negative and go up to €2160.13.

We collected the weather information using observed daily municipal weather conditions provided by *Météo France* for the whole period.[16] We computed the GDD as the sum of temperatures

[13] The models could be estimated equation-by-equation using standard ordinary least squares but, even if these estimates were consistent, they are generally not as efficient as SUR estimates (Zellner, 1962).

[14] This original database has been used by several studies (e.g. Boussemart et al., 2011; Carpentier and Letort, 2012; Bayramoglu and Chakir, 2016; Femenia and Letort, 2016).

[15] The typical rotation sequence in *Meuse* is Rapeseed-Wheat-(Wheat-)Barley. Barley is used to restore soil fertility.

[16] The finest level of location available in our dataset is the municipality (there were about 500 municipalities in *Meuse* during our study period). The weather information was provided for 8 km x 8 km *SAFRAN* units. Each unit

Table 2: Descriptive statistics (N=1,104)

Variables	Mean	S.D.	Min	Max
GDD_1 (for wheat and barley)	2512.20	82.30	2292.00	2730.00
GDD_3 (for rapeseed)	2444.19	92.98	2190.00	2692.00
GTP	434.90	89.33	250.40	578.10
Aggregated profit (€/ha)	847.59	215.76	230.90	1672.20
Wheat profit (€/ha)	859.76	281.09	-49.65	2033.53
Barley profit (€/ha)	653.35	237.24	17.56	1678.01
Rapeseed profit (€/ha)	811.24	277.44	-5.72	2160.13
Wheat yield (100kg/ha)	70.88	10.49	31.49	106.96
Barley yield (100kg/ha)	64.30	11.10	20.00	90.76
Rapeseed yield (100kg/ha)	33.59	6.60	7.96	50.26
Wheat price (€/100kg)	16.49	3.49	3.82	28.32
Barley price (€/100kg)	14.63	3.61	6.55	30.82
Rapeseed price (€/100kg)	35.05	6.32	11.93	63.81
Fertilizers for wheat (constant €/ha)	123.04	28.14	3.79	210.16
Fertilizers for barley (constant €/ha)	106.85	25.00	3.15	211.05
Fertilizers for rapeseed (constant €/ha)	122.30	29.81	3.55	247.84
Pesticides for wheat (constant €/ha)	160.10	44.25	8.45	377.63
Pesticides for barley (constant €/ha)	152.51	45.69	34.13	392.07
Pesticides for rapeseed (constant €/ha)	220.88	52.25	63.24	423.47
Fertilizers price (index)	1.17	0.21	0.91	1.51
Pesticides price (index)	0.98	0.03	0.94	1.01
Wheat area (%)	0.45	0.10	0.02	0.80
Barley area (%)	0.24	0.08	0.01	0.51
Rapeseed area (%)	0.31	0.09	0.02	0.95

above a threshold from the 1^{st} of March to the 31^{st} of August (which corresponds to the growing season in *Meuse*), accounting for all positive temperatures for wheat and barley (noted GDD_1) and for temperatures higher than 6°C for rapeseed (noted GDD_3).[17] We computed GTP as the sum of the precipitation during the growing season. Table 2 displays the descriptive statistics of GDD and GTP for our sample. It notably highlights the fact that GTP displays greater variability than GDD. Table 8 in the Appendix provides the coefficients of variation for GDD and GTP for the whole sample and per year (with or without centering on the individual variable means). It shows that about two thirds of the GDD variation is due to variations among individuals rather than to annual variations (resp. one third for variations in precipitation). Provided that the heterogeneity of prices between individuals and years is sufficient (see Table 7 in the Appendix), our identification strategy based on variations in both price and weather – conditionally on individual and annual FE – should hold. Also, because the correlations between prices and the weather variables are low (see Table 9 in the Appendix), our estimates should not suffer from multicollinearity issues.

4 Results

In Section 4.1 we present the results from reduced-form estimations when profits and yields are the dependent variables as in Deschênes and Greenstone (2007) and Schlenker and Roberts (2009). In Section 4.2, we compare these estimates with those from our structural estimations. We also examine how farmers proceed to agrochemical input adjustments and how it affects crop yields and profits.

4.1 Reduced-form Estimations

Table 10 in the Appendix presents the results of the reduced-form estimations of the farmers' profits on weather conditions during the growing season *à la* Deschênes and Greenstone (2007). It also presents equivalent results when crop yields are the dependent variables, in the spirit of

covers on average 4 municipalities. We thus attribute weather information at the municipal level using overlapping GIS coordinates. We then attribute weather conditions to farm i using the municipality in which farm i has its headquarters. Overall, the sample therefore covers 197 municipalities, i.e. about 39% of the *Meuse* municipalities appear at least once in our panel. Correcting for its unbalanced structure, on average 33% of the *Meuse* municipalities appear each year in our sample.

[17] We use the most commonly used formula to compute GDD, i.e. $GDD = T_{mean} - T_{base}$ for all $T_{mean} < 31.66$°C (Kolstad and Moore, 2020) and $T_{base} = 0$°C for wheat and cereals (resp. $T_{base} = 6$°C for rapeseed). This GDD formula is used by Deschênes and Greenstone (2007) in particular. An alternative specification of the effects of temperature on yields would be to distinguish beneficial GDD from heating degree-days (e.g. Lobell et al., 2013), i.e. the number of days whose average temperature exceeds a threshold (typically 29°C or more; e.g. Kolstad and Moore, 2020). We did not process to such a specification as the observed maximum daily temperature over the whole period is 28.4°C in our sample. The average temperature over the whole sample is 9.7°C.

Schlenker and Roberts (2009). The reduced-form estimates suggest that profits decrease with GDD and GTP following a convex relationship. Figure 6 in the Appendix displays such a non-linear relationship between profits and weather: while a marginal increase in GTP or GDD first reduces crop profits, high GDD and GTP values benefit farmers. The amplitudes of the responses are heterogeneous among crops but, overall, comparable to those found by Deschênes and Greenstone (2007).[18]

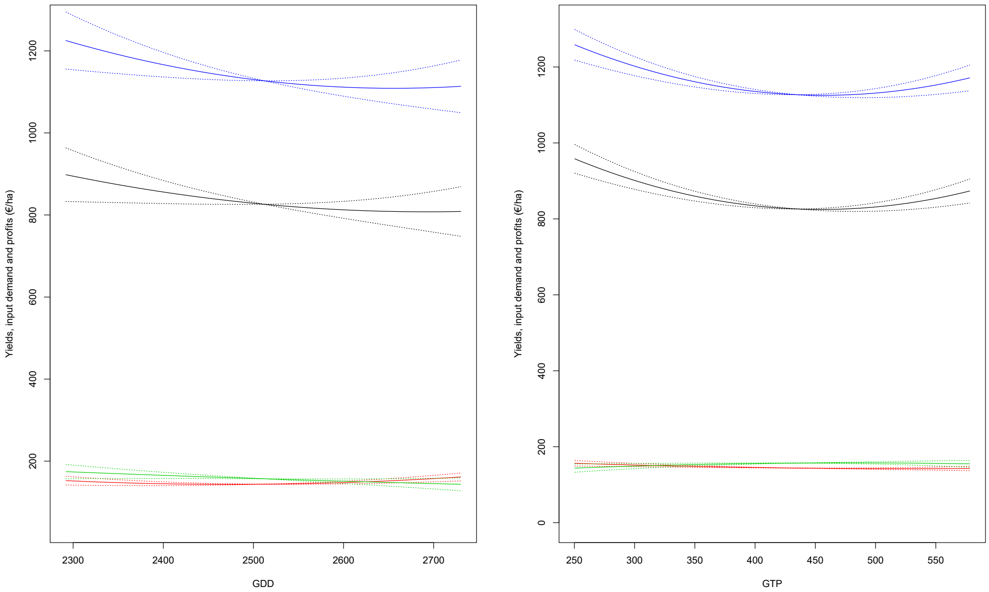
The effects of weather on crop yields are lower and flatter than those on crop profits (see Figure 6 in the Appendix). In particular, crop yields seem insensitive to GDD. Also, increasing GTP by one S.D. increases yields by only 0.5%, 0.7% and 0.3% for wheat, barley and rapeseed respectively (all these values are non-significantly different from zero), i.e. about five to fifteen times less than for profits. This result implies that a large proportion of weather variation impacts affect farmers' profits elsewhere than on the production side. In other words, this result suggests that farmers modify their variable input applications to cope with higher precipitation and temperatures (Mendelsohn and Massetti, 2017). This adaptation strategy could explain why wheat may become slightly more profitable with higher temperatures while its yields reduce (Figure 6). However, even if our results suggest adaptation, the use of reduced-form estimations prevents us from determining the formal adaptation strategy and its consequences. We investigate the mechanisms at stake in the next section.

4.2 Structural Estimations

Comparison between reduced-form and structural estimates Figure 2 presents the estimated responses of profits, yields and input applications for wheat on the observed weather distribution. Figures 3 and 4 exhibit similar relationships for barley and rapeseed. All these relationships are computed using the structural estimates (provided in Appendix 7.5), which, after verification, respect the properties defined for $f_j(\mathbf{x}_{ijt}; \mathbf{w}_{it})$ in Section 2.1.[19] While the precision of the structural estimates varies greatly among the set of parameters, the precision of the responses in Figures 2, 3 and 4 are satisfying. Table 3 presents the elasticities of these responses at the average point when using reduced-form or structural estimates. The estimated elasticities are not significantly different

[18] The main difference is that Deschênes and Greenstone (2007) found a positive concave relationship for both GDD and GTP, while we find a negative convex relationship (indicating somehow that our sample differs from US farmers).

[19] Computations at the average points show that both fertilizers and pesticides respect the usual non-decreasing and concave relationship with yields for the three crops, i.e. $\delta^0_{jkl} + \delta^{GDD}_{jkl} G\bar{D}D_{ijt} + \delta^{GDD^2}_{jkl} G\bar{D}D^2_{ijt} + \delta^{GTP}_{jkl} G\bar{T}P_{it} + \delta^{GTP^2}_{jkl} G\bar{T}P^2_{it} > 0$ and $\boldsymbol{\delta}_{j1}(\bar{\mathbf{w}}_{it})\boldsymbol{\delta}_{j2}(\bar{\mathbf{w}}_{it}) - \boldsymbol{\delta}^2_{j12}(\bar{\mathbf{w}}_{it}) > 0 \; \forall j \in [1;3]$ and $\forall (k,l) \in [1;2]^2$ (which is equivalent to $\boldsymbol{\gamma}^{-1}_{j1}(\bar{\mathbf{w}}_{it})\boldsymbol{\gamma}^{-1}_{j2}(\bar{\mathbf{w}}_{it}) - \boldsymbol{\gamma}^{-2}_{j12}(\bar{\mathbf{w}}_{it}) > 0 \; \forall j \in [1;3]$ and $\forall (k,l) \in [1;2]^2$, see Section 3.1). Because $\boldsymbol{\delta}_{j12}(\bar{\mathbf{w}}_{it}) > 0 \; \forall j \in [1;3]$, our estimates indicate that fertilizers and pesticides are substitutes at the average points.



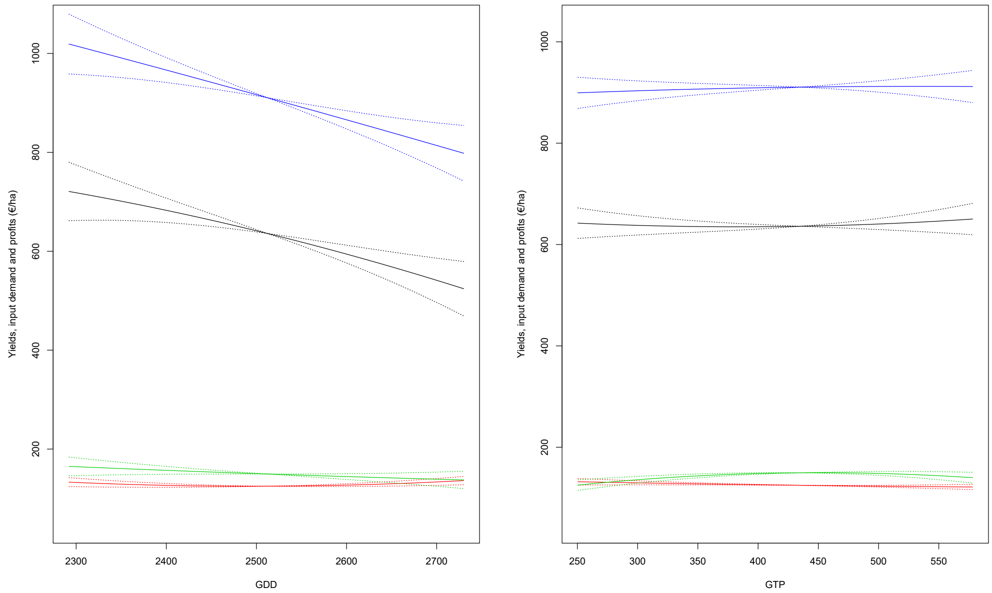
(a) Growing Degree-Days

(b) Growing Total precipitation

Figure 2: Changes in wheat profits, yields and input applications on weather during the growing season using structural estimates. *Fertilizer applications (red lines); Pesticide applications (green lines); Yields (blue lines); Profits (black lines). The 90% confidence intervals are computed using the delta method and shown with dashed lines. Yields and input applications are expressed in €/ha, multiplying the estimated quantities by average prices.*

in the two models, notably because reduced-from estimations lead to imprecise estimates. For example, while reduced-from estimations fail to identify a statistically significant elasticity for GDD, five out of these six elasticities are significantly different from zero using the structural estimates. The better efficiency of our structural estimates is likely due to four joint factors: (i) the use of price variations in addition to weather variations, (ii) the structure of the model in itself, which provides restriction on the estimates, (iii) the use of three equations instead of one, the variations in fertilizer and pesticide applications providing additional information for better identification and, related to the last two points, (iv) the mobilization of the SUR estimation method instead of the usual OLS. In addition to being more precise, the structural estimations provide larger average elasticities relative to GDD (in absolute values), suggesting that elasticities using reduced-form estimates are biased downward. However, structural and reduced-form estimates indicate both that (i) barley is the crop that is most affected by GDD, (ii) wheat is the least affected by GDD, (iii) GDD elasticities are larger for profits than for yields and (iv) the elasticities on GTP are closer to zero at the average points.

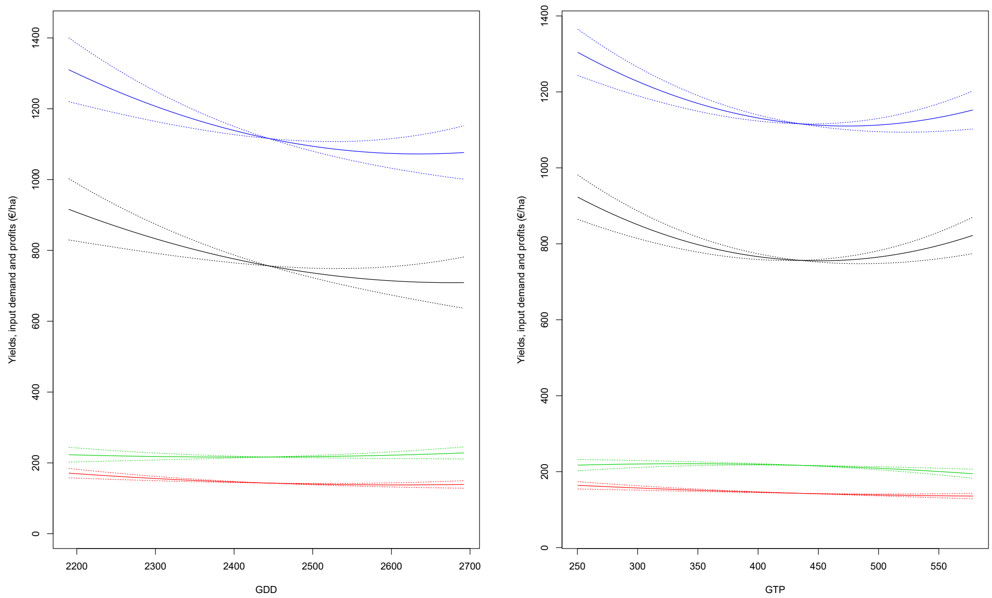
In more detail, comparing Figure 6 (in Appendix 7.3) with Figures 2, 3 and 4 confirms that the responses of crop profits to weather are flatter with the structural estimates but that crop yield



(a) Growing Degree-Days

(b) Growing Total precipitation

Figure 3: Changes in barley profits, yields and input applications on weather during the growing season using structural estimates. *Fertilizer applications (red lines); Pesticide applications (green lines); Yields (blue lines); Profits (black lines). The 90% confidence intervals are computed using the delta method and shown with dashed lines. Yields and input applications are expressed in €/ha, multiplying the estimated quantities by average prices.*



(a) Growing Degree-Days

(b) Growing Total precipitation

Figure 4: Changes in rapeseed profits, yields and input applications on weather during the growing season using structural estimates. *Fertilizer applications (red lines); Pesticide applications (green lines); Yields (blue lines); Profits (black lines). The 90% confidence intervals are computed using the delta method and shown with dashed lines. Yields and input applications are expressed in €/ha, multiplying the estimated quantities by average prices.*

responses are generally steeper. Higher GDD decrease the profits and yields for the three crops but with differing amplitudes. For example, the elasticities of barley profits and yields relative to GDD are -1.73% and -1.39% respectively, while they are equal to -0.59% and -0.56% for wheat (see also Table 3). Once again, precipitation during the growing season has a more limited impact on crop profits and yields. However, the estimated elasticities confirm that barley differs from the other crops with small beneficial impacts of GTP on profits and yields. Interestingly, while barley yield has a concave relationship with GTP, the relationship between barley profit and GTP is convex: for high GTP deviations, barley yield reduces while barley profit increases. This suggests that farmers adapt to high precipitation levels by reducing their variable input applications on barley. However, except for high deviations from normal weather conditions, the responses of crop profits and yields are in fact remarkably parallel.

Table 3: Elasticities of profits, yields and input applications depending on growing degree-days and growing total precipitation.

	Reduced-form estimations			**Structural estimations**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
$\varepsilon_{GDD}^{E(\pi_j)}$	**-0.34**	**-1.37**	**-0.46**	**-0.59**	**-1.73 *****	**-1.23 *****
	[-2.56:1.86]	[-4.39;1.65]	[-2.75;1.84]	[-1.26;0.07]	[-2.48:-0.97]	[-1.96;-0.49]
$\varepsilon_{GTP}^{E(\pi_j)}$	**0.18**	**0.38**	**-0.17**	**-0.06**	**0.03**	**-0.07**
	[-0.13;0.48]	[-0.04;0.80]	[-0.51;0.17]	[-0.14;0.01]	[-0.06;0.12]	[-0.17;0.03]
$\varepsilon_{GDD}^{y_j}$	**-0.52**	**-0.72**	**-0.70**	**-0.56 ***	**-1.39 *****	**-1.00 *****
	[-5.29;4.25]	[-7.07;5.62]	[-8.94;7.53]	[-1.11;-0.02]	[-1.95;-0.84]	[-1.56;-0.45]
$\varepsilon_{GTP}^{y_j}$	**-0.01**	**-0.00**	**-0.05**	**-0.05**	**0.02**	**-0.12 ****
	[-0.67.0.65]	[-0.88;0.87]	[-1.28;1.18]	[-0.11,0.01]	[-0.05;0.08]	[-0.19;-0.04]
$\varepsilon_{GDD}^{x_{j1}}$	**-**	**-**	**-**	**0.37**	**0.15**	**-1.07 *****
				[-0.28;1.01]	[-0.47;0.77]	[-1.67;-0.47]
$\varepsilon_{GTP}^{x_{j1}}$	**-**	**-**	**-**	**-0.10 ****	**-0.10 ****	**-0.24 *****
				[-0.18;-0.03]	[-0.18;-0.03]	[-0.32;-0.16]
$\varepsilon_{GDD}^{x_{j2}}$	**-**	**-**	**-**	**-1.12 ***	**-1.04**	**0.12**
				[-2.10;-0.15]	[-2.12;0.02]	[-0.27;0.52]
$\varepsilon_{GTP}^{x_{j2}}$	**-**	**-**	**-**	**0.06**	**0.06**	**-0.18 *****
				[-0.05;0.18]	[-0.08;0.19]	[-0.27;-0.09]

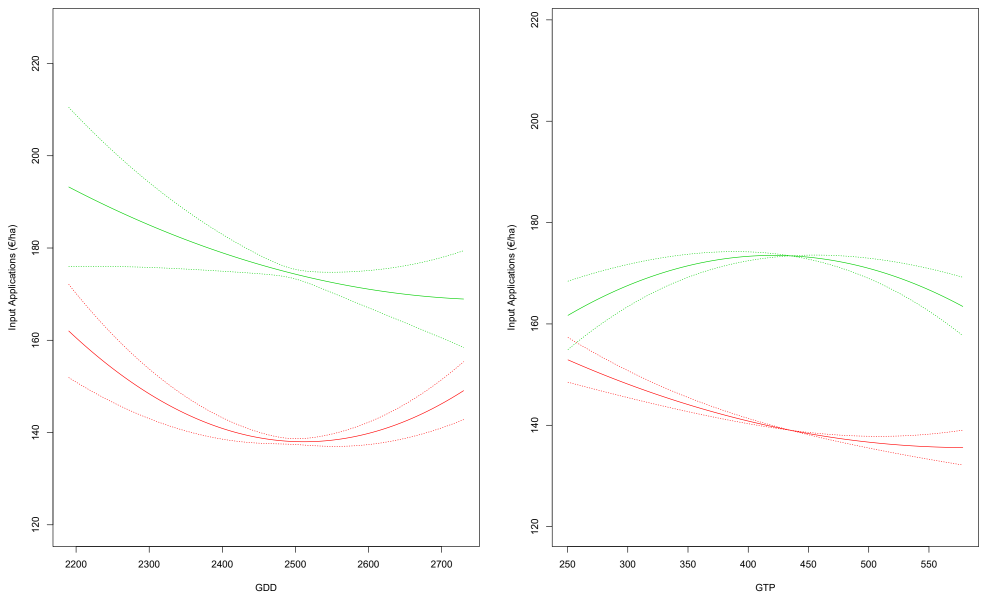
*Elasticities are computed at sample mean values. The 90% confidence intervals are computed using the delta method and displayed within brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.* x_{j1} *(resp.* x_{j2}*) are the applications of fertilizers (resp. pesticides) per hectare.*

Agrochemical input adjustments Figure 5 shows changes in fertilizer and pesticide applications on weather conditions using the aggregated responses over the three crops. The responses are more precisely estimated for fertilizers than for pesticides. This is coherent with the literature on pesticide applications (e.g. Bareille and Gohin, 2020; Femenia and Letort, 2016): farmers apply pesticides not only for their beneficial productive effects but also for their beneficial impacts on risk reduction. Overall, farmers tend to decrease pesticide applications when GDD increases. This reduction is mainly driven by wheat and barley (see Table 3). On the contrary, pesticide applications on rapeseed – which is already the most pesticide-intensive crop (see Table 2) – slightly increase with GDD. A detailed analysis of the structural estimates (Table 11 in Appendix 7.5) using relation (6) allows us to better understand the mechanisms at stake. First, GDD decreases the quantity of pesticides $\boldsymbol{\beta}_{j2}(\mathbf{w}_{it})$ required to attain the maximum yields $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$ for all crops, allowing for pesticide-savings at the margin. Second, GDD increases the productivity of pesticides for all crops (see the negative $\delta_{j2}(GDD_{it})$ in Appendix 7.5), which leads farmers to apply more pesticides *ceteris paribus*. Moreover, GDD also reduces (resp. increases) the substitution between fertilizers and pesticides for wheat and barley (resp. rapeseed, see the $\delta_{j12}(\mathbf{w}_{it})$ at the average points), which encourages farmers to apply less (resp. more) pesticides *ceteris paribus*. Comparing the estimates among the three crops suggests that farmers increase their pesticide applications on rapeseed at the average points due to the increased substitution between inputs induced by higher GDD (and vice-versa for wheat and barley).

The effects of GTP on pesticide applications are non-linear (Figure 5b). Pesticide applications present a positive concave relationship with GTP for wheat and barley (Figures 2b and 3b) but a negative concave relationship for rapeseed (Figure 4b). For high GTP deviations, pesticide applications are reduced on all crops. A detailed analysis of the structural estimates (Table 11 in the Appendix) suggests that this reduction is linked to a reduced productivity of pesticides for rapeseed ($\delta_{322}(\mathbf{w}_{it})$ increases with GTP) but a beneficial effect on input requirements for cereals ($\boldsymbol{\beta}_{12}(\mathbf{w}_{it})$ and $\boldsymbol{\beta}_{22}(\mathbf{w}_{it})$ increase with high GTP).[20] For small GTP deviations, the beneficial effects on $\boldsymbol{\beta}_{j2}(\mathbf{w}_{it})$ for wheat and barley are offset by the increased productivity of pesticides (see Table 11), which lead to limited increases in pesticide applications on cereals at the margin (see Table 3).

Figure 5 shows that fertilizer applications have a negative convex relationship with GDD and GTP. The curvature is stronger for GDD with a reduction of fertilizer applications when GDD is low before an increase when temperatures increase. On the contrary, fertilizer applications reduce as GTP varies from the minimum to the maximum observed level. In fact, the stronger non-linearity effect of GDD on fertilizer applications is partly due to a composition effect: the effects are heterogeneous among crops for GDD (increases for wheat and barley at the average point but

[20] In detail, a high positive deviation of GTP (i) decreases (resp. increases) the quantity of pesticides $\boldsymbol{\beta}_{j2}(\mathbf{w}_{it})$ required to attain the maximum yields $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$ for wheat and barley (resp. rapeseed), (ii) increases (resp. decrease) pesticide productivity $\boldsymbol{\gamma}_{j2}(\mathbf{w}_{it})$ for barley and wheat (resp. rapeseed) and (iii) reduces the substitution between fertilizers and pesticides for all crops.



(a) Growing Degree-Days (b) Growing Total precipitation

Figure 5: Aggregated changes in input applications on weather during the growing season using structural estimates. *Fertilizer applications (red lines); Pesticide applications (green lines). The 90% confidence intervals are computed using the delta method and shown with dashed lines. Input applications are expressed in € by multiplying the estimated quantities by the average prices in our sample. The aggregation is carried out by weighting the crop-specific input applications using observed crop shares.*

reductions for rapeseed) while fertilizer applications reduce for all crops with GTP (Table 3). A detailed analysis of the structural estimates suggest that the effects of GDD are mainly driven by the effect on $\boldsymbol{\beta}_{j1}(\mathbf{w}_{it})$ (i.e. the levels required to attain the maximum yields $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$), which increase for wheat and barley but decrease for rapeseed (in line with the estimated elasticities in Table 3). The effects of GTP on fertilizer applications, which decreases for all crops (see Table 3), are mainly driven by reduced substitution between inputs for all crops ($\boldsymbol{\delta}_{j12}(\mathbf{w}_{it})$ decreases for all crops).

These detailed results on changes in fertilizer and pesticide applications call for comment. First, these results indicate that farmers do adapt in response to weather fluctuations. These adjustments primarily lead to input-savings, which partly compensate for the potential impacts of weather on yields. Looking for example at the effect of GTP on rapeseed, a 1% increase in GTP reduces wheat revenues by 0.12%*33.59*35.05 = 1.41 €/ha while the negative impacts on rapeseed profits is limited at 0.07%*811.24 = 0.57 €/ha.[21] In other words, farmers cushion about 60% of the negative impact of a 1% increase in GTP on rapeseed. Indeed, the input-savings amount on average to

[21] The figures are computed using average levels in our sample (Table 2) and estimated average elasticities (Table 3).

0.24%*122.3*1.17 = 0.34 €/ha for fertilizers and 0.18%*220.88*0.98 = 0.39 €/ha for pesticides. Similarly, a 1% increase in GTP reduces wheat revenues by 0.66 €/ha, while wheat profits only decrease by 0.52 €/ha (i.e. about 20% less) as fertilizer applications decrease by 0.14 €/ha.[22] These effects on the potential of input-savings to reduce the negative impacts of weather on yields have been already suggested by Mendelsohn and Massetti (2017) for example. Jagnani et al. (2021) have verified such effects on maize. To our knowledge, this paper provides the first analysis giving evidence of such effects on wheat, barley and rapeseed. Second, GDD and GTP increase the productivity of the inputs, with two notable exceptions: (i) the productivity of fertilizers on wheat, which decreases with GDD and (ii) the productivity of pesticides on rapeseed, which decreases with GTP. This result, which would incite farmers to put more inputs, is however balanced by the overall increased effectiveness of the inputs (i.e., the negative $\boldsymbol{\beta}_{j2}(\mathbf{w}_{it})$ allow for reducing the required amount of inputs to reach the maximum yields). Overall, GDD has a greater effect on input productivity than GTP. Third, temperatures greatly impact substitution between fertilizers and pesticides, which partly explains how pesticides change along the temperature distribution. Indeed, GDD decreases the substitution between inputs for wheat and barley (incentivizing to reduction in pesticide use on cereals) but increases substitution for rapeseed (encouraging greater pesticide applications), which perfectly coincides with the pesticide uses in Figures 2, 3 and 4. Finally, our structural estimates suggest that the mechanisms at stake are (almost) always identical for wheat and barley,[23] which is consistent with the fact they are both cereals, thus providing evidence of the robustness of our results.

5 Simulations of Climate Change Impacts

In this section, we simulate the impacts of climate change on the agricultural sector in *Meuse* based upon the regional RCP 4.5 scenario in 2050. We use projections from the ALADIN (*Aire Limitée Adaptation dynamique Développement InterNational*) regional climate model from Météo-France's *Centre National de Recherches Météorologiques.*[24] There are 92 grid squares of 8 km x 8 km in *Meuse* and we compute the averages over these grids for 2050. Over the growing season, ALADIN predicts that the temperatures will increase on average by 1.06°C in 2050 compared to the 2006-2012 period, with $GDD_1 = 2,707$ and $GDD_3 = 2,649$ (i.e. higher by 7.8% and 8.4%

[22] Pesticide applications increase by 0.09 €/ha for a 1% increase in GTP but the elasticity is not significantly different from zero.

[23] The single difference is that, as previously mentioned, GDD increases the productivity of fertilizers for barley while reducing it for wheat.

[24] Data available at: https://www.umr-cnrm.fr/spip.php?article125&lang=en

respectively). ALADIN models show also that *Meuse* will become wetter with an expected average GTP of 545.6 (i.e. higher by 25.5% compared to the 2006-2012 period). These points belong to our range of observations in our 2006-2012 sample.

Table 4 shows expected profits, yields and input applications for each crop using our structural estimates and expected weather conditions in 2050 under the RCP 4.5 scenario, holding all the remaining elements constant.[25] These levels correspond to the levels of the estimated responses in Figures 2 to 4 under RCP 4.5 scenario conditions. We decompose changes in GDD and GTP before simulating the combined effects. Table 4 also presents changes compared to the average (initial) values in our sample. In accordance with the rest of the literature, we find that the higher temperatures should reduce crop profits and yields. Barley is particularly affected by the increased temperatures as yields (resp. profits) reduce by 11.01% on average (resp. 15.51 %). Reductions affecting wheat and rapeseed are statistically non-significant. On the contrary, the higher precipitation increase both wheat and rapeseed profits, while barley remains largely unaffected. As a consequence of these two effects, climate change in *Meuse* should mainly affect barley yields and profits (which would decrease in total by -10.84% and -14.01% respectively). These figures are comparable to those found by Gammans et al. (2017), who found a reduction of about 10% for barley yields in the whole of France under a similar RCP 4.5 scenario (which, as noted by Gammans et al. (2017), is markedly lower in France than in the United States). However, contrary to Gammans et al. (2017), we find no significant impacts of an RCP 4.5 scenario on wheat yields: the effects of GDD and GTP cancel each other out. Similarly, the negative and positive impacts of higher temperatures and precipitation cancel each other out for rapeseed. This may suggest that the specialized crop farms from our sample adapt more to weather fluctuations than the rest of France. This interpretation is supported by the fact that climate change negatively affects only barley, which is the least profitable crop in our study. Consequently, it is consistent that the expected negative impacts of climate change (if any) are focused on barley.

Evidence of adaptation of input applications to future climatic conditions is also clearly shown in Table 4. For example, higher temperatures should markedly increase fertilizer uses on wheat and barley, by 10.11% and 7.39% respectively, while pesticide applications should reduce. The opposite pattern is shown for rapeseed (although the effects are non-significant). In comparison, the greater precipitation should decrease the applications of both fertilizers and pesticides on *all* crops. The

[25] In detail, we assume constant technologies, constant crop allocations and constant prices. These elements are likely to change by 2050 (especially if climate change constitutes a major shock). Gouel and Laborde (2021) show, among others, that these elements are major drivers of the costs of climate change to agriculture. Our simulations should thus be taken as an illustrative exercise where the focus is on very short term adjustments of (crop-specific) input and output quantities.

greatest effect concerns pesticide applications on rapeseed, which decrease by 7.12%. The combined effects of higher temperatures and precipitation show that climate change will be likely to reduce pesticide applications but that the impacts on fertilizer applications will be heterogeneous depending on the crop. As explained in Section 4.2, the structural estimates suggest that reduction in pesticide applications on wheat and barley is mainly due to the beneficial effects of GDD and GTP on $\boldsymbol{\beta}_{122}(\mathbf{w}_{it})$ and $\boldsymbol{\beta}_{222}(\mathbf{w}_{it})$, i.e. the quantity of pesticide required to attain maximum yields $\boldsymbol{\alpha}_j(\mathbf{w}_{it})$. The reduction in pesticides applied to rapeseed is rather explained by the reduced productivity of pesticides under high GTP deviations (compared to the 2006-2012 average).

Table 4: Crop profits, yields and input applications per hectare in 2050 under an RCP 4.5 scenario

		Profits (€/ha)	**Yields (100kg/ha)**	**Fertilizers (c.€/ha)**	**Pesticides (c.€/ha)**
GDD					
	Wheat	**807.84**	**69.88**	**135.47 *****	**147.65**
		[755.75;859.94]	[66.40;73.36]	[128.40;142.55]	[133.79;161.51]
		-2.21%	*-1.412%*	*10.11% ****	*-7.77%*
	Barley	**537.36 *****	**57.22 *****	**114.74 ****	**141.48**
		[490.29;584.44]	[53.52;60.61]	[108.55;120.94]	[126.13;156.84]
		*-15.51% ****	*-11.01% ****	*7.39% ***	*-7.23%*
	Rapeseed	**709.62**	**32.29**	**118.19**	**229.23**
		[653.42;765.83]	[30.53;34.05]	[111.15;125.22]	[215.78;242.68]
		-6.18%	*-3.88%*	*-3.36%*	*3.78%*
GTP					
	Wheat	**851.18 ***	**72.33**	**121.83**	**159.46**
		[829.32;873.03]	[70.85;73.80]	[118.50;125.16]	[153.03;165.89]
		*3.04% **	*2.05%*	*-0.98%*	*-0.4%*
	Barley	**645.62**	**64.41**	**104.50**	**147.14**
		[624.06;667.18]	[62.85;65.97]	[101.46;107.54]	[139.56;154.71]
		1.5%	*0.17%*	*-2.2%*	*-3.52%*
	Rapeseed	**792.2 ***	**34.02**	**116.94 ***	**205.14 *****
		[764.34;820.06]	[33.15;34.89]	[113.35;120.54]	[198.11;212.17]
		*4.74% **	*1.27%*	*-4.38% **	*-7.12% ****
Total					
	Wheat	**832.90**	**71.32**	**134.26 ****	**147.01**
		[768.05;897.75]	[66.98;75.67]	[125.04;143.48]	[129.02;165.00]
		0.82%	*0.63%*	*9.12% ***	*-8.12%*
	Barley	**546.93 ****	**57.33 ****	**112.40**	**136.11**
		[486.89;606.89]	[52.98;61.67]	[104.18;120.61]	[115.69;156.54]
		*-14.01% ***	*-10.84% ***	*5.2%*	*-10.75%*
	Rapeseed	**745.46**	**32.71**	**112.83 ***	**213.49**
		[673.41;817.51]	[30.46;34.97]	[103.65;122.02]	[195.76;231.22]
		-1.44%	*-2.62%*	*-7.74% **	*-3.34%*

*Bold figures indicate the expected levels of profits, yields and input applications under an RCP 4.5 scenario in 2050 holding technology constant. The 90% confidence intervals are computed using the delta method and indicated within brackets. The italic figures indicate the percentage changes compared with the average 2006-2012 levels. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.*

Our framework allows us to disentangle the effects of future weather conditions on yields into the direct effects on plant growth and the farmers' adaptation effects (see Section 2.2). We decompose the change in yields due to these two effects in Table 5 using our estimates. We indeed find that farmers' adaptation has limited effect on barley yields: practically all of the reduction in barley yields is due to the direct effects of climate change on plant growth. Farmers' adaptation only reduces the negative direct effect on barley yields by 12.11%. On the contrary, our results suggest that farmers' adaptation has significant impact on wheat and rapeseed yields. We find that wheat yields slightly increase, by 44 kg/ha, under the RCP 4.5 scenario in 2050, which can be decomposed into a limited beneficial direct effect (+15 kg/ha) and a beneficial adaptation effect (+29 kg/ha). In other words, farmers' adaptation accounts for 65.91% of increased wheat yields but remains limited in absolute value. Finally, we find that the direct effects of climate change reduce rapeseed yields by 272 kg/ha but that adaptation limits the reduction of yields to only 88 kg/ha (Table 5). Adaptation thus limits the negative impacts of climate change on rapeseed by 67.65%. Overall, farmers' adaptation increases yields but the effects are only noticeable for wheat and rapeseed. In absolute values, the impacts of farmers are more than six (resp. two) times greater for rapeseed than for wheat (resp. barley). These results are in line with Moore and Lobell (2014), who found that farmers' adaptation in Europe has limited impacts on wheat and barley yields but large impacts for rapeseed yields.[26] Consequently, most of the benefits from adaptation on wheat and barley are due to input savings, in particular to reduction in pesticide applications (Table 4).

Table 5: Decomposition of climate change impacts on yields

	Wheat	**Barley**	**Rapeseed**
Changes in yields (100 kg/ha)	**0.44**	**-6.97 ****	**-0.88**
	[-3.95;4.39]	[-11.31;-2.63]	[-3.13;1.37]
Direct effects	**0.15**	**-7.93 ****	**-2.72 ***
	[-5.11;5.41]	[-5.42; -0.02]	[-4.18;-0.82]
Total of farmers' adaptation effects	**0.29**	**0.96**	**1.84**
	[-5.29;5.88]	[-1.58;3.50]	[-1.06;4.75]

*The figures represent the difference between the 2006-2012 period and 2050 at the average points. The 90% confidence intervals are computed using the delta method and indicated within brackets. * and ** indicate p-values lower than 0.1 and 0.05* .

The figures from Table 4 rely on the projection of future climate conditions on one hectare of each studied crop. In Table 6, we extrapolate these figures to the whole agricultural sector from

[26] A noticeable difference is that Moore and Lobell (2014) investigated the impact of adaptation over the long-term while we focus on short-term adaptation.

Meuse.[27] Holding current growing areas, prices and technology constant, we find that an RCP 4.5 scenario in *Meuse* will cost farmers on average three million euros, i.e. about 3.02% less than the initial value of the agricultural activity. The impacts range from -€ 9.49 million to +€ 3.41 million. This result is coherent with Deschênes and Greenstone (2007), who did not identify a statistically significant impact of climate change on agricultural profits. Our results indicate that GDD and GTP both have statistically significant effects of -€ 7.06 million and € 4.02 million respectively, highlighting, in line with the rest of the literature, that the largest impacts of climate change can attributed to warmer temperatures instead of varying precitipiations. The combined effect of GDD and GTP is, however, statistically non-significant.

Our structural estimates allow us to simulate the impact of climate change on fertilizer and pesticide applications, which can ultimately be monetized (Table 6). Using social cost values for fertilizers and pesticides from Sutton et al. (2011) and Bâ et al. (2015) in Europe and France respectively,[28] we estimate that climate change will reduce pollution damage in *Meuse* by € 6.14 million on average, i.e. about twice as much as the negative impacts on the agricultural sector. The benefits could actually be even greater, since the expected non-market impacts of climate change range from -€ 1.98 million to € 14.27 million. This reduction in damage corresponds on average to a cut by 3.64% in 2006-2012 levels. Further analysis actually suggests that all these gains come from the reduction in pesticide uses: on average, an RCP 4.5 scenario will increase fertilizer pollution by € 1.51 million (i.e. by 2.60%) but reduce pesticide pollution by € 7.65 million (i.e. by 6.92%). To the best of our knowledge, this exercise represents the first monetary valuation of climate change impacts on the application of agrochemical inputs responsible for negative externalities. This evaluation is obviously contingent on the quality of available data on the social costs of fertilizers and

[27] We used data from the French Agriculture Ministry to obtain the area under each crop in *Meuse* during the 2006-2012 period (see https://agreste.agriculture.gouv.fr/agreste-web/disaron/SAANR_DEVELOPPE_2/detail/). Over the period, wheat occupied an average of 76,434 ha, barley 33,841 ha and rapeseed 49,777 ha. The three crops together occupied 81.22% of the whole useful agricultural area of *Meuse*. UNIFA states that, on average, 22,214 tons/year of fertilizer were bought in *Meuse* (https://www.unifa.fr/statistiques-du-secteur) while BVN-D statistics indicate that an average of 527 tons/year of pesticides were bought in the region during the 2006-2012 period. (http://dataviz.statistiques.developpement-durable.gouv.fr/produits_phytopharmaceutiques/). We allocate these aggregated purchases in line with what we observed in our database from the Meuse Management Centre: we consider that, on average, 37%, 17% and 28% of fertilizers were applied to wheat, barley and rapeseed respectively in the period (18% were applied to other crops), while 36%, 17% and 31% of pesticides were applied to wheat, barley and rapeseed respectively (16% were applied to other crops).

[28] Sutton et al. (2011) indicate that the damage caused by one kg of CAN-fertilizer range from € 0.4 to € 6.8 in Europe. Relying on Bommelaer and Devaux (2011), Pretty et al. (2000) and Trasande et al. (2015), Bâ et al. (2015) consider that pesticides pollution cost from € 7.0 billion to € 28.4 billion in France in 2013 (mostly due to the negative health outcomes of insecticide uses). Given that the use of pesticides amounted to 70,000 tons in France in 2013, the social cost of pesticides can be valued at between 100 and 400 €/kg. We apply the central values of these studies to infer the social cost of fertilizers and pesticides pollution in Table 6.

pesticides. Our results thus suggest that, while climate change could be harmful to the agricultural sector, it could be beneficial to society as a whole through reductions in agrochemical inputs.

Table 6: Market and non-market impacts of an RCP 4.5 scenario in *Meuse* in 2050

	Market impacts (Million €)			**Non-market impacts (Million €)**		
	GDD	GTP	Total	GDD	GTP	Total
Wheat	**-1.40**	**1.92 ***	**0.52**	**1.02**	**0.44**	**1.46**
	[-5.38;2.86]	[0.25;3.59]	[-4.44;5.48]	[-4.61;6.64]	[-2.19;3.07]	[-4.74;7.66]
	-2.21%	*3.04% **	*0.82%*	*1.38%*	*0.59%*	*1.97%*
Barley	**-3.34 *****	**0.32**	**-3.02 ****	**0.72**	**1.05**	**1.77**
	[-4.93;-1.75]	[-0.41;1.05]	[-5.05;-0.99]	[-2.24;3.68]	[-0.40;2.49]	[-1.53;5.06]
	*-15.51% ****	*1.50%*	*-14.01% ***	*2.09%*	*3.04%*	*5.13%*
Rapeseed	**-2.33**	**1.78 ***	**-0.54**	**-0.87**	**3.79 *****	**2.91**
	[-5.12;0.47]	[0.40;3.17]	[-4.13;3.04]	[-4.50;2.76]	[1.90;5.67]	[-1.18;7.01]
	-6.18%	*4.74% **	*-1.44%*	*-1.43%*	*6.21% ****	*4.78%*
Total	**-7.06 ****	**4.02 ****	**-3.04**	**0.87**	**5.27 ****	**6.14**
	[-12.17;-1.94]	[1.74;6.31]	[-9.49;3.41]	[-6.44;8.18]	[1.73;8.82]	[-1.98;14.27]
	*-6.26% ***	*3.24% ***	*-3.02%*	*0.52%*	*3.12% ***	*3.64%*

Bold figures indicate average changes between the 2006-2012 period and 2050 under an RCP 4.5 scenario in Meuse *holding current growing areas and technology constant. The 90% confidence intervals are computed using the delta method and indicated within brackets. The italic figures indicate percentage changes compared to the average 2006-2012 levels. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.*

6 Concluding Remarks

The costs of climate change on agriculture depends critically upon farmers' adaptation. An increasing number of studies regress profit or yield deviations on weather variations – conditionally on individual and annual FE – in order to infer such costs while accounting for adaptation (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Gammans et al., 2017). However, the reduced-form estimations that are used prevents from disentangling the direct impacts of weather on plant growth (as captured by most crop simulation models – e.g. Asseng et al., 2015) from those due to farmers' adaptation. In fact, this reduced-form approach actually even prevents verification of whether farmers really adapt to weather fluctuations. Under these conditions, it remains unclear why economists should be better able than natural scientists to identify the consequences of climate change on agricultural production. For this reason, we proposed in this paper to (i) investigate how farmers adjust their input mix in response to weather fluctuations during the growing season, (ii) formally measure this adaptation strategy based on farmers' observed behavior and (iii) statistically assess how these input adjustments affect crop yields and profits.

We first proposed a decomposition of the effects of weather on profits based on four different mechanisms: (i) the direct effects on plant growth, (ii) average yield effects, (iii) input productivity effects and (iv) input demand effects, the combination of the last three effects corresponding to the total effects of farmers' adaptation. This decomposition sheds light on which mechanisms are accounted for by the different studies in the weather approach literature, depending on which dependent variable they use. We show that regressing profits on weather conditions allows for capturing all the determinants of the adaptation choices (i.e. all the above-mentioned mechanisms), but that the use of reduced-form estimation prevents them from being identified separately.

Using individual panel data from *Meuse* (France) for the 2006-2012 period, we then estimate crop-specific structural models (for wheat, barley and rapeseed) with one yield equation and two input-specific demand functions (for fertilizers and pesticides), conditionally on farm and year FE. We use weather and crop price variations together in order to identify both the direct weather effects and farmers' adaptation effects. This empirical strategy is possible because, unlike most other studies, we use an individual panel instead of an aggregated dataset. In addition to providing more robust and efficient estimates, freed from any aggregation biases (Damania et al., 2020; Fezzi et al., 2015), this database has the unique advantage of providing the details of input applications *by crop* as well as individual prices. These original elements come at the cost of a small number of observations, which could prevent the identification of precise estimates. Though small, our sample is representative of agriculture in north east France as *Meuse* is a typical region specialized in arable crops (as is the remainder of the *Paris Basin*) and our sample covers about one third of farmland in *Meuse*.

Our results provide several insights. First, our estimated elasticities for crop profits, yields and input applications (using both reduced-form and structural estimates) are all greater for GDD than for GTP. This highlights – if necessary – the crucial role of global warming in the agricultural sector. However, our results show that our structural model provides larger and more precise estimated elasticites than those obtained using reduced-form estimates. This feature already justifies the use of structural econometric models instead of estimating the usual reduced-form equations to specify the impacts of weather fluctuations on agriculture.

Second, our results suggest that farmers do adapt their input applications in response to weather changes. For example, we find that farmers in *Meuse* are likely to increase fertilizer applications by 2.60% but reduce pesticide applications by 6.92% under an RCP 4.5 scenario in 2050. Our structural estimates suggest that the reduced pesticide applications on wheat and barley is mainly explained by the beneficial effects of climate change on the quantity of pesticides required to attain maximum yields (i.e. farmers will need to apply smaller quantities of pesticides to achieve maximum yields under future climate conditions). The reduction in pesticide application on rapeseed is explained by the reduced productivity of pesticides under future precipitation. These results suggest that, overall, farmers' adaptation leads to beneficial input-savings.

Third, we find that crop yields are heterogeneously affected by future climate conditions. Barley yields are the most affected and are likely to be reduced by 10.84% under an RCP 4.5 scenario in 2050. This reduction is large and differs from the effects of climate change on the other two crops, which are non-significantly different from zero. Our approach allows us to identify the fact that, however, the direct weather impacts are likely to negatively affect rapeseed yields (an estimated shock of -272 kg/ha – ranging between -418 kg/ha and -82 kg/ha). Barley yields suffer from the largest shock (estimated at -793 kg/ha) but wheat growth seems insensitive to future climate conditions (the estimated shock is 15 kg/ha but is not significant). Our approach also allows for identifying the consequences of farmers' adaptation on crop yields. We find that farmers' adaptation, through the reorganization of the input mix, has beneficial impacts on all crop yields. Our results suggest that farmers' adaptation mainly increases rapeseed yields, for which 67.65% of the direct climate change effects are offset thanks to adaptation. By comparison, only 12.11% of the negative direct effects on barley yields are compensated for by adaptation. Overall, we find that wheat profitability in *Meuse* is likely to increase by 0.82% under an RCP 4.5 scenario in 2050 but that rapeseed and barley profitability are likely to decrease by 1.44% and 14.01% respectively.

Fourth, our approach allows for inferring the market costs of climate change (due to changes in agricultural profitability) as well as the non-market costs (due to changes in agrochemical applications responsible for negative externalities). Our central estimates indicate that the added value of agriculture in *Meuse* under an RCP 4.5 scenario in 2050 may reduce by €3.04 million (mainly due to the negative impacts on barley) but that farmers' adaptation should reduce negative externalities by €6.14 million (mainly due to reductions in pesticide applications). These welfare impacts suggest that society should benefit from farmers' adaptation to climate change. This result could have important policy implications, notably with regard to potential redistribution policies aimed at agriculture. Indeed, while several countries already provide climate-related subsidies to some of their farmers (e.g. French fruit farmers and livestock breeders are regularly compensated by the French government for their losses induced by extreme climate events), global warming is likely to amplify the need for such policies and call into question their legitimacy.

Our framework could be extended to cover several aspects. For example, we have relied on the – common but convenient – assumption that crop allocation was independent from weather in the growing season. However, recent works suggest that, if farmers do not rationally anticipate future weather, they do actualize their belief about future weather conditions based on past weather outcomes (Ji and Cobourn, 2020).[29] Such mechanism could be introduced in our analysis to estimate the impact of weather on crop allocation, and thus account for additional costs of climate change. Indeed, because the weather approach typically ignore such medium-run adaptation mechanisms, the underlying estimated market and non-market costs are likely to be biased downwards (Deschênes and Greenstone, 2007). The introduction of weather expectation in our framework would allow for measuring and accounting for the consequences of medium-run adaptation to climate change, which are still not commonly examined in the weather approach (Aragón et al., 2021; Cui, 2020). More generally, if efforts have been made recently to disentangle short-term from long-term adaptations (Kolstad and Moore, 2020; Mérel and Gammans, 2021; Moore and Lobell, 2014), more studies are still required to disentangle the direct climate change effects from farmers' long-term adaptation effects. We hope that our structural framework will help future researchers along this path.

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7 Appendix

7.1 Benchmark models

As a benchmark, we first estimate the crop profit per hectare, in the spirit of Deschênes and Greenstone (2007), i.e.:

$$\pi_{ijt} = \eta_j^{GDD} GDD_{ijt} + \eta_j^{GDD^2} GDD_{ijt}^2 + \eta_j^{GTP} GTP_{it} + \eta_j^{GTP^2} GTP_{it}^2 + \varepsilon_{ijt}^{\pi}, \tag{13}$$

where π_{ijt} is the crop-specific profit, defined as in relation (1) with naive anticipations for crop prices. The term ε_{ijt}^{π} is the error term and $\boldsymbol{\eta}_j(\mathbf{w}_{ijt})$ is the set of parameters to estimate. As in the remainder of the weather approach, we split the error term into $\varepsilon_{ijt}^{\pi} = \omega_{ij}^{\pi} + \vartheta_{jt}^{\pi} + \mu_{ijt}^{\pi}$ where ω_{ij}^{π} is the individual fixed effect, ϑ_{jt}^{π} is the temporal fixed effect (that captures notably the regional price effects) and μ_{ijt}^{π} is the remaining component of the error terms that is assumed to have white noise characteristics. We estimate relation (13) using ordinary least squares (OLS). The effects captured by $\boldsymbol{\eta}(\mathbf{w}_{ijt})$ are the effects of weather during the growing season on the profit; they capture the direct effects on the yields of the different crops, the effects of adaptation on yields (the average yield effects and the input productivity effects) and the effects on input expenditure. The difference between this approach and that of Deschênes and Greenstone (2007) is that we use the naive anticipations for output prices (and thus the computation of profits) instead of observed prices in t. This allows us to compare our estimated effects using our reduced-form and structural estimates considering the same form of crop price anticipations. Any difference between the utilization of actual profits instead of "expected" profits would imply that weather in t during the growing season affects p_{ijt}^{y}.[30]

We then estimate a similar model when the dependent variables are the observed crop yields, *à la* Schlenker and Roberts (2009). Formally, we estimate:

$$y_{ijt} = \psi_j^{GDD} GDD_{ijt} + \psi_j^{GDD^2} GDD_{ijt}^2 + \psi_j^{GTP} GTP_{it} + \psi_j^{GTP^2} GTP_{it}^2 + \varepsilon_{ijt}^{y}, \tag{14}$$

with ε_{ijt}^{y} the error term and $\boldsymbol{\psi}_j(\mathbf{w}_{it})$ the set of parameters to estimate. We split the error term into $\varepsilon_{ijt}^{y} = \omega_{ij}^{y} + \vartheta_{jt}^{y} + \mu_{ijt}^{y}$ where ω_{ij}^{y} is the individual FE, ϑ_{jt}^{y} is the temporal FE and μ_{ijt}^{y} is the remaining white noise. We estimate relation (14) with OLS.

[30] On the contrary, the lagged prices p_{ijt-1}^{y} are not affected by the weather in t (see Appendix 7.2).

7.2 Coefficients of variation and of correlation for crop prices and weather conditions

Table 7: Coefficients of variations for crop prices across the whole sample and per year (with and without centering on individual means)

	p_{ijt-1}			$p_{ijt-1} - \bar{p}_{ij}$		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Whole sample	0.21	0.25	0.18	-	-	-
2006	0.06	0.07	0.10	0.50	0.51	0,45
2007	0.12	0.14	0.06	0.54	0.84	7.09
2008	0.13	0.20	0.15	4.24	6.09	2.53
2009	0.12	0.16	0.13	0.41	0.46	0.55
2010	0.06	0.09	0.06	1.96	4.42	2.73
2011	0.11	0.15	0.11	1.56	0.98	0.69
2012	0.06	0.09	0.07	0.80	0.71	0.87

Table 8: Coefficients of variations for weather conditions across the whole sample and per year (with and without centering on individual means)

	$\mathbf{w}_{it}$			$\mathbf{w}_{it} - \bar{\mathbf{w}}_i$		
	GDD_1	GDD_3	GTP	GDD_1	GDD_3	GTP
Whole sample	0.03	0.04	0.21	-	-	-
2006	0.02	0.02	0.06	0.78	0.91	0.53
2007	0.02	0.03	0.07	0.80	0.79	0.51
2008	0.02	0.02	0.10	0.27	0.26	0.67
2009	0.02	0.02	0.05	0.41	0.55	0.68
2010	0.02	0.03	0.10	0.34	0.38	7.28
2011	0.02	0.02	0.11	0.53	0.53	0.46
2012	0.02	0.02	0.06	5.05	2.71	2.19

Table 9: Coefficients of correlation between crop prices and weather conditions (with and without centering on individual means)

	p_{i1t-1}	p_{i2t-1}	p_{i3t-1}
Levels $(\mathbf{z}_{ijt})$			
GDD_1	0.01	0.01	-
GDD_3	-	-	0.07
GTP	0.10	0.11	-0.26
Within $(\mathbf{z}_{ijt} - \bar{\mathbf{z}}_{ij})$			
GDD_1	0.03	0.06	-
GDD_3	-	-	0.03
GTP	0.15	0.12	-0.25

7.3 Reduced-form parameters

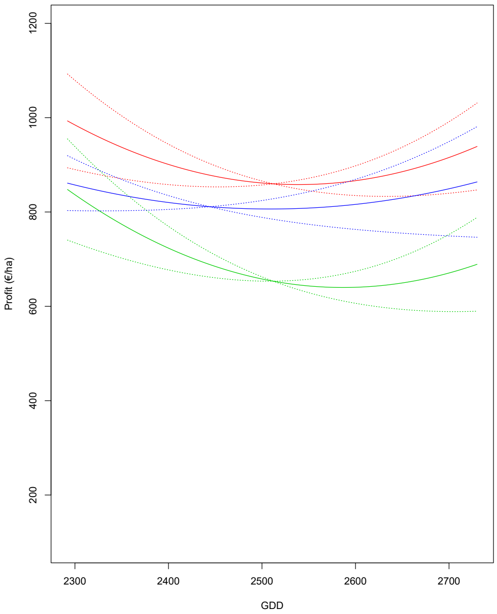
Table 10 presents the results of the reduced estimations of the farmers' profits and yields on weather conditions during the growing season.

Table 10: Reduced-form estimations of crop profits and yields (N=1,104)

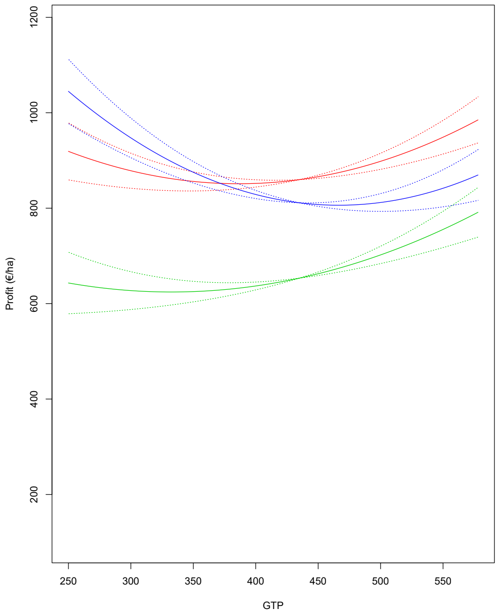
	Wheat		Barley		Rapeseed	
Variables	Profit	Yield	Profit	Yield	Profit	Yield
GDD	-11.12 ***	-0.084	-12.38 ***	0.009	- 5.87 *	-0.077
	(-3.03)	(-0.56)	(-3.09)	(0.05)	(-1.83)	(-1.08)
GDD^2	0.002 ***	0.000	0.002 ***	-0.000	0.001 *	0.000
	(3.02)	(0.455)	(3.02)	(-0.16)	(1.80)	(0.96)
GTP	-2.817 ***	-0.067 **	-1.844 **	-0.058	-4.752 ***	-0.53 ***
	(-3.59)	(-2.13)	(-2.18)	(-1.60)	(-5.42)	(-2.71)
GTP^2	0.004 ***	0.000 **	0.003 ***	0.000	0.005 ***	0.000 **
	(3.97)	(2.03)	(2.80)	(1.56)	(4.99)	(2.48)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Temporal FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.54	0.30	0.52	0.28	0.35	0.31

Student tests are indicated within brackets. *, **, *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.

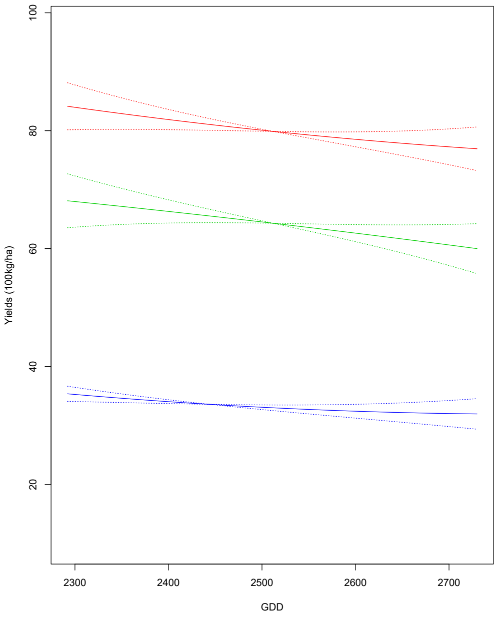
7.4 Estimated responses of crop profits and yields to weather during the growing season using reduced-form estimates



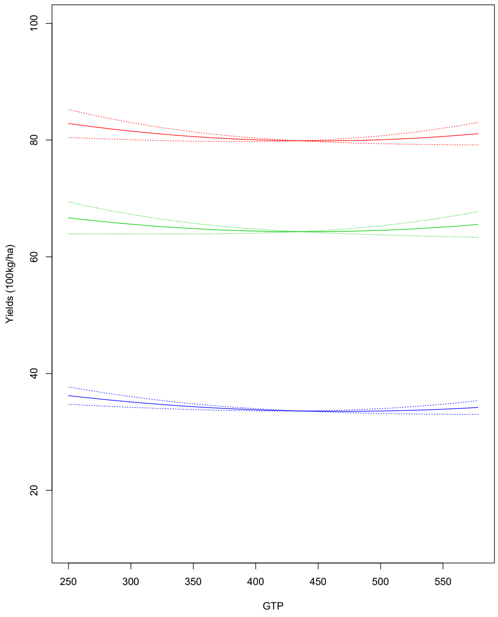
(a) Growing Degree-Days



(b) Growing Total precipitation



(c) Growing Degree-Days



(d) Growing Total precipitation

Figure 6: Estimated relationships between profits per hectare ((a) and (b)) and yields ((c) and (d)) and weather during the growing season using reduced-form estimates. *Wheat (red lines); barley (green lines); rapeseed (blue lines). The 90% confidence intervals are shown in dashed lines. We use* GDD_3 *for rapeseed and* GDD_1 *for wheat and barley.*

7.5 Structural parameters

Table 11 presents the results of the structural estimations of the farmers' profits on weather conditions during the growing season, as specified in equations (11) and (12).

Table 11: Structural estimates of aggregated and crop-specific profits (N=1,104)

Variables	α_j	β_{j1}	β_{j2}	δ_{j11}	δ_{j22}	δ_{j12}
Wheat						
1	-	-	-	-40,998.184	71,975.614	9,949.439
	-	-	-	(-0.946)	(1.334)	(0.298)
GDD	-0.277	1.741	-3.147	31.404	-54.567	-8.605
	(-1.365)	(0.872)	(-1.071)	(0.903)	(-1.238)	(-0.317)
GDD^2	0.000	-0.000	0.001	-0.006	0.012	0.002
	(1.280)	(-0.867)	(1.030)	(-0.817)	(1.314)	(0.452)
GTP	-0.202 ***	0.507	-1.235 *	-2.434	-38.636 ***	-13.325 *
	(-4.637)	(1.158)	(-1.782)	(-0.323)	(-3.409)	(-1.908)
GTP^2	0.000 ***	-0.001	0.002 **	0.000	0.045 ***	0.015 *
	(4.400)	(-1.562)	(2.002)	(1.334)	(3.612)	(1.915)
Barley						
1	-	-	-	41,116.455	113,337.184 **	70,010.106 **
	-	-	-	(1.254)	(2.232)	(2.589)
GDD	-0.024	0.319	-1.811	-33.324	-85.712 **	-55.121 **
	(-0.109)	(0.196)	(-0.594)	(-1.267)	(-2.069)	(-2.506)
GDD^2	-0.000	-0.000	0.000	0.007	0.018 **	0.012 **
	(-0.071)	(-0.206)	(0.543)	(1.379)	(2.115)	(2.641)
GTP	0.002	0.829 ***	-0.735	-8.874 *	-43.877 ***	-22.462 ***
	(0.061)	(3.102)	(-1.199)	(-1.823)	(-4.373)	(-3.926)
GTP^2	-0.000	-0.001 ***	0.001	0.008	0.050 ***	0.025 ***
	(-0.100)	(-3.554)	(1.273)	(1.463)	(4.390)	(3.935)
Rapeseed						
1	-	-	-	22,840.300	128,963.231	7.130
	-	-	-	(0.372)	(0.916)	(0.000)
GDD	-0.250 **	-1.372	-3.968	-16.362	-110.500	-1.972
	(-2.361)	(-0.705)	(-1.078)	(-0.315)	(-0.951)	(-0.035)
GDD^2	0.000 **	0.000	0.001	0.005	0.024	0.002
	(2.208)	(0.644)	(1.033)	(0.428)	(0.993)	(0.203)
GTP	-0.087 ***	-0.407	2.108 **	-35.675 **	16.928	-35.727 *
	(-3.295)	(-0.859)	(2.232)	(-2.381)	(0.465)	(-1.933)
GTP^2	0.000 ***	0.000	-0.003 **	0.034 **	-0.028	0.043 **
	(2.587)	(0.192)	(-2.591)	(2.156)	(-0.666)	(2.115)

All estimations include individual and temporal FE. Student tests are indicated within brackets. *, **, *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively. The rows "1" indicate the estimates that are independent of weather conditions.