Structural identification of weather impacts on crop yields: Disentangling agronomic from adaptation effects

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Abstract

A large literature has assessed the impacts of climate change on agricultural production by estimating reduced-form models of crop yields conditionally on weather and individual fixed effects. The estimates obtained are usually interpreted as the weather impacts on yields *once farmers have adapted*. Yet, only few attempts have documented that farmers do adapt to weather and none has verified that these adjustments actually impact crop yields. Our objective here is to unpack how weather affects agricultural production by developing a structural model that explicitly accounts for both the plants' biophysical and farmers' behavioral responses to weather. Considering adaptation during the growing season through fertilizer and pesticide applications, our approach allows us to distinguish the "direct" effects (i.e. the *agronomic* impacts of weather changes on plant growth *per se*) from the "indirect" weather effects via farmers' input choices (i.e. the *adaptation* impacts). We estimate the underlying structural model using farm-level data from the *Meuse* French department, which provides details of fertilizer and pesticide uses by crop. We show that the reduced-form and structural estimates indicate similar weather impacts on crop yields, for a large range of sensitivity analyses. Our structural estimates indicate that the adaptation effects are sizable and that farmers' adjustments reduce projected damage from climate change. In our illustrative case, farmers' adaptation offsets between one quarter to two thirds of the negative agronomic impacts of future warming on crop yields. Our analyses exhibit that commonly used reduced-form models of crop yields inherently capture these within-season behavioral responses to weather.

Keywords: Climate Change, Growing-Season Adjustments, Panel Econometrics, Structural Econometrics, Within-Season Adaptation.

JEL Codes: C33, Q12, Q54

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Introduction

Climate change has long been identified as a major threat to global agricultural production (Adams et al., 1990). First waves of natural science studies have used crop simulation models to assess its future impacts on plant growth through modification of the biophysical processes at stake, such as photosynthesis or photorespiration (Asseng et al., 2015). Although these direct impacts on plant growth are likely to adversely affect yields, farmers are expected to react to new climatic conditions by adapting their practices. As a result, considerable attention has been paid in the economic literature to better accounting for farmers' adaptation, notably by looking at *observational data*. Specifically, a large bulk of the economic literature has regressed observed crop yields on observed weather conditions during the growing season conditionally on individual fixed effects to measure, according to the common vision, the impacts of temperature and precipitation on agriculture *once farmers have adapted* (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011, 2013; Tack et al., 2015; Gammans et al., 2017; Mérel and Gammans, 2021; Wing et al., 2021; Wang, Rejesus, Tack, Balagtas, and Nelson, Wang et al.; Chen et al., 2023).[1] Though useful, this "yield-weather-panel" approach relies on reduced-form estimations where adaptation is not explicitly described and remains as a black box. Consequently, the identified impacts are an aggregated measure of both the direct weather impacts on plant growth (as measured by former crop simulation models – see Roberts et al., 2017)[2] and farmers' adaptation impacts,

[1]Although the literature has considered for a long time that this approach was able to provide estimates of the impacts of climate change on agricultural production taking into account "short-term adaptation" (typically changes in practices occurring within the growing season), the literature is discussing this assumption (e.g. Mérel and Gammans, 2021). In order to remain neutral regarding these debates, we refer to a change in agricultural practices within the growing season as the farmers' adaptation to weather conditions in the remainder of the paper.

[2]Early studies using crop simulation models focused on the relationship between weather and plant growth assuming constant cropping practices (Asseng et al., 2015), i.e. ignoring farmers' adaptation. Things are changing and some more recent crop simulation models account for a number of incremental adaptations (e.g. changing varieties or planting dates). Despite these additions, 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 often the maximization of crop yields, which differs from what economists consider to be a rational behavior.

without the possibility of measuring them separately. As such, it is still unclear whether the identified impacts from the yield-weather-panel approach really account for the adaptation impacts – in other words, whether they really differ from those measured by former crop simulation models. The objective of the paper is to clarify this issue.

Specifically, our main objective in this paper is to properly model and estimate the consequences of farmers' adaptation on crop yields, in order to assess its importance within the overall impacts of weather on yields. For this purpose, we propose a structural model derived from a profit-maximizing farmer program that allows us to simultaneously and separately measure both (i) the direct impacts of weather change on crop yields, independently of farmers' adaptation (referred to as *agronomic impacts*), (ii) the farmers' response to weather change through modifications in practices (what the literature usually calls *adaptation*) and (iii) the consequences of these adaptations on crop yields (called *adaptation impacts*). We build our identification strategy on the standards of the yield-weather-panel approach, exploiting farm-specific weather deviations from farm averages to explain our dependent variables (Blanc and Reilly, 2017). In doing so, we are able to check whether the usual reduced-form models give similar results to our structural model (grounded on microeconomic theory). This comparison allows us to verify whether the usual reduced-form estimates from the yield-weather-panel literature do really account for the "indirect" weather impacts resulting from farmers' adaptation – that have been only assumed so far – on top of the "direct" weather impacts on plant growth (that have been documented by agronomic studies). In other words, we verify whether the yield-weather-panel literature is really more appropriate than former crop simulation models at measuring weather impacts on crop yields.

As an illustrative example of adaptation, we investigate how farmers adjust pesticide and fertilizer applications to weather conditions during the growing season. Indeed, given that crop allocation can be considered as fixed during the growing season, fertilizer and pesticide applications remain the only possible adaptation strategy for farmers at that time (at least in rain fed regions). There are several reasons for presuming that farmers adjust their input applications to weather. For example, the agronomic literature indicates that higher temperatures and precipitation increase pest pressure (Rosenzweig et al., 2001; Bailey, 2004), possibly leading farmers to use more pesticides in these conditions. Weather changes can also influence input applications by affecting input productivity (Xia and Wan, 2008). In line with these agronomic insights, our structural model proposes a channel linking weather changes to (i) changes in fertilizer and pesticide productivity, which translates into (ii) changes in fertilizer and pesticide applications, ultimately allowing us to identify (iii) changes in crop yields (i.e. the adaptation impacts). The identification of these within-season adaptation impacts on top of the measure of the total impacts allows us to measure, by difference, the agronomic impacts.

We estimate our structural econometric model on an original panel dataset of crop farms from the French department of *Meuse*. While only available for a small area (6,211 square kilometers),[3] this dataset has the unique advantage of detailing fertilizer and pesticide applications *by crop*. This very useful information is usually unavailable in commonly used agricultural databases. This allows us to disaggregate the farmers' profits into three independent crop-specific systems (wheat, barley and rapeseed, which together account for about 80% of farmers' arable land in the sample), 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 prices together with temperatures and precipitation, conditionally on farm fixed effects. The use of prices is an important element of our model. Because farmers have greater incentives to adapt when crop prices are high (at least relatively to input prices), a similar weather shock can have different impacts on crop yields depending on the year (i.e. depending on the set of prices). We exploit this property to separately identify the agronomic and adaptation impacts.

[3]Though our study area is admittedly small, we provide evidence in the paper that the remaining weather variations available for identification after adjusting for individual fixed effects is comparable to those of previous studies exploiting national-level weather variations (e.g. Schlenker and Roberts, 2009).

Our contribution to the literature is threefold. First, we propose one of the first structural models to measure weather impacts on agriculture. A key strength of structural models is that they provide a clear representation and interpretation of the mechanisms at stake.[4] Despite this, structural models remain scarce in environmental economics (Timmins and Schlenker, 2009). The literature on the assessment of weather impacts on agriculture is no exception, even though structural models apparently seem suited to identifying the impacts of farmers' responses to exogenous weather shocks. To our knowledge, the first structural modeling in this literature was proposed by Kaminski et al. (2013). Their model notably accounts for farmers' crop-specific input adjustments to weather changes (as does ours), which translates into changes in crop-specific profits and, ultimately, into changes in crop allocation.[5] Yang and Shumway (2016) proposed a dynamic structural model to account for farmers' investments in response to weather changes. These two studies however depart from the standards of the yield-weather-panel literature by running *cross-sectional analyses* – instead of panel analyses – and including weather conditions for the *whole* year (instead of the growing season only).[6] To our knowledge, Sesmero et al. (2018) and Lemoine (2021) are the only studies from this literature to have ever proposed a structural model coupled to panel estimation techniques. However, they differ from our approach and the remainder of the yield-weather-panel literature by estimating the impacts of weather conditions on *net revenues* instead of yields. As pointed out by Fisher et al. (2012), net revenues fundamentally differ from yields as the econometrician cannot easily purge for the effects of farmers' storing behavior. As such, we are the first to our knowledge to propose a structural modeling approach that explains weather impacts on crop yields using the empirical standards of the yield-weather-panel literature.

[4] Another advantage of structural modeling is that estimates are less subject to measurement error biases.

[5] Ortiz-Bobea and Just (2013) proposed a similar structural model but, due to data limitation, do not estimate it.

[6] Note that, before these two studies, Seo and Mendelsohn (2008) proposed a structural extension of Mendelsohn et al. (1994)'s reduced-form "Ricardian" model. Their structural Ricardian model considers that farmers allocate their crops in order to maximize their annual profits such that these allocations reflect the best-adapted crops to the observed climate conditions. The difference from the two other studies is that Seo and Mendelsohn (2008) are interested in long-term adaptation to climate change, exploiting cross-sectional differences in *climate* conditions instead of those in *weather* conditions.

Second, we contribute to the emerging literature on the measurement of farmers' adaptation (Kawasaki, 2019; Aragón et al., 2021; Chen and Gong, 2021; Jagnani et al., 2021; Ramsey et al., 2021; Cui and Xie, 2022; Amare and Balana, 2023) by formally measuring, for each crop, how farmers adjust their fertilizer and pesticide applications during the growing season. Our structural estimates provide evidence that farmers do adjust their fertilizer and pesticide applications to weather changes. In particular, we find that farmers increase their fertilizer applications to cope with higher temperatures. Such within-season adjustments have already been identified in the literature (Sesmero et al., 2018; Chen and Gong, 2021). In addition to what is shown by the rest of the literature, our structural model allows us to statistically identify how these adjustments impact crop yields, ultimately enabling us to isolate farmers' adaptation impacts from the agronomic impacts.[7] In particular, our empirical application in *Meuse* suggests that farmers' adaptation *always* increases crop yields. It shows that the agronomic effects can be positive for marginal increases in temperature (for some crops), but that they are negative for non-marginal increases (for all crops). Our simulation exercise suggests that farmers' adaptation in *Meuse* offsets between one quarter to two thirds of the negative agronomic impacts of non-marginal increases in temperature.

Finally, we provide a methodological contribution to the yield-weather-panel literature by estimating and comparing structural and reduced-form models of the weather impacts on crop yields. We show that both approaches provide globally similar estimates of the total impacts of weather conditions during the growing season on crop yields. This result is valid for both *marginal* and *non-marginal* changes in temperatures and precipitation, as well as for multiple specifications and robustness checks. In particular, we find that our structural model reproduces the results of the usual reduced-form models in all but one specification. The exception occurs when comparing reduced-form and structural models with the additional inclusion of year fixed effects, which, as already pointed out by Fisher et al. (2012), purges

[7]None of the above-mentioned studies statistically identified the induced impacts of these changes in cropping practices on crop yields (or only recalculated them using back-of-the-envelope computations; see Cui and Xie, 2022, for example). Indeed, these studies cannot do better than these simplistic computations as, while providing evidence of farmers' adaptation, their models do not additionally measure input productivity.

most of the weather variations. Given that our structural model explicitly accounts for both the agronomic and adaptation impacts and that we identify that these adaptation impacts are non-null (at least in our illustrative case), this means that the yield-weather-panel approach does account for farmers' behavioral responses on top of plants' biophysical responses. In other words, the yield-weather-panel studies are conceptually better able than former crop simulation models to estimate weather impacts on crops yields.

The paper is organized as follows. Section presents the conceptual framework and details the main assumptions of our structural approach. Section details the empirical models, the econometric strategy and the summary statistics. Section describes the estimation results. Section simulates the impacts of non-marginal temperature increases on crop yields in *Meuse* using our estimates. Section discusses and concludes.

Conceptual Framework

Our conceptual approach consists of explaining how farmers adjust their input applications in response to changes in weather conditions during the growing season and how these within-season adjustments translate into crop yields. In other words, it consists of disaggregating the usual impacts measured in the yield-weather-panel literature to explicitly distinguish the direct impacts of weather on plant growth (*agronomic impacts*) from its indirect impacts through input adjustments (*adaptation impacts*). To measure the impacts of such farmers' adaptation on crop yields require to represent both the farmers' responses to weather changes in terms of input applications *and* the productive consequences of these adjustments. To facilitate their understanding, we propose to represent these embedded mechanisms in an explicit theoretical model. We present its formal description below.

Farmers' program during the growing season

Consider a risk-neutral farmer i growing J crops whose objective is to maximize their profit in year t according to the set of weather conditions during the growing season (noted $\mathbf{w}_{i,t}$)

and to the set of input and output prices.[8] The farmer's program in t can be split into two periods (Carpentier and Letort, 2012): (i) the period before the growing season during which the farmer decides on their crop allocation $\mathbf{s}_{i,t}$ anticipating the outcomes in the growing season and (ii) the growing season, during which the farmer's decision variables are their applications of agrochemical inputs $\mathbf{x}_{i,j,t}$ (in quantity/ha) on each crop $j \in \mathbb{J}$ ($x_{i,j,k,t} \geq 0$ for each input $k \in \mathbb{K}$). The farmer's profit maximization is thus a two-stage optimization process where they first choose their crop allocation based on their vector of expected crop-specific profits $E(\boldsymbol{\pi}_{i,t})$ and, in the second stage, they optimize each crop-specific profit $\pi_{i,j,t}$ (in €/ha) on $\mathbf{x}_{i,j,t}$ based on the weather conditions and anticipated prices, crop allocation being considered as fixed. We note $p^{y}_{i,j,t}$ the price of crop j for farmer i in agricultural campaign t and $\mathbf{p}^{\mathbf{x}}_{i,t}$ the corresponding vector of input prices, that are assumed to depend both on years – along with global markets – and farmers (due to heterogeneity of quality, volume and distance to the downstream or upstream markets; Fezzi and Bateman; 2011).

Because farmers are typically unaware of both prices and growing-season weather conditions in the first stage, they allocate crops by making anticipations about these elements. There have been long discussions about the appropriate form of farmers' price expectations in the literature (e.g. Nerlove and Bessler, 2001), but the appropriate form of expectations of the weather conditions have been less studied (one exception is Ji and Cobourn, 2021). However, because weather conditions in one location typically fluctuate around their average long-term values $\bar{\mathbf{w}}_i$, one can assume that $E(\mathbf{w}_{i,t}) = \bar{\mathbf{w}}_i$. Under this notation, weather realizations during the growing season typically come as surprises for farmers in the first stage. One can therefore assume that crop allocation is not affected by the particular weather realization during the growing season in t. Accordingly, we consider the crop allocation as

[8]For the remainder of the paper, the bold elements indicate vectors (or matrices) while italic elements indicate scalars. Latin capital letters refer to sets of scalars.

fixed in the remainder of this paper.[9] This assumption – usual in the yield-weather-panel approach – is empirically supported by Ji and Cobourn (2021).[10]

The anticipations are different in the second stage, at the time when farmers have already allocated their crops and can only choose their input applications. Indeed, if farmers still need to anticipate crop prices, they observe the input prices (i.e., $E(\mathbf{p}^x_{i,t}) = \mathbf{p}^x_{i,t}$). Similarly, farmers observe weather realizations in the second stage (i.e., $E(\mathbf{w}_{i,t}) = \mathbf{w}_{i,t}$). As a result, the second stage of the profit maximization equation can be rewritten, for each crop, as:

$$\pi_{i,j,t} = \max_{\mathbf{x}_{i,j,t}} \{E(p^y_{i,j,t})y_{i,j,t} - \mathbf{p}^{\mathbf{x}}_{i,t}{}'\mathbf{x}_{i,j,t} | y_{i,j,t} = f_j(\mathbf{x}_{i,j,t}\mathbf{w}_{i,t})\}, \tag{1}$$

where $y_{i,j,t}$ is the yield of crop j for i in t that depends on the weather conditions and input applications following the production function $f_j(\mathbf{x}_{i,j,t}; \mathbf{w}_{i,t})$. The production function respects the usual non-negative, non-decreasing, linearly homogeneous and concave relationship with $\mathbf{x}_{i,j,t}$. We assume that the production function is non-negative and linearly homogeneous with $\mathbf{w}_{i,t}$. The production function does not depend on crop allocation $\mathbf{s}_{i,t}$, i.e. we assume constant-return to area and non-jointness for the different crop-specific technologies.[11] The solution of program (1) is $\mathbf{x}^*_{i,j,t}$, i.e. the optimal input applications under $\mathbf{w}_{i,t}$ given the anticipated prices in the second stage. We note $y^*_{i,j,t}$ the corresponding crop yield.

[9]Doing so, we differ from previous structural models found in the literature (e.g. Seo and Mendelsohn, 2008; Kaminski et al., 2013). These studies are however cross-sectional studies, which exempts them from similar discussions due to the panel dimension of the data.

[10]Another argument in favor of the assumption that crop allocation is independent of weather in the growing season is that the panel approach – which uses individual fixed effects – would determine the correlation between $E(\mathbf{w}_{i,t}) - \bar{\mathbf{w}}_i$ and $\mathbf{s}^*_{i,t} - \bar{\mathbf{s}}^*_i$. Given our assumption on the form of weather expectations in the first stage, the first difference is null, which ultimately 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 are important drivers of crop allocation. In contrast with the rest of the literature, Aragón et al. (2021) showed that Peruvian farmers adapt their crop allocation to weather during the growing season. A possible explanation is that the planting date occurs *outside* the growing season in north American and European countries but *during* the growing season in Peru.

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

Disentangling marginal weather impacts on crop yields

The yield-weather-panel literature typically measures the impacts of weather conditions in the growing season on crop yields by implicitly accounting for farmers' adaptation described in program (1) *only*, where farmers adjust their agrochemical input applications but where other inputs (land, labor, capital) remain fixed (Deschênes and Greenstone, 2007). To explicitly represent the effects of farmers' adaptation on crop yields, we examine here how farmers respond to marginal weather changes and how these changes translate into crop yields. Assuming no effects on input and output prices,[12] we can disaggregate a marginal change in the z^{th} element of $\mathbf{w}_{i,t}$ (noted $\mathbf{w}_{i,t}^{(z)}$, e.g. the average temperature during the growing season) on $\pi_{i,j,t}$ as follows:

$$\frac{\mathrm{d}\pi_{i,j,t}}{\mathrm{d}\mathbf{w}_{i,t}^{(z)}} = E(p_{i,j,t}^{y}) \underbrace{\frac{\partial f_j(\mathbf{x}_{i,j,t}^{*}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{w}_{i,t}^{(z)}}}_{\text{Total impact on yields}} - \mathbf{p}_{i,t}^{\mathbf{x}}{}' \underbrace{\frac{\partial \mathbf{x}_{i,j,t}^{*}(\mathbf{w}_{i,t})}{\partial \mathbf{w}_{i,t}^{(z)}}}_{\text{Input adjustments}} . \tag{2}$$

Relation (2) states that a marginal weather change affects the crop-specific profit through both an effect on yields and an effect on input applications. The effect on input applications comes from the fact that farmers re-optimize input applications under new weather conditions. These input adjustments affect crop yields through $f_j(\mathbf{x}_{i,j,t};\mathbf{w}_{i,t})$ and, importantly, add to the initial shock of the marginal weather change on plant growth, together forming the "total weather impact". The yield-weather-panel literature typically measures this total impact when regressing crop yields on weather conditions, without distinguishing the two effects. We can however theoretically distinguish them by disaggregating the total weather

[12] The impacts of weather changes on farmers' program can typically be disaggregated into two main categories: the effects on quantities (output $y_{i,j,t}$ and input $\mathbf{x}_{i,j,t}$) and the effects on input and output prices. Because previous studies worked on small administrative areas (e.g. at the 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). Similarly, as we work on *individual* farmers, we assume that farmers are price-takers. In other words, we assume that input and output prices are unaffected by local weather shocks.

impact as:

$$\underbrace{\frac{\partial f_j(\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}}_{\text{Total impact}} = \underbrace{\frac{\partial f_j(\bar{\mathbf{x}}^*_{i,j,t}(\bar{\mathbf{w}}_i);\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}}_{\text{Agronomic impact}} + \underbrace{\frac{\partial \mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t})'}{\partial \mathbf{w}^{(z)}_{i,t}} \frac{\partial f_j(\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{x}_{i,j,t}})}_{\text{Adaptation impact}}, \tag{3}$$

where $\bar{\mathbf{x}}^*_{i,j,t}$ is the vector of input applications that maximizes program (1) under average weather conditions $\bar{\mathbf{w}}_i$ given the expected prices in the second stage. Relation (3) describes how the total impact of a marginal weather change on crop yields can be disaggregated into the *agronomic* and *adaptation* impacts. Accordingly, the agronomic impact can be defined as the impact of a marginal weather change on crop yields, *holding input applications unchanged.* Such effects are similar to those captured by former crop simulation models that only measured the changes in biophysical processes at stake (e.g. the effects of temperature on photosynthesis). They correspond to the direct effect of weather changes on crop growth, independently of farmers' behavior. By comparison, the adaptation impacts correspond to the changes in crop yields due to input adjustments. They are thus indirect weather effects, consecutive upon farmers' behavioral responses to weather changes.

Rational farmers adjust their input applications until the net benefits of adaptation are null at the margin (see Hsiang, 2016, for a discussion on the implications of the envelope theorem for the problem here). Formally, the optimal adaptation strategy is reached for $\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t})$ when:

$$E(p^y_{i,j,t})\frac{\partial \mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t})'}{\partial \mathbf{w}^{(z)}_{i,t}} \frac{\partial f_j(\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{x}_{i,j,t}} = \mathbf{p}^{\mathbf{x}}_{i,t}{}' \frac{\partial \mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}, \tag{4}$$

i.e., when the cost of adaptation equals its benefits. Specifically, the right-hand side of relation (4) defines the costs of adaptation, i.e. the costs of input adjustments in response to weather changes. These costs exactly correspond to the change in expenditures following the input adjustments in relations (2) and (3). 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) additional input expenditures. The left-hand side of relation (4) defines the expected benefits of adaptation in terms of induced impacts on yields (which can be positive or negative). These expected benefits are exactly equal to the value of the adaptation impacts in relation (3).

A close look at relation (4) indicates that the optimal adaptation strategy depends on (i) the technical properties of the production function, (ii) the weather conditions during the growing season and (iii) the input and expected output prices. In particular, as weather affects the availability or efficiency of agrochemical inputs (e.g. the assimilation of nutrients from fertilizers by the crop roots depends on soil humidity and temperature), weather changes are likely to change *input productivity*. Relation (4) indicates that rational farmers react to these changes in input productivity by adjusting their input applications. They do so until the marginal benefits of input adjustment equals the unit price of the input. Depending on the weather impacts on production, farmers thus adjust their input applications differently according to the inputs and crops considered. In particular, relation (4) states that farmers increase their input applications when the input becomes more productive under new weather conditions. In this case, farmers' adaptation is motivated by an objective of increasing crop yields. In the other case, when new weather conditions reduce input productivity, rational farmers reduce their input applications in order to benefit from input savings. If these mechanisms are at stake for a single input, weather conditions can also affect the complementarity/substitution relationship between different agrochemical inputs, ultimately affecting farmers' adaptation decisions.

We illustrate the theoretical insights of the previous paragraphs in Figure 1.[13] In this illustrative example, point A is the equilibrium under average weather conditions $\bar{w}$ while point C is the equilibrium under particular weather conditions w_1 (a particular temperature level for example). The total impact of weather change on crop yields is thus the distance along the y-axis between points C and A, equal to $f(\bar{x}^*, \bar{w}) - f(x_1^*, w_1)$ (negative here). This difference typically corresponds to what the yield-weather-panel approach usually measures. However, the total impact corresponds to a difference of two *optimized* situations, where

[13]For simplicity, we assume a single dimension to $\mathbf{w}_{i,t}$ and $\mathbf{x}_{i,t}$ and remove individual and year indices.

input applications are optimally adjusted to particular weather conditions. The adaptation behavior consecutive upon a change from $\bar{w}$ to w_1 corresponds here to the increase in input applications from $\bar{x}^*$ to x_1^*. A rational farmer has no reason to further increase their input applications. Indeed, a rational farmer increases their input applications until the marginal productivity of the input under the new weather conditions w_1 is equal to those under average weather conditions $\bar{w}$, i.e. equal to the ratio of input price to expected output price. This adaptation behavior has important consequences for the measurement of the total weather impacts. Indeed, the impacts of farmers' adaptation on crop yields add to the initial weather impacts on plant growth (the agronomic impacts) to form the total weather impacts. In accordance with the definitions above, the agronomic impacts are the distance along the y-axis between points B and A, holding the input applications at $\bar{x}^*$, while the adaptation impacts are the distance along the y-axis between points C and B, where input applications change. In our illustrative case, the adaptation impacts offset half of the direct weather impacts.

The analysis conducted in this section makes it clear that, to have a complete picture of the weather impacts on crop yields, one needs to separately and simultaneously measure (i) the direct impacts of a weather change on crop yields, (ii) the farmers' responses to such change through modifications of input applications (induced by the impact of the weather change on input productivity) and, ultimately, (iii) the consequences of these input adjustments for crop yields. We propose in the following section a structural model whose estimation is compatible with the identification of these mechanisms.

Empirical Models, Econometric Strategy and Data

Structural modeling

Production function. We presented our conceptual framework in Section using generic production functions. To formalize the structural model to estimate, we need to specify a

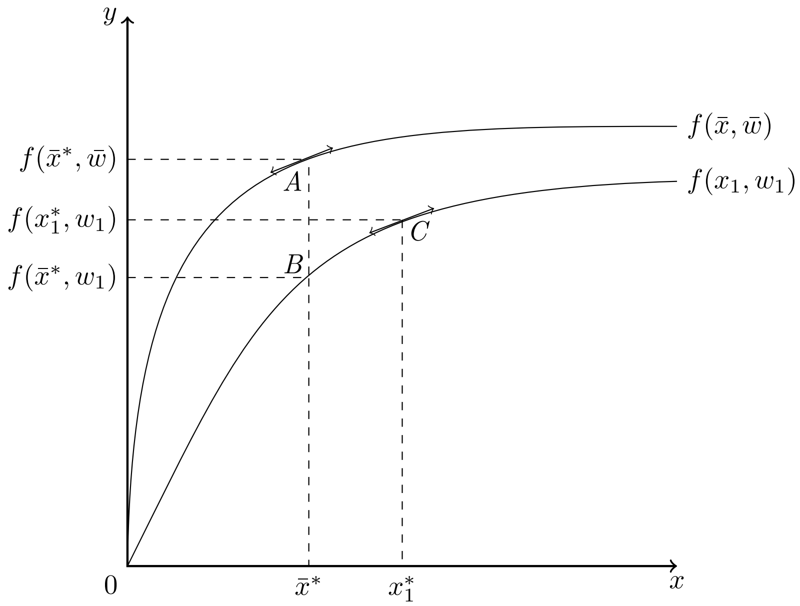

Figure 1: Disaggregation of the total weather effects into average weather conditions $\bar{w}$ and particular weather conditions w_1. Point A is the optimum under $\bar{w}$. Point B refers to the equilibrium under w_1 in the case of no adaptation. Point C is the optimum under w_1. $\bar{x}^*$ (resp. x_1^*) is the optimal input application under average weather conditions $\bar{w}$ (resp. particular weather conditions w_1) given the anticipated prices. The derivatives in points A and C are equal and correspond to the ratio of input price to expected crop price. The difference between the y-axis of points C and A corresponds to the total effect (negative here). The distance along the y-axis between points B and A corresponds to the agronomic effect (negative here). The distance along the y-axis between points C and B is the adaptation effect (positive here).

functional form of the production function for each crop $j \in \mathbb{J}$. Among the alternatives, we assume that the yields of crop j are quadratic functions of fertilizers ($k = 1$) and pesticides ($k = 2$) such that:

$$y_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\boldsymbol{\gamma}_{j,k,l}^{-1}(\mathbf{w}_{i,t})[\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) - x_{i,j,k,t}][\boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t}) - x_{i,j,l,t}], \tag{5}$$

where $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$, $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ and $\boldsymbol{\gamma}_{j,k,l}(\mathbf{w}_{i,t})$ are sets of crop(-input)-specific parameters ($j \in \mathbb{J}$ and $\{k; l\} \in \{1; 2\}^2$). They consist of the structural parameters of our model and are assumed to be known by the farmers.

The specification of relation (5) has been proposed by Femenia and Letort (2016) for the two inputs case as an extension of the production function initially proposed by Pope and Just (2003) for the single input case. As explained by Pope and Just (2003), the form of relation (5) is exactly equivalent to a standard quadratic production function but it additionally allows researchers to explicitly represent how technical changes in the production function translate into shifters of the input demand functions. This makes this property very useful to construct our structural model.[14] Following Femenia and Letort (2016), we can define the symmetric 2×2 matrix $\Gamma_j(\mathbf{w}_{i,t}) \equiv [\boldsymbol{\gamma}_{j,k,l}^{-1}(\mathbf{w}_{i,t})]$ that arranges these technical shifters. Specifically, we refer to $\boldsymbol{\gamma}_{j,1,1}^{-1}(\mathbf{w}_{i,t})$ and $\boldsymbol{\gamma}_{j,2,2}^{-1}(\mathbf{w}_{i,t})$ as technical shifters due to changes of the "own" productivity of fertilizers and pesticides on crop j ($\boldsymbol{\gamma}_{j,1,1}^{-1}(\mathbf{w}_{i,t}) > 0$ and $\boldsymbol{\gamma}_{j,2,2}^{-1}(\mathbf{w}_{i,t}) > 0$). We refer to the interaction term $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$ as the technical shifter due to the substitution/complementarity relationships between fertilizers and pesticides. A positive $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$ implies a substitution between the two inputs at the margin, while a negative $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$ implies cooperation. Finally, as explained by Carpentier and Letort (2012) the remaining sets of parameters in relation (5) have easy agronomic interpretations. Indeed, the term $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$ can be interpreted as the maximum yield of crop j in the sample ($\boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) > 0$). Similarly, $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ represents the quantity of input k required to achieve this maximum yield ($\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) > 0$), hereafter referred to as input requirements.[15]

While presenting easy agronomic interpretations of the $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$ and $\boldsymbol{\beta}_j(\mathbf{w}_{i,t})$ terms, the productivity of fertilizers and pesticides in relation (5) is a complex function of the terms defined above. Indeed, the productivity of input k on crop j is equal to:

$$\theta_j^k(\mathbf{w}_{i,t}) = \boldsymbol{\gamma}_{j,k,k}^{-1}(\mathbf{w}_{i,t})[\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) - x_{i,j,k,t}] + \boldsymbol{\gamma}_{j,1,2}^{-1}[\boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t}) - x_{i,j,l,t}], \tag{6}$$

where $\theta_j^k(\mathbf{w}_{i,t})$ is the aggregated productivity of input k on crop j ($k \neq l$). This relation calls for several comments. First, relation (6) states that the aggregated productivity of input k on crop j is marginally decreasing in $x_{i,j,k,t}$ for a positively definite matrix $\Gamma_j(\mathbf{w}_{i,t})$, i.e. since $\boldsymbol{\gamma}_{j,1,1}^{-1}(\mathbf{w}_{i,t})\boldsymbol{\gamma}_{j,2,2}^{-1}(\mathbf{w}_{i,t}) - \boldsymbol{\gamma}_{j,1,2}^{-2}(\mathbf{w}_{i,t}) > 0$. Under this assumption, the production

[14] Because these shifters are parameters of the production and input demand functions, relation (5) ultimately allows us to impose parameter restrictions between the supply and input demand functions (see below).

[15] According to relation (5), input applications exceeding $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ decrease crop yields. A rational farmer will choose the optimal input application such that $x_{i,j,l,t}^* \leq \boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ $\forall k \in \{1;2\}$ and $j \in \mathbb{J}$.

function defined in relation (5) is a non-decreasing and strictly concave function of $x_{i,j,k,t}$. We show in Section that this is the case for all inputs and all crops. Second, relation (6) states that an increase in the input requirements $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ increases the productivity of input k. Third, the productivity of input k on crop j depends on the technical shifters of input own productivity $\boldsymbol{\gamma}_{j,k,k}^{-1}(\mathbf{w}_{i,t})$. Given that $x_{i,j,k,t}^{*} \leq \boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$, an increase of $\boldsymbol{\gamma}_{j,k,k}^{-1}(\mathbf{w}_{i,t})$ increases the productivity of the input. Fourth, the productivity of input k on crop j depends on the substitution/complementarity shifters $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$. Given that $x_{i,j,l,t}^{*} \leq \boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t})$, an increase of $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$ implies that the productivity of input k on crop j increases *ceteris paribus*. Finally, the productivity of input k depends also on the input requirement of input l $(k \neq l)$ through these substitution/complementarity terms. For a positive (resp. negative) $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$, an increase of $\boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t})$ increases (resp. decreases) the productivity of input k. Similarly, the productivity of input k decreases (resp. increases) with $x_{i,j,l,t}$ when $\boldsymbol{\gamma}_{j,1,2}^{-1}(\mathbf{w}_{i,t})$ is positive (resp. negative), i.e. when the two inputs are substitute (resp. complementary) inputs. Overall, one can think about the productivity of input k on crop j as a decreasing affine function of $x_{i,j,k,t}$ where $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})\boldsymbol{\gamma}_{j,k,k}^{-1}(\mathbf{w}_{i,t})$ is the y-intercept (*modulo* the value of $\boldsymbol{\gamma}_{j,1,2}^{-1}[\boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t}) - x_{i,j,l,t}])$ and where the set of parameters $\boldsymbol{\gamma}_{j,k,k}^{-1}(\mathbf{w}_{i,t})$ determines the slope of the function. In line with the literature (e.g. Femenia and Letort, 2016), we show in Section that fertilizers present a greater estimated productivity than pesticides at the sample mean values for all considered crops.

Weather conditions. Our specification of the production function in relation (5) differs from Femenia and Letort (2016) by allowing the parameters to depend on weather conditions. Inspired by Lobell et al. (2011), we specify a quadratic relationship between yields and both average temperatures $(T_{i,t})$ and total precipitation $(P_{i,t})$ during the growing season such that:

$$\boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) = \alpha_j^0 + \alpha_j^T T_{i,t} + \alpha_j^{T^2} T_{i,t}^2 + \alpha_j^P P_{i,t} + \alpha_j^{P^2} P_{i,t}^2. \tag{7}$$

We extend this specification to agrochemical input requirement ($\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$) and technical shifters ($\boldsymbol{\gamma}_{j,k,l}^{-1}(\mathbf{w}_{i,t})$) $\forall\{k;l\} \in \{1;2\}^2$ and $j \in \mathbb{J}$:

$$\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) = \beta_{j,k}^{0} + \beta_{j,k}^{T} T_{i,t} + \beta_{j,k}^{T^2} T_{i,t}^{2} + \beta_{j,k}^{P} P_{i,t} + \beta_{j,k}^{P^2} P_{i,t}^{2}, \tag{8}$$

$$\boldsymbol{\gamma}_{j,k,l}^{-1}(\mathbf{w}_{i,t}) = \gamma_{j,k,l}^{0} + \gamma_{j,k,l}^{T} T_{i,t} + \gamma_{j,k,l}^{T^2} T_{i,j,t}^{2} + \gamma_{j,k,l}^{P} P_{i,t} + \gamma_{j,k,l}^{P^2} P_{i,t}^{2}. \tag{9}$$

Together with the specification of relation (5), these disaggregations of the structural parameters into relations (7), (8) and (9) allow us to smoothly capture the different channels through which weather affects crop yields. In particular, they allow us to capture the weather impacts on maximum crop yields through $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$ – independently of farmers' input applications – and on input productivity through $\boldsymbol{\beta}_j(\mathbf{w}_{i,t})$ and $\boldsymbol{\gamma}_j^{-1}(\mathbf{w}_{i,t})$.[16]

On top of these differential effects, the quadratic relationships of temperatures and precipitation specified into relations (7), (8) and (9) provide flexibility to capture the non-linear effects of weather conditions. While the quadratic formulation is usual for precipitation, the literature has often considered an alternative specification for temperatures, distinguishing beneficial from harmful cumulative temperatures depending on a temperature threshold.[17] If this specification has been useful to estimate the non-linear impacts of temperatures on crop yields (Schlenker and Roberts, 2009), there is no reason *a priori* to think that the same thresholds apply for input requirements and technical shifters. We thus prefer to use the more general – quadratic – form of average temperatures to specify these relationships. We however test the sensitivity of our results to alternative specification of temperature impacts in Section and show that our results are robust.

Structural model. The formulation of our structural model explicitly represents the set of optimal decisions of farmers under the particular technology and weather conditions, and the consequences of these decisions on crop yields. To formalize it, we first need to solve

[16] Kaminski et al. (2013) use a comparable disaggregation of a similar production function described in relation (5) but in the one-input case.

[17] These measures of cumulative temperatures are usually referred to as beneficial (or growing) and killing degree days in the literature (Schlenker and Roberts, 2009).

the farmers' program in relation (1) with our particular production function in relation (5) for both fertilizers and pesticides. Such resolution leads to the optimal demand function for input k on crop j:

$$x^*_{i,j,k,t} = \boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) - \frac{p^x_{k,t}\boldsymbol{\gamma}^{-1}_{j,k}(\mathbf{w}_{i,t}) + p^x_{l,t}\boldsymbol{\gamma}^{-1}_{j,1,2}(\mathbf{w}_{i,t})}{E(p^y_{i,j,t})(\boldsymbol{\gamma}^{-1}_{j,1,1}(\mathbf{w}_{i,t})\boldsymbol{\gamma}^{-1}_{j,2,2}(\mathbf{w}_{i,t}) - \boldsymbol{\gamma}^{-2}_{j,1,2}(\mathbf{w}_{i,t}))}, \tag{10}$$

with $k \neq l$. Relation (10) indicates that weather affects the optimal applications of input k through the sets of parameters $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ and $\boldsymbol{\gamma}^{-1}_{j,k,l}(\mathbf{w}_{i,t})$.[18]

We can then obtain the consequences of these optimal input applications by reinserting them into relation (5). This leads to the optimal yield for crop j:

$$y^*_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \frac{1}{2}\frac{(p^x_{1,t})^2\boldsymbol{\gamma}^{-1}_{j,1,1}(\mathbf{w}_{i,t}) + (p^x_{2,t})^2\boldsymbol{\gamma}^{-1}_{j,2,2}(\mathbf{w}_{i,t}) + 2p^x_{1,t}p^x_{2,t}\boldsymbol{\gamma}^{-1}_{j,1,2}(\mathbf{w}_{i,t})}{(E(p^y_{i,j,t}))^2(\boldsymbol{\gamma}^{-1}_{j,1,1}(\mathbf{w}_{i,t})\boldsymbol{\gamma}^{-1}_{j,2,2}(\mathbf{w}_{i,t}) - \boldsymbol{\gamma}^{-2}_{j,1,2}(\mathbf{w}_{i,t}))}. \tag{11}$$

Relation (11) indicates that weather affects the optimal yields only through the parameters $\boldsymbol{\alpha}_{j,k}(\mathbf{w}_{i,t})$ and $\boldsymbol{\gamma}^{-1}_{j,k,l}(\mathbf{w}_{i,t})$, but not through $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$.

Overall, our structural model consists of one yield equation (relation (11)) and two input demand equations (relation (10) for fertilizers and pesticides) for each crop $j \in \mathbb{J}$. The parameters $\boldsymbol{\gamma}^{-1}_{j,k,l}(\mathbf{w}_{i,t})$ are thus shared between the yield and input demand functions of the structural model (Pope and Just, 2003). As noted by Carpentier and Letort (2012), this kind of model is both primal and dual in its structure. The use of duality theory here allows us to determine the weather impacts on the technical shifters (through $\boldsymbol{\gamma}^{-1}_{j,k,l}(\mathbf{w}_{i,t})$) while still capturing the weather impacts on yields and input demand in the *primal* part of the model (through $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$ and $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ respectively). The addition of price variations (multiplied by weather variations) is an original feature of the structural modeling of the

[18]Relation (10) indicates that optimal input applications increase with input requirements $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ and decrease with technical shifter terms $\boldsymbol{\gamma}^{-1}_{j,k,l}(\mathbf{w}_{i,t})$ $\forall\{k;l\} \in \{1;2\}^2$. Similarly, optimal input applications increase when the expected crop price $E(p^y_{i,j,t})$ increases but decrease with the price of input k. They increase (resp. decrease) with the price of input l when the two inputs are substitutes (resp. complementary).

weather impacts on agriculture.[19] Such addition into our framework allows us to distinguish the farmers' behavioral responses to weather changes from the plants' biophysical ones.

Econometric Strategy

Our econometric strategy consists of comparing the estimated weather impacts on crop yields using reduced-form and structural models for wheat ($j = 1$), barley ($j = 2$) and rapeseed ($j = 3$). In the following section, we first present the estimated reduced-form model before turning to the presentation of the econometric specification of our structural model.

Reduced-form estimation. As a benchmark, we estimate the relationship between crop yields and weather conditions during the growing season using a reduced-form model in the spirit of the yield-weather-panel literature. Formally, we specify for each crop a quadratic relationship with both average temperature and total precipitation during the growing season, conditionally on farm fixed effects:

$$y_{i,j,t} = \psi_j^T T_{i,t} + \psi_j^{T^2} T_{i,t}^2 + \psi_j^P P_{i,t} + \psi_j^{P^2} P_{i,t}^2 + \vartheta_{i,j}^y + \varepsilon_{i,j,t}^y, \tag{12}$$

with $\vartheta_{i,j}^y$ the farm fixed effect, $\boldsymbol{\psi}_j(\mathbf{w}_{i,t})$ the set of parameters of interest and $\varepsilon_{i,j,t}^y$ the remaining error terms that are assumed to have white noise characteristics. The farm fixed effects capture the heterogeneous farm-specific time-invariant drivers of crop yields such as soil quality. The effects captured by $\boldsymbol{\psi}_j(\mathbf{w}_{i,t})$ are the total impacts of weather conditions during the growing season on crop yields. We estimate relation (12) using ordinary least squares (OLS).

The reduced-form model described in relation (12) is very similar to most of the models commonly used in the yield-weather-panel literature. In particular, it has two of the main characteristics of these models. First, in accordance with the common practice, relation (12) includes individual fixed effects. This means that we estimate the parameters $\boldsymbol{\psi}_j(\mathbf{w}_{i,t})$ using

[19] The addition of prices to ease the measurement of weather impacts on agriculture has also been proposed by Sesmero et al. (2018) in the case of net revenues (instead of yields in our case).

abnormal variations in weather conditions and crop yields. While the common practice is to work on aggregate data at the departmental, regional or country level, here we perform our analysis at the farm level and implement the fixed effects accordingly.[20] Second, as is commonly the case in this literature, relation (12) includes the average temperatures and total precipitation and their squared terms to estimate the non-linear weather impacts on crop yields. As discussed previously, one alternative would be to replace the linear and squared temperature terms by measures of beneficial and harmful degree days. We test the sensitivity of our results to this alternative in Section .

While similar for several dimensions, relation (12) may differ from the commonly used reduced-form models in its absence of specific correction for any temporal effects. In particular, researchers have often additionally included time trends or year fixed effects to control for the effects of technical progress or common annual shocks (Schlenker and Roberts, 2009; Fisher et al., 2012). While common, these inclusions are mainly justified when the number of years in the panel is large (Mérel and Gammans, 2021), which is not our case here (see Section). We test the sensitivity of our results to these alternatives in Section . These sensitivity analyses indicate that our results are robust to the inclusion of time trends but, as suggested by Fisher et al. (2012), not for the inclusion of year fixed effects.

Structural estimation. We estimate the structural model consisting of relations (10) and (11) for each crop. Specifically, we estimate for crop j the following system:

$$\begin{cases} y_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})\frac{(p^x_{1,t})^2}{2(E(p^y_{i,j,t}))^2} - \boldsymbol{\delta}_{j,2,2}(\mathbf{w}_{i,t})\frac{(p^x_{2,t})^2}{2(E(p^y_{i,j,t}))^2} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{1,t}p^x_{2,t}}{(E(p^y_{i,j,t}))^2} + \omega^y_{i,j} + \mu^y_{i,j,t}, \\ x_{i,j,1,t} = \boldsymbol{\beta}_{j,1}(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})\frac{p^x_{1,t}}{E(p^y_{i,j,t})} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{2,t}}{E(p^y_{i,j,t})} + \omega^x_{i,j,1} + \mu^x_{i,j,1,t}, \\ x_{i,j,2,t} = \boldsymbol{\beta}_{j,2}(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,2,2}(\mathbf{w}_{i,t})\frac{p^x_{2,t}}{E(p^y_{i,j,t})} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{1,t}}{E(p^y_{i,j,t})} + \omega^x_{i,j,2} + \mu^x_{i,j,2,t}, \end{cases} \tag{13}$$

[20] Bareille and Chakir (2023) estimate a Ricardian fixed effect model at the plot level using panel data on repeated farmland transactions involving the same plots.

with $\omega^y_{i,j}$ and $\omega^x_{i,j,k}$ the farm fixed effects, $\mu^x_{i,j,k,t}$ and $\mu^y_{i,j,t}$ the remaining error terms with white noise properties and $\boldsymbol{\delta}_{j,k,l}(\mathbf{w}_{i,t}) = \frac{\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})}{\gamma^{-1}_{j,1,1}(\mathbf{w}_{i,t})\gamma^{-1}_{j,2,2}(\mathbf{w}_{i,t})-\gamma^{-2}_{j,1,2}(\mathbf{w}_{i,t})}$ $\forall\{k;l\} \in \{1;2\}^2$.[21] These parameters $\boldsymbol{\delta}_{j,k,l}(\mathbf{w}_{i,t})$ are thus functions of the previous technical shifters $\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})$. As for the latter, they are shared between the equations of the system. Consistently with relation (5), a smaller $\boldsymbol{\delta}_{j,k,k}(\mathbf{w}_{i,t})$ implies that farmers use more input k when the input-output price ratio increases, suggesting that the productivity of input k increases. Similarly, a positive (resp. negative) $\boldsymbol{\delta}_{j,k,l}(\mathbf{w}_{i,t})$ implies that fertilizers and pesticides are substitute inputs (resp. complementary). We disaggregate $\boldsymbol{\delta}_{j,k,l}(\mathbf{w}_{i,t})$ as $\delta^0_{j,k,l} + \delta^T_{j,k,l}T_{i,t} + \delta^{T^2}_{j,k,l}T^2_{i,t} + \delta^P_{j,k,l}P_{i,t} + \delta^{P^2}_{j,k,l}P^2_{i,t}$. Given the potential correlation between the error terms of the system equations, we estimate relation (13) using estimators from seemingly unrelated equations (SUR).[22]

Finally, while relation (13) specifically uses observed prices for the inputs (farmers observe the input prices when applying fertilizers and pesticides) in the input/output prices ratio, it uses *expected* prices for the outputs. The form of crop price expectation is an usual source of debates in agricultural economics (Nerlove and Bessler, 2001). A common practice is to assume that farmers present *naive* expectations of crop prices (e.g. Carpentier and Letort, 2012; Kaminski et al., 2013; Femenia and Letort, 2016). Others assume that farmers present rational price expectations or use future prices at harvest time. Following Koutchadé et al. (2018), we assume that farmers in our sample have naive crop price expectations, i.e. that $E(p^y_{i,j,t}) = p^y_{i,j,t-1}$.[23] We test the sensitivity of our results to these alternative expectation forms in Section and show that they are robust.

[21]Note that the concavity of the production function is verified since $\boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})\boldsymbol{\delta}_{j,2,2}(\mathbf{w}_{i,t}) - \boldsymbol{\delta}^2_{j,1,2}(\mathbf{w}_{i,t}) > 0$. Our results in Section indicate that this is verified for the three crops considered.

[22]Note that the system specified in relation (13) exploits variations in both yields and input applications, implying that we exploit additional sources of variation compared to the commonly used reduced-form model described in relation (12). Indeed, for a population of I farmers growing crop j, our structural estimation uses $3 \times I$ observations (I yield observations for crop j, I observations of fertilizer applications on j and I observations of pesticide applications on j) instead of I observations only for the reduced-form case.

[23]Koutchadé et al. (2018) have tried to estimate a structural model using these different alternatives on a sample similar to ours (specifically an unbalanced panel of farms from *Meuse* between 2006 and 2011; see Section). They have concluded that the data generation process at stake supports the assumption of naive crop price expectations. In addition, Hsiang (2016) warned that the introduction of contemporaneous prices may introduce biases if they are affected by climate. This situation is unlikely to occur with naive crop price expectations.

Data Sources and Summary Statistics

Accounting dataset. Our primary data is an unbalanced panel of farms located in the French department of *Meuse* observed between 2006 and 2012. The panel is composed of 296 crop farms remaining in the database for an average of 3.73 years, constituting 1,104 farm×year observations in total.

Meuse is a rainfed agricultural department (NUTS3 region) located in north east France (see Figure A1 in the Online Appendix) 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 intensive cropping practices. Together, the farms of our sample occupy 31.09% of the whole useful agricultural area of *Meuse*. Although some farms cultivate peas, corn or sunflower, these are fairly marginal crops in our sample. By contrast, all the farms in our sample grow wheat, barley and rapeseed, which together occupy an average of 79.17% of farmers' arable area.

The database originates from the Meuse Management Center local accounting agency (*Centre de Gestion de la Meuse*). The Meuse Management Center is one of the two farm accounting agencies in the department. On top of their basic accounting service used for fiscal purposes, the Meuse Management Center offers a premium service to its members, which allows them to benefit from a detailed accounting analysis of their annual exercises. The information we use originates from the farms subscribing to this service. The unbalanced nature of the database comes from the fact that farms can seamlessly subscribe and unsubscribe to the premium service.

One of the main interests of using this farm-level dataset is that we can access detailed accounting information *per crop*. On top of information on crop yields and prices, this database provides crop-specific information on the net expenditures for each input.[24] Given

[24] We compute the input quantities applied by crop in constant €/ha dividing the net expenditure per hectare by the regional input price index provided by the French Department of Agriculture (*Agricultural Means of Production Purchasing Price Index*).

the accounting nature of the database, these net expenditures correspond to the value of the inputs *used* in a given calendar year on each crop, thus including changes in input inventories. Such information on input uses per crop is necessary for the estimation of our structural model as variations in input applications constitute two thirds of the observations used in the estimation procedure. The *Meuse* database is one of the few that provides such crop-level disaggregation for fertilizer and pesticide applications. Common agricultural databases – such as the farm accountancy data network in Europe – usually provide input expenditure at the farm scale, and not per crop. This explains why the *Meuse* database has been used by many studies on French agriculture (e.g. Boussemart et al., 2011; Carpentier and Letort, 2012; Femenia and Letort, 2016; Bareille and Letort, 2018; Koutchadé et al., 2018; Chakir and Thomas, 2022).

Weather variables. We use historical daily weather information for the whole period from *Météo France*.[25] Before computing our weather variables, we first reconstruct the distribution of temperature within each day using a sine interpolation between minimal and maximal daily temperatures, *à la* Schlenker and Roberts (2009). We then compute the average temperature during the growing season as the average of the reconstructed temperature distribution between February 1^{st} and July 31^{th}. This method provides better approximation of the average temperatures over the growing season than alternative methods relying on daily or monthly temperature averages only. One can interpret our measure of average temperatures as the accumulated temperatures (i.e. sum of beneficial and killing degree days) divided by the number of days during the growing season. We compute the total precipitation during the growing season as the sum of observed precipitation between February 1^{st} and July 31^{th}.

[25]The smallest-scale available location in our dataset is the municipality. There are about 500 municipalities in *Meuse*, for an average size of about 4 km $\times$ 4 km. The weather information was provided on 8 km $\times$ 8 km grid squares. Each unit thus covers on average 4 municipalities. We 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.

Summary Statistics. We provide the summary statistics on prices (deflated by the national consumer price index), yields and input uses for the three crops as well as weather conditions during the growing season in Table 1. On average, the highest yields are achieved for wheat, the highest prices are paid for rapeseed, while barley requires fewer inputs than wheat or rapeseed. Wheat and rapeseed are more profitable than barley, which is rather used as an intermediary crop in the usual crop rotation found in *Meuse*. The crop with the greatest yield variations is rapeseed, with a coefficient of variation of 6.60/33.59=0.20, followed by barley and wheat yields, with coefficients of 0.17 and 0.15 respectively. Regarding weather, Table 1 underlines the fact that precipitation displays greater variability than temperature in our sample, with associated coefficients of variation for temperature and precipitation of 0.05 and 0.27 respectively. This greater heterogeneity of precipitation is common in the literature (Fezzi and Bateman, 2015).

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

	Mean	**S.D.**	**Min**	**Max**
Average temperature (°C)	12.65	0.64	11.17	14.18
Total precipitation (mm)	408.81	109.72	198.10	591.27
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
Fertilizer applications for wheat (constant €/ha)	123.04	28.14	3.79	210.16
Fertilizer applications for barley (constant €/ha)	106.85	25.00	3.15	211.05
Fertilizer applications for rapeseed (constant €/ha)	122.30	29.81	3.55	247.84
Pesticide applications for wheat (constant €/ha)	160.10	44.25	8.45	377.63
Pesticide applications for barley (constant €/ha)	152.51	45.69	34.13	392.07
Pesticide applications for rapeseed (constant €/ha)	220.88	52.25	63.24	423.47
Fertilizer price (index)	1.17	0.21	0.91	1.51
Pesticide price (index)	0.98	0.03	0.94	1.01

Table 1 presents a situation where both the dependent and independent variables of interest display smaller variations than those usually exploited in the yield-weather-panel literature. The coefficients of variation of crop yields are for example twice as small in our case than in the case of Schlenker and Roberts (2009). This is not surprising. Indeed, the rich information in the *Meuse* database regarding input uses per crop comes at the cost of exploiting a smaller geographical area than those used in most yield-weather-panel studies,[26] which are often performed at national level (e.g. France for Gammans et al., 2017; US for Schlenker and Roberts, 2009).[27] However, our setting presents additional interests (on top of detailing input uses per crop). First, we use farm-level observations instead of aggregated observations at the county or departmental level. This should allow us to better account for fine-scale variations and facilitate the identification of the weather impacts on agriculture, which could otherwise suffer from aggregation biases (Fezzi and Bateman, 2015). Second, we use price variations on top of weather variations (in particular with the introduction of interaction terms between them). Table 1 shows that crop prices display levels of heterogeneity comparable with those of temperatures and precipitation. This additional source of variation should thus facilitate our identification strategy compared to previous studies.[28] Finally, based on an analysis of out-of-sample forecast performances of our reduced-form and structural models, we show in Section that the weather variations that remain after adjusting for farm fixed effects are comparable to recent papers from the literature.

Results

In this section, we first compare results from structural and reduced-form models and show that they provide similar estimated weather impacts on crop yields (Section). Second, we show that the structural and reduced-form models are equally able to produce out-of-sample forecasts (Section). Third, we provide evidence of the robustness of our results (Section).

[26]Note that our database is also relatively small in the time dimension. Indeed, it exploits only seven years of data, whereas previous studies generally cover longer time spans. While additional rounds of data would provide more information for inference, the used of individual fixed effects on long time periods rely on strong assumptions about the time variation of omitted characteristics, that could ultimately lead to biased estimates (Millimet and Bellemare, 2023).

[27]Note that, like ours, most studies that formally explain short-term adaptation behaviors in relation to weather changes are usually performed at regional scales (e.g. Cui and Xie, 2022; Jagnani et al., 2021; Ramsey et al., 2021).

[28]Our estimates should not suffer from any multicollinearity issue because correlations between prices and weather variables are low (see Table A1 in the Online Appendix).

Finally, we take the analysis of the structural estimates further in order to identify farmers' adaptation responses to weather changes and how these responses translate into changes in crop yields, ultimately providing separate measurements of the agronomic and adaptation effects (Section).

Estimating the weather impacts on crop yields: reduced-form and structural estimates

Marginal analysis. Here we compare the ability of our reduced-form and structural approaches to estimating the impacts of weather conditions during the growing season on crop yields. The results of the estimations of the reduced-form and structural models described in relations (12) and (13) are presented in the Online Appendix in Tables A2 and A3 respectively.[29]

Regarding the values of the reduced-form estimates (Table A2), we find that the yields have positive concave relationships with both temperature and precipitation for the three crops. This suggests that crop yields are highest at moderate temperatures and precipitation but decrease for extreme cold, hot, arid, or wet conditions. These results are common in the literature (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011; Tack et al., 2015).

The interpretation of the structural results is not as straightforward. Indeed, the linear and quadratic terms of average temperature and precipitation in the structural model affect crop yields in a complex way through the sets of parameters $\hat{\boldsymbol{\alpha}}_j$ and $\hat{\boldsymbol{\delta}}_j$ (see relation (13)). To facilitate comparison between the results of the reduced-form and structural estimations, we compute the weather elasticities on crop yields using the obtained estimates (in Tables A2 and A3) at the sample mean values (see Table 1). The computations to obtain the elasticities

[29] Table A4 in the Online Appendix reports, for the structural model, the properties of the estimated production functions for the three crops at the sample mean values. We recompute these elements using the structural estimates reported in Table A3. It shows that, for each crop, the production function respects the assumption of non-decreasing and concave relationship with both fertilizers and pesticides. We also report the aggregated productivity of fertilizers and pesticides for the three crops using relation (6).

are detailed in the Online Appendix . We report the values of the elasticities at the sample mean values in Table 2.[30]

Table 2: Reduced-form and structural estimates of weather elasticities on crop yields.

	Reduced-form			**Structural**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.53 ***	-0.63 ***	1.02 ***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.11)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.03 **	0.02	-0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)

NOTE. Elasticites are computed at sample mean values. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Table 2 shows that weather conditions during the growing season affect crop yields at the margin in a similar way in both the reduced-form and structural models. Looking for example at the impact of temperature on wheat yields, we find that an increase of 1% in the average temperature during the growing season increases wheat yields by 0.57% according to the reduced-form estimates, and by 0.53% according to the structural estimates. Perhaps even more remarkable, the two models agree that an increase of 1% in total precipitation during the growing season increases wheat yields by 0.03%. Similarly, the reduced-form and structural estimates provide the same weather elasticities for barley and rapeseed yields. The two types of model thus suggest similar aggregated weather impacts on crop yields in the three cases.

Given the ability of our structural estimations to reproduce the basic results of the reduced-form estimations, we now turn to the interpretation of the weather elasticities on crop yields *per se*. Table 2 first indicates that the different crops do not react similarly to a marginal increase in average temperature. This result has already been identified in the

[30] The elasticities of temperature corresponds here to an increase of 0.125°C at the sample mean value. Note that such an increase would have been different if we measured temperatures using the Fahrenheit or Kelvin scales (Hsiang, 2016). However, given that the estimates are more consistent for small increase compared to the mean (*a fortiori* for sturctural estimates; see Timmins and Schlenker, 2009), we prefer to rely on the Celsius scale. Indeed, a one percent increase in temperature would otherwise correspond to an increase of 0.545°F (corresponding to +0.3°C) and 2.857 K (corresponding to +2.857°C) with the two alternative scales. In other words, we would reason based on marginal increase three to twenty-three times greater than those obtained with the Celsius scale.

literature (e.g. Lobell et al., 2011). In our case, we find that a marginal increase in average temperature moderately decreases barley yields. All crops do not react negatively to an increase in temperature at the margin. Indeed, the same marginal increase in average temperature has respectively moderate and substantial positive impacts on wheat and rapeseed yields. Gammans et al. (2017) already underlined that barley yields suffer more from temperature increases than wheat yields in France. The large beneficial impacts of marginal increase in temperature on rapeseed are more difficult to interpret as, to our knowledge, we are the first to document weather impacts on rapeseed yields.

Non-marginal analysis. Table 2 only indicates the estimated relationship for *marginal* weather changes at the sample mean values. However, because climate change implies non-marginal changes in temperature and precipitation, one would ideally also compare the impacts of weather changes as predicted by the two methods over the whole distributions of temperature and precipitation. As such, Figure A2 in the Online Appendix displays the estimated relationships between crop yields and weather over the whole distribution of temperature and precipitation using the reduced-form estimates. Figures A3, A4 and A5 in the Online Appendix show similar relationships using the structural estimates. Comparing these figures shows that the estimated responses of crop yields to temperature and precipitation present similar quadratic shapes and curvatures. Overall, the two models provide similar projected impacts of non-marginal weather changes on crops yields. For example, an increase of one standard deviation in average temperature decreases wheat yields by 3.3% using the reduced-form estimates and by 2.9% using the structural estimates. Similarly, an increase of one standard deviation in total precipitation decreases wheat yields by 6.6% using the reduced-form estimates and by 6.2% using the structural estimates. We obtain similar results for barley and rapeseed.[31]

[31]Note in particular that, while marginal increases in average temperature can increase crop yields, non-marginal increases in average temperature decrease the yields of all crops above a threshold (see Figures A2 to A5).

Spatially-adjusted standard errors. The literature assessing weather impacts on economic outcomes has paid attention to the issue of the spatial autocorrelation in the error terms. To not take into account this phenomenon in the presence of spatially correlated weather conditions can conduct to smaller estimated standard errors than they truly are (Ortiz-Bobea, 2021). Since Schlenker et al. (2006), it has been common in the yield-weather-panel literature to correct the estimations for spatial dependence by clustering the obtained standard errors *à la* Conley (1999). If we can apply this solution for our reduced-form estimations, the complex structure of our structural model prevents us from correcting our standard errors for spatial dependence using this approach.[32] To address the issue of unobserved spatial dependence in our structural model, we opted for another clustering technique that has been previously used in the literature (Hsiang, 2016; Ortiz-Bobea, 2021). Specifically, we report block-bootstrapped standard errors clustered at the *Canton* $\times$ *Year* level in Tables A2 and A3 (Moulton, 1990; Abadie et al., 2023), on top of the robust – unclustered – standard errors.[33] We also report the standard errors obtained with the Conley (1999)'s correction for the reduced-form estimates.[34] The reduced-form results indicate higher stan-

[32]Specifically, we use the R command `nlsystemfit` to estimate the structural model as described in relation (13), notably with the constraints on the parameters $\boldsymbol{\delta}_{j,k,l}$ to be equal between the yield and input equations. However, neither the options nor the output formats of the command allow us to implement any of the common solutions to adjust standard errors for spatial dependence using Conley (1999)'s correction. To our knowledge, there is no available command in any statistical software that would allow us to control for spatial dependence when estimating a three-equations system with parameter restrictions.

[33]Cantons are the largest administrative divisions within French departments (30 cantons in total in our sample). They usually consist of a group of ten to fifteen municipalities in *Meuse*, with an average size of 15 km $\times$ 15 km. It is worth noting that similar clustering techniques at larger scales than the unit of analysis have already been employed in previous studies (e.g. Hsiang et al., 2013; Burke and Emerick, 2016). In particular, Hsiang et al. (2013) proceed to a block-bootstrap procedure where observations are re-sampled by year. Such procedure assumes spatial correlations across all farms of the sample, which would lead to larger standard errors than those obtained with our *Canton* $\times$ *Year* block-bootstrap procedure. While relevant in the case of Hsiang et al. (2013), the small number of years in our sample prevents us from applying such block-bootstrap procedure. To account for similar contemporaneous dependence in the bootstrapped samples, one would need to turn towards alternative clustering procedures such as the wild bootstrap procedure (Cameron et al., 2008), which is consistent even with small number of clusters (Canay et al., 2021). However, we do not implement such procedure here, as assuming similar correlations across farms located at different distances among each other may be excessive (Ortiz-Bobea, 2021). We rather consider that neighbored farms – those within a particular canton – present greater spatial correlations than farms located at the two opposite of the department.

[34]We correct the reduced-form estimations for spatial dependence using the code proposed by Ortiz-Bobea (2021). Here, we specified a threshold of 15 kilometers among farm headquarters' municipality centroids beyond which we assume no correlation. In other words, we assume that there is no spatial correlations with observations located outside the neighboring cantons (see Online Appendix). Given that *Meuse* region

dard errors when spatial dependence is accounted for (Table A2), but leaves our conclusions unchanged. In particular, all the reduced-form estimates remain statistically significant at the 1% level with the spatially-adjusted standard errors, with either the block-bootstrapped clustering procedure or the Conley (1999)'s one.[35] Similarly, we find – though not systematically – larger standard errors when spatial dependence is accounted for in the structural estimations (Table A3). However, these larger standard errors do not alter the results substantively. In particular, all the structural estimates that are statistically significant at the 5% and 1% levels with the unclustered standard errors are also statistically significant at the same levels with the clustered ones.

Though not invalidating the results of our reduced-form and structural estimations, the larger clustered standard errors compared to the unclustered ones indicate that the standard errors of our elasticities in Table 2 – obtained with the delta method and the robust, unclustered variance-covariance matrix – are likely narrower than they are in reality. Consequently, our results should not be interpreted as unambiguous proof of weather impacts on crop yields. There is already an abundant literature documenting these effects worldwide with appropriate corrections for spatial dependence (e.g. Schlenker and Roberts, 2009; Tack et al., 2015; Gammans et al., 2017). Our contribution is rather methodological, and should be interpreted as a comparison exercise of the usual reduced-form estimations with those from our original structural estimations in order to shed some light on the channels that drive the weather impacts on crop yields.

Comparison of out-of-sample forecast performance

Estimates obtained from reduced-form models are usually employed in the literature to make projections of the impacts of future climate change on crop yields. While the exercise

measures 6,211 square kilometers (see Figure A1 in the Online Appendix), this threshold implies that we assume that a farm located at the barycenter of the *Meuse* department presents positive spatial correlations with farms located in a surrounding area of about $(\pi \times 15^2)/6,211 \approx 11.5\%$ of the department.

[35] The two clustering procedures conduct to reduced-form standard errors that are similar in magnitudes (Table A2). This implies that, in our data, the *Canton* $\times$ *Year* clustering procedure accounts for similar spatial dependence than the Conley (1999)'s approach. These findings support the validity of our block-bootstrapped clustering correction for our structural estimations.

is subject to several limits (see for example Ortiz-Bobea, 2021, for a discussion of few issues in projecting climate change impacts on crop yields), one of the detrimental aspects of the quality of the projections is the out-of-sample forecast performance of the models used. A common method for assessing out-of-sample forecast performance is to drop part of the data and to compare their actual values with their predicted values using the remaining observations. In the case of a panel dataset, the common strategy is to estimate the model after dropping a particular subset of years before comparing the crop yield values to their predictions (Schlenker and Roberts, 2009). Accordingly, we estimate our reduced-form and structural models after dropping observations for the year 2010 and test their respective ability to predict the crop yield values for 2010.[36]

Figure 2 displays, for the three crops, the change in root-mean-square error (RMS) of the reduced-form and structural models with comparison to a reduced-form model including farm fixed effects only, where weather variables are removed. In other words, Figure 2 displays by how much the addition of weather variables to the reduced-form and structural models improves the out-of-sample forecast performance of crop yields in 2010 compared to the farm's average crop yield values from the other years.

Looking first at the reduced-form model outcomes, Figure 2 shows that the introduction of weather variables reduces the RMS by 3.0%, 4.6% and 3.3% for wheat, barley and rapeseed respectively. In comparison, Ortiz-Bobea et al. (2019) found in their studies of all US rain-fed counties that the reduction in RMS between comparable reduced-form models (one including weather variables compared to one without) was 3.0% for wheat. Similarly, Schlenker and Roberts (2009) found that introducing weather variables into their county-level, reduced-form model reduces the RMS from 0.6% for cotton to 6.4% for corn. Finally, closer to our study area, Gammans et al. (2017) found that the reduction in RMS between comparable reduced-form models was 6.6% and 4.8% for wheat and barley respectively. These figures

[36]We drop the year 2010 as it is the year with the smallest amount of spatial deviation in precipitation (about 30% less than in the other years). This reduces the variability in the predictions. We do not proceed to the selection based on temperature deviations, as all years present roughly similar deviations in temperature. Finally, note that the year 2010 is also located in the middle of our panel period, removing some potentially trend issues.

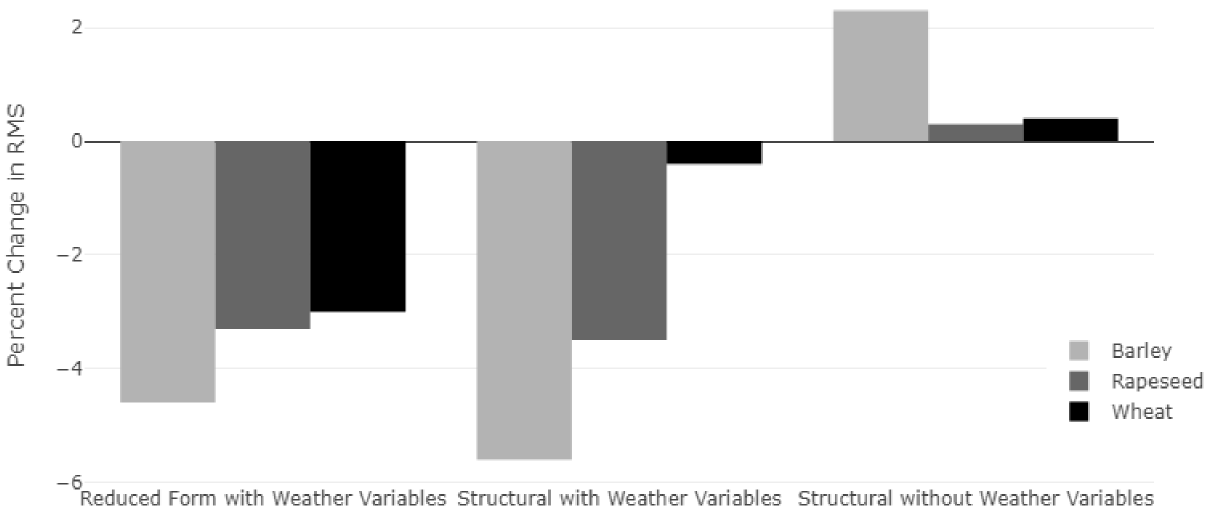

Figure 2: Out-of-sample forecast performance for various model specifications. Note. Bar charts display the percentage reduction in the RMS for each model in comparison with a baseline reduced-form model with no weather variables (expressed in percentages). Relative performance is measured according to the accuracy of each model to predict the crop yields in 2010, which we omitted from the sample ($\approx 17\%$ of all observations).

suggest that, while our study area is a small geographical region compared to the literature standards (typically at country or continent levels), the weather variation that remains after adjusting for individual fixed effects is comparable to recent papers from the literature (e.g. Schlenker and Roberts, 2009; Gammans et al., 2017; Ortiz-Bobea et al., 2019), thus yielding similar out-of-sample forecast performances.

Structural modeling comes with several modeling choices that are often difficult to test except by means of out-of-sample forecast analysis (Timmins and Schlenker, 2009). Figure 2 shows that, compared to a reduced-form model with farm fixed effects only, the structural model with weather variables reduces the RMS by 0.3%, 5.6% and 3.1% for wheat, barley and rapeseed respectively. These figures are comparable to the previous reduced-form studies from the literature. The structural model even seems to do a better job at predicting crop yields in our case, at least for barley and rapeseed. To further investigate this result, Figure 2 also plots the change in RMS for a structural model that excludes weather conditions (thus a similar model than those in relation (13) but accounting for prices and farm fixed effects only). It shows that, without the inclusion of weather variables, the structural model is in fact less able to provide reliable out-of-sample forecasts than the reduced-form model. This means that the additional information due to the inclusion of prices in the model does not compensate for the loss of flexibility imposed by the model structure. However, the increases in RMS remain limited (respectively +0.3%, +2.3% and +0.2% for wheat, barley and rapeseed).

Sensitivity analyses

So far, our results have shown that the structural model described in relation (13) provides (i) identical estimates of the weather impacts on crop yields to those obtained with commonly used reduced-form models (in our particular sample), (ii) identical ability to predict out-of-sample forecasts (in our particular sample) and (iii) identical results to those commonly obtained in the yield-weather-panel literature (from other samples). These insights constitute an important and necessary step before going further with the analysis of the channels explaining weather impacts on crop yields. However, we can wonder whether these results are driven by a true relationship between weather and crop yields or if they are the consequences of some of our empirical choices. To test the robustness of these results, we estimate the weather impacts on crop yields in reduced-form and structural models with alternative empirical choices regarding (i) the measurement of temperature during the growing season (see Appendix), (ii) the form of farmers' price expectations (see Appendix) and (iii) the time structure of the error terms (see Appendix). We show that our main results are robust to these choices. In particular, our original structural model replicates the usual reduced-form results in all but one specification. The exception occurs when the models additionally include year fixed effects, which, as already pointed out by Fisher et al. (2012), purge most of the weather variations. Finally, a placebo analysis using the weather conditions in autumn instead of those during the growing season indicates no significant effects of weather outside the growing season on crop yields (see Appendix). This suggests that our previous results are due to true relationships between crop yields and weather conditions in the growing season and not to measurement errors or spurious correlations.

Mechanisms: structural measures of adaptation and of its consequences on crop yields

This section aims to use the structural estimates reported in Section to investigate how farmers adjust their fertilizer and pesticide applications to weather changes during the growing season, why they do so and what are the impacts of these within-season adjustments on crop yields.

Input adjustments. On top of determining the weather impacts on crop yields, our structural estimates allows us to identify by how much input applications change when weather changes. Reproducing what we have done in Table 2, we use the structural estimates from Table A3 to recompute the weather elasticities of fertilizer and pesticide applications. The computations of these elasticities are detailed in the Online Appendix . We report their values at the sample mean values in Table 3.

Table 3: Weather elasticities on input applications.

	Temperature			**Precipitation**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Fertilizers	1.02 ***	1.34 ***	0.61 ***	0.10 **	0.02	0.20 ***
	(0.19)	(0.23)	(0.24)	(0.04)	(0.04)	(0.04)
Pesticides	-0.39 **	0.30	-0.19	0.11 **	0.09 **	-0.24 ***
	(0.20)	(0.27)	(0.20)	(0.04)	(0.04)	(0.03)

NOTE. Elasticites are computed at sample mean values. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Table 3 shows that farmers adjust their input applications to marginal weather changes during the growing season.[37] These within-season adjustments can be significant. In particular, results show that farmers increase their fertilizer applications by 0.61% to 1.34% in response to a 1% increase in temperature, and increase fertilizer applications by 0.02% to

[37]Figures A3, A4 and A5 in the Online Appendix display changes in fertilizer and pesticide uses over the whole distribution of temperature and precipitation.

0.20% in response to a 1% increase in precipitation.[38] This is consistent with farmers' implementation of diverse adaptation strategies documented in the literature in other parts of the world (e.g. Jagnani et al., 2021; Cui and Xie, 2022). Table 3 also indicates that farmers seem to mainly respond to weather changes by adjusting their fertilizer applications, pesticide applications responding much less to weather changes.[39] This is consistent with the results describing greater aggregated productivity of fertilizers than pesticides at the sample mean values (see Table A4 in the Online Appendix). More generally, this is consistent with the common wisdom of the literature that pesticides are damage-reducing inputs used for risk management (i.e. mainly used to reduce crop variance at the second order, on top of their productive purposes at the first order),[40] while fertilizers can be considered as a productive input only (e.g. Femenia and Letort, 2016).

Motives. The results displayed in Table 3 are coherent with the agronomic literature. On one hand, it is well known from agronomists that farmers are likely to react to weather changes by modifying their fertilizer applications. Indeed, agronomists have shown that weather during the growing season determines mineralization of fertilizers and thus nutrient availability (e.g. Raun and Johnson, 1999; Kay et al., 2006). In their meta-analysis of the literature, Xia and Wan (2008) have notably shown that greater average temperatures increase fertilizer productivity. Tremblay et al. (2012) extend this result to precipitation, which they show to increase nitrogen use efficiency. Our results for temperature and precipitation are thus consistent with these agronomic findings. Also, as in our case, Tremblay et al. (2012) and Chen and Gong (2021) found that fertilizer applications share a concave positive re-

[38]As in Table 2, a 1% increase in temperature at the sample mean values corresponds to a temperature increase by 0.125°C. A 1% precipitation increase corresponds to an increase by 4.67mm.

[39]For example, results show no significant changes in pesticide applications due to a marginal increase in temperature for barley and rapeseed. The only significant impact is estimated for wheat, where farmers reduce their pesticide applications by 0.39% following a 1% increase in temperature.

[40]A possible extension of our structural model would be to explicitly introduce the risk dimension. This may help to properly identify the weather impacts on farmers' pesticide use. One step in this direction may be to add some elements of the Lichtenberg and Zilberman (1986)'s damage control technology to our production function.

lationship with temperature, with moderate temperatures increasing fertilizer applications but extreme heat reducing fertilizer use.

On the other hand, the agronomic literature has also shown that weather can affect farmers' pesticide use. In their literature review, Delcour et al. (2015) explain that weather can affect pesticide applications through (i) changes in volatilization and degradation of pesticides, (ii) changes in pest resistance and (iii) changes in pest pressure (both temporally and spatially). While the last reason is often found in the literature as a cause of increasing pesticide use with higher temperatures (e.g. Rosenzweig et al., 2001; Bailey, 2004), the first two reasons are more rarely suggested as drivers of pesticide applications. Contrary to the third cause, which relates to the intrinsic need to use pesticides (changes in pest pressures), the first two are more closely related to changes in pesticide productivity. In particular, Bloomfield et al. (2006) suggest that higher temperatures stimulate microbial and chemical reaction rates, which accelerate the degradation of chemical components, thus reducing pesticide productivity. This incites rational farmers to apply fewer pesticides at the margin (as we find for wheat in Table 3). Finally, behavioral studies such as Jagnani et al. (2021) and Larsen and McComb (2021) suggest that farmers facing higher temperatures increase pesticide use at the beginning of the growing season, but reduce pesticide applications at the end of the growing season. This mixed agronomic evidence regarding pesticide use may explain why, for similar weather changes, we identify larger and more precisely estimated responses regarding farmers' fertilizer applications than farmers' pesticide applications (Table 3).

In line with these mixed agronomic insights, we show in Online Appendix that farmers in our sample do face heterogeneous incentives to adjust their input applications in response to marginal weather changes. If any regularity on the main motives explaining the input incentives can be derived from this complementary analysis developed in Appendix (see Table A9), the changes in input requirements seem to explain the changes in fertilizer (resp. pesticide) applications induced by temperature (resp. precipitation) changes. In other words, weather conditions seem to mainly affect the input productivity through the required amount of fertilizers and pesticides to achieve the maximum yields of the different crops. In line with the agronomic literature, we identify in this complementary analysis that the increase in fertilizer requirements at higher temperatures does increase fertilizer productivity.

Consequences. Informed about the extent and motives of farmers' adaptation, our structural approach ultimately allows us to measure the consequences of adaptation on crop yields. Specifically, we can disentangle the total effects of weather conditions on crop yields into the agronomic effects (i.e. the direct weather impacts on plant growth) and the adaptation effects (i.e. the indirect weather impacts due to farmers' behavioral responses). Table 4 reports in bold the weather elasticities of crop yields using our structural models, which constitutes the total effects of marginal weather changes on crop yields.[41] It also reports in italics the agronomic and adaptation impacts of marginal weather changes. We define the adaptation effects as the productive impacts of the input application adjustments at the sample mean values. As the sum of the two effects is equal to the total effects, we measure the agronomic effects as the difference between the total and the adaptation effects. These computations are detailed in Online Appendix .

Table 4: Weather elasticities on crop yields: total, agronomic and adaptation effects.

	Temperature			**Precipitation**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Total	0.53 ***	-0.63 ***	1.02 ***	0.03 **	0.02	-0.00
	(0.09)	(0.11)	(0.12)	(0.01)	(0.01)	(0.02)
Agronomic effects	0.22 **	-0.84 ***	0.89 ***	-0.01	0.02	-0.02
	(0.09)	(0.11)	(0.12)	(0.01)	(0.01)	(0.02)
Adaptation effects	0.31 ***	0.21 ***	0.12 ***	0.04 ***	0.00	0.02 **
	(0.02)	(0.03)	(0.02)	(0.01)	(0.00)	(0.01)

NOTE. Elasticites are computed at sample mean values. The elasticities of yields on temperature and precipitation are the same as those reported in Table 2 for the structural model. The sum of the agronomic and adaptation effects is equal to the weather elasticities of crop yields. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

The results from Table 4 allow us to identify whether the weather impacts on crop yields as usually measured in reduced-form models actually account for adaptation effects on top of the agronomic effects or not. Looking for example at the impact of temperature on wheat

[41] These effects are identical to the weather elasticities of crop yields reported in Table 2.

yields in Table 2, we find that a 1% increase in temperature during the growing season increases wheat yields by 0.53%. Table 4 indicates that, actually, the total effects of a 1% increase in temperature is due to the cumulative effects of a beneficial agronomic effect of 0.22% and a beneficial adaptation effect of 0.31%. About two thirds of the positive effect of temperature on wheat yields thus comes from the farmers' response to higher temperatures. While large, the positive effects of adaptation on crop yields are easy to understand. Indeed, we show in Table 3 that farmers substantially increase fertilizer applications in response to higher temperatures, for only a small reduction in pesticides. Given that fertilizer is the most productive input (see Table A4 in the Online Appendix), this large augmentation leads to substantial increases in wheat yields.

We identify similar results for barley and rapeseed yields, where input adjustments induced by warmer temperatures – as reported in Table 3 – increase crop yields. The adaptation effects induced by farmers' responses to warmer temperatures are thus positive for all crops. In particular, a 1% increase in temperature indirectly increases crop yields through input adjustments by 0.12% to 0.31% (see Table 4). The agronomic effects are more heterogeneous across crops. While we identify a slightly beneficial impact on wheat yields, the agronomic impacts on barley are negative and substantial, suggesting a large negative exogenous shock of marginal increase in temperature on plant growth. The adaptation effects reduce this negative shock by about a quarter. For rapeseed, the agronomic effects of warmer temperatures are positive and large: a 1% increase in temperature directly increases rapeseed yields by 0.89%. These results suggest that rapeseed is more suitable than cereals to be cropped under warming weather conditions *ceteris paribus*. The impacts of adaptation are however smaller on rapeseed than for wheat and barley.

In line with the results in Table 2, Table 4 only shows small marginal impacts of precipitation on crop yields. The highest impact of adaptation in response to a marginal increase in precipitation is for wheat yields, which increase by 0.04%. The total effects of an additional 1% of precipitation is 0.03%. For the two other crops, we identify no effects of marginal increases in precipitation on crop yields in total. The two patterns are however different for barley and rapeseed. Indeed, while we identify no effects of either the agronomic or adaptation effects of higher precipitation on barley yields, we find that the adaptation effects for rapeseed are positive (though small) and that the agronomic and adaptation effects cancel out each other.

The analyses developed above illustrate the interest of structural modeling in comparison with reduce-form modeling. In specifying the mechanisms underlying farmers' profit maximization objectives, we are able to distinguish the effects of an exogenous shock in production conditions (weather changes here) from those due to farmers' behavioral responses to such a shock (Timmins and Schlenker, 2009). We find that such adaptation effects are sizable and that they increase crop yields in most cases (i.e. in all except the impact of marginal precipitation change on barley yields). However, while farmers succeed in completely offsetting the negative impacts of precipitation on plant growth, they cannot do so for marginal increases in temperature.

Simulations

In this section, we investigate the potential impacts of non-marginal increases in temperature on crop yields in our sample using both the results of the reduced-form and structural models presented above. Specifically, we project the estimated impacts of uniform warming where average temperature increases by +1°C, +2°C or +3°C in comparison to our initial 2006-2012 panel, assuming all the remaining elements to be constant.

Expected impacts of warmer temperatures. Table 5 shows the initial averages of the crop yields in our sample for the period 2006-2012 (Panel A) and the predicted changes in crop yields under future temperatures using the results from our reduced-form model (Panel B) and structural model (Panel C). These changes correspond to the levels of the estimated responses in Figures A2 to A5 under additional 1°C to 3°C compared to average temperatures of the period 2006-2012, related to the initial average crop yields. These results call for several comments.

Table 5: Projections of the impacts of warmer temperatures on crop yields.

	Wheat			Barley			Rapeseed		
	+1°C	+2°C	+3°C	+1°C	+2°C	+3°C	+1°C	+2°C	+3°C
	A. 2006-2012 Averages								
Initial yields (100 kg/ha)	70.88	70.88	70.88	64.30	64.30	64.30	33.59	33.59	33.59
	B. Reduced-form Estimates								
Changes in yields (100 kg/ha)	-1.61 ***	-12.84 ***	-33.68 ***	-8.63 ***	-27.70 ***	-57.19 ***	-0.48	-7.23 ***	-20.27 ***
	(0.59)	(2.01)	(4.50)	(0.62)	(2.13)	(4.77)	(0.37)	(1.25)	(2.79)
	C. Structural Estimates								
Changes in yields (100 kg/ha)	-1.18 *	-10.66 ***	-28.42 ***	-8.36 ***	-27.03 ***	-55.99 ***	-0.36	-6.83 ***	-19.41 ***
	(0.63)	(2.11)	(4.69)	(0.68)	(2.25)	(4.96)	(0.38)	(1.29)	(2.86)
Agronomic effects	-3.72 ***	-22.31 ***	-55.30 ***	-11.16 ***	-37.65 ***	-79.54 ***	-0.44	-8.95 ***	-25.52 ***
	(1.02)	(3.54)	(7.77)	(1.23)	(3.99)	(8.56)	(0.77)	(2.44)	(5.14)
Adaptation effects	2.53 ***	11.66 ***	26.88 ***	2.80 ***	10.63 **	23.55 ***	0.08	2.13	6.11
	(0.73)	(3.73)	(8.67)	(0.62)	(3.98)	(9.31)	(0.10)	(2.15)	(5.31)

Note. Figures display predicted changes in crop yields, holding current growing areas and technology constant relative to the period 2006-2012. Panel A displays the initial crop yields in our sample. Panel B presents the predicted changes using the reduced-form estimates. Panel C presents the predicted changes using the structural estimates. For this panel, we report the estimated direct impacts of weather on plant growth (agronomic effects) and the estimated indirect impacts of weather via farmers' adjustments in input applications (adaptation effects). Below each estimate we report in brackets the standard errors obtained using the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

First, we find that reduced-form and structural results consistently indicate negative impacts of warmer temperatures. This is particularly true for barley and rapeseed, where the projected impacts display only marginal differences between the reduced-form and structural models. While larger than the two other crops, the differences between the two methods for wheat yields remain statistically null. This result is in line with results from Section and confirm that the reduced-form and structural models lead to similar estimation of total weather impacts on crop yields.

Second, the projections using the structural estimates indicate that the agronomic impacts of warmer temperatures are negative for the three crops but that the farmers' adaptation to these warmer temperatures allows them to offset part of these negative direct impacts. These adaptation effects are sizable and positive. Looking for example at the case of wheat yields, Table 5 indicates that an additional one degree Celsius induces a negative direct shock of -372 kg/ha (i.e. - 5% in comparison to the initial wheat yields for the period 2006-2012). This negative shock is however partly compensated for by farmers' adaptation, which increases wheat yields by 253 kg/ha. In other words, the farmers' adaptation offsets the negative direct impacts of the additional one degree Celsius on plant growth by about 253/372≈68%. Interestingly, we find that, *ceteris paribus*, farmers will have greater difficulty in offsetting the negative direct effects as future temperature further increases. Indeed, we find that farmers can only offset about half of the negative direct effects of an additional two or three degrees Celsius on wheat yield.

Third, crop yields are heterogeneously affected by an increase in temperatures. Indeed, in line with Section , we find that barley yields suffer much more from an increase in temperature than wheat or rapeseed yields. For example, while an additional one degree Celsius reduces wheat and rapeseed yields by about 1% to 2%, barley yields decrease by about 13%. This difference is maintained as the warming amplifies. Interestingly, crops are also heterogeneous in terms of the potential offset of farmers' adaptation. Indeed, while we already showed that farmers can offset about half to two thirds of the negative direct effects of warmer temperatures on wheat yields, farmers can only offset about a quarter of the negative direct effects of warmer temperatures on barley and rapeseed yields. Note finally that the adaptation effects on wheat and barley are about equal in absolute terms and that, once again, rapeseed stands out among the other crops as these adaptation effects are not precisely estimated for such large increases in temperatures.

Online Appendix presents similar projections than those displayed in Table 5 but using measurements of cumulative temperatures during the growing season, instead of those of average temperatures. The results are overall similar, with sizable adaptation effects that offset between 10% to 85% of the negative direct impacts from warmer temperatures. Interestingly, we find statistically insignificant aggregated impacts of warmer temperature on wheat yields in both models, while the agronomic and adaptation effects are significant at 1% or 5% (Table A10. Such aggregated impacts hide compensatory mechanism between the negative agronomic effects and the positive adaptation effects.

Limitations. While informative, our simulation exercise comes with several limits that we want to emphasize. First, we hold all elements other than temperature constant (e.g. technologies, crop allocations and prices). These elements will have changed by the time average temperatures have increased by several degrees Celsius. In particular, the relationship between farmers' input applications and weather will change in the future, either as a result of the increasing environmental regulations faced by farmers, or because of technical changes in the composition/application of fertilizers and pesticides (Kaminski et al., 2013).[42] Second, farmers can implement other adaptation strategies than simply adjusting input uses within the growing season. While these adjustments are the easiest to implement in the short term, farmers can also adjust to climate change in the long term, for example by adjusting their capital levels (Yang and Shumway, 2016) or by changing their crop allocation (Cui, 2020). Third, one should take our projections for large increases in temperature with caution as we obtained our parameters of interest using marginal analyses. Moreover, some temperatures we consider for our simulations are out of the range of observations of our initial 2006-2012 sample. Typically, the projections for +3°C should be taken as speculative and illustrative. As such, we believe that our projections are likely to be more consistent for a limited additional one degree Celsius than for larger increases in temperature. Fourth, as for the remainder of the paper, we do not adjust the standard errors – computed with the delta method – for spatial dependence. The consequence is that the standard errors reported in Table 5 are likely to be narrower than they truly are. Finally, our projections only account for a limited sample of farmers from the *Meuse* department. The insights obtained from the projections on such a limited area is of limited interest to infer the future impacts of climate change on agricultural production worldwide, or even in France. Given all these elements, our projections should rather be taken as an illustrative exercise where the focus is on the distinction between the agronomic and adaptation impacts of higher temperatures. We view these results as complementary to reduced-form studies performed at

[42] Institutions shaping farmers' decisions can also change in responses to climate change (see Henry, 2022, for example).

larger scales (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011; Gammans et al., 2017), wherein larger weather variations help to infer the future impacts of higher temperatures on crop yields. Our results provide a useful check for whether these studies do account for farmers' short-term adaptation on top of the direct agronomic impacts, as they claim.

Concluding Remarks

The impacts of climate change on agricultural production depend critically upon farmers' adaptation. To infer such climate impacts while accounting for adaptation, the large bulk of the economic literature has regressed observed crop yields on observed weather conditions during the growing season conditionally on individual fixed effects (Schlenker and Roberts, 2009; Lobell et al., 2011, 2013; Mérel and Gammans, 2021; Wing et al., 2021; Wang, Rejesus, Tack, Balagtas, and Nelson, Wang et al.; Chen et al., 2023). However, the reduced-form estimations that are usually considered in this yield-weather-panel literature makes it impossible to disentangle the direct impacts of weather on plant growth (as captured by most former crop simulation models – e.g. Asseng et al., 2015) from those due to farmers' adaptation. In fact, these reduced-form approaches actually even prevent to verify whether farmers really adapt to weather changes. Under these conditions, it remains unclear why economists should be better able than natural scientists to identify the consequences of climate change for agricultural production. For this reason, we estimate in this paper a structural model that formally accounts for both the plants' biophysical and farmers' behavioral responses to weather changes, and compare the obtained estimates to those obtained with usual reduced-form estimations. Formally, this structural model allows us to simultaneously and separately measure (i) the direct impacts of weather changes on plant growth (i.e. the agronomic impacts on crop yields), (ii) the farmers' adjustments of input applications in response to such changes (i.e. the farmers' adaptation *per se*) and (iii) the consequences of these within-season adjustments on crop yields (i.e. the adaptation impacts).

Using an original panel dataset from *Meuse* (France) detailing input uses per crop for the 2006-2012 period, we estimate our crop-specific structural models (for wheat, barley and rapeseed) composed of one yield equation and two input-specific demand functions (for fertilizers and pesticides), conditionally on farm fixed effects. We use weather and price variations together to identify, for each crop, farmers' adaptation and its consequences for crop yields – i.e. the adaptation impacts – separately from the agronomic impacts. These original elements come at the cost of an admittedly small geographical area, which could prevent the identification of precise estimates. We however provide evidence that the remaining weather variation after adjusting for individual fixed effects provides similar additional information in our case as in previous reduced-form studies from the yield-weather-panel literature applied to larger areas (e.g. Schlenker and Roberts, 2009; Gammans et al., 2017; Ortiz-Bobea et al., 2019).

Our results provide several important insights. First, our systematic comparison of the reduced-form and structural estimates indicate that the two approaches provide similar estimates of the total impacts of weather conditions on crop yields. These results are identical for both *marginal* and *non-marginal* changes in weather conditions, as well as for several specifications and robustness checks. Second, we find that farmers do adjust their input applications in response to weather changes. In particular, they increase their fertilizer applications in response to temperature increases, for all crops considered. They also increase their fertilizer applications when facing higher precipitation, though to a fewer extent. Globally, the weather impacts on pesticide applications are less precisely estimated and less consistent. In line with agronomic insights, our structural estimates suggest that the intensification of fertilizer applications is explained by the positive effects of temperature on fertilizer productivity, which leads rational farmers to apply more fertilizers. Third, we find that these within-season adjustments increase crop yields under both *marginal* and *non-marginal* increases in temperature and precipitation. By comparison, the agronomic impacts can be positive or negative for *marginal* changes in weather conditions but are always negative for *non-marginal* increases in temperature. In total, we find that the adaptation impacts offset by one quarter to two thirds the agronomic impacts of non-marginal increases in temperature, with heterogeneous effects depending on the crops and temperature increases considered. Last but not least, given that (i) our structural model explicitly accounts for both the agronomic and adaptation impacts and that (ii) we identify that these adaptation impacts are non-null (in our illustrative case study), this means that (iii) the usual yield-weather-panel approach does account for the consequences of farmers' adaptation for crop yields (on top of the direct impacts on plant growth). Economists have thus something to add to crop simulation approaches in our comprehension of the mechanisms behind the impacts of climate change on agricultural production.

As noted by Timmins and Schlenker (2009), structural modeling is of particular interest in environmental economics as it allows accounting for both the biophysical impacts of an exogenous shock and the agents' behavioral responses to such a shock. We showed here that such disaggregation is useful to understanding weather impacts on crop yields. However, structural modeling should not be considered as a substitute for reduced-form modeling – but, rather, as a complement. Structural modeling, while theoretically grounded, has inherent limitations and assumptions imposed by the model structure that are often unverifiable. In contrast, reduced-form modeling provides greater flexibility in terms of model specifications and error terms structure. Our own structural estimation is not exempt from these limitations, as we do not correct for example for spatial dependence between observations when recomputing the elasticities with the delta method. Therefore, our results should not be taken as conclusive evidence of weather impacts on crop yields. For a better appreciation of these impacts, we suggest the readers examining the yield-weather-panel studies working at country, continental or global scales (e.g. Schlenker and Roberts, 2009; Gammans et al., 2017; Wing et al., 2021), where a greater diversity of weather conditions is considered. Our contribution should rather be interpreted as an attempt to compare usual results from reduced-form estimations with those coming from our structural estimations to gain knowledge on the channels that drive the weather impacts on crop yields. To further advance the field, future structural modeling efforts could aim, among other factors, to estimate models for larger and more representative areas than ours, or refine the farmers' objective function by including dynamic or risk considerations (see Lemoine, 2021, for example).

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Online Appendices

Meuse location

Figure A1 displays the location of the *Meuse* department in France. It also displays the structure of the 31 *cantons* within the *Meuse* department. The *canton* is the largest administrative division within a department. It corresponds to the LAU 1 division in the European Union. The average distance between the centroids of two neighboring cantons is 15 km in *Meuse*.

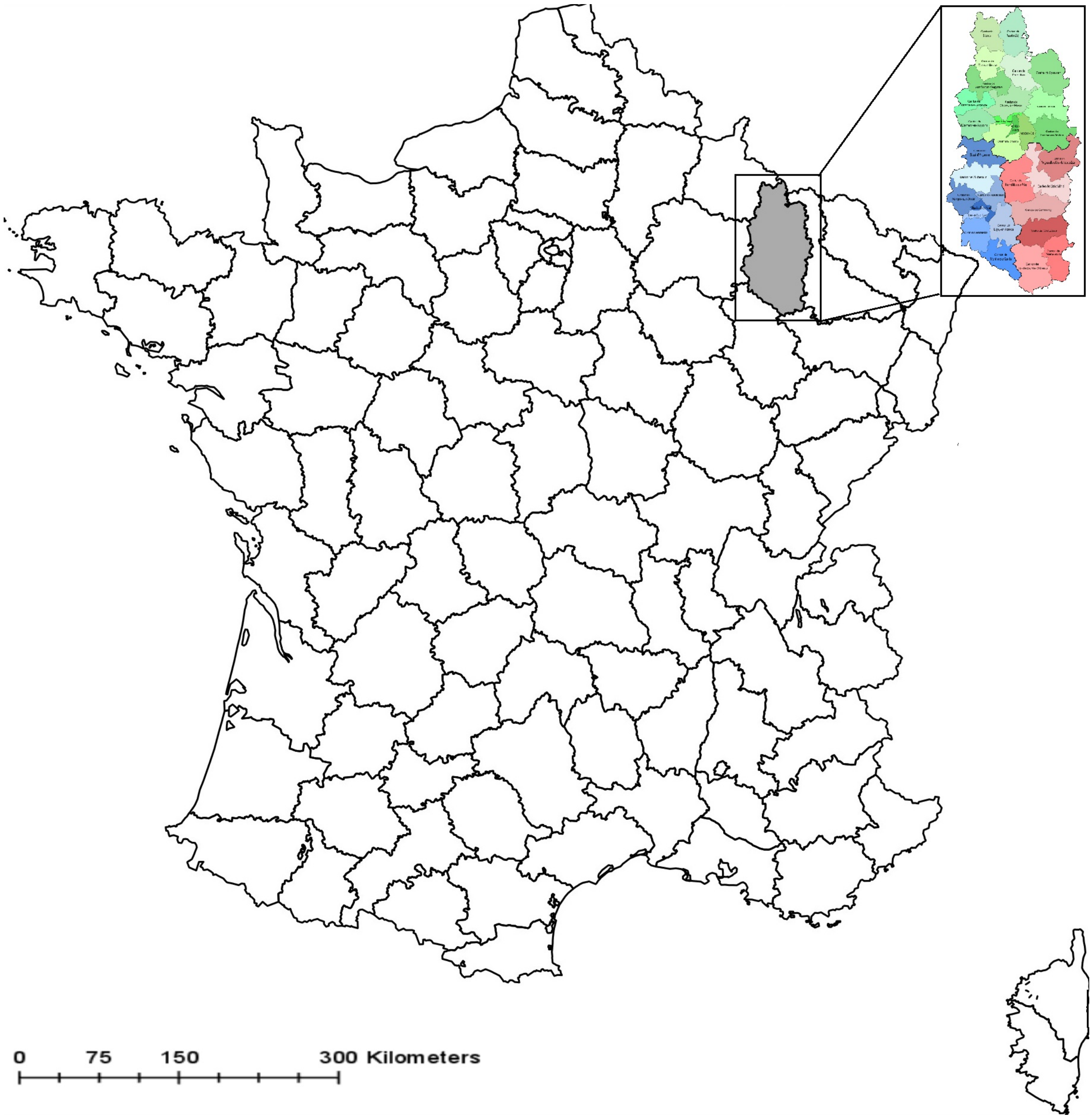


Figure A1: Location of *Meuse*. Note. The black borders are the limits of all the metropolitan French departments (NUTS3 regions). The *Meuse* department is indicated in grey. The zoomed image indicates the *cantons* within the *Meuse* department.

Correlations between crop prices and weather conditions in the sample

Table A1 displays the matrix of correlation between weather variables and crop prices in the *Meuse* sample after centering for farm averages (farm fixed effects).

Table A1: Coefficients of correlation between crop prices and weather conditions during the growing season

	Avg. Temp.	**Tot. Prec.**	**Wheat Price**	**Barley Price**	**Rapeseed Price**
Average Temperature	–	0.02	0.42	0.43	0.09
Total Precipitation	0.02	–	0.20	0.21	-0.19
Wheat Price	0.42	0.20	–	0.81	0.56
Barley Price	0.43	0.21	0.81	–	0.57
Rapeseed Price	0.09	-0.19	0.56	0.57	–

NOTE. The figures are the coefficients of correlations between weather variables $\mathbf{w}_{i,t}$ and crop prices $\mathbf{p}_{i,j,t}$ in the sample after centering for farm averages.

Reduced-form estimates

Table A2 presents the results of the Ordinary Least Square estimation of the reduced-form model specified in equation (12) for wheat, barley and rapeseed. In addition to reporting the robust standard errors in ordinary brackets, Table A2 displays in square brackets the clustered standard errors (clustered at the *Canton* $\times$ *Year* level), obtained by bootstrap over 200 replications (with replacement). We also report in braces the standard errors adjusted for spatial dependence using Conley (1999)'s procedure. To produce consistent standard errors with the two clustering procedures, we account for spatial correlations within 15 km around the observations, which correspond to the average distance between the centroids of two neighboring cantons in *Meuse* (see Appendix). Results in Table A2 confirms that the two procedures provide standard errors of similar magnitudes. In other words, the bootstrap procedure with cluster at the *Canton* $\times$ *Year* level accounts to similar level of spatial dependence than the Conley (1999)'s clustering procedure. The standard errors are 30% to 250% larger when accounting for spatial dependence, but all the reduced-form estimates remain statistically significant at the 1% level with the spatially-adjusted standard errors.

Table A2: Reduced-form estimates (N=1,104)

	Wheat	**Barley**	**Rapeseed**
Average Temperature	124.81 ***	128.51 ***	82.06 ***
	(13.77)	(14.57)	(8.52)
	[28.80]	[24.43]	[15.45]
	{36.57}	{27.67}	{15.88}
Average Temperature Squared	-4.81 ***	-5.22 ***	-3.14 ***
	(0.53)	(0.57)	(0.33)
	[1.10]	[0.95]	[0.59]
	{1.39}	{1.08}	{0.62}
Total Precipitation	0.07 ***	0.02	0.02 *
	(0.02)	(0.02)	(0.01)
	[0.03]	[0.02]	[0.01]
	{0.03}	{0.02}	{0.02}
Total Precipitation Squared	-0.00 ***	-0.00	-0.00 *
	(0.00)	(0.00)	(0.00)
	[0.00]	[0.00]	[0.00]
	{0.00}	{0.00}	{0.00}
Farm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	No	No	No
Time Trend	No	No	No
R^2	0.41	0.41	0.43

NOTE. This table reports the estimates of the effect of weather conditions during the growing season on crop yields using the reduced-form model presented in relation (12). Below each estimate we report the robust standard errors in ordinary brackets. We report in hooks the clustered standard errors obtained by bootstrap over 200 replications. We report in braces the standard errors adjusted for spatial dependence using Conley (1999)'s correction. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Structural estimates

Table A3 presents the results of the estimation of the structural model specified in equation (13) for wheat, barley and rapeseed. Note that the parameters $\boldsymbol{\delta}$ are jointly estimated with the $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ parameters such that their estimation relies on the exploitation of farm fixed effects as additional information. The R command `nlsystemfit` that we used for the estimation does not allow correction of the standard errors for spatial dependence (Henningsen and Hamann, 2008). In addition to the robust standard errors in ordinary brackets, we report in squared brackets the bootstrapped standard errors obtained over 200 replications (with replacement), clustered at the *Canton* × *Year* level. The standard errors are overall – but not always – greater when adjusted for spatial dependence. However, all the structural estimates that are statistically significant with the unclustered standard errors remain significant at the same statistical level (1%, 5% or 10%) with the spatially-adjusted standard errors. Interestingly, two of the estimates of $\delta_{2,1,1}$ which are not significant with the unclustered standard errors turns statistically significant at the 1% level with the clustered standard errors.

Table A3: Estimated structural parameters of crop profits (N=1,104)

	α_j	β_{j1}	β_{j2}	$\delta_{j,1,1}$	$\delta_{j,2,2}$	$\delta_{j,1,2}$
				A. Wheat		
Constant	–	–	–	-141,552.12 ***	-23,391.96	-20,954.83
	–	–	–	(37,483.92)	(33,227.42)	(29,102.41)
	–	–	–	[64,217.59]	[49,391.20]	[38,803.62]
Average Temperature	192.45 ***	2,215.49 ***	816.67 ***	20,609.95 ***	3,297.48	4,156.27
	(22.67)	(325.34)	(329.46)	(6,002.53)	(5,386.73)	(4,734.73)
	[42.76]	[583.33]	[368.60]	[10,193.10]	[8,037.61]	[6,294.73]
Average Temperature Squared	-7.45 ***	-86.16 ***	-32.71 ***	-796.41 ***	-127.65	-169.60
	(0.89)	(12.77)	(13.00)	(239.12)	(217.57)	(473.47)
	[1.65]	[22.73]	[14.63]	[403.25]	[324.85]	[255.08]
Total Precipitation	0.13 ***	2.91 ***	-0.88 *	496.45 ***	13.05 *	-22.57 ***
	(0.03)	(0.43)	(0.51)	(6.54)	(8.30)	(6.00)
	[0.04]	[0.55]	[0.69]	[8.52]	[9.63]	[7.97]
Total Precipitation Squared	-0.00 ***	-0.00 ***	0.00 **	-0.06 ***	-0.02 **	0.03 ***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Farm Fixed Effects	Yes	Yes	Yes	–	–	–
Year Fixed Effects	No	No	No	–	–	–
Time Trend	No	No	No	–	–	–
				B. Barley		
Constant	–	–	–	-2.16	26,999.15	-74,894.65 ***
	–	–	–	(2,848.51)	(31,032.53)	(24,987.35)
	–	–	–	[63.99]	[32,179.34]	[20,939.54]
Average Temperature	190.22 ***	1,216.77 ***	1,115.40 ***	-1,171.54	-4,334.57	12,617.91 ***
	(22.94)	(243.59)	(329.82)	(4,586.02)	(5,018.63)	(4,067.01)
	[38.26]	[281.64]	[461.46]	[340.48]	[5,225.85]	[3,433.02]
Average Temperature Squared	-7.66 ***	-47.28 ***	-44.63 ***	63.52	180.17	-514.41 ***
	(0.91)	(9.62)	(13.12)	(183.24)	(202.54)	(164.33)
	[1.51]	[11.22]	[18.47]	[21.01]	[212.49]	[139.73]
Total Precipitation	0.03	1.90 ***	-1.39 ***	28.17 ***	-4.17	-13.21 **
	(0.03)	(0.27)	(0.43)	(4.61)	(7.71)	(5.21)
	[0.04]	[0.34]	[0.62]	[6.35]	[9.60]	[6.93]
Total Precipitation Squared	-0.00 *	-0.00 ***	0.00 ***	-0.04 ***	0.01	0.02 **
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Farm Fixed Effects	Yes	Yes	Yes	–	–	–
Year Fixed Effects	No	No	No	–	–	–
Time Trend	No	No	No	–	–	–
				C. Rapeseed		
Constant	–	–	–	-234,547.46 ***	-58,097.29	156.48
	–	–	–	(78,300.03)	(96,381.73)	(70,501.74)
	–	–	–	[69,626.60]	[100,811.41]	[3,163.98]
Average Temperature	105.98 ***	1,673.28 ***	280.13	33,628.38 ***	7,510.58	951.66
	(13.46)	(353.43)	(462.47)	(12,850.34)	(15,511.11)	(11,545.15)
	[22.29]	[433.80]	[480.56]	[11,252.59]	[16,066.17]	[1,095.75]
Average Temperature Squared	-4.04 ***	-64.07 ***	-10.99	-1,318.82 **	-346.86	10.77
	(0.53)	(14.11)	(18.45)	(519.00)	(621.98)	(467.86)
	[0.86]	[17.23]	[19.14]	[451.27]	[638.20]	[58.05]
Total Precipitation	0.07 ***	2.78 ***	0.19	112.06 ***	9.05	- 61.70 ***
	(0.02)	(0.46)	(0.67)	(13.11)	(24.41)	(14.26)
	[0.03]	[0.77]	[0.92]	[17.73]	[28.45]	[25.45]
Total Precipitation Squared	-0.00 ***	-0.00 ***	-0.00	-0.14 ***	-0.10 ***	0.06 ***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)
	[0.00]	[0.00]	[0.00]	[0.01]	[0.03]	[0.02]
Farm Fixed Effects	Yes	Yes	Yes	–	–	–
Year Fixed Effects	No	No	No	–	–	–

Properties of the production functions and input productivity at the sample mean values

We report in Table A4 the properties of the production function evaluated at the sample mean values. It shows that all inputs display the expected aggregated value of the product $\hat{\boldsymbol{\delta}}'_{j,k,k}\bar{w}$ at the sample mean values (notably always positive for the own productivity shifters). The complementary/substitution terms show that fertilizers and pesticides are complementary inputs for barley but substitute inputs for wheat and rapeseed. The three crops present an estimated production function that respects the property $(\hat{\boldsymbol{\delta}}'_{j,1,1}\bar{\mathbf{w}})\times(\hat{\boldsymbol{\delta}}'_{j,2,2}\bar{\mathbf{w}})-(\hat{\boldsymbol{\delta}}'_{j,1,2}\bar{\mathbf{w}})^2 > 0$. These properties imply that the three production functions that we estimated respect the assumption that crop yield $y_{i,j,t}$ has a non-decreasing and concave relationship with $x_{i,j,k,t}$.

Table A4: Properties of the production function and underlying estimated productivity of fertilizers and pesticides

	Wheat	**Barley**	**Rapeseed**
	A. Properties		
$\hat{\boldsymbol{\delta}}'_{j,1,1}\bar{\mathbf{w}}$	759.46	548.18	804.71
$\hat{\boldsymbol{\delta}}'_{j,2,2}\bar{\mathbf{w}}$	314.35	371.70	444.22
$\hat{\boldsymbol{\delta}}'_{j,1,2}\bar{\mathbf{w}}$	46.18	-175.23	28.57
$(\hat{\boldsymbol{\delta}}'_{j,1,1}\bar{\mathbf{w}}) \times (\hat{\boldsymbol{\delta}}'_{j,2,2}\bar{\mathbf{w}}) - (\hat{\boldsymbol{\delta}}'_{j,1,2}\bar{\mathbf{w}})^2$	236,608.50	173,049.60	356,649.40
	B. Aggregated Productivity		
Fertilizer productivity θ_j^1	0.20	0.10	0.07
Pesticide productivity θ_j^2	0.04	0.00	0.02

Note. The table displays the properties of the estimated production function at the sample mean values.

Based on relation (6), we recompute the value of the aggregated productivity of input k for crop j θ_j^k at the sample mean values. The aggregated productivity θ_j^k includes both the elements related to the input productivity and complementary/substitution terms. This value indicates by how much crop yields increase in absolute terms when input applications increase by one unit at the sample mean values. Table A4 shows that all inputs present a positive productivity at the margin. Interestingly, we find that the aggregated productivity of fertilizers is about three to fifteen times greater than the aggregated productivity of pesticides. This is consistent with the role of pesticides as a damage-reducing input (on top of its productive purposes), while fertilizers can be considered as a productive input only (Femenia and Letort, 2016).

Elasticities of crop yields on weather conditions during the growing season

This Appendix presents how to compute the weather elasticities of crop yields using the reduced-form and structural estimates.

For the reduced-form model, one can straightforwardly recomputes the weather elasticities using relation (12). For example, the elasticity of crop yields with regard to average temperatures is simply equal to:

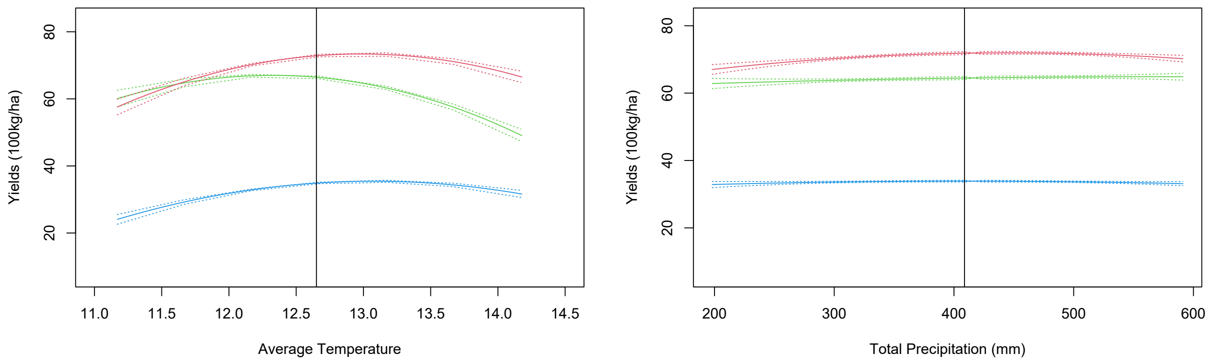
$$\xi_{y_j}^T = \frac{\partial y_j}{\partial T}\frac{\bar{T}}{\bar{y}_j} = (\hat{\psi}_j^T + 2\hat{\psi}_j^{T^2}\bar{T})\frac{\bar{T}}{\bar{y}_j}.$$

The computation is more complex for the structural model. The elasticities of crop yields on weather conditions can be computed using relation (11). For example, the elasticity of crop yields on temperature $\xi_{y_j}^T$ is equal to:

$$\begin{aligned}\xi_{y_j}^T =&(\hat{\alpha}_j^T + 2\hat{\alpha}_j^{T^2}\bar{T} - 0.5\frac{(\bar{p}_1^x)^2}{(E(\bar{p}_j^y))^2}(\hat{\delta}_{j,1,1}^T + 2\hat{\delta}_{j,1,1}^{T^2}\bar{T}) - 0.5\frac{(\bar{p}_2^x)^2}{(E(\bar{p}_j^y))^2}(\hat{\delta}_{j,2,2}^T + 2\hat{\delta}_{j,2,2}^{T^2}\bar{T})\\ &- \frac{\bar{p}_1^x\bar{p}_2^x}{(E(\bar{p}_j^y))^2}(\hat{\delta}_{j,1,2}^T - 2\hat{\delta}_{j,1,2}^{T^2}\bar{T}))\frac{\bar{T}}{\bar{y}_j}.\end{aligned}$$

Summary of the impacts of weather conditions during the growing season on crop yields using the reduced-form estimates

Figure A2 shows the estimated relationships between crop yields and weather conditions over the whole distribution of temperature and precipitation. These relationships are recomputed by reinserting the reduced-form estimates from Table A2 into relation (12).



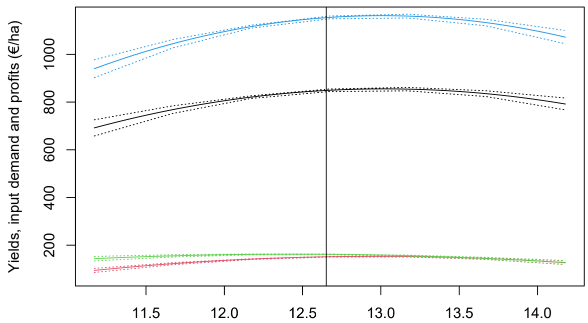
(a) Average Temperature (°C)

(b) Total Precipitation (mm)

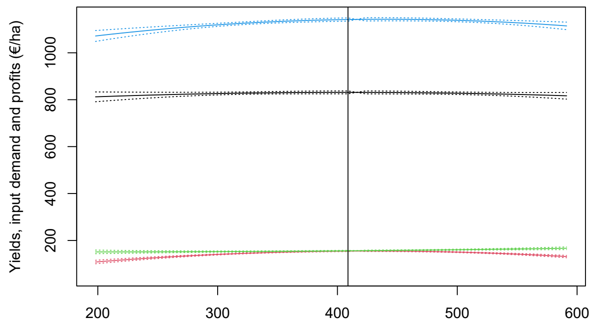
Figure A2: Estimated relationships between yields and weather conditions during the growing season using reduced-form estimates. Note. Wheat (red lines); barley (green lines); rapeseed (blue lines). The 90% confidence intervals are computed using the delta method and shown with dashed lines. The vertical lines display the weather conditions at the sample mean values.

Summary of the impacts of weather conditions during the growing season on crop profits, yields and input applications using the structural estimates

Figures A3, A4 and A5 show the changes in input uses, crop yields and profits over the whole distribution of temperature and precipitation. The relationships are recomputed by reinserting the structural estimates into relations (10) and (11) respectively. Changes in crop profits are recomputed using relation (1) such that crop profits are equal to crop revenues (yield times price) minus fertilizer and pesticide costs.

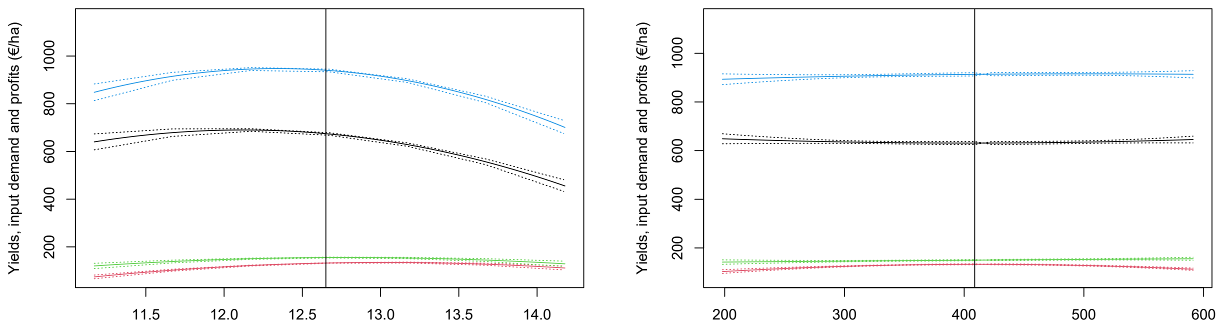


(a) Average Temperature (°C)



(b) Total Precipitation (mm)

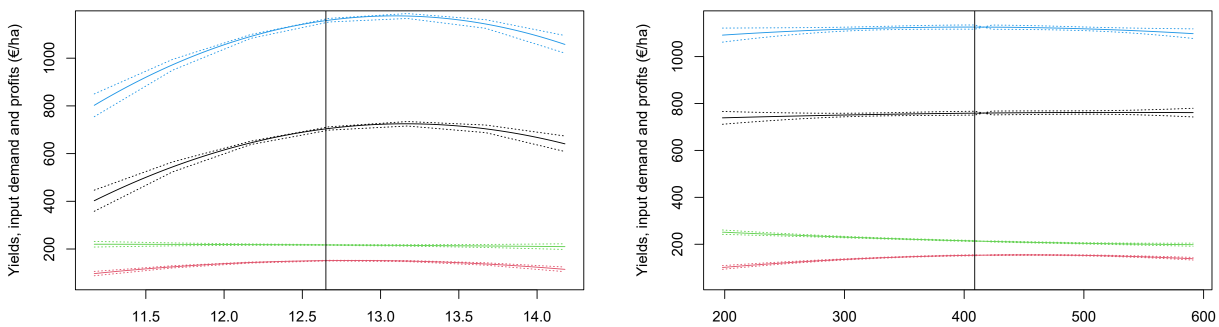
Figure A3: Changes in wheat profits, yields and input applications depending on weather conditions during the growing season using the structural parameters. NOTE. Fertilizer applications (red lines); Pesticide applications (green lines); Yields (blue lines); Profits (black lines). The 90% confidence 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. Changes in profit are recomputed using equations (1) and (5). The vertical lines display the weather conditions at the sample mean values.



(a) Average Temperature (°C)

(b) Total Precipitation (mm)

Figure A4: Changes in barley profits, yields and input applications depending on weather conditions during the growing season using the structural parameters. Note. 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. Changes in profit are recomputed using equations (1) and (5). The vertical lines display the weather conditions at the sample mean values.



(a) Average Temperature (°C)

(b) Total Precipitation (mm)

Figure A5: Changes in rapeseed profits, yields and input applications depending on weather conditions during the growing season using the structural parameters. Note. 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. Changes in profit are recomputed using equations (1) and (5). The vertical lines display the weather conditions at the sample mean values.

Sensitivity analysis: cumulative temperature instead of average temperature

One of the greatest contribution of Schlenker and Roberts (2009) was to show that crop yields depend non-linearly on temperature, and that this relationship could be well approximated by two terms separately accounting for the time spent under beneficial (moderate) and harmful (extreme) temperatures. These insights are in line with the agronomic literature that usually separates cumulative temperatures into measurements of beneficial and killing degree days. As such, we follow Schlenker and Roberts (2009) and re-estimate the reduced-form and structural models in relations (12) and (13) using beneficial and killing degree days instead of the average temperature and its square term. The beneficial and killing degree days are measured following the sine interpolation procedure proposed by Schlenker and Roberts (2009). Formally, we compute beneficial degree days during the growing season as $\int_{T_{base}}^{T_{max}} \min\{T - T_{base}, T_{max} - T_{base}\}\Phi(T)\,dT$ with $T_{base} = 10°\text{C}$ and $T_{max} = 30°\text{C}$. $\Phi(T)$ is the reconstructed distribution of temperature during the growing season using the sine interpolation between minimal and maximal daily temperatures (Schlenker and Roberts, 2009). Accordingly, we compute killing degree days during the growing season as $\int_{T_{max}}^{\infty}(T - T_{max})\Phi(T)\,dT$. As in the benchmark, the growing season lasts from February 1 to July 31. The reduced-form and structural models additionally include the sum of the precipitation during the growing season as well as its squared term.

Table A5 presents the elasticities of crop yields on temperature and precipitation during the growing season using measures of cumulative temperature instead of average temperature. Along with the change in functional form, the elasticities are different from those using average temperatures in Table 2. In particular, elasticities of crop yields on temperature are two to three times lower with the measures of beneficial and killing degree days than with the average temperature measures.[A1] Our main result however remains the same: we

[A1]Even if the elasticities obtained with measures of beneficial and killing degree days are lower than those obtained with average temperatures, the relative impacts of temperatures on yields are conserved among the three crops, with negative impacts for barley yields (non-significant in Table A5) and positive impacts observe no difference between the elasticities obtained with the reduced-form and structural estimations. This suggests that our original structural model replicates the usual reduced-form results, whatever the functional form used to specify the relationship between yields and temperature.

Table A5: Weather elasticities on crop yields with cumulative temperature during the growing season.

	Reduced-form			**Structural**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Temperature	0.25 ***	-0.05	0.42 ***	0.24 ***	-0.06	0.52 ***
	(0.07)	(0.04)	(0.09)	(0.07)	(0.04)	(0.09)
Precipitation	-0.02	0.00	-0.14 ***	-0.03	0.02 *	-0.15 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)

NOTE. Elasticites are computed at sample mean values. The reduced-form and structural models include beneficial degree days (time spent between from 10°C to 30°C) and killing degree days (time spent above 30°C) instead of the average temperature and its squared term in relations (12) and (13). Below each estimate we report in brackets the standard errors obtained with the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

for wheat and rapeseed yields. The two functional forms also indicate that rapeseed is the most positively affected by marginal increases in temperature.

Sensitivity analysis: price expectations

The form of farmers' expectations of output prices has been the subject of much research in agricultural economics (Nerlove and Bessler, 2001). While a common practice is to assume, as we did, that farmers have naive expectations of crop prices (e.g. Carpentier and Letort, 2012; Kaminski et al., 2013; Femenia and Letort, 2016; Koutchadé et al., 2018), other practices assume rational price expectations (e.g. Sesmero et al., 2018) or use future crop prices (e.g. Miao et al., 2016). We thus successively re-estimate our structural model described in relation (13) changing the assumption of naive price expectations for (i) the assumption of rational price expectations and (ii) the use of future prices. For the first case, we assume that farmer i in year t expects $E(p_{i,j,t}) = p_{i,j,t}$. For the second case, we assume that farmer i in year t expects $E(p_{i,j,t}) = p^f_{j,t}$. While crop prices are available at the farm level when using naive or rational price expectations, the use of future prices imposes the use of common prices for all farms each year. Future prices are determined using information from the Euronext marketplace (delivered at Rouen market, located about 300 km from *Meuse*). For each year of the period 2006-2012, we define $p^f_{i,t}$ as the average of the future prices for delivery between June 1 and September 31 as observed March 31 of each year (at the moment when farmers apply most of their pesticide and fertilizer). The data has been collected through the Refinitiv Eikon platform.

Table A6 presents the elasticities of crop yields on temperature and precipitation during the growing season obtained using the alternative assumptions for farmers' crop price expectations. To facilitate the comparison, Table A6 also reports the elasticities obtained with the reduced-form model described in relation (12), where prices are not used to infer weather impacts on crop yields. The elasticities are recomputed at sample means using estimates obtained from the OLS and SUR estimations of reduced-form and structural models respectively. Those obtained using the estimates from the structural models in the right-hand columns change for the different price expectation assumptions. Panel A presents the elasticities obtained assuming that farmers have naive expectations of crop prices. Because we assumed naive price expectation in the benchmark, the reported estimates are the same as those reported in Table 2.

Table A6: Weather elasticities on crop yields with alternative assumptions for price expectations.

	Reduced-form			Structural		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
	A. Naive Price Expectations					
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.53 ***	-0.63 ***	1.02 ***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.11)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.03 **	0.02 *	-0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	B. Rational Price Expectations					
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.60 ***	-0.71 ***	1.03 ***
	(0.09)	(0.11)	(0.12)	(0.10)	(0.11)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.03 ***	0.04 **	-0.03 *
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
	C. Future Prices					
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.32 ***	-0.65 ***	1.08 ***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.10)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.02 *	0.04 **	0.0.3
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)

Note. Elasticites are computed at sample mean values. They are reported for alternative crop price expectations in the structural model. Panel A reports the elasticities obtained assuming naive expectations ($E(p_{i,j,t}) = p_{i,j,t-1}$), as in the benchmark model. Panel B displays the elasticities obtained assuming rational price expectations ($E(p_{i,j,t}) = p_{i,j,t}$). Panel C reports the elasticities obtained using future prices at the beginning of the growing season as price expectations ($E(p_{i,j,t})$ $= p^f_{j,t}$). For comparison purposes, we report the elasticities obtained with the reduced-form models on the left-hand columns, where estimates are only obtained using information on weather conditions (and no additional information on prices). Below each estimate we report in brackets the standard errors obtained with the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Table A6 indicates that the elasticities obtained with the structural model assuming rational price expectations (Panel B) are statistically equal to those obtained assuming naive price expectations (Panel A). Similarly, the elasticities obtained with the structural model using future prices (Panel C) are statistically identical to those using alternative price expectation forms, despite larger differences with those obtained in the reduced-form approach. Above all, the elasticities obtained with the reduced-form model are equal to those obtained with the structural model whatever the form of price expectations, showing evidence of the robustness of our approach.

Sensitivity analysis: time trends and year fixed effects

In order to purge the estimates from the effects of any technical progress or common annual shocks, econometricians seeking to estimate weather impacts on crop yields have often included time trends (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011; Gammans et al., 2017) or, more rarely, year fixed effects (e.g. Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). These inclusions of additional terms to control for the effects of time are notably common when the number of years in the panel is large (Mérel and Gammans, 2021). While our panel relies on a small number of years (2006-2012), we test the robustness of our result by successively re-estimating the reduced-form and structural models described in relations (12) and (13) with the addition of time trend and year fixed effects.

Table A7 presents the elasticities of crop yields on temperature and precipitation during the growing season for several assumptions on the structure of the error terms. The elasticities are recomputed at sample means using estimates obtained from the OLS and SUR estimations of reduced-form and structural models as in relations (12) and (13) for Panel A, with the addition of time trends for Panel B and with the addition of year fixed effects for Panel C. For the structural model, the time trends and fixed effects are introduced into the three estimated equations of relation (13).

Panel B shows that the inclusion of time trends does not affect the precision of the estimation but reduces the elasticities of crop yields compared to the benchmark (Panel A). However, these differences are not statistically significant, suggesting that our results are robust to the inclusion of time trends. More importantly, the elasticities obtained with the reduced-form and structural models remain similar even after the introduction of time trends.

The inclusion of year fixed effects yields somewhat different results (Panel C). Indeed, the addition of year fixed effects reduces the precision of the estimations, with elasticities of wheat and rapeseed yields (resp. barley yields) on temperature turning non-significant in the reduced-form model (resp. structural model). The other elasticities also see their standard

Table A7: Weather elasticities on crop yields with alternative assumptions on the time dimension of the error terms.

	Reduced-form			Structural		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
	A. Without Time Dimension					
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.53 ***	-0.63 ***	1.02 ***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.11)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.03 **	0.02 *	-0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
	B. With Time Trends					
Temperature	0.31 ***	-0.93 ***	1.01 ***	0.31 ***	-0.81 ***	1.05 ***
	(0.10)	(0.11)	(0.13)	(0.10)	(0.12)	(0.13)
Precipitation	-0.04 *	-0.04 *	0.00	-0.03	-0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	C. With Time Fixed Effects					
Temperature	-0.13	-0.81 ***	-0.04	1.18 ***	0.07	1.28 ***
	(0.19)	(0.23)	(0.24)	(0.14)	(0.18)	(0.20)
Precipitation	0.04 *	0.05 *	-0.00	0.01	0.04	-0.04
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	-0.03

Note. Elasticites are computed at sample mean values. They are reported for alternative assumptions regarding the structure of the error terms. Panel A reports the elasticities obtained assuming no time shocks or trends outside variations in weather conditions. Panel B displays the elasticities obtained with the addition of time trends. Panel C reports the elasticities obtained with year fixed effects. Below each estimate we report in brackets the standard errors obtained with the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

errors increase with the inclusion of year fixed effects. These results suggest that there may have not been enough weather variations left after purging for year effects. This issue has been pointed out by Fisher et al. (2012) when investigating weather impacts on US counties' crop yields and profits for an area about 800 times larger than *Meuse*. The consequence of this over-purge is that, for the first time in this study, some recomputed elasticities show differences between those obtained with the reduced-form models and those obtained with the structural models. These differences may come from several aspects of the structural model (e.g. addition of prices, several equations, parameter constraints across equations). They may also simply be due to the insufficient remaining variations in weather conditions in our small panel – both in its temporal and spatial dimensions – after controlling for farm and year fixed effects. Especially, these differences suggest that one should not trust our reduced-form and structural results when adding year fixed effects, at least on such a small panel.

Placebo analysis: impacts of the weather conditions in the autumn following the harvest

One could wonder whether our results are driven by a true relationship between weather conditions and crop yields or if they are driven by some measurement errors or spurious correlations occurring in our panel (spurious correlations that could even be exacerbated by the structure of our model). To test the second hypothesis, we run a placebo analysis, based on the idea that future weather conditions cannot influence past crop yields. Specifically, we replace the measures of weather conditions during the growing season in relations (12) and (13) by similar measures of weather conditions but in *autumn* following the growing season (specifically from October 1 to December 31). As harvest of the three crops typically occurs in July in *Meuse*, there is no reason to assume that autumn weather conditions in year t affect crop yields in t.

Table A8 presents the elasticities of crop yields on temperature and precipitation during the autumn following the harvest instead of those in the growing season. We identify no significant effects of weather conditions in autumn on yields. This placebo analysis suggests that our previous results inform on the true relationship between crop yields and weather conditions in the growing season and that our results do not seem to be driven by measurement errors or spurious correlations.

Table A8: Weather elasticities on crop yields in autumn.

	Reduced-form			**Structural**		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Temperature	-0.01	0.06	0.03	0.04	0.12	0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)
Precipitation	-0.03	-0.24 ***	0.05	0.04	-0.27 ***	0.05
	(0.06)	(0.08)	(0.07)	(0.06)	(0.08)	(0.07)

NOTE. Elasticites are computed at sample mean values. The reduced-form and structural models include autumn average temperatures for year t instead of average temperatures during the growing season in relations (12) and (13). Below each estimate we report in brackets the standard errors obtained with the delta method. *** indicates p-values lower than 0.01.

Elasticities of input applications on weather conditions: computation of the total, requirement, specific-productivity and substitution effects

Formula. The elasticities of input applications on weather conditions can be computed using relation (10). For example, the elasticities of applications of input k on crop j with respect to temperature $\xi^T_{x_{j,k}}$ is equal to:

$$\xi^T_{x_{j,1}} = (\hat{\beta}^T_{j,1} + 2\hat{\beta}^{T^2}_{j,1}\bar{T} - \frac{\bar{p}^x_1}{E(\bar{p}^y_j)}(\hat{\delta}^T_{j,1,1} + 2\hat{\delta}^{T^2}_{j,1,1}\bar{T}) - \frac{\bar{p}^x_2}{E(\bar{p}^y_j)}(\hat{\delta}^T_{j,1,2} + 2\hat{\delta}^{T^2}_{j,1,2}\bar{T}))\frac{\bar{T}}{\bar{x}_{j,1}}.$$

Analysis. Our structural framework allows a deeper investigation of the drivers explaining farmers' adaptation. Specifically, relation (10) states that input applications depend on weather conditions according to three sets of parameters: (i) the set of input requirement parameters $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ that specify the levels of inputs to apply to attain maximum yields $\boldsymbol{\alpha}_{j,k}(\mathbf{w}_{i,t})$, (ii) the set of parameters $\boldsymbol{\delta}_{j,k,k}(\mathbf{w}_{i,t})$ that is an inverse measure of the input "own" productivity and (iii) the set of parameters $\boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})$ that is an inverse measure of the substitution/complementary relationship between fertilizers and pesticides. In particular, at sample mean values, the input applications (i) increase with input requirement parameters ($\hat{\boldsymbol{\beta}}'_{j,k}\bar{\mathbf{w}} > 0$), (ii) decrease with the inverse measure of input specific productivity ($\hat{\boldsymbol{\delta}}'_{j,k,k}\bar{\mathbf{w}} > 0$) and (iii) may either increase or decrease with the inverse measure of the substitution/complementary terms ($\hat{\boldsymbol{\delta}}'_{j,1,2}\bar{\mathbf{w}} \geq 0$ or < 0).[A2] Changes in weather conditions can however change these incentives at the margin, which ultimately encourages farmers to change their input applications.

[A2] One can verify the properties of the production function using the structural estimates from Table A3 and sample mean values from Table 1. Table A4 in reports such properties. It shows in particular that all inputs have a positive marginal productivity ($\hat{\boldsymbol{\delta}}'_{j,k,k}\bar{w} > 0$ for all crops). The value of $\hat{\boldsymbol{\delta}}'_{j,1,2}\bar{w}$ is negative for barley but positive for wheat and rapeseed (Table A4), implying that fertilizers and pesticides are complementary inputs (resp. substitute inputs) at the margin for barley (resp. for wheat and rapeseed). One can verify that $\hat{\boldsymbol{\beta}}'_{j,k}\bar{w} > 0$ for all crops using similar calculus.

In particular, one can disaggregate the elasticities of input applications with respect to weather conditions as:

$$\xi^T_{x_{j,1}} = \underbrace{(\hat{\beta}^T_{j,1} + 2\hat{\beta}^{T^2}_{j,1}\bar{T})\frac{\bar{T}}{\bar{x}_{j,1}}}_{\text{Changes in requirement}} - \underbrace{\frac{\bar{p}^x_1}{E(\bar{p}^y_j)}(\hat{\delta}^T_{j,1,1} + 2\hat{\delta}^{T^2}_{j,1,1}\bar{T})\frac{\bar{T}}{\bar{x}_{j,1}}}_{\text{Changes in productivity}} - \underbrace{\frac{\bar{p}^x_2}{E(\bar{p}^y_j)}(\hat{\delta}^T_{j,1,2} + 2\hat{\delta}^{T^2}_{j,1,2}\bar{T})\frac{\bar{T}}{\bar{x}_{j,1}}}_{\text{Changes in substitution}}.$$

The marginal impacts of changes in temperature can be disaggregated as the sum of (i) the changes due to a modification of input requirement, (ii) the changes due to a shift of input productivity and (iii) the changes due to an evolution of the substitution/complementary relationship between inputs. Table A9 displays how marginal increase in temperature or precipitation changes these different sets of parameters for each crop and input.[A3]

Table A9 displays complex relationships between input applications and weather conditions. Indeed, the diverse drivers of input applications are differently affected by temperature and precipitation for the three crops and two inputs. For example, the increase in fertilizer applications due to a marginal increase in temperature can hardly be attributed to a single factor as the three elements are significantly (either positively of negatively) affected by temperature. The impacts of a marginal increase in precipitation on fertilizer applications may even be harder to attribute to a single factor as most elements are non-significantly affected by precipitation. Despite these difficulties, we try in the following to attribute the patterns of input changes displayed in Table 3 to either the modification in input requirement, own productivity or substitution terms.

First, changes in fertilizer applications due to a marginal increase in temperature seems to be due to several factors. In one hand, we find that the fertilizer requirement ($\boldsymbol{\beta}_{j,1}(\mathbf{w}_{i,t})$) increases at the margin with temperature for the three crops. This means that farmers need

[A3]Looking for example at the case of how temperature changes input requirements, Table A9 reports the value of $(\hat{\beta}^T_{j,k} + 2\hat{\beta}^{T^2}_{j,k}\bar{T})\bar{T}/\bar{x}_{j,k}$ for each crop and input. This calculus illustrates how input requirement $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ changes with a marginal increase in temperature. A positive value would imply that input requirements increase with temperatures and that, *ceteris paribus*, farmers increase their input applications. We proceed to the same type of calculus for the productivity terms (i.e. $(\bar{p}^x_k/E(\bar{p}^y_j))(\hat{\delta}^T_{j,k,k} + 2\hat{\delta}^{T^2}_{j,k,k}\bar{T})\bar{T}/\bar{x}_{j,k})$ and substitution/complementary terms (i.e. $(\bar{p}^x_l/E(\bar{p}^y_j))(\hat{\delta}^T_{j,1,2} + 2\hat{\delta}^{T^2}_{j,1,2}\bar{T})\bar{T}/\bar{x}_{j,k})$. A positive value of the former implies that the input productivity increases for a marginal increase in temperature, ultimately inciting farmers to increase their input applications. A positive (resp. negative) value of the latter term implies that the two inputs become more substitutes (resp. more complementary).

Table A9: Weather effects on input requirement, productivity and substitution

	Temperature			Precipitation		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
	A. FERTILIZERS					
Total	1.02 ***	1.34 ***	0.61 ***	0.10 **	0.02	0.20 ***
	(0.19)	(0.23)	(0.24)	(0.04)	(0.04)	(0.04)
Requirement	3.66 ***	2.30 **	5.40 ***	-0.05	-0.05	-0.64 ***
	(0.94)	(0.91)	(1.26)	(0.16)	(0.15)	(0.22)
Shifter	-3.54 ***	-4.41 ***	-0.96	0.06	0.25	-0.17
	(1.36)	(1.48)	(1.66)	(0.24)	(0.27)	(0.28)
Substitution	0.89	3.44 ***	-3.83 ***	0.08	-0.18	1.10 ***
	(0.94)	(1.32)	(1.42)	(0.20)	(0.25)	(0.25)
	B. PESTICIDES					
Total	-0.39 **	0.30	-0.19	0.11 **	0.09 **	-0.24 ***
	(0.20)	(0.27)	(0.20)	(0.04)	(0.04)	(0.03)
Requirement	-0.84	-1.15	0.12	0.03	0.32 **	-0.39 **
	(0.78)	(0.95)	(1.02)	(0.15)	(0.17)	(0.18)
Shifter	-0.35	-1.36	2.19 *	0.00	-0.08	-0.52 **
	(1.10)	(1.21)	(1.15)	(0.20)	(0.24)	(0.22)
Substitution	0.80	2.82 ***	-2.51 ***	0.08	-0.14	0.66 ***
	(1.02)	(1.07)	(0.93)	(0.18)	(0.21)	(0.16)

NOTE. Elasticites are computed at sample mean values. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

to apply larger quantities of fertilizer to achieve maximum yields ($\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$) when temperature increases. However, on the other hand, the own productivity of fertilizers ($\boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})$) decreases with temperature, leading rational farmers to apply less fertilizer when temperature increases. Finally, the substitution terms ($\boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})$) have heterogeneous effects among crops. Fertilizer seems to be more widely substituted with pesticides for wheat and barley when temperature increases, but more complementary for rapeseed. Temperatures thus affect the technical substitution/complementary relationship between inputs. The joint – cumulative – effects of changes in own productivity and substitution terms are however negative for the three crops. Thus, the overall increase in fertilizer applications displayed in Table 3 seems mostly due to an increase in input requirements.

Second, changes in pesticide applications due to a marginal increase in temperature appears to be less dependent on changes in input requirements. Indeed, pesticide requirements are not significantly impacted by an increase in temperature at the margin. Similarly, the productivity terms of pesticide remains unaffected by temperature for wheat and barley. The productivity terms of pesticide are only significantly positive for rapeseed, where a marginal increase in temperature increases the productivity of pesticides. However, this increase seems completely offset by the changes in the substitution terms,[A4] the two effects cancelling each other out. While not significantly different from zero, the tendency of farmers to apply more (resp. less) pesticide to barley (resp. rapeseed) when temperature increases seems mainly driven by the impacts of temperature on the substitution/complementary relationship between inputs.

Third, changes in fertilizer applications due to a marginal increase in precipitation are difficult to attribute to any particular phenomenon, at least for wheat and barley, where all the terms are non-significantly affected by weather changes. The pattern is different for rapeseed, where (i) input requirement reduces with precipitation, (ii) the productivity term remains unaffected and (iii) the two inputs become more widely substituted. The significant increase in fertilizer applications displayed in Table 3 thus seems explained by the modification of the substitution terms.

Fourth, the changes in pesticide applications due to a marginal increase in precipitation seem to be globally explained by changes in input requirements. Indeed, these are the only significantly estimated parameters for barley. They also seem to drive the negative shifts in pesticide applications to rapeseed as the productive and substitution terms offset each other. This result is consistent with the results from Kaminski et al. (2013), who identified the impacts of precipitation on input requirement terms as the main drivers of the reduction in input uses under wetter weather conditions.[A5]

[A4]Note that the effects of a marginal increase in temperatures on the substitution terms is about similar for pesticide and fertilizer for the three crops. This is due to the fact that the marginal effect of temperature on these terms is identical *modulo* the input price that changes between the two inputs (see Appendix **??**).

[A5]Kaminski et al. (2013) estimated a similar structural model to ours for Israeli agriculture data and found that precipitation can reduce input productivity.

Disaggregation of the elasticities of crop yields on weather conditions into agronomic and adaptation effects

The elasticity of crop yields on weather conditions reported in the Appendix can be disaggregated as:

$$\begin{aligned}
\xi_{y_j}^T &= \underbrace{(\frac{\partial f(\mathbf{x}_j(\bar{\mathbf{w}});\mathbf{w})}{\partial T})\frac{\bar{T}}{\bar{y}_j}}_{\text{Agronomic effects}} + \underbrace{(\frac{\partial f(\mathbf{x}_j(\mathbf{w});\bar{\mathbf{w}})}{\partial \mathbf{x}_j(\mathbf{w})}\frac{\partial \mathbf{x}_j(\mathbf{w})}{\partial T})\frac{\bar{T}}{\bar{y}_j}}_{\text{Adaptation effects}} \\
&= \underbrace{(\frac{\partial f(\mathbf{x}_j(\bar{\mathbf{w}});\mathbf{w})}{\partial T})\frac{\bar{T}}{\bar{y}_j}}_{\text{Agronomic effects}} + \underbrace{\xi_{x_{j,1}}^T \theta_j^1(\bar{\mathbf{w}})\frac{\bar{x}_{j,1}}{\bar{y}_j} + \xi_{x_{j,2}}^T \theta_j^2(\bar{\mathbf{w}})\frac{\bar{x}_{j,2}}{\bar{y}_j}}_{\text{Adaptation effects}},
\end{aligned}$$

where $\xi_{x_{j,1}}^T$ (resp. $\xi_{x_{j,2}}^T$) is the elasticity of fertilizer (resp. pesticide) application on temperature (see Appendix). $\theta_j^1(\bar{\mathbf{w}})$ (resp. $\theta_j^2(\bar{\mathbf{w}})$) is the productivity of fertilizer (resp. pesticide) at the sample mean values (see Appendix). The adaptation effects can be interpreted as the sum of the productive effects of the change in fertilizer and pesticide applications at the sample mean values. The agronomic effects are measured as the difference between the total effects $\xi_{y_j}^T$ and the adaptation effects.

Simulations: cumulative temperature instead of average temperature

Table 5 in the main text displays the projections of the impacts of warmer temperatures on crop yields using the estimates obtained with average temperature during the growing season. In the same lines, we project similar increases in temperature on crop yields using measurements of cumulative temperatures instead, distinguishing between beneficial and killing degree days (as in Online Appendix). Table A10 shows the initial averages of the crop yields in our sample for the period 2006-2012 (Panel A) and the predicted changes in crop yields under future temperatures using the results from our reduced-form model (Panel B) and structural model (Panel C) with measurements of cumulative temperatures. The findings presented in Table A10 are qualitatively similar to those of Table 5, with comparable outcomes between the reduced-form and structural models. Here too, we identify negative and significant agronomic effects, but positive adaptation effects. With this specification, the adaptation effects tend to offset between 10% and 85% of the detrimental agronomic impacts of warmer temperatures. Finally, it should be noted that, in the case of wheat, the impact of higher temperatures is statistically insignificant in both models. This outcome hides compensatory mechanism between the significant negative agronomic effects and the significant positive adaptation effects.

Table A10: Projections of the impacts of warmer temperatures on crop yields using measurements of cumulative temperatures during the growing season.

	Wheat			**Barley**			**Rapeseed**		
	+1°C	**+2°C**	**+3°C**	**+1°C**	**+2°C**	**+3°C**	**+1°C**	**+2°C**	**+3°**
				A. 2006-2012 Averages					
Initial yields (100 kg/ha)	70.88	70.88	70.88	64.30	64.30	64.30	33.59	33.59	33.5
				B. Reduced-form Estimates					
Changes in yields (100 kg/ha)	-0.39	-1.29	-2.99	-6.54 ***	-12.56 ***	-17.55 ***	-0.86 **	-3.85 ***	-10.51
	(0.59)	(1.32)	(2.36)	(0.59)	(1.23)	(2.00)	(0.36)	(0.93)	(2.0
				C. Structural Estimates					
Changes in yields (100 kg/ha)	-0.47	-1.64	-3.95	-5.87 ***	-11.24 ***	-15.61 ***	-1.06 ***	-4.40 ***	-11.61
	(0.65)	(1.51)	(2.88)	(0.63)	(1.32)	(2.00)	(0.37)	(0.95)	(2.1
Agronomic effects	-2.11 **	-7.93 ***	-27.22 ***	-6.61 ***	-13.95 ***	-23.41 ***	-1.44 ***	-5.18 ***	-12.85
	(0.93)	(2.35)	(5.54)	(0.88)	(1.78)	(3.20)	(0.53)	(1.77)	(4.6
Adaptation effects	1.65 **	6.29 ***	23.28 ***	0.74 **	2.71 *	7.80 **	0.38	0.78	1.2
	(0.68)	(2.59)	(6.51)	(0.32)	(1.55)	(3.37)	(0.52)	(1.40)	(4.8

Note. Figures display predicted changes in crop yields, holding current growing areas and technology constant relative to the period 2006-2012. Panel plays the initial crop yields in our sample. Panel B presents the predicted changes using the reduced-form estimates. Panel C presents the predicted char using the structural estimates. For this panel, we report the estimated direct impacts of weather on plant growth (agronomic effects) and the estimated i rect impacts of weather via farmers' adjustments in input applications (adaptation effects). Below each estimate we report in brackets the standard error ained using the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.