

Indirect Estimation of Yield-Price Elasticities

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Abstract

While it is most common to estimate yield-price responses directly by regressing yields on prices, they may also be estimated indirectly by estimating fertilizer use elasticities and using basic optimization theory to derive yield-price elasticities. Indirect estimation has a practical advantage in terms of precision, for unpredictable weather variation makes yields a noisy measure of farmer's endogenous input use decisions. Indirect estimation suggests that yield-price elasticities are unlikely to be larger than .04 for US corn, .11 for soybeans, and .13 for wheat. Because indirect estimation delivers considerably smaller standard errors than direct estimation, these upper bounds are much tighter than existing estimates.

1 Introduction

Although they play a crucial role in determining the environmental effects of changes in agricultural markets, the magnitudes of intensive crop supply responses have weak and largely outdated empirical foundations. While existing studies on yield-price elasticities have relied on regressing realized yields directly on prices, such elasticities may instead be indirectly estimated by estimating input use elasticities and then using economic theory to map to yield elasticities. Indirect estimation delivers considerably more precisely estimated elasticities, and suggests that yield-price elasticities used in influential policy reports are far too high.

Agricultural intensification (yield gains) is the magic bullet when it comes to the trade-off between food production and environmental destruction. Extensive agricultural supply responses – i.e., expansion of agricultural land into natural terrain – has tremendous costs in terms of ecological destruction and greenhouse gas emissions. While intensification is not without environmental costs – e.g. synthetic nitrogenous fertilizer have a substantial carbon footprint – the externalities associated with intensification are generally much smaller than with extensification (Burney et al., 2010).

The relative magnitudes of yield elasticities and acreage elasticities determine whether equilibrium supply responses come primarily from intensification or acreage expansion. Thus, if yield elasticities are larger, more of the supply response comes from intensification, and the environmental impacts of increased food production are much smaller. Because they make such a big difference in the assessment of environmental impacts, yield elasticities have become a point of contention in the evaluation of biofuels policy. Berry (2011) questioned Tyner et al.'s (2010) use of a yield-price elasticity of .25, arguing that there was no empirical evidence to support a yield elasticity so high. While Houck and Gallagher (1976) found evidence to support yield-price elasticities for US corn as high as .25 and significantly different from zero, subsequent work by Menz and Pardey (1983) and Choi and Helmberger (1993) estimated yield-price elasticities for US corn which were insignificantly different from zero, and with standard errors suggesting yield-price elasticities were unlikely to be larger than .3. More recently, Berry and Schlenker (2011) argue that yield-price elasticities for major US crops are unlikely to be larger than .1.

Theory provides a mapping between fertilizer use elasticities and expected yield elasticities. Consequently, there are two potential approaches to estimating how expected yields respond to price changes: direct estimation of how yields respond to prices, or indirect estimation by estimating the fertilizer use elasticities and using the theoretical mapping.¹ The only economic assumption required for the mapping is that farmers choose input levels optimally. While the mapping does not hold strictly in the aggregate when the set of cultivated fields may change, I show that indirect estimates of yield elasticities with respect to output prices are positively biased (and therefore still useful for estimating upper bounds) under plausible conditions.

From Houck and Gallagher (1976) to Berry and Schlenker (2011), studies on yield elasticities have relied on a direct regression of realized yields onto prices. However, the indirect approach is more precise. Optimization implies that *expected* yields and fertilizer use are directly proportional, and therefore direct estimation of yield elasticities by regressing expected yields on prices would theoretically have the same level of precision as indirect estimation. However, expected yields are not realistically observable; in practice, direct estimation involves regressing *realized* yields on prices. As in all regressions, the precision of the estimates depends in part on the variability of the error term, and unpredictable variation in weather leads to a relatively large variance in the error term in a direct yield-price regression. Indirect estimation avoids this source of noise.

Precision is not the only reason for revisiting the topic of yield-price elasticities. With the exception of Berry and Schlenker (2011), all of the studies of yield elasticities cited above are based on pre-1990

¹There have been many studies on fertilizer demand (Griliches, 1959; Burrell, 1989; Denbaly and Vroomen, 1993; Kaufmann and Snell, 1997; Williamson, 2011), but none of them take the step of relating input use elasticities to yield elasticities. Choi and Helmberger (1993) follow an estimation strategy which is closer to the indirect approach I propose, but their strategy relies on additionally estimating how yields depend on input levels, an estimation which suffers from the same problem as the direct approach – randomness in yields introduced by weather makes it relatively less precise.

data, typically including data beginning in the 1950's or 60's and extending through the 70's. One concern with estimates based on such old data is that technological change may have changed yield elasticities. Another serious concern comes from the fact that United States agriculture was in a state of transition during the 1960's and early 70's, and it was not until later in the 70's that the use of synthetic fertilizer was pervasive.² Indeed, Menz and Pardey (1983) find evidence of a structural shift in fertilizer usage patterns in the early 1970's. Thus, older estimates may conflate the decision of how much fertilizer to use with the decision of whether or not to adopt synthetic fertilizer, whereas only the former decision is of practical relevance in the United States today.

It should be noted that much of the agronomic literature on fertilizer use and yields focuses on the question of what the optimal level of fertilizer use is (e.g., Cerrato and Blackmer (1990); Johnson and Raun (2003)). The uncertainties in the optimal level of fertilizer use calls into question a basic assumption of the indirect estimation approach: that farmers know the production functions for their fields and maximize profits accordingly. Despite this, the assumption of optimal input decisions has been popular in the agricultural economics literature (e.g., Houck and Gallagher (1976); Choi and Helmberger (1993)). While a more flexible model of farmer behavior which does not rely on optimization and perfect information could be estimated in principle, estimating a flexible model along such lines would probably require detailed micro data on farmer behavior, and the lack of such data has been a constraint on the literature on intensive crop supply responses to date.

My indirect estimates suggest that the yield elasticity with respect to output price is unlikely to be larger than .04 for US corn, .11 for soybeans, and .13 wheat. In contrast, direct estimation cannot rule out yield-output-price elasticities as high as .27 for corn, .46 for soybeans, and .19 for wheat. Point estimates of yield-price elasticities are insignificantly different from zero in all cases, and so they may be considerably closer to zero than the upper bounds suggest.

This paper focuses how crop yields respond to price changes through the channel of fertilizer use decisions. Other yield-price responses – e.g., endogenous farm capital investment or technological change – are beyond the scope of this paper.

Section 2 develops the theory behind the indirect estimation approach. Section 3 describes the data and specific regressions that I estimate. Section 4 presents the results, and Section 5 concludes.

²According to the 2007 US Census of Agriculture, 266 million acres were treated with commercial fertilizers while 310 acres of cropland were harvested. In 1964, 151 million acres were fertilized, and 287 million acres were harvested. According to the Economic Research Service, Nitrogen applied to corn increased from 58 pounds per acre in 1964 to 135-140 pounds per acre in recent years. By the late 1970's, farmers were already applying over 130 pounds per acre.

2 Theory

2.1 One input

A farmer growing corn chooses the fertilizer application rate L to maximize expected profits:

$$L^*(P_Y, P_L) = \arg \max_L \{P_C Y(L) - P_L L\} \quad (1)$$

where P_Y is the expected price of the output, P_L is the price of fertilizer, and $Y(L)$ is the expected yield at input level L . It should be emphasized that the farmer's decision is made with respect to *expected* yields and prices – fertilizer input decisions are typically made shortly before or after planting, before unpredictable weather events during the growing season determine the realized yields.

The first-order condition for the optimal input choice L^* is

$$\frac{dY(L^*)}{dL} = \frac{P_L}{P_Y}. \quad (2)$$

Thus, the optimal fertilizer application rate depends only on the ratio of input and output prices, and we can write $L^*(P_r)$ where $P_r = P_L/P_Y$.

Applying the chain rule, the price ratio ends up relating the yield derivative and the input use derivative:³

$$\frac{dY(L^*)}{dP_r} = \frac{dY(L^*)}{dL} \frac{dL^*}{dP_r} = P_r \frac{dL^*}{dP_r}. \quad (3)$$

Applying the implicit function theorem to (2), we can see that the yield derivative and fertilizer use derivative with respect to price are both proportional to the second derivative of the production function:

$$\begin{aligned} \frac{dY(L^*)}{dP_r} &= P_r \left(\frac{d^2 Y(L^*)}{dL^2} \right)^{-1} \\ \frac{dL^*}{dP_r} &= \left(\frac{d^2 Y(L^*)}{dL^2} \right)^{-1}. \end{aligned}$$

Equation (3) can also be expressed in the form of elasticities:

$$\mathcal{E}_{Y, P_r} = P_r \frac{L^*}{Y^*} \mathcal{E}_{L, P_r} = \frac{P_L L^*}{P_Y Y^*} \mathcal{E}_{L, P_r} \quad (4)$$

where $\mathcal{E}_{L, P_r} \equiv \frac{P_r}{L^*} \frac{dL^*}{dP_r}$ and $\mathcal{E}_{Y, P_r} \equiv \frac{P_r}{Y^*} \frac{dY^*}{dP_r}$.

³Technically, we must assume that $Y(L)$ is concave, twice continuously differentiable and that $L^*(P_r)$ is at an interior solution to guarantee that $\frac{dL^*}{dP_r}$ is well defined.

Thus, assuming that farmers' decisions satisfy the first-order condition (2), one may calculate the yield elasticity using the fertilizer-use elasticity, input expenditures, and expected revenues.

2.2 Aggregation

Given that all farmers face the same prices and all choose inputs optimally, the relationship between yield and fertilizer use elasticities holds in the aggregate for a fixed group of active farms, even if those farms have different production functions. Given that equations (3) and (3) hold for each farm, the equations can be summed or averaged across farms and will still hold. Thus, the mapping from input use to yield elasticities holds in the aggregate, with the input level L^* referring to the average input use across farms.

However, the potential pitfall with aggregation comes from the fact that the set of fields which plant a given crop may change over time. For example, if the set of fields in corn is growing, then aggregate changes in nitrogen fertilizer used for corn production will reflect not only changes in the optimal usage levels for incumbent corn fields, but will also include fertilizer used on new corn fields. In other words, equations (3) and (4) do not apply to newly planted fields because input use is not at an interior solution, and therefore we cannot take the derivative of yields with respect to input use for such fields.

I argue that, fortunately, acreage responses are likely to introduce positive bias into indirect estimates of aggregate of yield-price elasticities, meaning that indirect estimation still provides an effective tool for estimating upper bounds on yield-price elasticities.

To make this argument formally, I must expand the notation. Suppose average yields are defined as follows:

$$\bar{Y}(P_r) \equiv \frac{\int_0^{A^*(P_r)} Y_i^*(P_r) di}{A^*(P_r)}$$

where i indexes fields, A_i is the acreage of field i , $Y_i^*(P_r)$ are the optimal yields for field i with price ratio P_r , and $A^*(P_r)$ is the equilibrium acreage with all fields such that $i \leq A^*(P_r)$ being planted.

The aggregate yield elasticity is the elasticity of $\bar{Y}(P_r)$ with respect to P_r . Combined, an average yield elasticity and an acreage elasticity imply a supply elasticity. For many purposes, knowing the yield elasticities for individual fields would be ideal, but for applications depending on supply elasticities, knowing average yield elasticities is sufficient.

Define average fertilizer use similarly:

$$\bar{L}(P_r) \equiv \frac{\int_0^{A^*(P_r)} L_i^*(P_r) di}{A^*(P_r)}$$

where $L_i^*(P_r)$ is the optimal level of per-acre fertilizer use in field i (conditional on the field's being planted).

We can now restate formally the difficulty with aggregation. While optimal input use implies

$$\forall i : \frac{dY_i^*(P_r)}{dP_r} = P_r \frac{L_i^*(P_r)}{dP_r},$$

the aggregate relationship does not hold:

$$\frac{d\bar{Y}(P_r)}{dP_r} \neq P_r \frac{\bar{L}(P_r)}{dP_r}$$

because of the endogeneity of $A^*(P_r)$. However, I argue that the indirect aggregate estimate provides a lower bound for the aggregate yield elasticity with respect to P_r (or an upper bound on the yield elasticity with respect to the output price) given a plausible assumption.

Proposition 1. *Assuming that marginal fields are no more profitable than the average cultivated field in terms of expected revenues and fertilizer costs,*

$$\mathcal{E}_{\bar{Y}, P_r} \geq P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r}.$$

Furthermore, since $\mathcal{E}_{\bar{Y}, P_Y} = -\mathcal{E}_{\bar{Y}, P_r}$,

$$\mathcal{E}_{\bar{Y}, P_Y} \leq -P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r}.$$

While it is theoretically possible for the revenues net of fertilizer costs for marginal fields to be higher than fields which are already planted, it would be extremely surprising.

Proof. Using Leibniz's rule, the aggregate yield elasticity can be written:

$$\mathcal{E}_{\bar{Y}, P_r} = \frac{P_r}{\bar{Y}(P_r)} \frac{\int_0^{A^*(P_r)} \frac{dY_i^*(P_r)}{dP_r} di}{A^*(P_r)} + \mathcal{E}_{A^*, P_r} \left(\frac{Y_{A^*(P_r)}^*(P_r) - \bar{Y}(P_r)}{\bar{Y}(P_r)} \right). \quad (5)$$

where $Y_{A^*(P_r)}^*(P_r)$ denotes the yield of the marginal field. A similar equation holds for the aggregate fertilizer elasticity:

$$\mathcal{E}_{\bar{L}, P_r} = \frac{P_r}{\bar{L}(P_r)} \frac{\int_0^{A^*(P_r)} \frac{dL_i(P_r)}{dP_r} di}{A^*(P_r)} + \mathcal{E}_{A^*, P_r} \left(\frac{L_{A^*(P_r)}^*(P_r) - \bar{L}(P_r)}{\bar{L}(P_r)} \right). \quad (6)$$

Multiplying equation (6) by $P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)}$ and rearranging,

$$\frac{P_r}{\bar{Y}(P_r)} \frac{\int_0^{A^*(P_r)} \frac{dY_i^*(P_r)}{dP_r} di}{A^*(P_r)} = P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r} - P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{A^*, P_r} \left(\frac{L_{A^*(P_r)}^*(P_r) - \bar{L}(P_r)}{\bar{L}(P_r)} \right). \quad (7)$$

Finally, substituting equation (7) into equation (5),

$$\mathcal{E}_{\bar{Y}, P_r} = P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r} + \mathcal{E}_{A^*, P_r} \left(\frac{Y_{A^*(P_r)}^*(P_r) - \bar{Y}(P_r)}{\bar{Y}(P_r)} - P_r \left(\frac{L_{A^*(P_r)}^*(P_r) - \bar{L}(P_r)}{\bar{Y}(P_r)} \right) \right).$$

Given that the acreage-price elasticity is negative, the bias of the indirect estimate $P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r}$ has the same sign as

$$P_Y \left(Y_{A^*(P_r)}^*(P_r) - \bar{Y}(P_r) \right) - P_L \left(L_{A^*(P_r)}^*(P_r) - \bar{L}(P_r) \right),$$

which is precisely how the profits of a marginal field differ from the average cultivated field (accounting only for the costs of the modeled input). Given the assumption, the difference in profits is negative, so the bias in the indirect estimate of the yield elasticity with respect to P_r is also negative. Conversely, $-P_r \frac{\bar{L}(P_r)}{\bar{Y}(P_r)} \mathcal{E}_{\bar{L}, P_r}$ has positive bias as an estimate of the yield elasticity with respect to P_Y . \square

2.3 Multiple inputs

This theory extends to the case of multiple inputs. Let $\mathbf{L} = (L_1, \dots, L_J)$ be a vector of J inputs, and $\mathbf{P} = (P_1/P_Y, \dots, P_J/P_Y)$ be the vector of input-output price ratios. The first-order condition (2) becomes

$$\nabla_{\mathbf{L}} Y = \mathbf{P}. \quad (8)$$

The derivative condition (3) becomes

$$\nabla_{\mathbf{P}} Y^* = (J_{\mathbf{P}} \mathbf{L}^*)' \mathbf{P}. \quad (9)$$

where $J_{\mathbf{P}} \mathbf{L}^*$ is the Jacobian of the optimal input choice vector \mathbf{L}^* with respect to \mathbf{P} . The elasticity condition (4) becomes

$$\mathcal{E}_{Y, \mathbf{P}} = \mathcal{E}'_{\mathbf{L}, \mathbf{P}} X(\mathbf{P}) \quad (10)$$

where $X(\mathbf{P}) = \left(\frac{P_1^* L_1}{P_Y^* Y^*}, \dots, \frac{P_J^* L_J}{P_Y^* Y^*} \right)$ is a vector containing the ratio of expenditure to expected revenue for each input, and $\mathcal{E}_{\mathbf{L}, \mathbf{P}}$ is the matrix of input use-price elasticities; i.e.,

$$\mathcal{E}_{\mathbf{L}, \mathbf{P}} = \begin{bmatrix} \mathcal{E}_{L_1, P_1/P_Y} & \cdots & \mathcal{E}_{L_1, P_J/P_Y} \\ \vdots & \ddots & \vdots \\ \mathcal{E}_{L_J, P_1/P_Y} & \cdots & \mathcal{E}_{L_J, P_J/P_Y} \end{bmatrix}.$$

Finally, note that the yield elasticity with respect to the output price (holding input prices fixed), can simply be obtained by summing the yield-input price elasticities for each input; i.e.,

$$\frac{\partial \ln Y^*}{\partial \ln P_Y} = \sum_{j=1}^J \frac{\partial \ln Y^*}{\partial \ln (P_j/P_Y)} \frac{d \ln (P_j/P_Y)}{d \ln (P_Y)} = - \sum_j \frac{\partial \ln Y^*}{\partial \ln (P_j/P_Y)} \quad (11)$$

since $\frac{d \ln (P_j/P_Y)}{d \ln (P_Y)} = -1$ for all j (given that P_j is fixed).

Finally, the argument behind Proposition 1 extends naturally to the case of multiple inputs, so assuming that the revenues net of total fertilizer costs for the average cultivated field is higher than for marginal fields, we can conclude that

$$\bar{\mathcal{E}}_{Y, P_Y} \leq - \sum_j \sum_{j'} X_{j'}(\mathbf{P}) \bar{\mathcal{E}}_{L_j, P_{j'}/P_Y}.$$

3 Data and estimation

In this section, I describe the implementation of the indirect estimation approach for US corn, soybeans, and wheat. Indirect estimation is based on estimates of input use elasticities for nitrogenous fertilizers (abbreviated by N), phosphates (P), and potash (K). For comparison, I also compute direct estimates of yield-price elasticities.

3.1 Data

Data on fertilizer use and prices were obtained from the National Agricultural Statistics Service and date back to 1990 (with some missing years). Fertilizer application data is available for each crop in most of the states where the crop is prominent. State-level fertilizer price data is more sparse, so national average prices paid are used when state-level prices are missing. The nitrogen price is derived from the price of anhydrous ammonia; the phosphate price, from the price of superphosphate 44-46%; the potash price, from the price of muriate of potash 60-62%.⁴

⁴Prices were converted to prices per nutrient short ton using chemical masses. For example, the price of nitrogen is the price per short ton of ammonia times 17/14. Data on fertilizer use are in terms of nutrient tons, so converting prices

Expected output prices are taken from futures prices obtained from the Chicago Board of Trade. The expected prices for corn and soybeans are the average prices in January for contracts with delivery in the November or December. For winter wheat, the expected price for year t is the average price in the September of year $t - 1$ for contracts with delivery in December of year t .

While realized yields are used in the direct estimation of yield elasticities, indirect estimation calls for a measure of expected yields (see equation (4)). Expected yields are computed using the county-level yield forecasts computed by Scott (2013), and then aggregating to the state level by taking an average weighted by harvested acreage.⁵

3.2 Empirical models

I begin by estimating yield-price elasticities directly, using the following regression:

$$\ln(Y_{st}) = \alpha \ln(P_t) + f(t) + \alpha_{0s} + \varepsilon_{st} \quad (12)$$

where s indexes US states, t indexes years, Y_{st} is the realized yield, P_t is the expected output price, $f(t)$ is a time trend, and α_{0s} is a state fixed effect. I estimate equation (12) separately for corn, soybeans, and winter wheat. The parameter α is the direct estimate of the yield-price elasticity. For equation (12) and all regression equations with a time trend, I use a cubic spline with three knots for $f(t)$.

I also estimate the following more flexible direct model:

$$\ln(Y_{st}) = \sum_j \alpha_j \ln(P_t/P_j) + f(t) + \alpha_{0s} + \varepsilon_{st} \quad (13)$$

where j indexes inputs, $\sum_j \alpha_j$ is the yield-price elasticity (with respect to the output price, holding input prices fixed), and the inputs included are nitrogen, phosphate, and potash.

Indirect estimation of yield-price elasticities begins with estimates of input use elasticities. I estimate a restricted model of input use elasticities with cross-price elasticities set to zero,

$$\ln(L_{jst}) = \gamma_j \ln(P_t/P_j) + f(t) + \alpha_{0js} + \varepsilon_{jst}, \quad (14)$$

where L_{jst} is the per-acre input use for nutrient j in state s during year t (by crop).

in this way is necessary to compute fertilizer expenditure appropriately.

⁵Note that these measures of expected yields could not be plugged into the direct estimation approach, for they are constructed without using input and output prices – they only smooth over technological change and eliminate weather variation.

Table 1: Average share of expected revenue spent on nutrient inputs

	Nitrogen	Phosphate	Potash
Corn	0.069	0.045	0.031
Soybeans	0.019	0.059	0.046
Winter wheat	0.083	0.068	0.034

US-wide averages, 1990-2010 based on NASS reports.

I also estimate an input use model with a full set of first-order input use elasticities:

$$\ln(L_{jst}) = \sum \gamma_{jj'} \ln(P_t/P_{j'}) + f(t) + \alpha_{0js} + \varepsilon_{jst}. \quad (15)$$

I estimate equations (14) and (15) separately for each crop. As a robustness check, I also estimate differenced versions of equations (14) and (15) which feature differenced input use and price ratios but omit the time trend and fixed effects.

3.3 Indirect estimation example

Indirect estimation requires two inputs: estimates of the revenue shares of input expenditures, and estimates of input use elasticities. Table 1 presents revenue shares of input expenditure for each crop and nutrient, based on averages of such shares across states and years (weighted by harvested area). Table 2 presents input elasticities (estimates of equation (15)) for corn with a full set of cross-price input use elasticities (equation (15)). Together, these two tables present the numbers we need to indirectly compute a yield-price elasticity.

As described in Section 2.3, the indirect estimate is computed by multiplying the matrix of input use elasticities by the vector of revenue shares,

$$\begin{pmatrix} -.0146 & .1439 & -.0899 \\ -.0840 & .2321 & .0107 \\ -.1247 & .2749 & .1503 \end{pmatrix} \begin{pmatrix} .0689 \\ .0450 \\ .0305 \end{pmatrix} = \begin{pmatrix} -.0086 \\ .0288 \\ -.0011 \end{pmatrix},$$

and then summing the resulting vector to find a yield-price elasticity of .019.

All indirect yield-price elasticities presented in Table 4 are estimated according to this indirect procedure. Standard errors on the indirect estimates are derived by sampling input use elasticity matrices from their estimated asymptotic distribution, and then constructing a simulated distribution of yield elasticities by computing the indirect estimate for each matrix of sampled input use elasticities.

Table 2: Input use elasticities for corn

	$\ln(x_{N,corn})$	$\ln(x_{P,corn})$	$\ln(x_{K,corn})$
$\ln(P_{corn}/P_N)$	-0.0146 (0.0329)	-0.0840 (0.0480)	-0.125 (0.0330)
$\ln(P_{corn}/P_P)$	0.144 (0.0936)	0.232 (0.104)	0.27 (0.0791)
$\ln(P_{corn}/P_K)$	-0.0899 (0.0899)	0.0107 (0.0917)	0.150 (0.0686)
Observations	251	251	250

Standard errors with clustering by year in parentheses. Regressions include cubic spline with three knots and state-level dummy variables.

3.4 On endogeneity

Although the literature on fertilizer demand has largely ignored simultaneity problems, it is worth considering whether unobservable factors which shift the fertilizer demand curve could create bias when estimating equation (14) or (15).

One might argue that shifts in fertilizer prices are likely to be driven almost entirely by exogenous factors shifting the supply of fertilizer. For example, the natural gas price is plausibly the main determinant of the price of ammonia (and other nitrogenous fertilizers, which are all derived from ammonia), and ammonia production accounts for less than 1.5% of natural gas use in the United States. Furthermore, there are many firms in the fertilizer manufacturing industry producing homogeneous chemical products, so demand shifts are not likely to affect markups.⁶

Furthermore, fertilizer application rates in the US have been relatively stable in the US since the late 1970's,⁷ and changes in crop acreage are generally very gradual, so it's not clear that there are any factors which would shift the demand curve for fertilizer substantially in the short run, and fertilizer production is arguably constant returns to scale in the long run, so gradual changes in the demand curve might not affect prices.

⁶According to 2011 USGS Minerals Yearbook publications, there were 13 companies actively producing ammonia (activated nitrogen) in the US in 2011, six companies mining phosphate rock, and three companies producing potash. Producers of fertilizer nutrients also face substantial import competition. In recent years, almost 40% of activated nitrogen consumed in the US has been imported, about 10% of phosphate rock, and over 80% of potash. See USGS Minerals Yearbooks for details.

⁷See, for example, USDA "Fertilizer Use and Price" reports, <http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx>.

Table 3: Direct yield elasticity estimates

	ln(Y_{corn})		ln($Y_{soybeans}$)		ln(Y_{wheat})	
ln(P_{crop})	0.245 (0.140)		0.203 (0.122)		-0.0348 (0.105)	
ln(P_{crop}/P_N)		-0.0395 (0.0762)		-0.0719 (0.0809)		-0.0733 (0.0767)
ln(P_{crop}/P_P)		-0.184 (0.147)		0.0873 (0.177)		0.0803 (0.149)
ln(P_{crop}/P_K)		0.181 (0.0847)		0.110 (0.108)		-0.0523 (0.124)
Observations	495	495	410	410	460	460
Yield Elasticity	0.245	-0.0421	0.203	0.125	-0.0348	-0.0453
95% CI	(-0.0506,0.540)	(-0.353,0.269)	(-0.0543,0.461)	(-0.210,0.460)	(-0.256,0.186)	(-0.357,0.267)

P_{crop} refers to P_{corn} , $P_{soybeans}$, or P_{wheat} , corresponding to the dependent variable. Standard errors with clustering by year in parentheses. Regressions include cubic spline with three knots and state-level dummy variables.

On the supply side, there are undoubtedly large sources of variation in costs, at least for the production of nitrogenous fertilizers. The price of natural gas is highly volatile, and natural gas accounts for on the order of 90% of ammonia production costs Yara (2012), and ammonia is the main input for all nitrogenous fertilizers.

Thus, I argue that endogeneity is probably not a large concern when estimating fertilizer use elasticities.

4 Results

Table 3 presents direct estimates of yield-price elasticities for all three crops. All 95% confidence intervals for the yield-price elasticity contain zero, and the narrowest confidence interval has an upper bound of .27 for corn, .46 for soybeans, and .19 for wheat.

In contrast, indirect estimates presented in Table 4 are considerably more precise. The largest upper bounds for 95% confidence intervals are just over .03 for corn, .1 for soybeans, and .13 for wheat. In all cases, indirect estimation provides unambiguous gains in precision.

Furthermore, my estimates pin down the magnitude of yield-price elasticities considerably more precisely than other estimates in the literature. After Houck and Gallagher (1976), the trend has been

Table 4: Indirect yield-price elasticity estimates

Regression specification	Cross-price elasticities	Corn	Soy	Wheat
levels	no	0.021 (0.011,0.031)	0.059 (0.017,0.101)	0.008 (-0.039,0.056)
levels	yes	0.019 (0.006,0.032)	0.036 (-0.001,0.072)	0.034 (-0.039,0.107)
differences	no	0.006 (-0.004,0.016)	-0.011 (-0.046,0.023)	0.002 (-0.124,0.128)
differences	yes	0.009 (-0.006,0.023)	-0.024 (-0.058,0.010)	0.031 (-0.027,0.089)

95% Confidence intervals with clustering by year in parentheses.

towards yield-price elasticities for US corn which are insignificantly different from zero, with standard errors getting smaller. Menz and Pardey (1983) and Choi and Helmberger (1993) were not able to rule out yield-price elasticities as large as .3. Berry and Schlenker’s (2011) unpublished results are compatible with yield-price elasticities for US corn as large as .1. My indirect estimates suggests that the yield-price elasticity for US corn is unlikely to be larger than .04.

5 Conclusion

Indirect estimation proves to be a useful tool in obtaining relatively precise estimates of yield-price elasticities. Both direct and indirect estimation deliver point estimates of yield-price elasticities which are insignificantly different from zero, but indirect estimation is considerably more precise, providing evidence against high values of yield-price elasticities which would be compatible with the direct estimates. My indirect estimates suggest that yield-price elasticities are quite small for major US crops – probably no greater than .04 for corn, .11 for soybeans, and .13 for wheat.

My results indicate that yield-price elasticities as high as .25 (used in Tyner et al. (2010)) are far too high, at least for the US. Given Scott’s (2013) estimates of long run acreage-price elasticities on the order of .4 for US cropland, acreage responses appear to be the dominant component of crop supply response in the long run.

References

- Berry, Steven**, “Biofuels Policy and the Empirical Inputs to GTAP Models,” Technical Report 2011.
- **and Wolfram Schlenker**, “Technical Report for the ICCT: Empirical Evidence on Crop Yield Elasticities,” Technical Report 2011.
- Burney, Jennifer A., Steven J. Davis, and David B. Lobell**, “Greenhouse gas mitigation by agricultural intensification,” *Proceedings of the National Academy of Sciences*, 2010.
- Burrell, A.**, “THE DEMAND FOR FERTILISER IN THE UNITED KINGDOM,” *Journal of Agricultural Economics*, 1989, 40 (1), 1–20.
- Cerrato, M. E. and A. M. Blackmer**, “Comparison of Models for Describing Corn Yield Response to Nitrogen Fertilizer,” *Agronomy Journal*, 1990, 82.
- Choi, Jung-Sup and Peter G. Helmberger**, “How Sensitive are Crop Yields to Price Changes and Farm Programs?,” *Journal of Agricultural and Applied Economics*, 1993, 25, 237–244.
- Denbaly, Mark and Harry Vroomen**, “Dynamic Fertilizer Nutrient Demands for Corn: A Co-integrated and Error-Correcting System,” *American Journal of Agricultural Economics*, 1993, 75 (1), 203–209.
- Griliches, Zvi**, “Distributed Lags, Disaggregation, and Regional Demand Functions for Fertilizer,” *Journal of Farm Economics*, 1959, 41 (1), pp. 90–102.
- Houck, James P. and Paul W. Gallagher**, “The Price Responsiveness of U.S. Corn Yields,” *American Journal of Agricultural Economics*, 1976, 58 (4), pp. 731–734.
- Johnson, G. V. and W. R. Raun**, “Nitrogen Response Index as a Guide to Fertilizer Management,” *Journal of Plant Nutrition*, 2003, 26 (2), 249–262.
- Kaufmann, Robert K. and Seth E. Snell**, “A Biophysical Model of Corn Yield: Integrating Climatic and Social Determinants,” *American Journal of Agricultural Economics*, 1997, 79 (1), pp. 178–190.
- Menz, Kenneth M. and Philip Pardey**, “Technology and U.S. Corn Yields: Plateaus and Price Responsiveness,” *American Journal of Agricultural Economics*, 1983, 65 (3), pp. 558–562.
- Scott, Paul T.**, “Dynamic Discrete Choice Estimation of Agricultural Land Use,” *Working Paper*, 2013.
- Tyner, Wallace E., Farzad Taheripour, Qianlai Zhuang, Dileep Birur, and Uris Baldos**, “Land Use Changes and Consequent CO2 Emissions due to US Corn Ethanol Production: A Comprehensive Analysis,” Technical Report 2010.

Williamson, James M., “The Role of Information and Prices in the Nitrogen Fertilizer Management Decision: New Evidence from the Agricultural Resource Management Survey,” *Journal of Agricultural and Resource Economics*, 2011, 36 (3), 552–572.

Yara, “Yara Fertilizer Industry Handbook,” Technical Report 2012.