Supply response at the field-level: disentangling area and yield effects

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Abstract

Agricultural price supply response is thought to occur mainly through changes in acreage rather than through yield increase. Many studies find that yields respond weakly to prices, leading to the counter-intuitive idea that yields are insensitive to prices. In this paper, I argue that this result is likely due to the use of aggregated data: county- or state-level yields are averages, whose composition itself is affected by price changes. When area expansion is done by cultivating less fertile fields or by foregoing rotation, this composition effect reduces average yields, even if yields increase on each individual field.

To disentangle the effect of the intensive and composition effect on county-level yields, I run an analysis at the field level, constructing a dataset of remotely-sensed crop choice and yield data for corn and soybeans for close to half million fields in the US Midwest. Results indicate that the field-level yield elasticity to prices is high for corn, at 40%. When the same elasticity is estimated on a pseudo county-level panel, estimates drop at 30%. Taking advantage of the presence of a subsample of fields that are always rotating, I show that the difference in estimates can be fully attributed to the composition effect. This confirms the hypothesis that estimates based on aggregate data underestimate the relationships at the field-level level.

1 Introduction

In his 1809 opus *On the Principles of Political Economy and Taxation*, Ricardo discussed the situation in which land of decreasing quality was set into production to respond to the demand of an increasing population. Although Ricardo's discussion focused on the impact of the price increase on land rents, it is interesting to note the implications concerning yields. If soil productivity differs importantly among the field classes, it is possible that average yields actually decrease after the price increase, despite a positive response of all fields. This *ecological fallacy*, where a relationship at the aggregate level needs not be representative for the relationship at the individual level[1], stems from the fact that the aggregate yield variable is an average, whose composition itself changes. This makes interpretation of the results ambiguous: when observing yield changes at the aggregate level only, it is not possible to infer whether these changes are due to changes in individual yields, or whether they are due to a composition effect of the average yield.

The lack of interpretability of aggregated data has been acknowledged in many studies such as Roberts et al. (2013), Beddow and Pardey (2015) or Miao et al. (2016), but remains so far unaddressed. As a typical example, Miao et al. (2016) find that the yield response to prices for soybeans is close to zero statistically, conceding however that this result "could also be indicative of the intensive [yield] and extensive margin [area] effects offsetting each other". As a result, it is difficult to draw policy-relevant implications from supply response analysis, for a same estimate could be obtained under very different scenarios.

In this study, I focus on the case of maize and soybeans in the US Midwest. While Ricardo's stylised fact of yields decreasing due to use of less fertile soils does not really hold in this case (the total surface devoted to corn and soybeans is pretty stable over time in the Midwest), yields decreases can happen here when expanding a crop by foregoing rotation. Rotation of corn and soybeans has been found to lead to a 2% to 10% increase in yields, and close to 5% savings in fertiliser application (Farmaha et al., 2016b). As acreage response to corn prices is rather high (Hendricks et al., 2014 find an elasticity of 0.4), this suggests the possibility of a decrease in county-level average yields.

To investigate this, I use field-level data derived from satellite observation, spanning the period 2000-2015. Using the crop data layer from USDA (Boryan et al., 2011), pixel-level yields estimates from Lobell and Azzari (2017) and fields boundaries, I obtain the yield and crop history for close to a half million fields situated in the Corn Belt. This allows me to measure supply response at the field level, and to understand the composition effect in aggregate data.

2 Literature review

Supply response Methods to estimate supply response can be divided in two broad groups, structural approaches and empirical ones. In the structural approach, one seeks to estimate parameters of production or profit functions, and derive the elasticity based on theoretical relationships. On the other side, the empirical approach directly regress production, acreage or yield on a price variable.

[1]Ecological fallacy is the term used mainly in political science, see King (1997) for a classical treatment.

Choice of the method is often dictated by the type of available data: the structural approach is rather used with farm-level data, while the empirical approach relies more often on aggregate data. As a consequence, the structural approach is found more often in studies in developing countries, where official data is rare and farm surveys are often undertaken by researchers. On the other side, most studies in the US for example rely on the empirical approach.

The structural approach is based on modelling the producer optimisation problem. This can be done either by estimating the production functions (primal approach) or profit functions (dual approach). It relies heavily on the choice of a specific functional form. A second important choice concerns whether one consider the farmer to be unconstrained regarding access to inputs and outputs. If the farmer is considered unconstrained, as is done for most studies in developed countries, standard theory from the firm applies. On the other side, studies focusing on developing countries introduce various constraints such as marketing, credit or labour limitations, leading to the so-called farm-household model (Singh et al., 1986). Endogeneity issues arise in the structural approach due to the so-called transmission problem and to unobserved productivity characteristics, so that instrumental variables are required.

The empirical approach is based on the work of Nerlove (1956), which investigates the response of expected output to expected prices:

$$A_t^\star = \beta_0 + \beta_1 \hat{P}_{t|t-1} + \epsilon_t \tag{1}$$

Where A_t^* refers to desired planted area, and $\hat{P}_{t|t-1}$ refers to expectation at time *t-1* of harvest price at time t. As neither expected area nor expected prices are observed, these need to be specified by the analyst. Effective area is usually specified as a distributed-lag adjustment between planned area $A_t^\star$ and past area A_{t-1}:

$$A_t = A_{t-1} + \gamma(A_t^\star - A_{t-1}) \tag{2}$$

For the expected price, various assumptions have been used, ranging from extrapolative, adaptive, (quasi) rational, or the use of futures markets (see Nerlove and Bessler, 2001 for an extensive review). Nerlove initial specification was an adaptive expectation :

$$\hat{P}_{t|t-1} = \hat{P}_{t-1|t-2} + \delta(P_{t-1} - \hat{P}_{t-1|t-2}) \tag{3}$$

Once the two processes specified, the Nerlove model leads to an estimable reduced-form where actual output depends on lags of actual output and lags of prices. The structural elasticity parameter is then derived as a ratio of the reduced-form parameters.

In the original work of Nerlove (1956), only one of the two adjustments was assumed, and, by setting the other expected variable to its observed value (i.e. setting either $A_t^\star = A_t$ or $\hat{P}_{t|t-1} = P_{t-1}$), this leads to the reduced form:

$$A_t = \alpha_0 + \alpha_1 P_{t-1} + \alpha_2 A_{t-1} + \nu_t \tag{4}$$

The short–run supply response parameter is simply α_1, while the long-run parameter is $\alpha_1/(1-\alpha_2)$. Interestingly, the latter corresponds also to the structural supply response parameter β_1 in the initial structural equation (1). An issue with the reduced-form (4) is that two different structural interpretations (adaptive expectation for prices and distributed lag adjustment for expected area) lead to the same reduced-form.[2] This implies that the two theories are *observationally equivalent*, rendering a structural interpretation of the parameters difficult. In his following book Nerlove (1958) considered the case where both expected variables were used (i.e. (2) and (3) are set into (1)), leading to an augmented reduced-form:

$$A_t = \alpha'_0 + \alpha'_1 P_{t-1} + \alpha'_2 A_{t-1} + \alpha'_3 A_{t-2} + \nu'_t \tag{5}$$

The long-run supply response parameter becomes now $\alpha'_1/(1-\alpha'_2-\alpha'_3)$. Although this version of the Nerlove model has the advantage of leading to a clearer interpretation of the structural parameters, the simpler version with only one lag of the dependent variable has been mostly used.

Subsequent changes of the model have focused mainly on specifying the price expectation process (3). Eckstein (1984, 1985) shows that a rational expectation model leads to the same reduced-form representation as in the simple Nerlove reduced-form (4). Gardner (1976) suggested using futures prices as proxy for the expected prices. Under this approach, the price equation does induce a lag of acreage in the reduced-form, although the lag may be introduced assuming a partial adjustment process for acreage.

Statistical estimation of the reduced-form faces several issues. Nerlove (1958) pointed out that residuals were serially correlated, and suggested several approaches to deal with this. Brandow

[2]Note however that the dynamic properties of the ν_t term differ depending on the structural model, which could inform a test to discriminate between the two theories.

(1958) criticised the fact that the simple Nerlove model did not include exogenous controls, which can introduce omitted variable bias. Another concern, raised by Braulke (1982), is the potential multi-collinearity between A_{t-1} and P_{t-1}. Diebold and Lamb (1997) discuss the fact that the long-term parameter is a ratio of coefficients, which causes the estimator to have infinite moments and be bi-modal. Addition of a lagged dependent variable also introduces bias in the estimation, leading even to inconsistent estimates in the panel case (Nickell, 1981). While the issue is usually ignored in the standard case, it has been addressed in the panel case using Arellano and Bond (1991) GMM estimator (Haile et al., 2016; de Menezes and Piketty, 2012). The GMM approach consists in using the second lag of the dependent variable as instrument, which is highly problematic in this context since some formulations of the Nerlove model imply the presence of the second lag as explanatory variable, contradicting the exclusion restriction.

Concerns about the endogeneity of the price and error term have received more recent attention (Choi and Helmberger, 1993; Roberts and Schlenker, 2013; Hendricks et al., 2015). Roberts and Schlenker (2013) focused on aggregate total supply Q_t, and argued that yield shocks can be correlated to prices. To summarise and simplify the argument, let $Q_t = A_t \cdot Y_t$ (where A_t and Y_t are respectively acreage and yield), and taking logs: $q_t = a_t + y_t$, where lower case letters denote variable in logs. Yield is decomposed into a long term (y_t^{LT}) and short term deviation (y_t^{ST}) component, also interpreted as *yield shock*. The latter can be further decomposed into a predictable and an unpredictable component, $y_t^{ST} \equiv \hat{y}_{t|t-1}^{ST} + \tilde{y_t}^{ST}$. Assuming that yield deviations are exogenous to prices, and using futures prices as in Gardner (1976), leads to following model:

$$q_t = \alpha + \beta p_{t|t-1} + y_t^{LT} + \hat{y}_{t|t-1}^{ST} + \tilde{y_t}^{ST} + \nu_t = \alpha + \beta p_{t|t-1} + \tilde{\nu}_t \tag{6}$$

Endogeneity arises if the futures price adjusts to yield trends or predictable yield deviations, i.e. if $p_{t|t-1} = f(y_t^{LT}, \hat{y}_{t|t-1}^{ST})$. If this is the case, estimation of production on price alone will suffer from the omitted asymptotic variable issue. As prices are likely negatively correlated with yield shocks, this will lead to under-estimation of the true parameter.

Roberts and Schlenker (2013) suggested adding y_t^{ST} in the main equation,[3] and using y_{t-1}^{ST} as instrumental variable, arguing that the storage model ensures that past yield shocks affect current production only through prices (due to carry-over from the previous year). This is possible under the assumption that past yield shocks do not influence present shocks.

[3]The term y_t^{LT} is also implicitly taken into account by using a time spline in the main equation.

Rotation Very few papers in the supply response literature have addressed the fact that many crops are grown in rotation. This is surprising since in the most productive states in the US Corn Belt, rotation practices are predominant. Indeed, in the 3I states, [4] close to 80% of the fields are grown in a rotation pattern, usually alternating corn with soybeans. I introduce here briefly stylised facts regarding rotation, and discuss in the next section how to incorporate rotation in traditional supply response models.

The benefits of rotating maize and soybeans are multiple, and subject to some discussion in the agronomy literature (Farmaha et al., 2016a). Rotation mechanisms operate mainly through a reduction in pests and fixation of nitrogen by soybeans. The effects of rotation are a boost in yields, as well as reduced need of nitrogen. Estimates of the yield boost vary among studies. Porter et al. (1997) study a small sample of experimental plots in Minnesota and Wisconsin, and report a 15% increase in maize yields when previously cropped with soybeans, with some heterogeneity where lower-yielding fields see a higher increase, close to 25%. Similar numbers were obtained for soybeans. Another set of experimental data, used by Hennessy (2006) and Livingston et al. (2015), suggests rotation effects increasing yields for both crops by 25%. Farmaha et al. (2016a) on the other side use observational data from high-productivity irrigated fields in the western U.S. Corn Belt. They find lower rotation effects, from 2%-5% for maize and 6% to soybeans. Data on fertiliser use indicated that producers were reducing the amount of nitrogen by 6%. All these papers note that maize shows a one-year memory, i.e. there will be no difference between a $\langle SSM \rangle$ and $\langle MSM \rangle$ sequence. On the other side, soybeans is usually found to exhibit a two-year memory, fields with two previous years of maize ($\langle MMS \rangle$) giving higher yields than fields with one year of maize and soybeans previously ($\langle SMS \rangle$).

3 Model

3.1 Individual supply in presence of rotation effects

Rotation effects in production functions have been modelled in various ways, with the main differences being in the way the rotation effects are taken into account, and in the way dynamics are introduced. An early strand of literature used mathematical programming to derive optimal rules in a static framework, see El-Nazer and McCarl (1986) or Musser et al. (1985). Dynamic programming methods based on Bellman equations have been used, see Thomas (2003) on the crop choice in pres-

[4] The 3I states are Iowa, Illinois and Indiana.

ence of nitrogen carry-over, or Livingston et al. (2015); MacEwan and Howitt (2011) specifically on rotations. Although interesting, these methods have the drawback that they do not lead to closed-form estimators. On the other side, the framework of Hennessy (2006) provides a clear modelling framework of rotation effects amenable to direct estimation, that I adopt here.

Hennessy (2006) considers two effects of rotation, the *input saving* effect α and the *yield boost* effect β. The input saving effect arises from nutrient carry-over from the previous period(s), and is assumed to be perfectly substituable with chemical fertiliser. This implies that the total amount of nutrient n_t for crop is equal to the sum of chemical fertiliser F_t and the input-saving effect α, $n_t = F_t + \alpha$. Further, this input-saving effect depends on the type of crop succession, which we will write as α^i_j, i.e. when crop i follows crop j, leading to $n^i_t = F^i_t + \alpha^i_j$. The second effect of crop rotation is the yield *boost effect* β^i_j (for crop i following crop j), which is assumed to enter additively. These two elements lead to the following yield production function:

$$Y(F, i, j) = y^i(F^i_t + \alpha^i_j) + \beta^i_j$$

Given that crop j was planted at previous period $t-1$, crop $i^\star$ is chosen for period t if $\pi^{i^\star}(p, w, i^\star, j) > \pi^i(p, w, i, j) \forall i \neq i^\star$, where π^i is the profit function for crop i depending on the output price p and fertiliser price w. Hennessy (2006) makes the critical assumption that both the input-saving α^i_j and yield boost β^i_j effects do not depend on previous level of nutrient n_{t-1} or on actual level of fertiliser F_t. While this restrictive assumption departs from the nitrogen carry-over literature[5], it has the advantage of alleviating the need for dynamic programming tools. Furthermore, it allows us to focus on our question of interest, yield supply response in the short term, for a given crop choice.

An important implication of the perfect substitutability assumption between input saving α and chemical fertiliser is that the optimal nutrient level $n^\star_t$ does not depend on the previous crop status.[6] This in turn implies that the difference in yield for crop i between rotation $\langle ji \rangle$ or rotation $\langle ki \rangle$ is equal to the difference in respective yield boosts, i.e. $\tilde{Y}(p, w, i, j) - \tilde{Y}(p, w, i, k) = \beta^i_j - \beta^i_k$. A further consequence of the previous result is that yield response to prices will be the same, irrespective of the rotation status ,a prediction that can be tested empirically.

[5]Thomas (2003) uses for example a specification similar to $\alpha^i_j = m^j(n_{t-1})$.

[6]To see this, note that, for two different previous crops j or k, first order conditions $y'(F^{*i}_j + \alpha^i_j) = w/p$ and $y'(F^{*i}_k + \alpha^i_k) = w/p$ will both lead to the same available nutrient $n^\star_t = F^{*i}_j + \alpha^i_j = F^{*i}_k + \alpha^k_j$.

3.2 Aggregate supply: a simple Ricardian model

Turning now to aggregate supply, I analyse here a model with farm heterogeneity, and its impact on aggregate supply. To get intuition for the composition effect, I describe here a continuous version of the *Ricardian* case, where land of lower quality gradually enters production. The yield function is $y(p,\theta)$, and depends on prices p and land quality θ. Yields are assumed to be increasing in land quality θ, i.e. $\partial y(p,\theta)/\partial\theta > 0$. Yields respond positively to prices, following standard producer theory. Let $\theta^\star(p)$ be the *minimum quality threshold* at which profit is non-negative given prices p, i.e. $\pi(\theta^\star,p) = 0$. Fields with higher land quality $\theta \geq \theta^\star$ enter production, while fields with lower quality ($\theta < \theta^\star$) do not produce. An increase in prices reduces the minimum quality threshold ($\frac{d\theta^\star(p)}{p} < 0$), inducing more fields to enter production. Let further $f(\theta)$ be the density of θ, and $F(\theta)$ its cumulative distribution function. Normalising the land quality over the $[0,1]$ interval, the average yield is given by:

$$\bar{y}(\theta^\star(p),p) = \int_{\theta^\star(p)}^{1} f(\theta)y(p,\theta)d\theta/(1-F(\theta^\star(p)))$$

Figure 1 gives a simple illustration of the Ricardian model. In the first panel, an assumed distribution of the land quality θ is shown. The minimum land quality $\theta^\star(p)$ is set at the value of 0.6: all fields with $\theta > \theta^\star$ produce (i.e. $1-F(\theta^\star(p))$ fields produce). The second panel shows the yield as a function of θ (and p implicitly) and average yield $\bar{y}(\theta^\star(p),p)$.

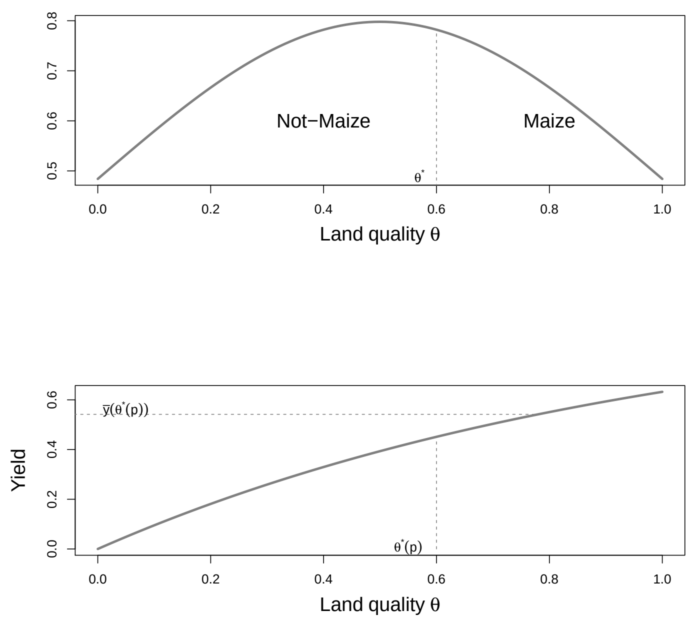
The derivative of average yields with respect to prices is (see appendix A.1 for the full derivation):

$$\frac{\partial\bar{f}(p)}{\partial p} = \frac{\int_{\theta^\star}^{1} f(\theta)\frac{\partial y(p,\theta^\star)}{\partial p}d\theta(1-F(\theta^\star)) - f(\theta^\star(p))\frac{d\theta^\star(p)}{dp}\left[\int_{\theta^\star}^{1} f(\theta)[y(p,\theta^\star)-y(p,\theta)]d\theta\right]}{(1-F(\theta^\star))^2} \tag{7}$$

The first term in the numerator represents the intensive margin response, and corresponds to the *average yield response* of fields already producing. Under the standard assumption of positive individual supply response $\frac{\partial y(p,\theta)}{\partial p} > 0$, this term is positive. The second term corresponds to the composition effect of the extensive margin. It is composed of the (weighted) acreage response term $\frac{d\theta^\star(p)}{dp}$ multiplied by the average yield difference among producers $\int_{\theta^\star}^{1} f(\theta)[y(p,\theta^\star)-y(p,\theta)]d\theta$. With the assumption of yields increasing in θ ($\frac{\partial y(p,\theta)}{\partial\theta} > 0$), and of entry of lower quality land ($\frac{d\theta^\star(p)}{p} < 0$), we have that

Figure 1: Ricardian model: continuous version

(a) Distribution of θ



(b) Productivity and average yield at $\bar{p}$

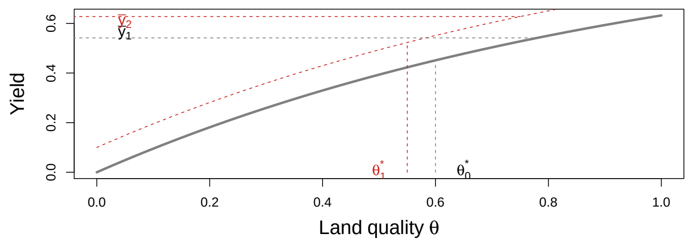
$y(p, \theta^{\star}) < y(p, \theta) \quad \forall \theta < \theta^{\star}$, so that the second term is negative.

This formula formalises the decomposition of the aggregate response into the average positive response of *incumbent* producers, and the composition effect due to the entry of new producers. As these new producers have lower yields, the composition effect reduces the aggregate response.

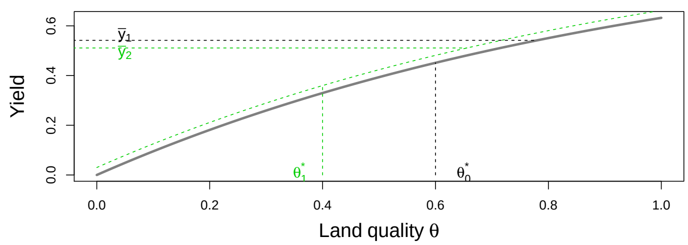
Whether the overall impact of the price increase will be negative or positive depends on the respective strength of the intensive and extensive margins. Figure 2 illustrates two possible cases. The first panel shows a case where there is a strong intensive margin (displacement of the curve) and small extensive one (new point $\theta^{\star}(p')$). The resulting average yield is higher than before. The second panel depicts the opposite situation, where a weak intensive combined to a strong extensive margin responses lead to a decrease in the average yield.

Extension of the theoretical model to the case where land expansion comes from rotation instead of a Ricardian marginal land can be made following the same idea. Hendricks et al. (2014) assume that rotation types $\langle S \rangle$, $\langle M \rangle$ and $\langle MS \rangle$ are naturally ordered over a *corn-propensity* index θ. Fields with

Figure 2: Effect of a price increase



(a) Large intensive margin, low extensive



(b) Low intensive margin, high extensive

lowest propensity $\theta < \theta^1$ are cultivated to soybeans in monoculture ($\langle S \rangle$), fields with intermediate propensity $\theta^1 \leq \theta < \theta^2$ are cultivated in rotation ($\langle SM \rangle$), while fields with high propensity $\theta^2 \leq \theta$ are cultivated to corn in monoculture ($\langle M \rangle$). See Figure 8 in the Appendix, Page 30 for an illustration. The assumption here is that there is no direct switching from $\langle S \rangle$ fields to $\langle M \rangle$ fields. This assumption seems constraining, but in practice it does not appear to be very restrictive, as few fields are found to follow such transition. In this model, an increase in corn prices will lower the two thresholds θ^1 and θ^2. Lowering of θ^2 corresponds to rotation fields $\langle MS \rangle$ switching now to corn-monoculture $\langle M \rangle$ fields. This is the case where the benefits of rotations a now offset by the increase in corn price, so it becomes profitable to grow corn again, even if it has a lower yield. Conversely, lowering of θ^1 corresponds to soy-monoculture fields $\langle S \rangle$ entering now a rotation scheme. The final effect on the share of rotating fields $\langle SM \rangle$ is ambiguous, and depends on the (weighted) changes in θ^1 and θ^2.

Turning now to the assumption on the productivity along the corn-propensity θ dimension, I assume now that it follows the production function discussed above in Subsection 3.1. That is, rotating fields $\langle SM \rangle$ will benefit from the yield boost β and fertiliser-saving α. In that case, a price increase will increase the share of fields in corn-monoculture, $\langle SM \rangle$ to $\langle M \rangle$, increasing the parts of fields without rotation effect. However, the loss in $\langle SM \rangle$ will be partially compensated by the gain in $\langle SM \rangle$ due to a decrease in $\langle S \rangle$ fields. That is, contrary to the Ricardian case, in the rotation case, the composition effect itself is not necessarily negative. It is worth coming back to the model's restriction that $\langle S \rangle$ fields can only transition to $\langle SM \rangle$, and not to $\langle M \rangle$. This restriction turns out to affect only effects in the long term, which I have not discussed so far. Indeed, whether a $\langle S \rangle$ turns in period 2 into the $\langle SM \rangle$ or $\langle M \rangle$ type will not change the share of M fields in period 2, nor will change the amount of fields with rotation benefits at period 2. It is only considering a longer horizon that the distinction would matter, but this is not the focus of this paper.

A similar expression to Equation (7) can be obtained for the derivative of the average yield in the rotation model. It is not reproduced here as it does not add much clarity to the discussion. I turn instead in the next subsection to an empirical decomposition that can be estimated from data.

3.3 Comparing individual and aggregate response: a decomposition

The goal of this study is to compare individual and aggregate estimates of the yield response. A first approach to do so is to compare estimates based on field-level (*micro*) and county-level data (*macro*). Such a direct comparison suffers however from the fact that there are other reasons why the *macro* estimator differs from the *micro* one: aggregation bias due to heterogeneity of the coefficients (Hendricks et al., 2014), aggregation bias due to mis-specification of the functional form and simple sampling variation all suggest that these estimators should differ.

To allow for a more precise comparison of the estimates, I decompose here the aggregate intensive margin response into its individual intensive and extensive components. This provides a way to obtain macro response based on the micro parameters only. These micro-based macro estimates will then be compared to the ones obtained from the benchmark model, testing the hypothesis that these estimates are equal. Obtaining similar estimates form the two methods would prove useful, as it could justify using the decomposition at a more disaggregated level, investigating for example the presence of spatial heterogeneity in the intensive and extensive margin.

Rewrite the crop choice variable c_{it}, attributing value of 1 for maize, and 0 for soybeans. Denote field area by a_i, and total maize acreage by $A_t^M = \sum_i a_i c_{it}$, $A_t^S = \sum_i a_i(1 - c_{it})$. The short term response is given by:[7]

[7] See Hendricks et al., 2014, page 1479.

$$\partial A_t^M / \partial p_t^M = \sum_i a_i (c_{i,t-1} \beta_{MM}^A + (1 - c_{i,t-1}) \beta_{SM}^A) = A_{t-1}^M \beta_{MM}^A + A_{t-1}^S \beta_{SM}^A$$

The average maize yield $\bar{y}_t^M$ is decomposed into average yield from rotations $\langle M \rangle$ and from sequences $\langle S \to M \rangle$, $\bar{y}_t^M = \alpha_t^{MM} \bar{y}_t^{MM} + \alpha_t^{SM} \bar{y}_t^{SM}$. α_t^{SM} is the share of the area devoted to $\langle S \to M \rangle$ sequences over total area cultivated to maize, i.e. $\alpha_t^{SM} \equiv \frac{A_t^{SM}}{A_t^{MM} + A_t^{SM}} = \frac{A_t^{SM}}{A_t^M}$. Differentiating this average yield with respect to prices gives:

$$\begin{aligned} \frac{\partial \bar{y}_t^M}{\partial p_t^M} &= \alpha_{MM} \frac{\partial \bar{y}_t^{MM}}{\partial p_t} \quad + \alpha_{SM} \frac{\partial \bar{y}_t^{SM}}{\partial p_t^M} + \frac{\left[\partial A_t^{SM} / \partial p_t \cdot A_t^{MM} - \partial A_t^{MM} / \partial p_t \cdot A_t^{SM} \right] \bar{y}_t^{SM}}{(A_t^M)^2} \\ &\quad + \frac{\left[\partial A_t^{MM} / \partial p_t \cdot A_t^{SM} - \partial A_t^{SM} / \partial p_t \cdot A_t^{MM} \right] \bar{y}_t^{MM}}{(A_t^M)^2} \end{aligned}$$

Given the linearity assumptions made in the crop choice and yields equations (**??**) and (**??**), one gets (see Appendix A.2):

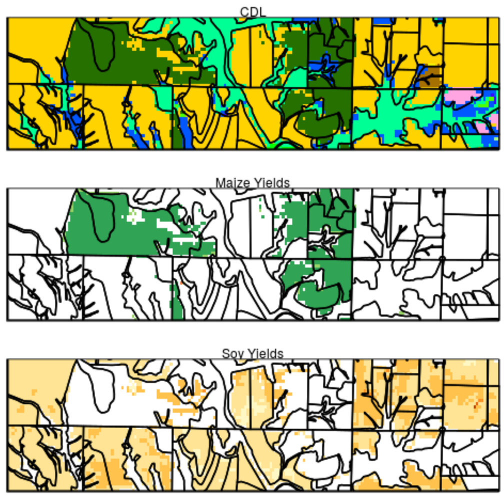
$$\frac{\partial \bar{y}_t^M}{\partial p_t^M} = \beta_M^Y + \alpha_{SM} \gamma + \frac{\alpha_{SM} A_{t-1}^M \beta_{MM}^A - \alpha_{MM} A_{t-1}^S \beta_{SM}^A}{A_M} \cdot (\bar{y}_{MM} - \bar{y}_{SM}) \tag{8}$$

The first two terms represent the individual intensive margin response, allowing for a possibly different response from $\langle S \to M \rangle$ fields compared to $\langle S \to M \rangle$ ones. The last term represents the *composition* effect, and is composed of the yield differential $\bar{y}_{MM} - \bar{y}_{SM}$ and area response. The yield differential $\bar{y}_{MM} - \bar{y}_{SM}$ corresponds to the average yield boost loss. The area response is a function of the actual share of each type and their supply response. This decomposition illustrates the claim that aggregate intensive response encompasses both the individual intensive and extensive margins.

4 Crop and yield data

To conduct an analysis at the field-level, I assemble data from three main sources: a crop classification at the pixel level, a yield map for the corresponding corn ans soybeans pixels, and a field boundary dataset. Figure 3 illustrates the three datasets combined. The first panel shows the crop classification, together with the field boundaries. The second panel shows the yield predictions for the pixels for which the CDL predicts maize. The third panel shows the soybeans yield predictions.

Figure 3: Illustration of the CDL , yield and boundary data



4.1 Crop classification

The crop data comes from the USDA Crop Data Layer (CDL) dataset (Boryan et al., 2011). The CDL classifies Landsat pixels of 30m$\times$ 30m into a large number of classes. The accuracy of the classification for maize and soybeans in the Corn Belt is very high, in general above 95%[8]. Corn and soybeans appear in multiple distinct classes, including categories such as corn and soybeans only, but also double-crop categories such as "Winter Wheat and Corn" or "Soybeans and Cotton". Due to the small share of the alternative classes, I focus on the main corn and soybeans categories.

4.2 Yield data

The yield predictions are based on the scalable satellite-based crop yield (SCYM) method of Lobell et al. (2015) and Jin et al., 2017. The method predict yields based on a satellite-derived vegetation index.[9] Parameters linking the vegetation-index to predicted yields are derived from an agronomic crop growth model. In brief, the agronomic model is used to simulate multiple realisations of yields and vegetation index. The simulated replications are used to estimate a regression between vegetation index and yields. These estimated parameters are used in turn to predict yield based on the satellite-observed vegetation index. The advantage of this method is that it does not make use of ground data for calibration purpose. When ground data is available, it can be used as validation, leading to

[8]See `https://www.nass.usda.gov/Research_and_Science/Cropland/metadata/meta.php`

[9]The methods uses the so-called Green Chlorophyll Vegetation index (GCVI) which is similar in spirit to the more widely known normalised difference index, NDVI.

out-of-sample (i.e. test) measure of fit, instead of in-sample measures (training).[10]

Lobell et al. (2015) test the accuracy of their maize and soybeans predictions in Illinois, Iowa and Indiana using data for ~10'000 fields obtained from the USDA Risk Management Agency. They find prediction R^2 between 0.14 and 0.58 for the state-year maize pairs, while the R^2 on the full sample is 0.35. Predictions for soybeans are less accurate, ranging between 0.03 and 0.5. Prediction bias in $Y^{True} = \alpha + \beta\hat{Y} + \epsilon$ arises both in the intercept and slope, although there is no clear tendency in over- or under-estimation of the values. Disaggregation of the bias suggests that it is commodity, year and state specific. Farmaha et al. (2016c) use the SCYM method in Nebraska in a study on yield gap, and obtain predictions R^2 ranging from 0.12 to 0.34, with a tendency to over-estimate yield. Lobell and Azzari (2017) use also the SCYM method to study yield heterogeneity at the county level. They predict field-level yield for maize and soybeans in Illinois, Iowa and Indiana, from 2000 to 2015. Averaging their yield prediction at the county level, they find R^2 of 0.67 and 0.74 for maize and soybeans respectively when comparing these with USDA county estimates. The SCYM is found to over-estimate yields, with larger bias at higher yields. The authors use then the USDA county averages to calibrate their data.

4.3 Field boundaries

An issue with the CDL data is that the analysis is done at the pixel-level, while we are interested in field-level analysis. There exists however a dataset of fields boundary, the USDA Common Land Unit (CLU).[11] Unfortunately, the actual dataset is not publicly available, so that only a copy of the 2009 version can be used.

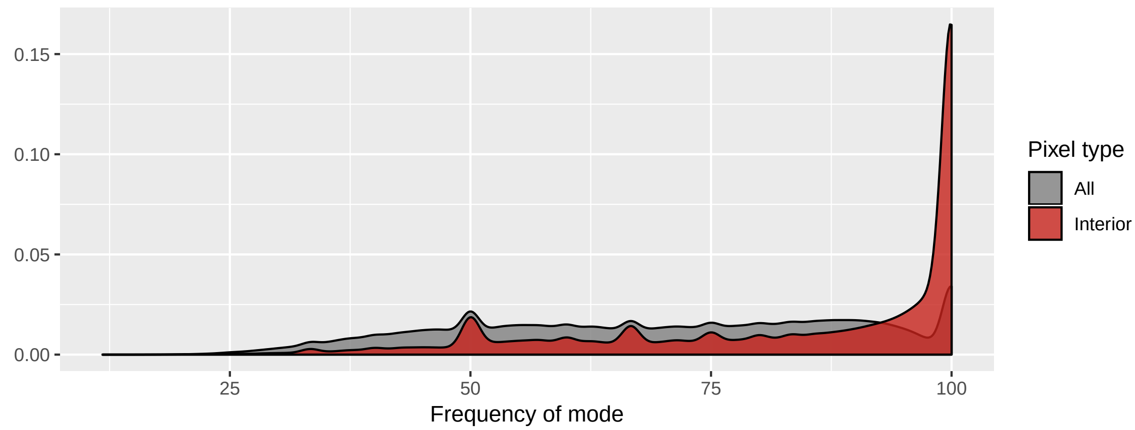
Two issues arise when using this dataset. Firstly, as the data is from 2009, fields boundaries may have changed. Drastic changes are unlikely, but cultivation of two different crops in the same field is possible. The second issue is that given that the CDL analysis is at the pixel level, instead of being at the field level, pixels in a field can contain multiple crop classes. Preliminary investigations showed clear cases of border contamination, where pixels at the edge of the field were attributed other classes (in particular classes corresponding to bush/forest elements).

These two issues call for specific rules for the attribution of a crop to a given field. Hendricks et al. (2014) used a *centroid-offset* rule, where the field's class is attributed according to the class of the pixel

[10] As such, the comparisons of R^2 between SCYM and direct calibrated regression in Lobell et al. (2015); Burke and Lobell (2017) are not valid as they compare training and tests R^2.

[11] `https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index`

Figure 4: Agreement of pixel classification, over all fields, 2015 data



that lies at a certain distance of the field's centroid. This procedure suffers from two issues: firstly, it is not guaranteed that the centroid offset falls within the field itself. Second, if there are really two crops cultivated in one field, the method will attribute only one class. Arguably, the arbitrariness of the offset rule should guarantee that there is no bias in which class will be chosen.

Another method is followed by Stevens (2015), who selects the mode of the classes found within a field. This method does not suffer from the issue of the centroid falling outside the field, yet also can attribute one class whenever there are actually two. To avoid this issue, I focus on fields with a relatively high classification agreement, i.e. I set a minimum threshold on the frequency of the mode. Further, I only take into account for this calculation interior pixels, i.e. pixels that do not touch the border of the field. This avoids to consider mixed pixels, that are potentially contaminated by elements outside of the field.

Figure 4 shows the frequency of the mode, with either all pixels taken into account, or only the interior ones. This is made for all plots in the nine states, using CDL classification for 2015. It is interesting to see that although the field boundaries were made in 2009, there is still a relatively good agreement for the year 2015. One can see that taking only interior pixels instead of all pixels leads to a much better result: a much larger proportion of the fields have 90% or more of the pixels showing the same value. One see furthermore a few bumps around the value of 50%, 66% and 75%. This suggests that the field was planted to two distinct crops (or more), using either a 1/2, 1/3 or 1/4 proportion.

To retain only fields with a good classification accuracy, the threshold was set at a minimum of 85% over all years considered (2008-2015). This is arguably a rather strict value, but it ensures that the data considered is how high quality. This is particularly important for the yield data, for which we want to make sure that we are not averaging over contaminated pixels, which can have a drastic effect on the final yield estimate. In fact, using the high-quality classification fields only, the correlation between NASS county yields and averages from the SCYM dataset is improved.

4.4 Weather data

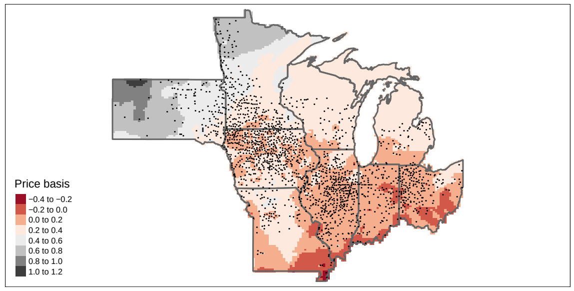
Weather variables are introduced as control variables to avoid omitted variable bias. While it is reasonable to think that weather is not influenced by prices, it is still the case that prices might anticipate weather events later in the season. To prevent this, I include a large set of weather controls from the DAYMET dataset (Thornton et al., 2017), which is at a resolution of 1000m $\times$ 1000m. The dataset includes precipitation, minimum and maximum temperatures, as well as partial pressure of water vapour. These daily measures are averaged per month, and squared terms are included. Growing degree days (GDD) will be included later on, following the work of Schlenker and Roberts (2006, 2009).

4.5 Price variables

Price variable $\boldsymbol{p}_{it}^{M}$ and $\boldsymbol{p}_{it}^{S}$ are futures quotations for post-harvest delivery (December for maize and November for soybeans), quoted pre- and in-season. The pre-planting period is defined to be the month of February and March. This is chosen earlier than actual planting times which are Mid April to May for maize, and May to June for soybeans. Given that the choice of crop is almost only between maize and soybeans, the planting period relevant to maize is also the one relevant for soybeans. Finally, this is also the period chosen by Hendricks et al. (2014). The pre-planting price is also relevant for the yield equation, as farmers can influence yields by choosing specific types of hybrids or the sowing densities. Later on, I shall include as well a post-planting price, which shall be defined as the May-June period. This is intended to reflect within season adjustments, such as fertiliser application. Given the sunk costs already supported, it is expected that post-planting price changes will have a smaller effect compared to pre-planting ones in the yield equations.

Futures prices are adjusted for the local basis, which is taken as the difference between the closest delivery futures price and the local spot price at neighbouring elevator. The basis is measured at the same period that the price is defined, i.e. for pre-planting prices, I use an average of February-March futures (for the December maturity) and an average of the basis at the same period.

Figure 5: Location of elevators and basis interpolation (corn, March 2014)



The cash prices were obtained from elevator data found in Bloomberg[12]. I end up with a dataset of close to 2000 elevators points. Data at the field level is obtained by spatial interpolation from neighbouring elevators. I use inverse distance weighting; interpolation parameters are obtained by cross-validation. It might be objected that possible transportation costs should be considered, taking for example at distance to the elevator. However, given that I use a fixed-effects strategy at the field-level, there is no need for such an adjustment, as it will get absorbed by the fixed-effects.

Figure 5 shows the location of the grain elevators and a smooth representation of the local basis. The location of the elevators follows closely where corn and soybeans are planted, compare with Figure 7 on Page 29.

On ethanol refineries There is an extensive literature (see Motamed et al., 2016 for references) finding that ethanol refineries have an impact on local maize acreage response. Motamed et al. (2016) for example find that the elasticity of maize acreage with respect to local refining capacity is about 1.5. As local refineries are likely related to the price variable, this suggests that one should add a refinery vicinity variable to avoid omitted variable bias. This however raises the concern that we are adding a so-called *bad control* (see Angrist and Pischke, 2008 section 3.2.3). Bad control happens when the control variable is itself endogenous to the outcome variable. This is unfortunately likely to be the case here, where location of refineries itself depends on acreage response. This is at least the argument made by Motamed et al. (2016), motivating their search for IV variables. Besides this, effects of the refinery location are likely to translate into changes in the local basis (as found by McNew and Griffith, 2005). This implies that the yield response I am measuring is also including the effect of refineries. This only changes the interpretation of the response coefficients: they include not only year-to-year variations, but also more longer term variations.

[12]Bloomberg disseminates data originally collected by Data Transmission Network and Geograin. Data was geo-located, and databases were consolidated, averaging quotations over close vicinities.

5 Identification strategy and results

The main objective of the empirical analysis is to obtain reliable estimates of the supply response at the field level. Although yield response is the main interest, acreage response will also be investigated. The second objective is to compare the field level estimates with estimates based on aggregate data. The research hypothesis is that yield response at the aggregated level is under-estimating micro response, due to the composition effect of acreage response in average yields.

5.1 Empirical approach

The identification strategy relies on a fixed-effects specification, at the field level (or county level for aggregate data). This has the advantage of controlling for unobserved soil and farmer characteristics. There are however further challenges in the estimation. For one, there is the threat of reverse causality, with yield response possibly affecting prices back. Second, there is a potential endogeneity between crop choice and yield response.

To investigate the possible reverse causality, I use the fact that I can use pre- and within-season quotations of futures prices for post-harvest delivery. This amounts to using a temporal exclusion restriction: crop choice happens after the pre-planting price is quoted, ruling out that yields affect pre-planting price. On the other side, post-season prices are expected not to influence yield management decisions, and should be zero. A non-zero finding could indicate the presence of reverse causality. The argument that pre-season prices should not be endogeneous to yields is however threatened in the case that pre-season prices anticipate within season events: if a drought is anticipated, expectation of lower yields would increase even pre-planting prices. To address this, I use a rich set of weather controls, including monthly precipitation, temperatures and humidity, together with their squared terms. As a robustness analysis, I estimate also IV regressions, where weather from the previous year is used as an instrument. This follows the argument of Roberts and Schlenker (2013) that, through the effect of storage, past weather shocks act as a demand shock.

To address the potential endogeneity between crop choice and yield response, I make use of a unique feature of the dataset at hand. It turns out that there is a large subsample of the fields which, over the whole period considered, always rotated, or always cultivated maize.[13] The subsample of *always rotaters* is pretty large, 34%, while the fields always used for corn amount to 5%, see Figure 11 in the Appendix, page 31 for an illustration. On these fields, the area response is zero, and crop

[13]There is also a subsample which always cultivated soybeans, but it is extremely small, less than 0.01%

choice perfectly predictable given last year's choice. This ensures that estimating yield response on each subsample will be free of any endogeneity between crop choice and yield.

The subsample of *always rotaters* proves also useful when testing for statistical aggregation bias. Using this subsample, I reconstruct a pseudo county-panel, averaging yields over each county-year pair. Because there is no area response on this subsample, coefficients from the field-level panel and the pseudo county panel should be the same, except for purely statistical aggregation bias.

The same procedure is repeated using what I call the *mixed* subsample, i.e. fields that have been rotating at least once, and repeated a corn-corn or soy-soy at least once. Under the assumption of a one year rotation-memory, these are the fields where crop choice is responsive to price variations. This implies that on this subsample, there might be an endogeneity between crop choice and yields. Further, on that same sample, there might be a difference between field-level and pseudo county-level estimates. The availability of both always rotaters and mixed rotaters provides a unique opportunity to test for statistical aggregation bias, endogeneity between and crop choice and composition bias.

The yield equation to be estimated is:

$$y_{it}^{M} = \alpha_i + \beta_{MM,M}^{Y} \boldsymbol{p}_{it}^{M} + \beta_{MM,S}^{Y} \boldsymbol{p}_{it}^{S} + \gamma_{MM}^{Y} \boldsymbol{x_{it}} + \epsilon_{it}$$

$\boldsymbol{p}_{it}^{M}$ is a vector of futures prices as described in section 16, x are the weather covariates. I use different specifications of the model, where I include different sets of p and w. In the first specification, model (1) I use the March price (i.e. pre-planting) only, without covariates. In model (2), I add early covariates: weather in the months of January to March. In model (3), I add all months up to August. In model (4), I include also the May, July and September difference from the previous month.[14]

Regressions using both the price of corn and soybeans proved unstable to estimate, with high variations in the estimates depending on small changes in the specification. This is typical outcome due to a multicollinearity issue: corn and soybean prices are indeed highly correlated. Unfortunately, the sample at hand starts in 2008, and does not include the 2007 high price episode, when prices of corn and soybeans diverged more than usual. To address the problem, I include only the own price in the yield equations: this is theoretically justified by the fact that once the crop is planted, the price of soybeans will not affect the yield of corn, and vice-versa.

Table 20 shows the results for the *always rotaters* subsample, using field-level data.

[14] Note that the local basis is computed based on the difference between the local spot price and the future price of the closest delivery (while the main futures prices is for delivery post harvest). Within season delivery maturities are March, May, July and September.

Table 1: Regression: corn yield, on always rotaters, field-level data

	Weather: none	Weather: early	Weather: all	Weather: all
Price March	-0.435^{***}	-0.200^{***}	0.469^{***}	0.499^{***}
	(0.002)	(0.003)	(0.010)	(0.011)
Δ Price May				-0.092^{***}
				(0.016)
Δ Price July				-0.116^{***}
				(0.015)
Δ Price Sep				0.073^{***}
				(0.011)
Num. obs.	810318	810318	810318	810318
Num N obs	209697	209697	209697	209697
Num T obs (ave)	3.864	3.864	3.864	3.864
N. variables	1	25	89	92
R^2	0.390	0.695	0.796	0.796

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Coefficients are elasticities, derived from a log-log specification. Interestingly, we see that without any controls, and even controlling for only the beginning of the season, we get negative coefficients. On the other side, once controlling for weather up till August, the coefficient turns positive. This suggests that markets do anticipate weather shocks and their consequence on yields, and that a regression on prices alone captures this a part of anticipated *reverse causality*. Once properly controlling for weather, we get a large response coefficient, with an elasticity of 40%. This is much larger than what is found elsewhere in the literature: Miao et al. (2016) estimate an elasticity of 23%. Turning now to the last column that includes also the difference in prices of May, July and September, results are a little surprising. We see that price "news" in May and July have a negative impact, and further that the September price still has an impact. As mentioned before, one would expect the within-season and post season prices to have a much smaller effect, even zero for the post-season one. It should be noted however that the specification is in differences with respect to the initial price of March. If one looks at coefficients of prices directly, one obtains values of respectively 0.591, 0.024, -0.189 and 0.073. This aligns more with the expectation: most of the time adjustment seems to occur before and within the season. In July, crops have reached a fairly mature stage, so that fertiliser adjustments are mostly nonexistent. At that point, we get a negative estimate of the price, which probably captures the reverse causality part: markets have now a fair estimate of the forthcoming production, and hence prices reflect anticipated yields. This does not explain however why the September price is positive, which will need further investigation.

Turning now to the soybeans estimates, these are shown in Table 21. We see that a phenomenon

Table 2: Regression: soybeans yield, on always rotaters, field-level data

	Weather: none	Weather: early	Weather: all	Weather: all
Price March	-0.054^{***}	0.166^{***}	0.409^{***}	0.370^{***}
	(0.002)	(0.005)	(0.020)	(0.020)
Δ Price May				0.814^{***}
				(0.060)
Δ Price July				0.232^{***}
				(0.039)
Δ Price Sep				-0.258^{***}
				(0.016)
Num. obs.	239775	239775	239775	239775
Num N obs	63959	63959	63959	63959
Num T obs (ave)	3.749	3.749	3.749	3.749
N. variables	1	25	89	92
R^2	0.320	0.579	0.633	0.634

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3: Regression: soybeans yield, on always rotaters, field-level data

	Corn: Mixed	Corn: Always CS	Corn: Always C	Soy: Mixed	Soy: Always CS
Own Price	0.437^{***}	0.469^{***}	0.053	0.441^{***}	0.409^{***}
	(0.008)	(0.010)	(0.029)	(0.032)	(0.020)
Num. obs.	1152334	810318	73277	138585	239775
Num N obs	308817	209697	9449	50888	63959
Num T obs (ave)	3.731	3.864	7.755	2.723	3.749
N. variables	89	89	89	89	89
R^2	0.804	0.796	0.685	0.637	0.633

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

similar to the corn sample happens: without control, the price estimate is negative, while controlling for weather, it turns out to be positive, as expected. The elasticity response in model 3, that controls for full weather during the season, is large too, around 40%. Finally, looking at within season prices, the price difference in May appears to have a strong positive sign. Given that soybeans are planted typically one to two months after corn, this could justify the discrepancy compared to the corn estimates.

I turn now to estimating the preferred model, model (3), on the other subsamples: the *always-corn* and the mixed rotation sample. Table 21 shows the coefficient on the own price for each subsample. When comparing the always-rotaters and mixed subsamples, results are remarkably similar (In fact, the difference is not statistically significant, as confidence intervals overlap), This suggests that the endogeneity stemming from the dependence between crop choice and crop yield is likely to be very small.

On the other side, the coefficient from the *always-corn* is very different, and actually not different from zero. This is likely due to the fact that corn-monoculture fields are fields with high productivity. Yield response to fertiliser shows strong decreasing returns (see Figure 10 in the Appendix, page 31), and it is likely that the mono-culture fields are already on the plateau segment, where yields barely respond to fertiliser increases.

As a final step, I now reconstruct a pseudo county-level panel, taking county averages for each year. I do this for each subsample separately. This allows me conduct two tests: test whether there is statistical aggregation bias on the *always-rotaters* subsample (where composition effect is ruled out a priori). And then test for an aggregate aggregation and composition bias on the *mixed* subsample. Results are show in Figure 23. On the always-rotaters, the difference between field-level and pseudo county-level difference is remarkably small for the corn sample. It is somewhat larger for soy, but in any case it is not significant. This suggests that there is no statistical aggregation bias. On the other side, when looking at the mixed subsample, there is a clear and statistically significative difference between the field-level and the pseudo county-level estimates. The pseudo county-level estimate is lower, at about 30%. This makes it much closer to the county-level based estimates of Miao et al. (2016), who found a value of 23%.

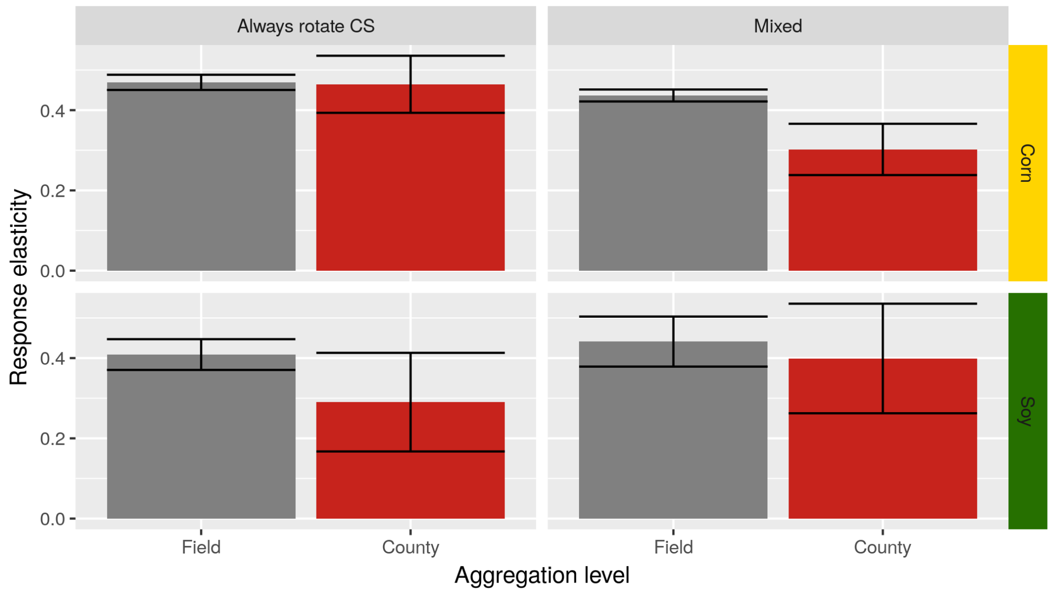
Assuming that the purely statistical aggregation bias is the same between the two subsamples, one can attribute the difference between field-level and county-level estimates as the composition bias itself. This goes in line with the evidence discussed in the introduction that the rotation penalty leads to an under-estimate of the field-level relationship.

6 Conclusion

This paper investigates the yield price elasticity of corn and soybeans in the US Corn Belt. Previous literature based on county-level data found a rather small response, leading some authors to argue that yields barely respond to prices. This comes at odd with micro-evidence that farmers adjust their fertiliser level or planting seed density to output prices. In this paper, I argue that this is mainly due to a composition effect owing to the reliance on county-aggregated averages. If area responds also to prices, the composition of the average changes. As area expansion is mainly done through using marginal land of lower fertility, or foregoing rotation and its benefits, the composition effect possibly reduces the average yields.

To investigate this, I build a large dataset of over half a millions fields in the US Corn Belt, using

Figure 6: Yield response elasticity



a novel dataset of corn and soybean predictions based on satellite data. I take advantage of a specific feature of the dataset, the presence of a large number of fields who always rotated. This provides me a clean sample free of possible endogeneity, and free of the composition effect. Estimating price yield response on this subsample, I find a high response of 40%. When I create a pseudo county-level panel based on this same subsample, I get identical estimates. I repeat then the same exercise for a subsample where rotation is not always practised, and hence where area expansion is made foregoing the benefits of rotation. Comparing the field-level and pseudo county-level panel estimates, I find that the field-level response is very close to the always rotaters subsample. On the other side, the pseudo county-level panel has a lower response, of about 30%, getting closer to estimates found elsewhere in the literature. This confirms the research hypothesis that county-level *macro* estimates are underestimating the field-level *micro* estimates.

This is current ongoing work, and important steps will be added in the near future. Area response will be estimated, together with the rotation benefits. This will allow a micro-based decomposition of the composition bias. Later on, as robustness check, I will also use an IV approach, to verify that I am obtaining correct causal estimates of my parameters. Finally, a finer investigation of the response to in-season prices will be carried through, using a new dataset of field-level planting dates, which will allow to use stronger temporal restrictions on my estimates.

A Derivations

A.1 Derivation of equation 7

Note that notation here differs slightly from the notation in the main text. Yield function y has to be sibstituted for f, density and cumulative functions $f()$ and $F()$ become $g()$ and $G()$. Finally, the main text describes the case where land above $\theta^\star$ produces, while the proof below is for the case where fields below $\theta^\star$ do produce.

We want the derivative of $\bar{f}(p) = \int_0^{\theta^\star(p)} g(\theta)f(p,\theta)d\theta / G(\theta^\star(p))$ with respect to prices. Using Leibniz rule for the integral, together with the ratio rule, leads to:

$$\frac{\partial \bar{f}(p)}{\partial p} = \frac{\left[g(\theta^\star(p))\, f(p,\theta^\star(p))\frac{d\theta^\star(p)}{dp} + \int_0^{\theta^\star} g(\theta)\frac{\partial f(p,\theta)}{\partial p}d\theta\right] \cdot G(\theta^\star) + \int_0^{\theta^\star} g(\theta)f(p,\theta)d\theta \cdot g(\theta^\star)\frac{d\theta^\star(p)}{dp}}{G(\theta^\star)^2}$$

The first and third terms in the numerator can be combined into (omitting the dependency of $\theta^\star$ on p):

$$\begin{aligned}
g(\theta^\star)\frac{d\theta^\star(p)}{dp}\left[f(p,\theta^\star)G(\theta^\star) - \int_0^{\theta^\star} g(\theta)f(p,\theta)d\theta\right] &= \\
g(\theta^\star)\frac{d\theta^\star(p)}{dp}\left[\int_0^{\theta^\star} g(\theta)f(p,\theta^\star)d\theta - \int_0^{\theta^\star} g(\theta)f(p,\theta)d\theta\right] &= \\
g(\theta^\star)\frac{d\theta^\star(p)}{dp}\left[\int_0^{\theta^\star} g(\theta)[f(p,\theta^\star) - f(p,\theta)]d\theta\right]
\end{aligned}$$

Bringing this term back into the main equation leads to:

$$\frac{\partial \bar{f}(p)}{\partial p} = \frac{\int_0^{\theta^\star} g(\theta)\frac{\partial f(p,\theta)}{\partial p}d\theta G(\theta^\star) + g(\theta^\star(p))\frac{d\theta^\star(p)}{dp}\left[\int_0^{\theta^\star} g(\theta)[f(p,\theta^\star) - f(p,\theta)]d\theta\right]}{G(\theta^\star)^2}$$

A.2 Derivation of empirical response

The short term expected yield is decomposed into yields of $\langle M \rightarrow M\rangle$ and $\langle S \rightarrow M\rangle$ fields:

$E[y_{it}^M|x_{it}, c_{it-1}] \equiv E[y_{it}^M|c_{it} = 1, x_{it}] = E[y_{it}^M|c_{it} = 1, c_{it-1} = 1,\ x_{it}]P(c_{it} = 1|c_{it-1} = 1) + E[y_{it}^M|c_{it} = 1, c_{it-1} = 0,\ x_{it}]P(c_{it} = 1|c_{it-1} = 0)$

The derivative of the expected yield is given by:

$$\begin{aligned}\frac{\partial E[y_{it}^M|x_{it}]}{\partial x_{it}} &= \frac{\partial E[y_{it}^M|c_{it}=1, c_{it-1}=1,\, x_{it}]}{\partial x_{it}} P(c_{it}=1|c_{it-1}=1) + \frac{\partial E[y_{it}^M|c_{it}=1, c_{it-1}=0,\, x_{it}]}{\partial x_{it}} P(c_{it}=1|c_{it-1}=0) \\ &+ \frac{\partial P(c_{it}=1|c_{it-1}=1)}{\partial x_{it}} E[y_{it}^M|c_{it}=1, c_{it-1}=1,\, x_{it}] + \frac{\partial P(c_{it}=1|c_{it-1}=0)}{\partial x_{it}} E[y_{it}^M|c_{it}=1, c_{it-1}=0,\, x_{it}]\end{aligned}$$

Note that as c_{it} takes values of 0 or 1, we have $P(c_{it}=1|c_{it-1}=1) = E(c_{it}|c_{it-1}=1)$. The last line simplifies then to:

$\frac{\partial E[c_{it}=1|c_{it-1}=1]}{\partial x_{it}} E[y_{it}^M|c_{it}=1, c_{it-1}=1,\, x_{it}] + \frac{\partial E[c_{it}=1|c_{it-1}=0]}{\partial x_{it}} E[y_{it}^M|c_{it}=1, c_{it-1}=0,\, x_{it}]$.

A.3 Figures

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Figure 7: Corn and soybeans location

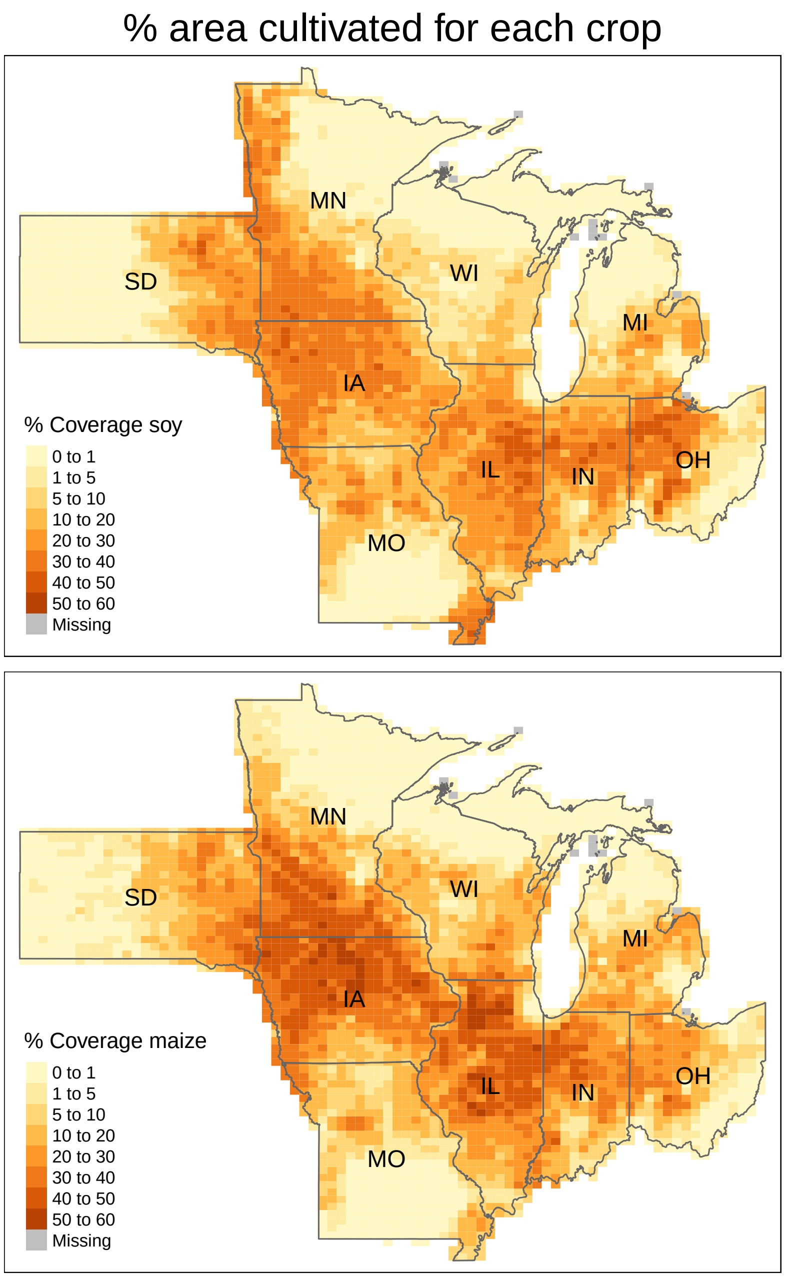

Figure 8: Corn-propensity model

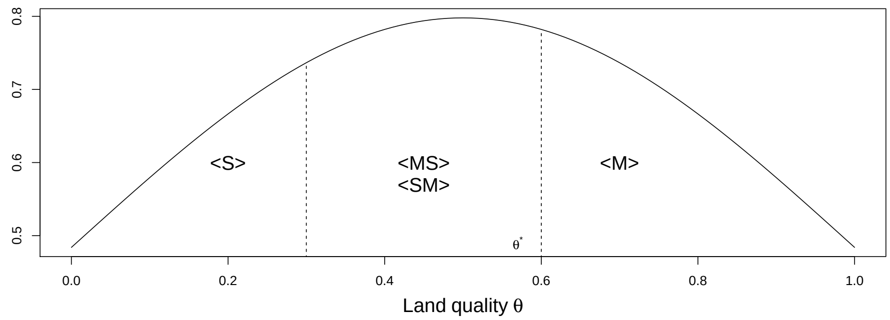

Figure 9: Crop shares, by year

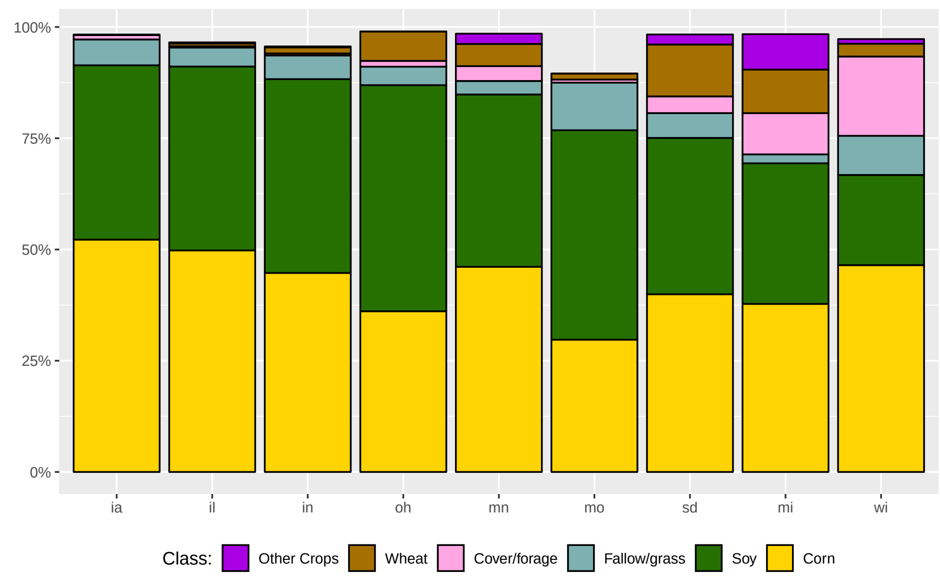

Figure 10: Corn yield response to fertiliser

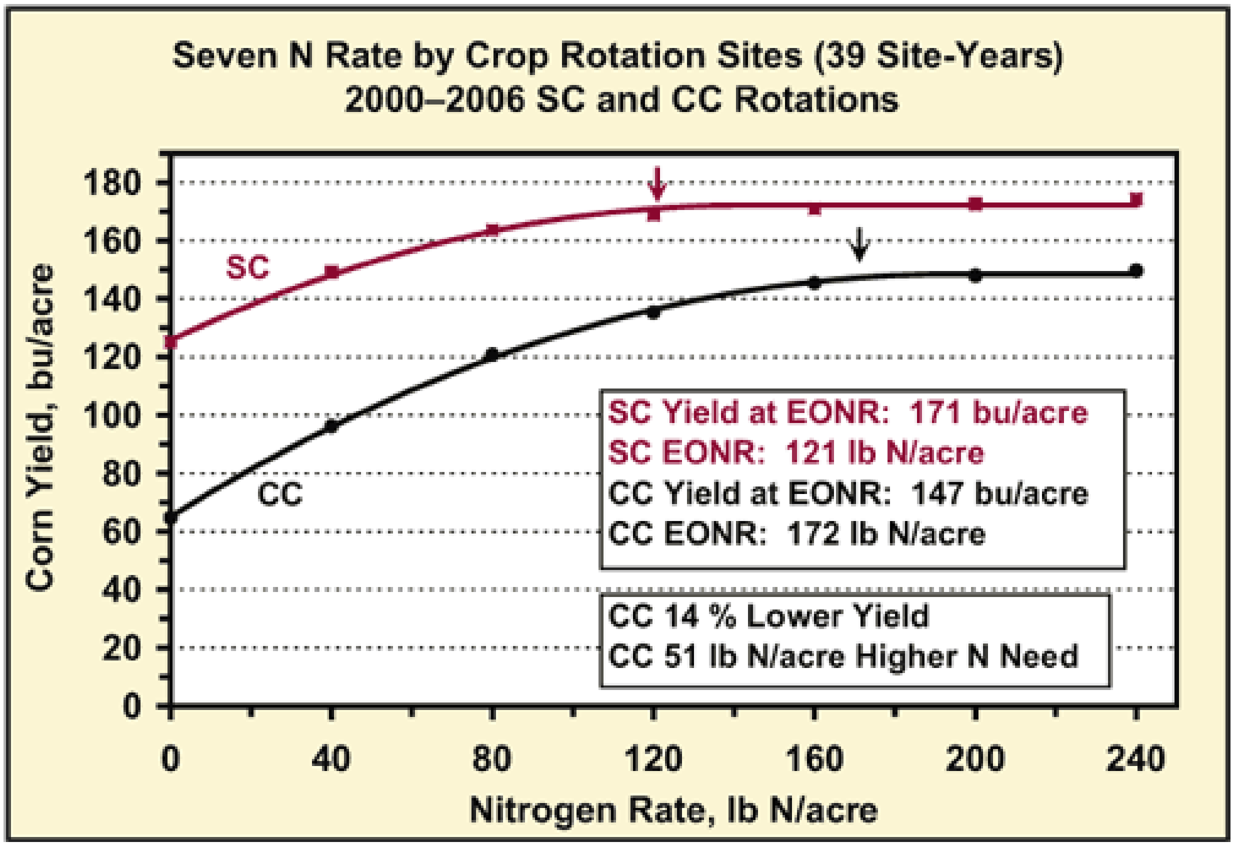

Figure 11: Conditional rotation history, 2000-2010

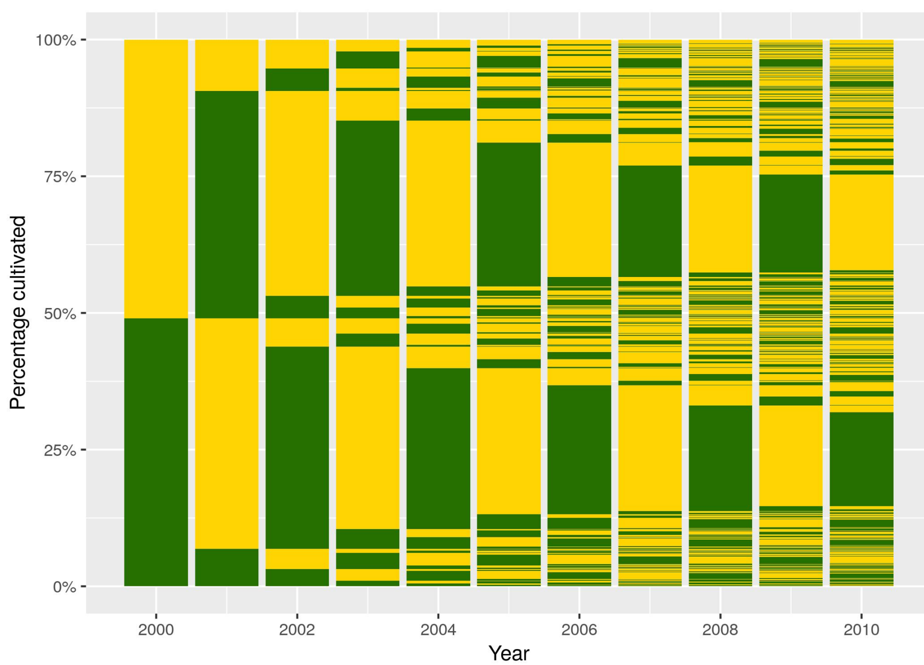

Figure 12: Crop shares, by year