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The impact of public and private R&D on farmers' production decisions: econometric evidence for Midwestern states, 1960-2004

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Keywords
profit function, Midwest agriculture, public research, technology, GMOs, multiple-inputs multiple output, crops

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The Impact of Public and Private R&D on Farmers' Production Decisions: Econometric Evidence for Midwestern States, 1960-2004

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Abstract: The objective of this paper is to identify the impact of public and private agricultural research on multi-output multi-input profit maximizing decisions of Midwestern farmers. The main hypothesis is that investments in public and private R&D shift outward the supply curves for crop and livestock outputs and, in some cases, reduce the demand for inputs. The study uses state aggregate data for eight Midwestern states over 1960-2004. The own-price elasticities of demand for all inputs are shown to be negative, being larger for agricultural chemicals and energy that for farm capital services, labor and other materials. Additional public agricultural research increases the supply of crop and livestock outputs but biases revenue shares toward crop output. Additional private R&D as in adoption of GM corn varieties shifts outward the supply curves for crops and livestock outputs but biases revenue shares towards crop output. In contrast, an increase in the adoption of GM soybean varieties increases livestock output and deceases crop output. Public agricultural research reduces the demand for capital services and energy and increases the demand for agricultural chemicals, other materials, and labor. An increase in the availability of GM soybean varieties increases the demand for capital services, agricultural chemicals and other materials and has weak negative effects on the demand for labor and energy. GM corn variety adoption reduces the demand for energy but other effects are quite small.

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Introduction

Agricultural research performed by both the private and public sectors has been shown by Huffman and Evenson (1989, 2006a), Huffman et al. (2002), and Yee et al. (2002) to significantly impact the supply of agricultural outputs, demand for inputs and/or total factor productivity. This has been a methodological step forward relative to studies that have approximated technology with a time trend (Mundlak 2001). In the U.S., the public sector undertakes basic research on which the private sector develops applied technologies. The most dramatic success of public agricultural research was the early development of commercial hybrid corn varieties in the 1930s, which were then reproduced and marketed by private seed companies (Griliches 1960, Huffman and Evenson 1993). During the ensuing seventy years, the private sector has taken control both of developing and marketing of hybrid corn varieties. Soybean varieties before 1950 were largely adapted from hay and not seed production, but since then, the primary product is the soybean. Over 1950-1980, new soybean varieties were largely developed in the public sector (Huffman and Evenson 1993), but since the 1980s, the private sector has largely taken control of both developing and marketing them. For example, in 1994, the private sector accounted for 64 percent of soybean varietal development resources (Fernandez-Corneji 2004). Improvement in breeding practices in poultry, swine, dairy and beef cattle has also occurred over time (Huffman and Evenson 1993; Narrod and Fuglie 2000). For the most part, these improvements have been concentrated in the private sector (Huffman and Evenson 2006a).

In addition to enhanced genetic materials, farmers' cultural and management practices for crop and livestock production have steadily changed. Starting in the 1970s, herbicide application to field crops was introduced to reduce the need for field cultivation and hand weeding. Also, as a result of the mid-70's energy crisis new "reduce tillage practices" were developed that largely eliminating the need for using the moldboard plow and heavy disking in seedbed preparation. By the 1990s, no-till farming was widely adopted in the Midwest. The mid-90s also brought new genetically engineered (GE) or modified (GM) field crop varieties containing herbicide tolerance and insect resistance (Fernandez-Cornejo and McBride 2000, NRC 2010). Second and third generation GE/GM traits are now available in corn and cotton varieties. These varieties provide a type of biological alternative to chemical control of pests, which is widely recognized as reducing the pesticide load on the environment because the new pesticides are much less toxic than the ones that have been replaced by the GE/GM technology (NRC 2010).

The primary objective of this paper is to identify the impact of public and private agricultural research on multi-output multi-input profit maximizing decisions of Midwestern farmers. The main hypothesis is that investments in public and private R&D shift outward the supply curves for crop and livestock outputs and, in some cases, reduce the demand for farm inputs. These changes are consistent with increasing multifactor productivity. The study uses state aggregate data for eight Midwestern states, 1960-2004. The data on quantities of outputs and inputs and their prices are the most up-to-date that are available from the Economic Research Service (ERS). The public agricultural research data are the most up-to-date from Huffman and Evenson (2006) and Huffman (2009). The private agricultural research variables are the adoption rates for privately developed and marketed GE/GM corn and soybean varieties, which were first marketed in 1996 (ERS and NRC 2010). The eight Midwestern States of this study account for more than 65 percent of the US harvested acreage in corn and soybeans. This is also a region where farmers rely primarily on natural rainfall for watering their crops, rather than on irrigation.

Following Diewert (1971), Lau (1976), Chambers (1988), Bairam (1998) and Mundlak (2001), production decisions are derived from a profit rather than a cost function (Huffman et al. 2002). The main reason being that farmers make plans for producing outputs and using inputs jointly. Moreover, successfully estimating a system of output supply and input demand functions derived from an underlying profit function is more difficult econometrically than estimating a system of input demand functions derived from an underlying cost function. In this study, two supply functions, one for livestock and one for crop outputs, and five input demand functions (one each for farm capital services (excluding land), farm labor, energy, agricultural chemicals, and other materials) are fitted to Midwestern state aggregate data, 1960-2004. New estimates of the impacts of public agricultural research on farmers' production decisions extents the results of Huffman and Evenson (1989, 2006) and Lim and Shumway (1997), and the new estimates of impacts of GE/GM corn and soybean varieties on production decisions are the first in the literature.[1]

The organization structure of the paper is as follows. The second section gives a brief introduction to the development of genetically engineered or modified crops in the United States. Section three presents an aggregate model of production. Section four describes the data and empirical measures of the variables. Section five presents the econometric model. Section six presents the empirical results and includes some comparisons with earlier studies. The final section presents some conclusions.

Genetically Engineered Field Crops in the U.S.

Since the 1940s, application of chemical insecticides has been the main method for controlling insects in many crops, and since the 1970s, herbicides have replaced cultivation and hand weeding for control of weeds in U.S. field crops. In 1999, U.S. expenditure on insecticides was 3 billion dollars, or 33 percent of the world market. Forty-five percent of the insecticides applied were devoted to the agricultural sector. Although insecticides were initially hailed as a miraculous method to eliminate pest problems, the widespread use of particular insecticides has resulted in the development of tolerance by the target pests (Zilberman 2004), high rates of insecticide application, and low effectiveness of these chemicals in some areas. In addition, high rates of application of insecticides have frequently caused environmental and human contamination.

In the United States, the use of herbicides in agriculture has increased dramatically since the 1950s; herbicide use is now greater than the combined use of insecticides and fungicides. Plants exhibit varying levels of tolerance to herbicides. Some plants are highly sensitive and can be damaged or killed by very low doses of certain herbicides, while plants that have high tolerance can be unaffected by herbicides that

[1] Although we recognize that the farm program for field crops experienced a major change in 1996 Farm Bill, there is not simply way to include this and other program effects. However, our crop output prices include deficiency payments and the land area includes acreage enrolled in the Conservation Reserve Program.

kill other plants. Hence, farmers have used private sector developed herbicides to selectively control weeds in field crops for more than 40 years. New private sector developed crop varieties that carry herbicide-tolerant genes are minimally affected by application of a particular herbicide while at the same time killing targeted weeds. To farmers, currently available herbicide tolerant crops represent an innovation that allows them to simplify herbicide application to a single broad-spectrum herbicides, thereby simplifying farm management decision making. However, in a few areas weeds have adapted to the herbicide, and farmers then need to make further modifications in their production practices (NRC 2010).

The discovery of DNA in 1953 and a gene splicing technique in 1973 set the stage for genetic engineering of new crop varieties in the 1990s. This was largely accomplished by the transfer of insect resistance genes into commercial crop cultivars. One type of insect resistance (IR) has been obtained by insertion of *Bacillus thuringensis* (Bt), a soil bacteria that makes many insects become ill and die, and this new Bt technology has been effective in controlling particular insect pests in some field crop. For example, Bt cotton is mainly effective in controlling tobacco budworms and less effective in controlling the cotton bollworm. Early Bt corn varieties provided resistance primarily to the European corn borer and were somewhat protective towards the corn earworm, the Southwestern corn borer and to a lesser extent the cornstalk borer (Fernandez-Cornejo and McBride 2002). Hence, insect resistant crop varieties have emerged as another solution to farmers' plant insect pest problems.

Newly developed GE/GM crop varieties that are available to farmers can be broken down into 3 types of GE traits: "IR (insect resistant)", "HT (herbicide tolerant)" and "stacked (combinations of HT and IR)". With Bt genetically engineered into a crop variety, plant parts become toxic to target insects and kill them. With HT genetically engineered into a crop variety, the plant is resistant to a particular commercial herbicide; for example, Monsanto's Roundup contains the active ingredient glyphosate. Hence, for Roundup Ready soybean varieties, farmers plant the HT variety and, roughly one month after emergence of the crop and accompanying weeds, the farmer applies the commercial herbicide Roundup, which kills all of the plants in the field, except for the Roundup Ready Soybean plants. This then leaves the treated soybean fields largely free of weeds. Moreover, the effectiveness of applying the herbicide Roundup to Roundup Ready soybean plants is not sensitive to modest deviations in the application date, which is a major advantage to farmers that have off-farm jobs, other competing uses for their time, or face uncertain rainy weather conditions. Because farmers always face weed problems in their fields and soybean plants are not competitive against tall weeds, and because of the wide window for applying Roundup to the soybean varieties, HT soybean varieties have become very successful in the United States. In contrast, corn is a strong competitor against weeds, and HT corn varieties have been less successful than soybean varieties. Likewise, European corn borer infestation is random, not occurring every year. Hence Bt for European corn resistance has not been as popular with farmers as HT. The recent development of GM protection to corn root worm holds more potential because the rootworm is a persistent pest. Hence, GM corn varieties have one to three main traits. GM soybeans varieties are primarily herbicide-tolerant. GM cotton varieties have one or two traits, for Bt and/or HT.

In 1995 no significant acreage of U.S. crops was planted to biotech crop varieties, and in 1996 the rate of adoption was low, being higher for Bt cotton and HT soybeans than for Ht corn and cotton or Bt corn (figure 1). Bt cotton has been adopted in some areas of the South, but not in other areas where insect problems, including tolerance to chemical insecticides, were less severe. The HT cotton adoption rate surpassed Bt cotton adoption by 1998, reflecting the fact that weeds are a persistent problem in cotton, and HT cotton has experienced higher adoption rates than Bt cotton through 2007.

Although the adoption rate for HT soybean varieties was initially lower than for Bt cotton, HT soybean varieties have experienced very rapid adoption rates over 1997-2007, except for a brief setback in 2000. The adoption rate in 2007 was about 90 percent of planted acres. HT and IR corn varieties were adopted more slowly by U.S. farmers, but by 2007, HT and IR corn variety adoption rates had reached about 50 percent (figure 1). In the U.S. in 1996, biotech crop variety shares for planted acres were 17 percent for cotton, 7 percent for soybeans and 4 percent for corn. But in 2007, these shares had increased to 91 percent for soybeans, 87 percent for cotton and 73 percent for corn.

The adoption of GM crop varieties by states in the U.S. is conditioned by cropping patterns: the extent to which farmers in a particular state plant soybeans, corn or cotton (see ERS 2008; Ryan and Runge 2003). For example, of the eight Midwestern states in this study, Indiana, Missouri, and Iowa farmers were the leaders in HT soybean varietal development by 2000—with roughly 60 percent of planted soybean acreage (see figure 2).[2] By 2007, GM soybean adoption rates converged across these states to roughly 90 percent.

GM corn varietal adoption rates for IR, HT and combined IR and HT over 1996-2007, are displayed in figure 3. They show that Minnesota, Iowa, and Missouri have been the leaders in adoption of GM corn varieties. Ohio and Indiana farmers have lagged far behind. However, figure 3 does show that there was a decline in GM corn adoption rates in the Midwestern states over 1999-2001. By 2007, more than 70 percent of the planted corn acres in Minnesota, Iowa and Missouri were planted to GM varieties.

Of all the states that had adopted biotech varieties as of 2007, 60 percent of the value of biotech corn production was attributed to Iowa, Illinois, Minnesota and Nebraska, and fifty-four percent of the value of biotech soybean production came from Iowa, Illinois, Minnesota and Indiana. In contrast, 68 percent of the value of biotech cotton production yielded from Texas, California, Mississippi and Georgia.

The Model of Aggregate Production

Following Huffman and Evenson (1989), Shumway et al. (1988) and Bairam (1989), the structure of agriculture at the state level is assumed to be approximated by a flexible aggregate multi-output and input profit function. Applying Hotelling's lemma to this function, obtain a set of aggregate agricultural output

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[2] The data from 2000-2007 are taken directly from ERS (2008). We extended the data for Ht soybeans and for GM corn containing HT, IR, or stacked HT and IR, by state from 2000 to 1996, assuming the pattern for each state going back in time was similar to the pattern for the U.S. data, including a zero adoption rate for all traits in 1995. Because of seeming inconsistencies in the disaggregated GM trait adoption data for corn over 1996-1999, we did not extend data backward for HT and IR corn separately.

supply and input demand functions (Lau 1976; Fuss and McFadden 1978; Chamber 1988). The profit function framework has an advantage over a cost function approach in that outputs are left hand side variables to be explained by output and input prices, but, with a cost function framework, outputs are used to explain input demand. When farmers in one state are a small supplier of U.S. (or world) output and demand for U.S. (or world) agricultural inputs, these prices can reasonably be assumed to be exogenous.

Three common flexible form profit functions are the trans-log (Diewert 1974), normalized quadratic (Lau 1976), and generalized Lontief (Diewert 1971). Among these functional forms, Chambers et al (2008) have shown that the normalized quadratic revenue function, which is a special case of the profit function, performs best in simulation experiments. In empirical studies, supply and demand functions that are derived from the normalized quadratic profit function have as dependent variables quantities of output and input. In contrast, for the translog profit function, the associated choices functions or dependent variables are profit shares. Since profit can be negative and small, this makes the dependent variables quite noisy. Examples of successful uses of the normalized profit function that represent agricultural technology at the state level are Shumway (1983), Shumay et al. (1988), and Huffman and Evenson (1989).

Let there be n+m+1 net outputs y_i. Of these, n+1 are outputs with $y_i > 0$, $i = 0, \ldots, n$, that are produced with m inputs with $y_i < 0$, $i = n+1, \ldots, n+m$. Furthermore, there are K quasi-fixed or environmental factors denoted by $z_k \geq 0$, $k = 1, \ldots, K$. Let P_0 be the price of one of the outputs, and call it the numeraire price which can be set to be 1. All prices are positive and the normalized price of the n outputs and m inputs can be defined as $p_i = P_i/P_0$, $i = 1,\ldots,n+m$.

The exact algebraic form of the normalized quadratic function is given by:

$$\Pi = \alpha_0 + \sum_{i=1}^{n+m} \alpha_i p_i + \sum_{k=1}^{K} \beta_k z_k + \frac{1}{2}\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} \alpha_{ij} p_i p_j + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} z_k z_l + \sum_{i=1}^{n+m}\sum_{k=1}^{K} \varphi_{ik} p_i z_k \tag{1}$$

This function as written is linearly homogeneous in prices and also has a Hessian matrix of constants, so that the local convexity in prices implies global convexity (Lau 1976).

Input Demand, Output Supply. Given the normalized quadratic profit function (1), a set of n + m output supply and input demand can obtained directly by applying Hotelling's lemmas:

$$y_i^* = \alpha_i + \sum_{j=1}^{n+m} \alpha_{ij} p_j + \sum_{k=1}^{K} \varphi_{ik} z_k,\ i = 1,\ \ , \mathrm{n} + \mathrm{m}. \tag{2}$$

Then, the supply equation for the numeraire output is obtained residually:

$$y_0^* = \alpha_0 + \sum_{k=1}^{K} \beta_k z_k - \frac{1}{2}\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} \alpha_{ij} p_i p_j + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} z_k z_l\ . \tag{2'}$$

The supply equation for the numeraire output, equation (2'), is obtained residually from (1) and (2). Hence, the optimal choice equations derived from this normalized quadratic profit function are linear function in unknown parameters, and equation (2) is linear in normalized prices and quantities of quasi-fixed factors, equation (2 and 2'). The partial elasticity output and input decisions with respect to prices is derived from equations (2) and (2')

$$\eta_{ij} = \frac{\partial \ln y_i^*}{\partial \ln p_j} = \alpha_{ij} p_j / y_i^* \qquad i, j = 1, \ldots, \mathrm{n} + \mathrm{m}$$

$$\eta_{i0} = \frac{\partial \ln y_i^*}{\partial \ln p_0} = -\frac{1}{y_i^*}\sum_{j=1}^{n+m} \alpha_{ij} p_j \qquad i = 1, \ldots, \mathrm{n} + \mathrm{m} \tag{3}$$

$$\eta_{0j} = \frac{\partial \ln y_0^*}{\partial \ln p_j} = -\frac{p_j}{y_0^*}\sum_{i=1}^{n+m} \alpha_{ij} p_i \qquad j = 1, \ldots, \mathrm{n} + \mathrm{m}$$

$$\eta_{00} = \frac{\partial \ln y_0^*}{\partial \ln p_0} = \frac{1}{y_0^*}\sum_{i=1}^{n+m}\sum_{j=1}^{n+m} \alpha_{ij} p_i p_j\ .$$

To be consistent with concavity of the profit function, the own-price elasticities of output supply is expected to be positive and those of input demand to be negative. Inputs i and j are designated as "substitutes" when $\eta_{ij} > 0$ and as "compliments" when $\eta_{ij} < 0$. Outputs i and j are designated “substitutes” if $\eta_{ij} < 0$ and as complements if $\eta_{ij} > 0$. Given estimates of the α’s, β’s, γ’s and φ’s, the partial elasticities can be evaluated at the sample means of p’s and z’s.

Impacts of Quasi-Fixed Factors. We are especially interested in the impacts of public agricultural research and availability of GE soybean and corn varieties on farmers’ production decisions, but also the impact of land (availability) and pre-season precipitation. Pre-season precipitation was chosen are the appropriate weather variable because it is known to farmers at planning and planning time. Although crop yields are also impacted by weather conditions during the growing and harvesting seasons, farmers input decisions are largely made at planning/planting time before actually growing and harvesting season weather is realized.

It is commonly believed that agricultural research (public and private) has a favorable effect on technologies that are intensive in agricultural chemical and machinery services. In addition, Huffman and Evenson (1989) found that additional public agricultural research had a slight bias effect toward fertilizer and fuel usage and against machinery and labor input usage, and Huffman and Evenson (2006a,b) and Huffman (2009) showed that public agricultural research increases agricultural productivity.[3]

To explore the tendency of quasi-fixed factors to bias farmers’ production decisions, we adopt Antle’s (1984) measure and expand it to multi-output technology, as in Huffman and Evenson (1989). The results is a measure of the impact on revenues shares and cost shares for y_i* due to a change in z_k. Let total revenue n + 1 outputs be denoted by

$$\Pi_R = y_0^* + \sum_{i=1}^{n} p_i y_i^* > 0, \tag{4}$$

and the total cost of the m variable inputs is denoted by

[3] For other approaches, see Clark and Youngblood (1992), Karaginnis and Mergos (2000), Pardey and Craig (1989), Mckay et al. (1983), and Lambert and Shonkwiler (1995).

$$\Pi_C = \sum_{i=n+1}^{n+m} p_i y_i^* < 0. \tag{5}$$

Then the revenue share for the i^{th} output is denoted by

$$s_i^R = \frac{p_i y_i^*}{\Pi_R} > 0, \tag{6}$$

and the cost share for the i^{th} variable input is denoted by

$$s_i^c = \frac{p_i y_i^*}{\Pi_C} > 0. \tag{7}$$

The bias effect on revenue (cost) shares due to a marginal change in a quasi-fixed factor is defined as the percentage change in the *i*-th revenue (or factor cost) share due to a 1 percent change in z_k. The algebraic expression for revenue biases (except for the numeraire good) is defined as:

$$B_{ik}^R = \frac{z_k}{s_i^R}\frac{\partial s_i^R}{\partial z_k} = z_k \left[\frac{\varphi_{ik}}{y_i^*} - \frac{\left(\beta_k + \sum_{i=1}^{n} \varphi_{ik} p_i + \sum_{l=1}^{K} \beta_{kl} z_l \right)}{\Pi_R} \right], \qquad i = 1,\ldots,n. \tag{8}$$

and using (8) and the fact that in this study revenue for livestock (v) and crop (c) output shares sum to 1 (= $s_v^R + s_c^R$), then algebraic expression for the bias on the numeraire output (crop) is

$$B_{ck}^R = -\frac{s_v^R}{s_c^R} B_{vk}^R. \tag{9}$$

The bias effect on the i^{th} variable input cost share due to a change in z_k is

$$B_{ik}^C = \frac{z_k}{s_i^C}\frac{\partial s_i^C}{\partial z_k} = z_k \left[\frac{\varphi_{ik}}{y_i^*} - \frac{\sum_{i=n+1}^{n+m} \varphi_{ik} p_i}{\Pi_C} \right], \qquad i = n+1,\ldots,n+m. \tag{10}$$

For both outputs and inputs, $B_{ik} > 0$ ($B_{ik} < 0$) denoted a “favorable” (“unfavorable”) effect of z_k on y_i*, which means that when z_k increases, the revenue (or factor’s cost) share of y_i* increases (decreases). The bias effect is neutral if $B_{ik} = 0$.

The quasi-fixed factors will change profit if they are permitted to change over time. A shadow-value measure of the impact of a marginal change in a quasi-fixed factor, given (1) is

$$\lambda_k = \frac{\partial \Pi}{\partial z_k} = \beta_k + \sum_{l=1}^{K} \beta_{kl} z_l + \sum_{i=1}^{n+m} \varphi_{ik} p_i \qquad k = 1, \ldots, \mathrm{K}. \tag{11}$$

Equation (11) can be evaluated at the sample mean values of the p’s and z’s.

The Data and Variables

Data from the agricultural sector’s state accounts, 1960-2004, are key data for the econometric analysis of production decisions. The state level data on quantities and prices of inputs and outputs have been prepared under the leadership of Eldon Ball at ERS. Outputs of farms are divided into two groups: crop (consisting of grain, forage and fiber produced) and livestock (consisting of livestock and livestock products). Variable farm inputs are capital services, labor, energy and chemicals (fertilizer and chemical pesticides), and other farm materials. We define five quasi-fixed factors: land services, public agricultural research stock, GE corn varietal availability and GE soybean varietal availability, and pre-season precipitation deviation (defined as the deviation from normal amounts). The production decisions of farmers in the states IA, IL, IN, MI, MN, MO, OH and WI are of interest in this study. See table 1 for the list of variables.

In the ERS agricultural state accounts, output is defined as gross production leaving the farm, rather than real value added. The measure of output starts with disaggregated data for physical quantities and market prices of crops and livestock. The output quantity for each crop and livestock category includes quantities of commodities sold off the farm, additions to inventory, and quantities consumed as part of final demand in farm households during the calendar year, but excludes intermediate goods produced and consumed on the “farm”. State output accounts include interstate shipments to intermediate farm demand. The price for each disaggregated output reflects the value of that output to the sector by adding subsidies and subtracting indirect taxes.

Based on the above information, two output indices─livestock and crops—for each state have been constructed as Tornquist indexes of farm outputs.   Livestock consists of meat animals, poultry and eggs, dairy products and others.[4] Crop output includes food grains, feed crops, oil crops, sugar crops, vegetables and melons, Christmas, ornamental and fruit trees.[5]

For the aggregate farm sector, the USDA’s farm labor accounts were developed as matrices of hours worked and compensation per hour for laborers, cross-classified by sex, age, education, and employment class—employee versus self-employed and unpaid family workers. By combining the aggregate farm sector matrices with state-specific demographic information, state-by-year matrices of hours worked and hourly compensation are constructed, each with cells cross-classified by sex, age, education, and employment class, and with each matrix linked to the USDA’s hours worked and compensation totals. For each state and year, self-employed and unpaid family workers are imputed the mean wage earned by hired workers with the same demographic characteristics, because labor compensation data for self-employed and unpaid family workers are not available. Indices of farm labor input are constructed for each state using the demographically cross-classified hours and compensation data. Farm labor hours having higher marginal productivity (wages) are given larger weights in forming the index of farm labor input than are hours having lower marginal productivities, which explicitly adjusts indices of farm labor input for quality change in farm labor hours.

[4] Also includes wool, mohair, horses, mules, honey, beeswax, goats, rabbits, and fur animals.
[5] Also includes floriculture, forest products, mushrooms, legume and grass seeds, hops, popcorn and flax fiber and seed.

Capital input includes services of durable equipment and inventories. Construction of time series measures of capital input and prices for the associated capital services for each state are based on the capital stock and implicit rental prices for each asset type in each state (Ball et al. 1999). Capital stocks are developed from data on investments, by way of a perpetual inventory method where past investments are weighted by relative efficiency and summed. Implicit rental prices for each asset are based on the correspondence between the purchase price of the associated asset and the discounted value of future service flows derived from the asset. The index of capital services input for each state is obtained by aggregating over the different capital assets, weighted by the asset-specific rental prices. Service prices for capital services input are constructed as the ratio of the total current dollar value of capital service flows divided by the associated capital quantity index.

The materials input in the ERS data set refers to intermediate input used in production during the calendar year, whether withdrawn from beginning inventories or purchased from outside the farm sector. These farm inputs include fertilizer, pesticides, fuels/electricity, feed/seed/livestock and other services.[6] We then categorized these inputs into three groups: energy, agricultural chemicals and other materials. The energy input includes petroleum fuels, natural gas and electricity. Agricultural chemicals consist primarily of fertilizers and pesticides. Other materials are the residual obtained after subtracting energy and agricultural chemicals from total material input, and include seeds, machinery services hired and contract labor. Prices for all outputs and inputs in all years are relative to the 1996 Alabama level.

Turing the quasi-fixed factors, land is measured in constant quality units by compiling data on land area and average value per acre for each Agricultural Statistics District in each state. The land area in each district and use category is reported in the Census of Agriculture. For non-Census

[6] Also includes purchased services, such as contract farm labor services, custom hired machine services, machine and building maintenance and repairs, irrigation fees paid public sellers of water, and miscellaneous farm production items.

years, the percentages in each district and use category are interpolated between Census years. Conservation reserve land is included in the land quantity index. Land values per acre are taken from the annual Agricultural Land Values Survey.

The public agricultural research stock for an originating state is used as a proxy for the "true" measure of public agricultural research that impacts farm production decisions. The public agricultural research stock is the summation of weighted past public sector investments in agricultural research with a productivity enhancing emphasis (Huffman 2009, Huffman and Evenson 2006a,b) in 1996 dollars. Although a free-form lags structure of the impacts of public agricultural research expenditures on farm production decisions might be incorporated, Griliches (1998) has argued that we have considerably more information about the likely lag pattern. He suggested that the impact of research and development on agricultural productivity or on farm output and input decisions most likely has a short gestation period with little or no impact, then blossoms into significant positive impacts, and eventually becomes obsolete. Huffman and Evenson (2006) and Huffman (2009) approximated this pattern by imposing a trapezoidal timing weights are a two-year lag with no impact. The research stock is computed by summing past real research expenditures with a two through 34 year lag and the following trapezoidal shaped timing weights. At first, a two-year gestation period is imposed during which the impacts of public agricultural research capital on productivity are negligible. Then, impacts are assumed to be positive and represented by linearly increasing weights for the next seven years, followed by six years of maturity during which weights are high and positive. There are then linearly declining weights for the next twenty years that eventually go to zero (See figure 4).[7]

[7] In this paper, we have ignored possible interstate spillin effects of public agricultural research so as to concentrate on estimating the impacts of other factors on production. This does risk causing some biases in estimated coefficients.

Farmers' adoption rates for GM corn and soybean varieties in each state and year are described in the second section of the paper. The pattern by state of the adoption rate for corn and soybean varieties is displaced in figures 2 and 3.

Pre-season precipitation in each year and state is computed as the deviation of current precipitation from its 30 year average level for the months of October to March before each growing season.[8] Sample mean values of the variables are displaced in table 1.

The Econometric Model

In the econometric model, crop output supplied is chosen as the numeraire commodity, equation (2) becomes a system of six equations: livestock output supplied and five input demand equations for variable inputs, and a random disturbance term (μ_{it}) is appended to the seven equations. A working hypothesis is that the amount of crop and livestock output produced in each state is small in the total US and world markets for outputs and inputs. This allows us to treat normalized prices as given. Also, a trend (t) is incorporated into model to help insure we have covariance stationary multivariate time series. This time trend also controls for other trend-dominated factors that could otherwise confuse interpretation of our empirical results (Nelson and Plosser 1982, Wooldridge 2002).

Now collect together the seven behavior behavioral equations of the production system and re-parameterize the model as follows to facilitate discussing autocorrelation

$$Y_{it} = X_{it}\delta_i + \mu_{it},\ \mathrm{i} = 1, ...7;\ t = 1, \ldots 45, \qquad (12)$$

where $\mu_{it} = \rho\ \mu_{it\text{-}1} + \varepsilon_{it}$ is an AR(1) stochastic process where ε_{it} is uniformly distributed with a zero mean, variance σ_i^2, and uncorrelated over time (Greene 2003). To estimate this model, first fit all

[8] The precipitation data from 1960 to 1994 is obtained from ERS's archived data product 92008. Data from 1995 to 2004 are forecast values using exponential smoothing based on each state's historical data (Hamilton 1994).

seven choice equations without cross-equation restrictions, and the use the associated residuals to estimate one value for ρ, $\hat{\rho}$ here is in fact 0.979 with a t-value of 115. Using $\hat{\rho}$, we then transform (12) into model where the variables are expressed as pseudo first-differences:

$$Y_{it} - \hat{\rho}\, Y_{it\text{-}1} = (X_{it} - \hat{\rho}\, X_{it\text{-}1})\, \delta_i + \varepsilon_{it}*. \tag{13}$$

Under an assumption that that each states quantity supplied of crop and livestock output and demand for inputs is small in the total US market and world market, the producers of each state are treated as price takers. Then the production system can be estimated in a straight forward way as a difference seemingly-unrelated (SUR) regression model with cross equation restrictions (Greene 2008, Zellner 1962, Barton 1969).

The Empirical Results

The estimated coefficients for the agricultural supply and input demand system obtained by fitting seven output supply and input demand equations for eight Midwestern states, 1960-2004, to the (44x8) 352 total observations are reported in table 2 and 3. In viewing table 3, it is obvious that there are many more explanatory variables in the crop output supply (numeraire commodity) equation. The estimated coefficients in table 2 needed to derive the own-price elasticities (equations 3) reported in table 4 are statistically strong for, except for the two supply equations. The impacts of available land on choices are sizeable and statistically strong. The impact of public agricultural research and availability of GE/GM soybean varieties are mixed—some coefficients are significantly different from zero and others are not. The impact of the availability of GE/GM corn varieties is somewhat weaker than for GM soybean varieties. The impact of trend is to reduce or leave unchanged outputs supplied and inputs demanded.

Estimates of Input and Output Price Elasticities. Own- and cross-price elasticities are obtained by evaluating equation (3) at the sample mean value of the associated quantities and prices (table 1) and are reported in table 4. All own-price elasticities are negative for inputs and positive for outputs, which are as expected. The crop and livestock output supply responses are, however, inelastic, being 0.021 for livestock and 0.127 for crop output. All five of the variable input demand equations have negative own-price elasticities. Moreover, the input demand elasticities are quite small for capital services and labor (-0.040 and -0.66, respectively); more modest in size for energy and other materials (-0.354 and -0.288, respectively), and somewhat larger for agricultural chemicals (-0.591). Some plausible reasons exist for the seemingly small size of own-price elasticities of livestock and crop supplied. First, the true size may be small. Second, our output supply equations are yearly average prices received by farmers adjusted for government program payments, which incorporates consider speculation by farmers about the optimal time to sell inventories. Third, the output prices might have an endogenous component. An expected price at planning/planting time, at least for crop output, might lead to a larger supply elasticity (Huffman and Evenson 1989).

The cross-price elasticities for inputs provide information on which inputs are substitutes and complements (table 4). Farm capital services are substitutes for energy and agricultural chemicals but a complement for labor and other materials. All inputs are a substitute for farm labor, except for capital services. Energy is a substitute for all other inputs, and agricultural chemicals are a substitute for all other inputs. Other materials are a substitute for labor and agricultural chemical but a complement for capital services, energy and other materials. However, the cross-price elasticities are quite variable in size, being relatively small in many cases. Between the two outputs, cross-price effects are small positive suggesting a type of synergy in Midwestern U.S. agriculture.

Input-output cross- price elasticities indicate the magnitudes of supply and demand curve shifts due to a change in a cross-price (table 4). An increase in the price of livestock output increases the demand (rightward shift) for variable inputs, except for labor. In contrast, an increase in the price of crop output increases the demand for labor and other materials, but reduces the demand for capital services, energy and agricultural chemicals. Input prices also affect output supplied. An increase in the price of capital services decreases the supply (leftward shift) of livestock output but increases the supply of crop output; an increase in the wage to labor increases the supply livestock output but reduces the supply of crop output; an increase in the price of energy increases the supply of livestock output and reduces the supply of crop output; and increases in the price of agricultural chemicals or other materials reduces both the supply of livestock and livestock output.

Impacts of Quasi-Fixed Factors. We have impacts of quasi-fixed factors on the supply of outputs and demand for inputs; bias effects on revenue and cost shares of a change in these factors; and on the shadow value of a marginal change in one of these factors. First, consider the impact of a change in a quasi-fixed factors on output supply and input demand in Midwestern agriculture (see table 2 and 3). An increase in the quantity of available land increases livestock and crop output supplied and the demand for all five variable inputs (rightward shifts). An increase in public agricultural research increases the livestock and crop output supplied and increases the demand for labor, agricultural chemicals and other material inputs but reduces (leftward shift) in the demand for capital services and energy. An increase in the availability of GM soybean varieties increases livestock but reduces crop output and increases the demand for farm capital services, agricultural chemicals and other materials. It, however, reduces the demand for labor and energy. An increase in the availability of GM corn varieties increases weakly livestock and crop output supplied and the demand for labor and other materials but reduces the demand for capital services, energy and agricultural chemicals. An increase in pre-season precipitation increases crop output supplied but reduces livestock output supplied, and increases the demand for capital services, labor, and other materials but reduces the demand for energy and agricultural chemicals.

Second, as quasi-fixed factors change they the transformation function and these shifts are summarized by evaluating equations (8)-(1), using coefficient estimates from tables 2 and 3 and variable means from table 1. Additional land biases input cost shares toward energy, agricultural chemicals and other materials inputs, but against capital services and labor. Additional land also biases output revenue shares toward crops and against livestock output. Additional public agricultural research biases input cost shares toward agricultural chemicals and other materials but against capital services, labor and energy. Additional public agricultural research also biases revenue shares toward crops and against livestock. A higher adoption rate for GM soybeans biases input cost shares toward capital services, energy and agricultural chemicals but is relatively neutral on shares for labor and other materials. It biases revenue shares towards crops and away from livestock. A higher rate of GM corn adoption biases input cost shares away from agricultural chemicals and has minimal impact individually on the other input cost shares, although the sum of these small changes must offset the larger impact on agricultural chemicals. Higher GM corn adoption biases revenue shares toward crops and against livestock. The effects on revenue and cost shares of a change in pre-season precipitation is zero due to the mean value of pre-season precipitation being zero.

Third, the shadow values equations (11) are also evaluated at the sample mean of the data. The shadow value of a $1 (constant 1996 dollars) increase in agricultural land services is $2,841; a $1 (constant 1996 dollars) increase in public agricultural research stock is $1,390 per year; a 1 percentage point increase in GM soybean varieties is $389 million; a 1 percentage point increase in share of corn acreage planted to GM hybrid corn varieties is $577 million; and an additional inch of pre-season precipitation is $634 million. These values seem quite large, but standard errors in some cases are also most likely large, especially given the number of small t-values in table 3.

Discussion. Several previous studies have reported output supply and input demand elasticity estimates for U.S. agriculture at the region or state level. They include Ball (1988), Huffman and Evenson (1989), Lim and Shumway (1997), Shumway and Lim(1993), Shumway et al. (1988), and Vasavada and Chambers (1986). These studies, however, differ, not only in functional form of the choice functions, but also in the number and definition of variable input and output groups, observation unit (states or regions), time period covered and conditioning variables, i.e., the list of quasi-fixed factors, estimation method, and points at which elasticities are evaluated. Their findings for price elasticities of output supply and input demand vary widely. Compared with relevant studies, the magnitudes of our findings for own- and cross-elasticities are relatively small.

Vasavada and Chambers (1986) focused on aggregate output measures and estimated the long run output supply and input demand elasticities for a normalized quadratic value function. They found the own-price elasticity for labor to be -0.51, which is much larger than our estimate. In their study, capital services are found to be an inferior factor, with positive elasticity 0.12, but we find a negative own-price elasticity of demand. Their finding for the elasticity of intermediate materials is -0.34, but we have separate own-price elasticities for energy of -0.354, of agricultural chemicals of -0.591 and of other materials of -0.288. They have an estimate for the elasticity of the aggregate output is 0.54, which is substantially larger than own-price elasticity of supply of crop output of 0.127 and of livestock output of 0.021.

Ball (1988) modeled multi-product supply response in agriculture with a trans-log profit function over the period 1948-79. He found the price elasticity of livestock supply to be elastic, at 1.089. Even though he used different output and input categories than we do, he obtained own-price elasticities that were larger in absolute value than ours.

Shumway has conducted several studies on multi-product supply and input demand in U.S. agriculture. In his 1997 study with Lim, they examined U.S. agricultural crop and livestock relationships in the context both of duality and time-series econometrics. They estimated both the co-integrated and the traditional models using quadratic and trans-log functional forms, respectively. Their study utilized Ball's aggregate annual data series for U.S. agricultural production for the period 1948-91. A summary of their results is presented in table 4. Their estimates for output supply and input demand own-price elasticities under the trans-log functional form are generally larger than our findings and their quadratic functional form estimates are similar Their price elasticity of livestock supply is 1.01, which is very close to Ball's (1988) findings. The magnitudes of their elasticity estimates using the quadratic profit function estimates are closer to ours, except that they obtain unexpectedly negative own-price elasticities for crop output and positive own-price elasticities for capital and materials inputs.

Huffman and Evenson (1989) discussed biases caused by public agricultural research and other policies for U.S. cash grain farms. They used different output and input categories, so it's hard to make a full-scale comparison.

Conclusions

Output supply and input demand functions have been fitted to state aggregate data for eight U.S. Midwestern states, 1960-2004, and they are consistent with an aggregate profit function framework. Supply elasticities for crop and livestock outputs are positive but small. The own-price elasticities of demand for all inputs are shown to be negative, being larger for agricultural chemicals and energy that for farm capital services, labor and other materials. Additional public agricultural research, a quasi-fixed factor, is shown to increase the supply of crop and livestock outputs and the demand for agricultural chemicals and other materials but to reduce the demand for capital services, labor and energy. An increase in the adoption of GM soybean varieties (resulting from private R&D) increases the supply of livestock output but reduces the supply of crop output. It also increases the demand for farm capital services, agricultural chemicals and other materials and weakly reduces the demand for labor and energy. The impact of an increase in the adoption of GM corn varieties (also resulting from private R&D) reduces the demand for energy but other effects on input demand are quite weak.

The shadow value of public and private agricultural research (availabilityof GM soybean and corn varieties) are shown to be positive and sizeable.

Future research will explore the effects of disaggregating crop output and using crop prices that are available to farmers at planning/planning time.

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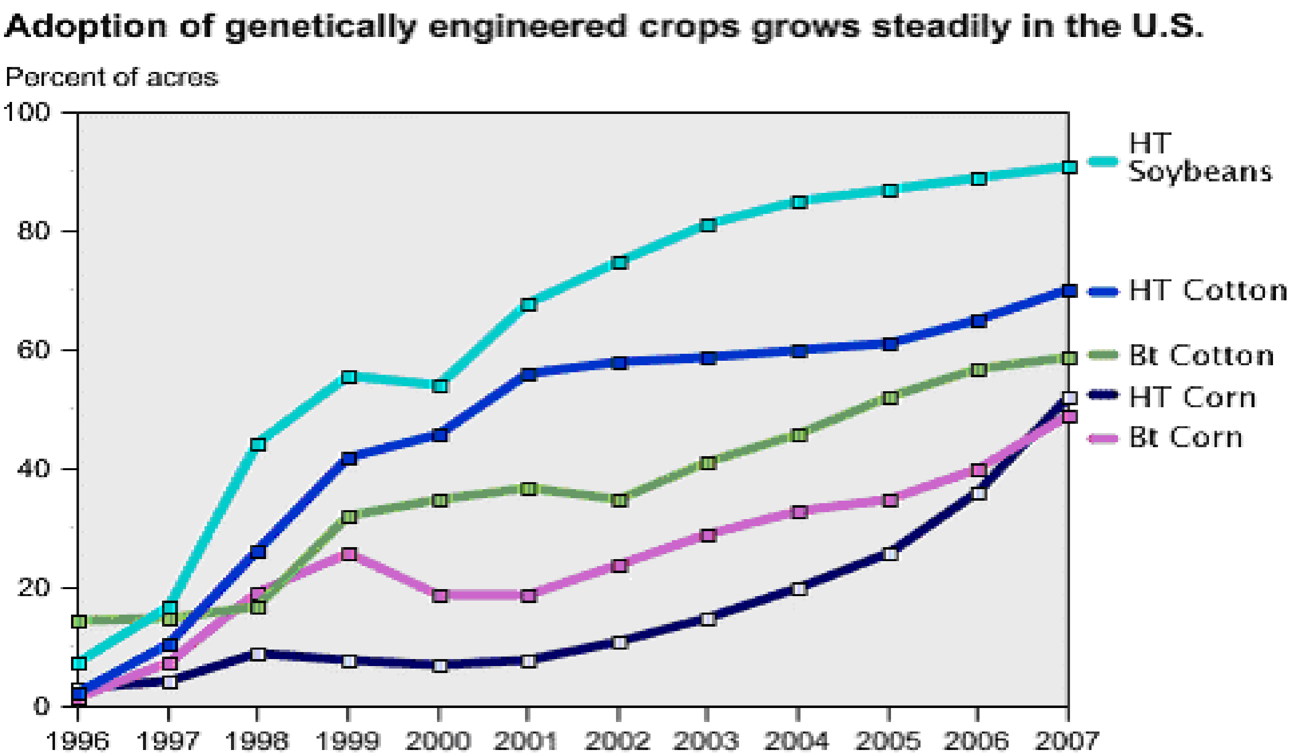
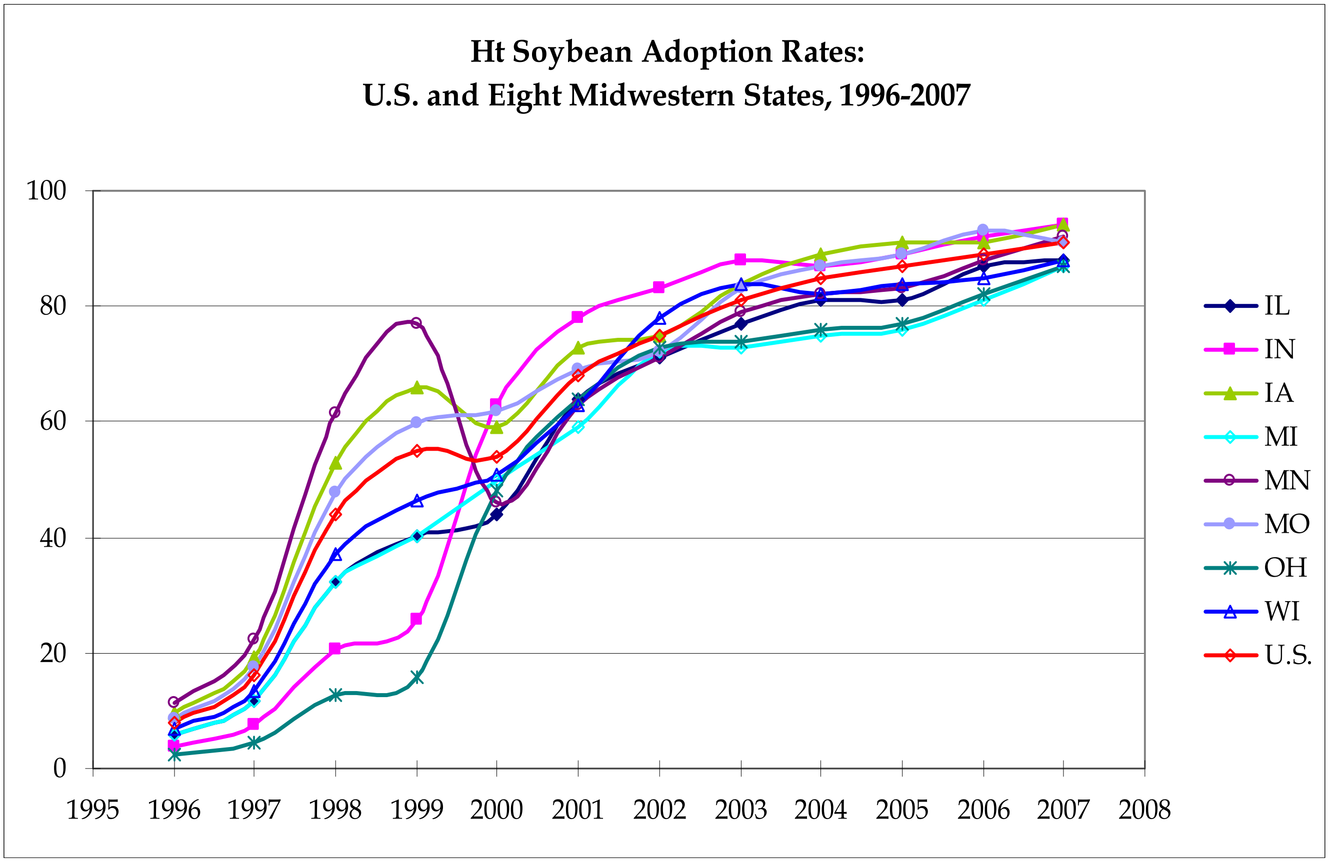
Figure 1.



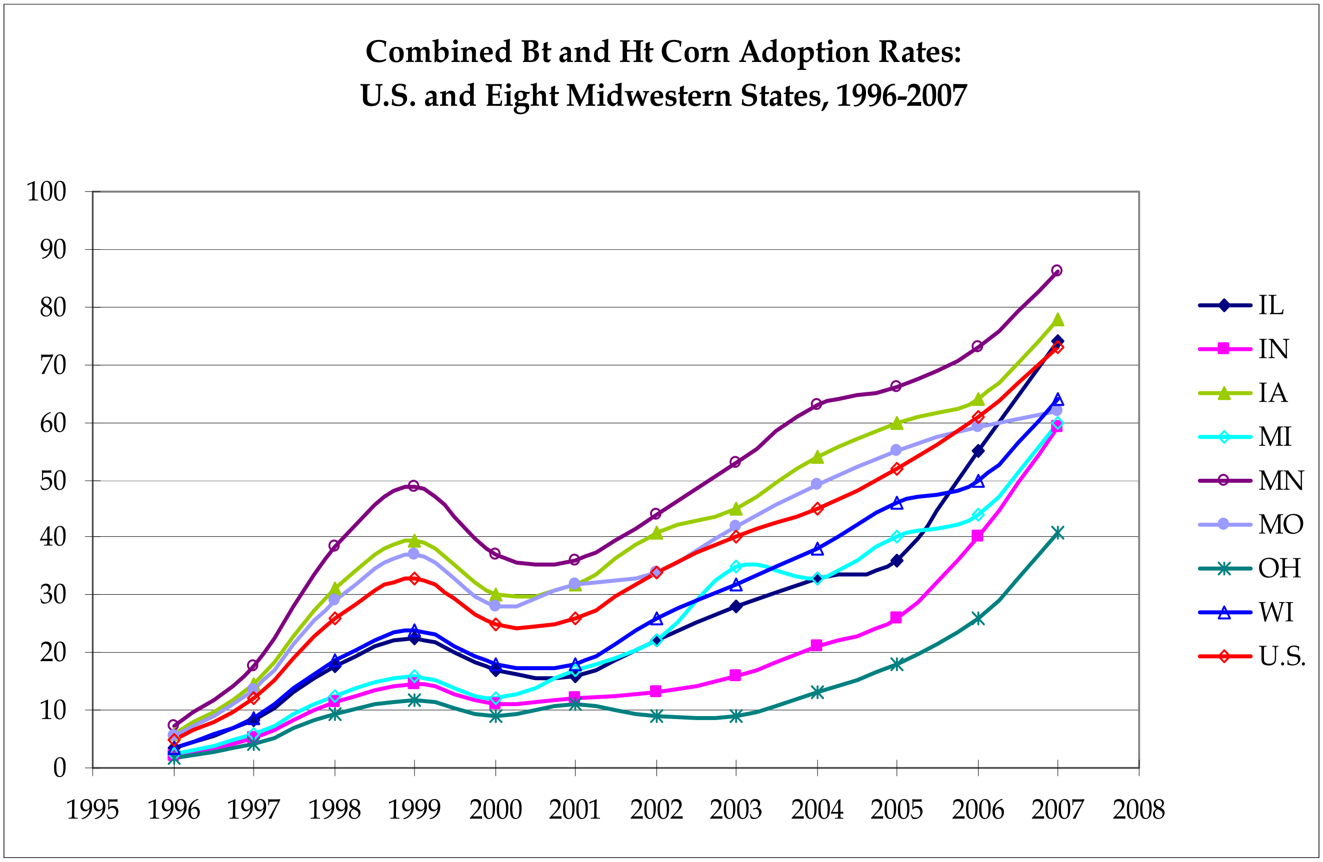
Source: Fernandez-Cornejo 2008

Figure 2



Source: ERS (2008) for 2000-2007; our estimates for 1996-1999.

Figure 3



Source: ERS (2008) for 2000-2007; our estimates for 1996-1999.

Figure 4. Public Agricultural Research Timing Weights

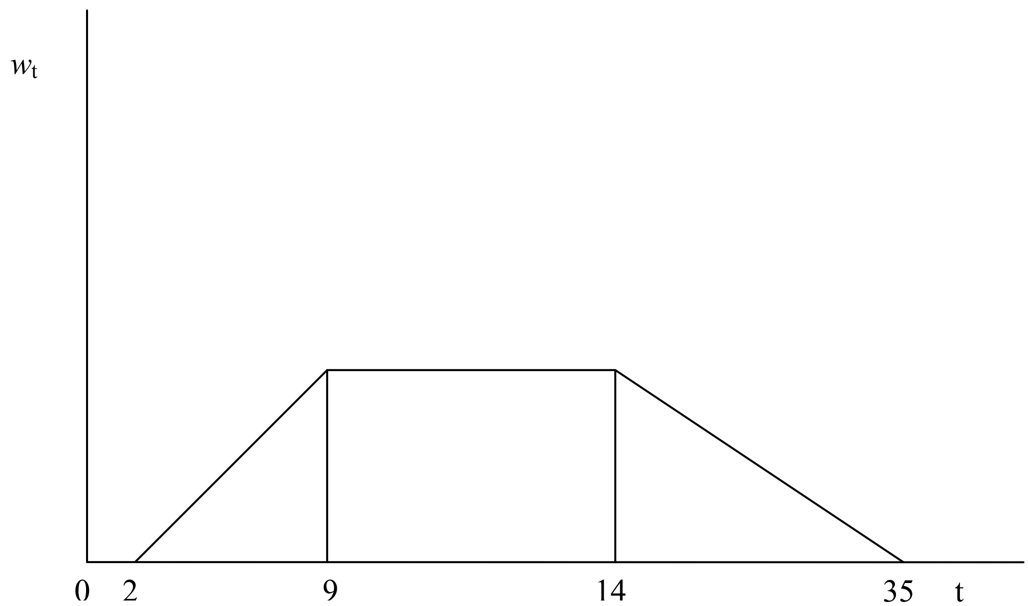


Table 1. Variable Names and Summary Statistics for U.S. Agriculture in Eight Midwestern States, 1960-2004

Variables	Mean	St.Dev
Quantities[1]		
Crop Output (y_c)	3.81	1.97
Livestock Output (y_v)	3.15	1.54
Capital Services (y_k)	-1.54	0.55
Labor (y_h)	-3.89	1.59
Energy (y_e)	-0.29	0.10
Ag Chemicals (y_a)	-0.68	0.39
Other Materials (y_m)	-2.51	1.13
Prices[2]		
Crop Output (P_c)	numeraire	
Livestock Output (p_v)	0.92	0.14
Capital Services (p_k)	0.76	0.35
Labor (p_h)	0.58	0.42
Energy (p_e)	0.93	0.32
Ag Chemicals (p_a)	0.84	0.16
Other Materials (p_m)	1.12	0.26
Profit (Π)	-0.37	
Revenue (Π_R)	6.71	
Cost (Π_C)	-7.08	
Quasi-Fixed Factors		
Land Services (Z_L)[3]	0.87	0.24
Public Ag Research (Z_r)[4]	30.05	10.71
GM Soybean Varieties (Z_s)	0.11	0.24
GM Corn Varieties (Z_c)	0.04	0.11
Pre-season Precipitation (Z_p)[5]	0.00	2.49

[1] Value $1,000,000,000 in 1996 prices of Alabama
[2] Crop price in nominal relative to 1996 in Alabama; other prices are normalized prices, e.g., p_v is the nominal price of livestock output divided by the nominal price of crop output.
[3] Value $1,000,000,000 in 1996 prices in Alabama
[4] $1,000,000 in 1996 prices of Alabama
[5] Deviation from 30 norms or mean

Table 2. Estimation of an IV SUR Model with First-Order Autocorrelation of a System of Output Supply and Input Demand Equations with Restrictions: Eight Midwestern States, 1960-2004 (asymptotic t-or z-values in parentheses; N = 44x8 = 352 observations per equation)[1]

	Supply Equation	Demand Equations				
Variables	**Livestock**	**Capital**	**Labor**	**Energy**	**Ag-chemical**	**Other Materials**
Normalized Prices:						
Livestock (p_v)	0.0711	-0.0598	0.0298	-0.0077	-0.0826	-0.0138
	(0.86)	(-2.28)	(0.60)	(-0.81)	(-2.17)	(-0.25)
Capital (p_k)	-0.0598	0.0801	0.0378	-0.0745	-0.0244	0.0135
	(-2.28)	(1.89)	(2.23)	(-5.02)	(-0.94)	(0.54)
Labor (p_h)	0.0298	0.0378	0.4394	-0.0105	-0.0149	-0.0637
	(0.60)	(2.23)	(4.41)	(-1.72)	(0.55)	(-1.27)
Energy (p_e)	-0.0077	-0.0745	-0.0105	0.1099	-0.0420	-0.0120
	(-0.81)	(-5.02)	(-1.72)	(11.68)	(-4.30)	(-1.30)
Ag-chemical (p_a)	-0.0826	-0.0244	-0.02149	-0.0420	0.4779	-0.2733
	(-2.17)	(-0.94)	(-0.55)	(-4.30)	(10.75)	(-7.84)
Other Materials (p_m)	-0.0138	0.0135	-0.0637	-0.0120	-0.2733	0.6450
	(-0.25)	(0.54)	(-1.27)	(-1.30)	(-7.84)	(10.16)
Fixed Factors:						
Land (Z_L)	1.6054	-1.2285	-2.9785	-0.8000	-1.6907	-4.0314
	(1.20)	(-2.81)	(-1.11)	(-5.08)	(-2.30)	(-2.81)
Public Research (Z_L)	0.0435	0.0141	-0.0007	0.0038	-0.0153	-0.0138
	(2.19)	(2.16)	(-0.02)	(1.59)	(-1.40)	(-0.65)
GM Soybeans (Z_s)	0.1775	-0.2145	0.2803	0.0196	-0.2599	-0.0935
	(0.70)	(-2.58)	(0.56)	(0.65)	(-1.88)	(-0.35)
GM Corn (Z_c)	0.4179	0.0234	-0.1074	0.0660	0.1471	-0.3284
	(1.08)	(0.18)	(-0.14)	(1.43)	(0.69)	(-0.79)
Preseason	-0.0038	-0.0015	-0.0111	0.0007	0.0011	-0.0022
Precipitation (Z_p)	(-1.49)	(-1.78)	(-2.14)	(2.41)	(0.78)	(-0.80)
Time (t)	-0.0014	0.0023	-0.0022	0.0001	0.0009	0.0011
	(-1.60)	(8.21)	(-1.24)	(1.39)	(1.85)	(1.23)
Intercept	0.0707	-0.0880	0.0497	-0.0144	-0.0422	-0.0922
	(3.71)	(-14.01)	(1.30)	(-6.37)	(-4.00)	(-4.50

04-23-10

Table 3. Estimate of the numeraire (crop output) equation with cross-equation restrictions (to coefficients in table 2)

Variable	Coefficient	t-value	Variable	Coefficient	t-value
Z_L	39.1080	2.04	$.5(Z_L)^2$	3076.656	2.02
Z_r	0.1722	0.71	Z_LZ_r	5.312	0.26
Z_s	38.7174	1.00	Z_LZ_s	5.393	0.01
Z_c	-20.5248	-0.26	Z_LZ_c	-129.853	-0.19
Z_p	0.0723	2.18	Z_LZ_p	0.403	0.20
t	-0.0023	-0.12	Z_LZ_t	-1.295	-1.43
$.5(p_v)^2$	0.0711	0.86	$.5(Z_r)^2$	-0.111	-0.35
p_vp_k	-0.0598	-2.28	Z_rZ_s	-1.993	-0.67
p_vp_h	0.0298	0.60	Z_rZ_c	6.038	1.29
p_vp_e	-0.0077	-0.81	Z_rZ_p	-0.024	-0.61
p_vp_a	-0.0826	-2.17	Z_rt	-0.003	-0.24
p_vp_m	-0.0138	-0.25	$.5(Z_s)^2$	-29.320	0.98
$.5(p_k)^2$	0.0801	1.89	Z_sZ_c	-8.074	-0.24
p_kp_h	0.0378	2.23	Z_sZ_p	18.369	0.49
p_kp_e	-0.0745	-5.02	Z_st	-0.835	-0.92
p_kp_a	-0.0244	-0.94	$.5(Z_c)^2$	56.304	0.95
p_kp_m	0.0135	0.54	Z_cZ_p	-26.678	-0.43
$.5(p_h)^2$	0.4394	4.41	Z_ct	0.377	0.20
p_hp_e	-0.0105	-1.72	$.5(Z_p)^2$	0.003	0.61
p_hp_a	-0.0149	-0.55	Z_pt	-0.004	-2.34
p_hp_m	-0.0637	-1.27	$.5t^2$	-0.000	-0.16
$.5(p_e)^2$	0.1099	11.68	Constant	0.170	1.01
p_ep_a	-0.0420	-4.30			
p_ep_m	-0.0120	-1.30			
$.5(p_a)^2$	0.4779	10.75			
p_ap_m	-0.2733	-7.84			
$.5(p_m)^2$	0.6450	10.16			
					4-23-10

Table 4. Output Supply and Input Demand Elasticities: Eight Midwestern States, 1960-2004[1]

	Elasticity w.r.t. prices of						
Quantity	Capital	Labor	Energy	Ag-chemical	Other Materials	Livestock Output	Crop Output
Inputs							
Capital	-0.040	-0.014	0.045	0.013	-0.010	0.036	-0.033
	(-1.89)	(-2.23)	(5.02)	(0.94)	(-0.54)	(2.28)	
Labor	-0.007	-0.066	0.003	0.003	0.018	-0.007	0.056
	(-2.23)	(-4.41)	(1.72)	(0.55)	(1.27)	(-0.60)	
Energy	0.196	0.021	-0.354	0.122	0.046	0.024	-0.056
	(5.02)	(1.72)	(-11.68)	(4.30)	(1.30)	(0.81)	
Ag-chemical	0.027	0.013	0.058	-0.591	0.453	0.112	-0.072
	(0.93)	(0.55)	(4.30)	(-10.75)	(7.84)	(2.17)	
Other Materials	-0.004	0.015	0.004	0.091	-0.288	0.005	0.176
	(-0.54)	(1.27)	(1.30)	(7.84)	(-10.16)	(0.25)	
Outputs							
Livestock	-0.014	0.006	-0.002	-0.022	-0.005	0.021	0.017
	(-2.28)	(0.60)	(-0.81)	(-2.17)	(0.25)	(0.86)	
Crop	0.009	-0.033	0.004	0.011	-0.131	0.013	0.127

[1] Evaluation of equation (3) at the sample mean value of the variables from table 1 and using coefficient estimates taken from table 2. t- or z-values in parentheses; evaluated at the sample of prices and quantities.
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Table 5. Estimates of Bias Effects in Production Decisions w.r.t. Quasi-Fixed Factors: Eight Midwestern States, 1960-2004[1]

	Quasi-Fixed Factors			
Production Decisions	Land	Public Ag Research	GM Soybean Adoption	GM Corn Adoption
Inputs				
Capital	-0.336	-0.383	0.013	-0.002
Labor	-0.268	-0.054	-0.015	-0.000
Energy	1.353	-0.467	-0.012	-0.012
Ag-chemical	1.199	0.672	0.039	-0.012
Other Materials	0.801	0.170	0.001	0.007
Outputs				
Livestock	-368.020	-5.892	0.644	-0.339
Crop	279.900	4. 480	-0.490	0.258

[1] Evaluation of equation (9) and (10) at sample mean value of the variables from table 1 and using estimated coefficients from table 2 and 3. All bias effects for pre-plant precipitation are zero because the mean value of this variable in zero.

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Table 6. Output Supply and Input Demand Own-Price Elasticities from Lim and Shumway (1997)

	Functional Form	
Quantity	**Translog**	**Quadratic**
Inputs		
Capital	-0.26	0.22
Labor	-0.43	-0.13
Materials	-0.63	0.28
Outputs		
Livestock	1.01	0.10
Crop	0.69	-0.05