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The Impact of Public and Private R&D on Farmers' Production Decisions: 1960-2004

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The Impact of Public and Private R&D on Farmers' Production Decisions: 1960-2004

Abstract: The objective of this paper is to examine the changing structure of agriculture in Midwestern US States over 1960-2004. Major factors causing change are relative output and input prices, public agricultural research and adoption of GM corn and soybean varieties. However, GM corn and soybean varieties only became available starting in 1996. We choose an aggregate multi-output-multi-input variable profit-function framework and estimate the derived output supply and input demand functions. The output groups are: soybean, corn, wheat, and livestock, and the (variable) input groups are farm capital services, labor, energy, chemicals, and "other materials." (Quasi-) fixed inputs are land, GM soybean and GM corn adoption rates, public agricultural research, and preseason weather. We show that a higher GM-soybean adoption rate (or displacement of non-GM varieties) has its primary impact on the demand for farm energy but biases input choices toward farm chemicals and labor but away from other inputs. The adoption of GM corn varieties has its primary effect on decreasing the demand for farm capital services and labor and biases input decisions toward farm chemicals, energy, and "other materials" but away from other inputs. The shadow value of an increase in the GM-soybean and GM-corn adoption rates is positive, and for GM corn, the shadow value is much larger than the GM technology fee. Our results show that the structure of Midwestern agriculture changed as a result of the adoption of GM-corn and soybean varieties, and these impacts are expected to grow as later data become available.

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 increase the supply of agricultural outputs, and reduce the demand for some of the inputs and/or increase total factor productivity. This is a preferred methodology relative to approximating technology with a time trend, as in Mundlak (2001) and some other studies. In the United States, 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 hybrid corn varieties in the late 1920s and 1930s. These hybrids were reproduced and marketed by private seed companies (Griliches 1960, Huffman and Evenson 1993). During the ensuing seventy years, the private sector took control of developing inbred lines and producing and marketing commercial hybrid seed corn.

Before 1950, soybean varieties were adapted to forage and hay but not seed production. This changed over the next two decades. Now soybeans are grown by farmers for their production of beans, which are a source of oil and high protein meal. 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 increasingly taken control of developing commercial soybean varieties and their marketing. For example, in 1994, the private sector accounted for 64 percent of soybean varietal development resources (Fernandez-Corneji 2004). Wheat is a third important crop in the Midwest—hard red spring and durum wheat in Minnesota and soft red winter wheat in the other states. Early wheat varieties for farmers were reproductions of imported seeds from Europe. Since the mid-1930s, new wheat varieties were developed by the public sector and marketed by private seed companies (Geigel and Huffman 1986). Improvements in breeding practices and livestock feeding systems for poultry, swine, dairy and beef cattle have also occurred over time (Huffman and Evenson 1993; Narrod and Fuglie 2000). For the most part, these

livestock and poultry 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, commercial herbicides became available for helping to control weeds in field crops. The use of herbicides reduced the need for field cultivation and hand weeding. Also, as a result of the mid-1970's energy crisis new "reduce tillage practices" were developed that largely eliminated the use of energy- and machinery-intensive seedbed preparation involving large-horsepower tractors pulling large moldboard plows and heavy disks (Rahm and Huffman 1984). By the 1990s, no-till farming was widely adopted in the Midwest.

The GM crop revolution started due to a large investment made by the private sector, especially Monsanto, and the first GM-field crop varieties became available to farmers in 1996 in the United States (Huffman forthcoming). Soybean, corn, and cotton varieties became available with genetically engineered herbicide tolerance (HT), and cotton and corn varieties became available that were engineered for insect resistance (IR) (Fernandez-Cornejo and McBride 2000, NRC 2010). Second generation GM traits of herbicide tolerance and insect resistance became available by 2000 for cotton, and for corn shortly thereafter. Third generation GM corn varieties became available to some farmers in 2010. These contained eight transgenes, three for above ground insect resistance, three for below ground insect resistance, and two for herbicide tolerance. These IR varieties provide a biological alternative to commercial chemical insect application, widely recognized for reducing the pesticide load on the environment and risks to human health (NRC 2010). HT soybean, corn, and cotton provide more effective weed control than with earlier herbicides. The key herbicide in this process is *Roundup*, which is environmentally and human health friendly relative to earlier herbicides used for weed control (NRC 2010). In contrast, GM-wheat varieties have not been released to US farmers. The primary reason is the negative image that GM wheat has in the export market (Taylor et al. 2003).

The objective of this paper is to examine the changing structure of agriculture in Midwestern US States over 1960-2004. Major factors causing change are relative output and input prices, public agricultural research and adoption of GM corn and soybean varieties. However, GM-corn and soybean varieties only because available starting in 1996. The exact dates covered in the empirical analysis are constrained by data currently available. The eight Midwestern States chosen for this study account for more than 65 percent of the US harvested acreage in corn and soybeans, but no one state dominates production. On average each state accounts for only 8 percent of US production. We adopt an aggregate multi-output-multi-input restricted-expected profit function because we believe it provides the best framework for examining the impact of prices and new technologies on farmers' production decisions. Our results show that the structure of Midwestern agriculture has been impacted by the adoption of GM-corn and soybean varieties, and these impacts are expected to grow as later data become available. In addition, they show that public agricultural research has increased the supply of all major outputs produced by Midwestern farmers and demand for all major input groups so as to increase aggregate farm profit. The marginal real social rate of return on investment in public agricultural research in the Midwestern States over the study period is quite high and almost certainly larger than for alternative public investments.

The paper unfolds in the following sections.

Changing Technology of Farm Production

In the Midwest, corn, soybean, and wheat have been the dominant field crops since the 1960s. With the discovery of the first successful double cross corn hybrids in the 1930s, hybrid corn swept Midwestern States over the 1930s (Griliches 1960; Huffman and Evenson 1993, pp. 155-162). However, hybrid corn was not only a method by which hybrid seed corn varieties replaced open pollinated seed corn varieties, but it also provided a mechanism by which the principles of hybridization could be used to breed new, and in some cases, superior hybrid seed corn varieties that over time would replaced older

ones. In the 1960s, corn breeders moved to single-cross hybrids to obtain higher yielding corn varieties. GM corn varieties first became available to farmers in 1996. The first GM-corn varieties contained either herbicide tolerance or insect resistance, but in a few years, both traits were included in many of the hybrid corn varieties sold to farmers in the Midwest. Since the 1930s, planting rates for hybrid seed corn increased by roughly a factor of four as complementary technologies, including better weed and insect control, have been developed.

Soybeans were first grown in the United States for hay and forage, but gradually, the demand for soybean oil and meal grew. Along with them grew the demand for soybeans. Early genetic improvement of soybeans occurred using superior imported varieties from Asia. Later, a successful public soybean improvement program emerged in the United States. Private sector development of new soybean varieties became significant only since 1980, reflecting improved breeders' rights with the Plant Variety Protection Act of 1970, and the ability of breeders to make steady yield improvements. The soybean plant is extremely photoperiod sensitive. This day-length sensitivity means that any soybean variety performs well only within a relatively small geo-climatic area. Plant breeding has made it possible to expand the range of geo-climates in which soybeans yield relatively well, including into the Lake States. Before 1960, farmers purchased seed beans from other farmers or from private seed companies. In succeeding years, the farmer generally saved his own seed and planted it. This type of seed would eventually need to be replaced because genetic resistance to pests would break down. During the pre-GM era of the 1980s, the private sector made rapid progress in developing and selling seed beans to farmers (Huffman and Evenson 1993, pp. 162-167). By 1990, 70 percent of the seed beans planted annually were purchased commercially.

The soybean plant is not competitive against weed pressure, and in the 1960s farmers were using field cultivation and hand weeding to control weeds. Later, new herbicides were developed to help with weed control in soybeans. However, it was sometimes difficult to obtain good weed control with these

herbicides. The invention of GM-soybean varieties for herbicide tolerance was a major step forward in providing farmers with effective, low cost, and environmentally friendly weed control (NRC 2010).

Wheat is a crop that has been grown in the United States since 1611. Early improvements were from imported varieties, and by 1900, public sector wheat improvement programs were underway. In Minnesota, hard red spring (and durum) wheat are grown, but in other Midwestern States, soft red wheat varieties are dominant. Wheat improvement in the United States remains a public sector activity with the private sector engaged in seed reproduction, certification and sale to farmers. Although GM wheat for herbicide tolerance was developed by the early 2000s, it has not been released to farmers for planting because there is a major concern about potential poor reception to it in the international wheat market (Wilson et al. 2003; Taylor et al. 2003). On this score, the main difference between wheat and corn is that corn is grown primarily for livestock feed, but wheat is grown primarily for food. Soybean is grown primarily for oil and meal, but soybean oil loses it genetically modified ingredients in the oil refining process and soybean meal is fed to livestock.

Through the 1950s, livestock production was an important part of almost every Midwestern farm's production. A large number of farms were diversified: growing corn, small grains, and hay, and raising cattle and hogs. In the 1950s collecting dairy bull semen and artificially inseminating (AI) dairy cows became a method for genetic improvement of dairy cows. As the demand for low-fat milk grew in the 1980s, dairy farmers turned to the Holstein breed, which produces large volumes of low-fat milk. AI was possible because of the highly domesticated nature of dairy cows and technical advances in freezing and storing bull semen. It was four to five decades later before the widespread application of poultry and swine artificial insemination, and even today only a modest share of US beef cows are artificially inseminated. The genetic improvement of farm animals has been slow relative to crops like corn, because livestock improvement has low genetic potential and breeding has been largely under the control of

farmers and not scientists. However, cross-breeding, combined with rigorous selection and testing, has been an effective way for farmers to make some improvements in swine and beef cattle.

The organization of livestock production is relatively free of constraints due to seasonal and spatial attributes, but its specialization is driven by available technology and the ratio of the wage-rate to rental-rate-on-capital (Huffman and Evenson 2001). Production has been organized in sequential phases or split phases across farms in order to reduce disease problems. Advances in animal health products, animal feeding, housing and equipment, and management have made it possible to accelerate growing and finishing phases of livestock and poultry by concentrating animals and birds into confined animal and poultry production systems. This approach has greatly increased animal densities and populations, and consequently a brought a dramatic reduction in the number of farms producing hogs, dairy, swine, poultry and beef. Huffman and Evenson (2001) show that specialization of livestock production on farms in the United States progressed very slowly over 1950-1958, then a little more rapidly over 1958-1964, and then somewhat more rapidly until 1969 before leveling off through the mid-1980s. They show that relatively little change in crop specialization of farms occurred before 1964, but it increased rapidly over 1964-1974, and then flattened out to the mid-80s. Growing specialization of farms has continued since then. They also show that average farm size increased relatively rapidly over 1950-1974, then flattened out through the mid-1980s before increasing at a modest rate in the 1990s.

What is the US experience with GM crops? In 1995, no acreage of US 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 or cotton or *Bt*-corn (figure 1). Some areas were ripe for a new type of insect control due to building tolerance to existing insecticides (Zilberman 2004). *Bt*-cotton was 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. New GM-technology fears in 1999 slowed GM crop adoption in 2000.

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 have been adopted more slowly by US farmers, but by 2007 the adoption rate for HT- and IR-corn varieties reached 50 percent (figure 1). In 1996, biotech crop-variety adoption rates were 17 percent for cotton, 7 percent for soybeans and 4 percent for corn. Nevertheless, in 2007, these shares had increased to 87 percent for cotton, 91 percent for soybeans and 73 percent for corn.

In the Midwest, farmers' adoption of GM-crop varieties is affected by anticipated pest pressure and crop rotation (see ERS 2008; Runge and Ryan 2003). For example, of the eight Midwestern States in this study, Indiana, Missouri, and Iowa farmers were the leaders in HT-soybean varietal adoption by 2000—covering roughly 60 percent of planted soybean acreage (see figure 2).[1] By 2007, GM-soybean adoption rates converged across these states to roughly 90 percent.

GM-corn adoption rates for IR, HT and combined IR and HT traits 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 a decline in GM-corn adoption rates in the Midwestern States over 1999-2001. By 2007, more than 70 percent of the corn acres in Minnesota, Iowa and Missouri were planted to GM varieties.

[1] 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 US 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.

Of all the states that had adopted biotech varieties as of 2007, 60 percent of the value of biotech corn production is attributed to Iowa, Illinois, Minnesota, and Nebraska, and 54 percent of the value of biotech soybean production is attributed to Iowa, Illinois, Minnesota, and Indiana.

The Model of Aggregate Production

The contributions of technology, conventional and non-conventional, to production can be examined using production/transformation function or profit function frameworks. With the production function approach, output is regressed on inputs and approximations for productivity. However, with competitive behavior and a well-behaved production (or transformation) function, a one-to-one relationship exists between the production (or transformation) function and its dual, the profit function (Nadiri 1982; Chambers 1988). The dual approach yields a set of optimal *derived* output supply and input demand functions where output and input prices and one or more indicators for technology determine the quantity of inputs demanded and outputs supplied. In this environment, prices of outputs and variable inputs are exogenous variables in the dual approach. In contrast, if the production function is fitted directly, the inputs and outputs are all choices, so the endogenous regressor problem is likely to be severe.

Hence, the profit-function approach dramatically reduces concerns about endogenous regressors, but it is challenging to successfully estimate the derived output supply functions. The central problem is that some of the own-price elasticities may be negative rather than positive. Why is this? With state agricultural productivity having a strong positive trend, the quantity supplied of major crops is increasing at the same time that the relative price is largely unchanged or declining. In figure 4, which covers 1960-2004, there is roughly no trend in the plot of the relative price of corn against the quantity of corn produced in Iowa. In figure 5, which also covers the same period, there is a slightly positive trend between price and quantity. The challenge is to find a good proxy for technical or productivity change to shift the supply curve rightward or outward fast enough that we can identify a positive sloped supply curve.

Huffman and Evenson (1989), Shumway et al. (1988) and Bairam (1998) have found it fruitful to examine the structure of agricultural production in state aggregate data starting from a flexible aggregate multi-output and multi-input restricted profit function. Consider a multi-output multi-input production and define y_i , $i = 0,1,\ldots,$ n+m, to be the outputs and variable inputs. Of these, let y_0 be the numeraire commodity (one output) and $y_i > 0$, $i = 1, \ldots,$ n, be n other outputs. This leaves m variable inputs where $y_i < 0$, $i =$ n+1, …, n+m. Furthermore, define z_k to be (quasi-) fixed inputs or environmental factors, and let there be K of them, or $z_k \geq 0$, $k = 1, \ldots,$ K. These are the type of factors that are either not under the control of firm operators, are under the control of firm operators but require some time and adjustment costs, or are only partially under the control of firm operators. Hence, the associated transformation (or production) function is $F(y_0, y_1,\ldots, y_n, y_{n+1},\ldots. y_{n+m}; z_1,\ldots, z_K) = 0$. Under competition in the input and output markets and well-behaved technology, the associated normalized-restricted-expected-profit function is then $\pi = F(p_1,\ldots, p_n, p_{n+1},\ldots. p_{n+m}; z_1,\ldots, z_K)$ where P_0 is the price of y_0, and $p_i = P_i/P_0$, where P_i is the nominal price of y_i, $i = 1,\ldots,$n+m.[2]

To see that the normalized-restricted-profit-function is a flexible for investigating production technology (Nadiri 1982, p. 450-456), apply Hotelling's lemma to the restricted profit function. By taking first derivatives of the profit function with respect to prices of outputs and variable inputs, a set of output supply and input demand functions are derived. Moreover, the first derivatives of the profit function with respect to the quantity of (quasi-) fixed factors is equivalent to the first derivative of the production (transformation) function.[3] Hence, one obtains a set of *derived* aggregate agricultural output supply and

[2] Normalized profit functions with fixed or quasi-fixed factors are called *normalized restricted profit functions* (Nadiri 1982, p. 453). The *expected* profit function incorporates expected prices of the y_is, rather than actual prices. We ignore issues of risk and environmental quality.

[3] Consider the closely related short-run profit functions, $\pi_S = F(p_1,\ldots, p_n, p_{n+1},\ldots. p_{n+m}; z_1,\ldots, z_K) - p_z z$ where $z = (z_1,\ldots, z_K)$ and $p_z = (p_{z1},\ldots, p_{zK})$ where $p_{zi} = P_{zi}/P_0$ is the normalized price of z_i. Then, the optimal rate of use of z is defined by the envelope condition $\partial F( )/\partial z = p_z$ and $z^* = \zeta(p_1,\ldots, p_n, p_{n+1},\ldots. p_{n+m}, p_{z1},\ldots, p_{zK})$. The normalized long-run profit function then becomes $\pi_L = G(p_1,.., p_n, p_{n+1},.. p_{n+m}, p_{z1},.., p_{zK})$. However, if z_k is actually fixed, has significant adjustment costs or is only partially under the control of firms then the actual rate of use of z_k might be quite different from the optimal rate of use, or $\partial F( )/\partial z \neq p_z$ (Nadiri 1982).

variable input demand functions and a set of shadow-value functions for the quasi-fixed factors. If the shadow value and opportunity cost of these (quasi-) fixed factors are not equal, then the production plan is not at a long-run equilibrium (Nadiri 1982).

Three common flexible-form profit functions are the trans-log (Diewert 1974), normalized quadratic (Lau 1976), and generalized Leontief (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, the normalized-quadratic-restricted-expected-profit function has the nice feature that dependent variables are the quantity of outputs supplied and (variable) inputs demanded. In contrast, for the translog profit function, the associated dependent variables are profit shares. However, profit can be negative, positive or zero, which makes these shares very noisy. Shumway (1983), Shumway et al. (1988), and Huffman and Evenson (1989) have successfully employed the normalized-restricted-profit function and its associated output supply and input demand functions to examine the structure of aggregate farm production at the state level.

The exact algebraic form of the normalized-quadratic-restricted-expected-profit function for this study is:

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

The profit function (1) is linearly homogeneous in expected output and input prices and also has a Hessian matrix of constants, so that the local convexity in prices implies global convexity (Lau 1976). It has K quasi-fixed and environmental factors.

Derived Input Demand and Output Supply Functions. Given (1), the derived expected output supply and input demand equations follow directly from Hotelling's lemma:

$$y_i^* = \alpha_i + \sum_{j=1}^{n+m} \alpha_{ij} p_j + \sum_{k=1}^{K} \phi_{ik} z_k \,,\ i = 1,\ \ , \text{n + m.} \qquad (2)$$

The equation for the numeraire commodity is obtained residually: $y_0^* = \pi - \sum_{j=1}^{n+m} p_i y_i^*$, and substituting equation system (2) for y_i^*, the optimal quantity of the numeraire output y_0 is obtained:

$$y_0^* = \alpha_0 + \sum_{k=1}^{K} \beta_k z_k - \frac{1}{2} \sum_{i=1}^{n+m} \sum_{j=1}^{n+m} \alpha_{ij} p_i p_j + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} z_k z_l \,.^4 \qquad (2')$$

Equations (2) and (2′) are linear functions of the unknown parameters of the profit function; α_i's, α_{ij}'s, φ_{ik}'s, β_k's and β_{kl}'s.

Given (1), the slopes of (2) are second derivatives of the profit function, and cross-equation symmetric conditions are imposed, i.e., $\alpha_{ij} = \alpha_{ji}$, $i \neq j$, i, j = 1,…,n+m. Also, this set of restrictions extends to the equation for the numeraire output (2′). Since we do not claim to be testing production theory, we have imposed homogeneity of degree 1 and symmetry of cross-price effects on (2) and (2'). These restrictions reduce the number of unknown parameters in the model, which reduces the burden placed on the data when the model is estimated.

Given (2) and (2′), responsiveness of output and input decisions to a price change is summarized in the following elasticities:

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

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

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

[4] Including lagged values for the (m+n) dependent variables in each of the output supply and input demand equations is purely ad hoc.

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

Own-price elasticities of outputs supplied and inputs demanded are expected to be positive and negative, respectively. Moreover, inputs *i* and *j* are designated "substitutes" when $\eta_{ij} > 0$ and "complements" when $\eta_{ij} < 0$, and outputs *i* and *j* are designated "substitutes" if $\eta_{ij} < 0$ and as complements if $\eta_{ij} > 0$. Consistent with a well-behaved transformation function, we expect a majority of the input-input cross-price elasticities to be positive, and a majority of the output-output cross-price elasticities to be negative.

The Shadow-Value Equations. Also, from Hotelling's lemma, the shadow-value equations (Nadiri 1982) for the quasi-fixed and environmental factors associated with the normalized-quadratic-restricted-expected-profit function are

$$\lambda_k = \frac{\partial \pi}{\partial z_k} = \beta_k + \sum_{l=1}^{K} \beta_{kl} z_l + \sum_{i=1}^{n+m} \phi_{ik} p_i \ , \ k = 1, \ldots, \text{K}. \tag{4}$$

Given estimates for β_k, β_{kl} and ϕ_{ik} and values for z_l and p_i, the shadow-value equations are in principle estimable. If the marginal cost of z_l is available, then the shadow price (λ_k) and the marginal cost of z_l can be compared. If they are not significantly different, then z_l can be interpreted as being at a long-run "equilibrium" rate of use (Nadiri 1982).

Bias Effects on Production of z_l. A change in the z_k can twist the transformation function, and in doing so, changes the optimal quantities of outputs and inputs in a relative sense. Antle (1984) suggests one measure of bias caused by a change in z_k, and Huffman and Evenson (1989) generalized it to multiple output technology. Denote total revenue over (n + 1) optimal outputs as

$$\pi_R^* = y_0^* + \sum_{i=1}^{n} p_i y_i^* > 0, \tag{5}$$

and total cost over *m* optimal inputs as

$$\pi_C^* = \sum_{i=n+1}^{n+m} p_i y_i^* < 0. \tag{6}$$

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

$$s_i^R = \frac{p_i y_i^*}{\pi_R^*} > 0, \tag{7}$$

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

$$s_i^c = \frac{p_i y_i^*}{\pi_C^*} > 0. \tag{8}$$

The so-called "bias effect" on optimal revenue (cost) shares for y_i^* due to a marginal change in z_k is defined for outputs and inputs. The algebraic expression for the bias in optimal revenue shares (except for the numeraire good) is defined as:

$$B_{ik}^R = \frac{z_k}{s_i^R}\frac{\partial s_i^R}{\partial z_k} = z_k\left[\frac{\phi_{ik}}{y_i^*} - \frac{\left(\beta_k + \sum_{i=1}^{n}\phi_{ik}p_i + \sum_{l=1}^{K}\beta_{kl}z_l\right)}{\pi_R}\right] \leq \geq 0,\ i = 1,...,n, \tag{9}$$

and using (9) and the fact that revenue shares sum to 1 (= $s_w^R + s_s^R + s_c^R + s_v^R$), the algebraic expression for the bias in the numeraire output (wheat) is obtained:

$$B_{wk}^R = -\frac{s_s^R}{s_w^R}B_{sk}^R - \frac{s_c^R}{s_w^R}B_{ck}^R - \frac{s_v^R}{s_w^R}B_{vk}^R. \tag{10}$$

The bias for the i^{th} input's optimal cost share due to a marginal change in z_k is defined as:

$$B_{ik}^C = \frac{z_k}{s_i^C}\frac{\partial s_i^C}{\partial z_k} = z_k\left[\frac{\phi_{ik}}{y_i^*} - \frac{\sum_{i=n+1}^{n+m}\phi_{ik}p_i}{\pi_C}\right] \leq \geq 0,\ i = n+1,...,n+m. \tag{11}$$

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

The Data and Empirical Definitions of Variables

This study attempts to identify the impact on agricultural production in eight Midwestern States of replacing non-GM corn and soybean varieties with GM varieties. The eight states what is sometimes referred to as the Corn Belt States and Lake States. These are important states for the production of corn and soybeans in the United States, but no one state dominates the production of these crops. In addition to corn and soybeans, we also include wheat production because it is a small-grain crop that is grown in Midwestern States, but it is a non-GM crop because no GM-wheat varieties have been released for sale to farmers.[5] Livestock is of secondary interest to this study, so we aggregate livestock and livestock products produced into one output category. However, we acknowledge that livestock production has undergone major structural change in the Midwest since 1960 with rapid consolidation of swine, egg, and beef finishing into large confined operations (Huffman and Evenson 2006).

Hence, our output categories are: corn (for grain), soybeans, wheat, and livestock (and livestock products). Harvested corn for silage and other feed grains are assumed to be consumed by livestock within the state where they are produced, and therefore, are not considered directly in the analysis.[6]

To construct output measures for corn, soybean, and wheat, we start with data on bushels of corn, soybean and wheat harvested by state and year from USDA-NASS files, and create Tornquist index numbers of these quantities. The composite livestock output index includes the quantities of livestock and livestock products sold, and additions to inventory (and quantities consumed directly by the household) on a calendar year basis, as derived by Eldon Ball at ERS using methods described in Ball (1999, 2002). See also Ball et al. (2010)

[5] Wheat is included as an output because it is the most important small grain produced in the Midwestern States, and because no GM wheat has been released for planting. Hence, wheat production provides an interesting contrast to corn and soybeans where GM crop varieties first became available in 1996 and considerable progress has been made with the development of new GM varieties and traits (Fernandez-Cornejo 2008, Huffman 2009, NRC 2010).
[6] In early experimentation, we had a single crop aggregate, but that model did not perform well.

Variable farm inputs are grouped into five categories to provide a number of inter-relationships that can be examined econometrically, but that are not too large to cause estimation to fail. To reduce the job of data construction, we build upon the large investment made by ERS in measuring farm inputs at the state level over 1960-2004 (Ball et al. 2010). The input categories are farm capital services, including farm durable equipment and buildings (but excluding land) and breeding livestock, labor (self-employed, unpaid family and hired), energy (petroleum fuels, natural gas, and electricity), chemicals (commercial fertilizer and chemical pesticides) and other materials (includes primarily purchased livestock and livestock feed and seed, machine hire and contract labor). The quantities of these inputs are expressed in index numbers.

Six factors are chosen as (quasi-) fixed in our empirical research. First, consider farmland. The amount of land used in farm production by any farmer in a state and year is clearly a choice, but when we move to agriculture at the state level, opportunities for increasing acreage in any given year and state are quite limited. In the Midwest, farmland is slowly being converted to permanent nonfarm uses—housing and shopping mall development, location of manufacturing sites and general expansion of cities, and roads and highways. Also, some of the highly erodible farmland is under contract for the Conservation Reserve Program (CRP). A landowner can break his or her CRP contract and bring this land into production, but this triggers a sizable penalty and has seldom occurred. Moreover, any additional land that might be brought into crop production is likely to be inferior quality to existing cropland. For these reasons, we believe the best choice is to treat farmland as quasi-fixed. Our measure of farmland is the one available in the state accounts of ERS, which is an index of constant quality units (Ball et al. 2010). We assume that in each state

and year, farmland is allocated to corn, soybean, wheat, and livestock production and to CRP land.[7] Later, we will to do some testing of the endogeneity of land.

Second, consider indicators for GM-corn and soybean adoption. An important issue for this study is how to represent the effects of farmers planting GM-corn and soybean varieties on farm production. One important feature of this problem is that when farmers plant GM hybrid-corn varieties, they are replacing non-GM-seed corn with GM-seed corn on a kernel-per-kernel basis.[8] Likewise, when farmers plant GM-soybean varieties, they are replacing non-GM-soybean seed for GM soybean seed on a bean-for-bean basis. Hence, the adoption of GM-hybrid seed corn (GM-soybean seed) is approximately an equal displacement of non-GM hybrid seed corn (soybean seed). However, the USDA-NASS does not collect expenditure data from farmers on the GM vs non-GM nature of farm seed purchases, but they do collect data on crop- and trait-specific GM-adoption rates.

When farmers plant GM-soybean varieties, the bean plants are resistant to a target herbicide that roughly kills every plant in the bean field that is not genetically engineered to be herbicide tolerant (HT), e.g., *Roundup Ready* plants survive the application of the herbicide *Roundup*. Planting GM-soybean varieties allows farmers to replace the use of more expensive, less effective and more toxic herbicides and hand-weeding. It also gives farmers great weed control while at the same time providing a sizable window for effective application of the herbicide for which soybean plants have tolerance (Fenandez-Cornejo 2008). HT corn has many of the same advantages, although corn is more competitive against weeds than soybeans, and the herbicide Atrazine can be used on non-GM corn to control broadleaf weeds. However, Atrazine

[7] Here, we ignore the CRP payments. They are not central to this study.
[8] Note. The price is obviously higher for GM than non-GM hybrids.

use has contaminated ground water in the Midwest, and consumption of this polluted water is associated with birth defects, some forms of cancer and other health problems (Wikipedia 2011).

Insect resistant (IR) corn with the *Bt* gene is resistant to the European corn borer and somewhat resistant to the corn earworm and stock worm. *Bacillus thuringiensis* (*Bt*) is a bacteria that occurs naturally in the soil and with genetic engineering, *Bt* corn is transformed into a powerhouse producing insecticide to protect itself. Early *Bt*-corn varieties provided resistance primarily to the European corn borer and were somewhat protective against the corn earworm, the southwestern corn borer and to a lesser extent the cornstalk borer (Fernandez-Cornejo and McBride 2002). Later, *Bt*-corn varieties also carried resistance to the corn rootworms, which are a pest that reduces and weakens the root structure of the corn plants.

Several advantages exist for *Bt* corn varieties. First, the level of toxin expressed can be very high, thus delivering a lethal dosage to target insects. Second, the corn plant produces the toxin throughout its life and the toxin is expressed relatively uniformly throughout all plant parts. Hence, *Bt* provides season-long protection against target insects, but has no significant effect on other insects.[9] Third, the toxin expression can be modulated by using tissue-specific promoters, and GM resistance replaces the use of synthetic pesticides in an attempt to kill target insects. Fourth, the *Bt* toxin expressed in the corn plants is not toxic to humans or animals. Although the European corn borer is not a persistent major pest in most areas of the Midwest, it is a continual concern of all Midwestern corn farmers. New evidence shows that farmers planting non-GM corn hybrids are major beneficiaries from other farmers planting *Bt*-corn hybrids because area-wide moth counts have been steadily declining as the Bt-corn adoption rate in an area increases (Hutchinson et al. 2010).

[9] *Bt* produces spores that form the crystal protein insecticide δ-endotoxins. The protein toxin is active against species of the order Lepidoptera, Diptera, Coleoptera, Hymenoptra and nematodes. When these insects ingest toxin laden crystals, chemicals in their digestive track activate the toxin. It inserts into the insect's gut cell-membrane and dissolves it and eventually causes death of the insect (Wikipedia).

Clearly, GM-corn and soybean varieties provide new production opportunities for Midwestern farmers, and planting GM crop varieties may raise expected farm profits. The question is how to represent these effects in our production framework. Sexton and Zilberman (2011) have undertaken an international study of the impact of GM crop varieties on crop production in 25 countries over 1990-2008. They view GM-crop varieties as damage control technology, making it possible for plants to yield closer to their maximum potential. In the empirical work, they pooled data across crops (corn, soybean, cotton, and canola) and included year, country and crop fixed effects and fitted an aggregate production function, regressing total grain (bean, cotton) production against total land area allocated to a given crop and the area of that crop planted to GM crop varieties. They then interpret the estimated coefficient on GM crop acreage as the net (yield) benefit to planting GM crop varieties, and this coefficient is positive and statistically significant. However, they do not worry much about the endogeneity of total or GM crop acreage and ignore the fact that other inputs also affect production.

Building on USDA-NASS data, one indicator of the extent of GM crop usage is the GM-seed adoption rate (or non-GM seed displacement rate) for corn and soybean by state. Over 1996-2004, the GM adoption rate for soybean is only for HT-soybean seed and for hybrid corn is for HT, *Bt*, or HT+*Bt* hybrid corn varieties. The GM adoption rate has major appeal; it has a lower bound at zero and an upper value of 100 percent. NASS provides data for these GM adoption rates for Midwestern States starting in 2000. However, GM-corn and soybean varieties were first planted in 1996, but NASS only provides data on the adoption rate for GM varieties at the national level over 1996-1999. We use a graphing procedure, constraining the 1995 GM adoption rate at zero and the 2000 GM adoption rate to be equal to NASS's state- and crop-specific estimates, but

also including information about the trend in the crop's adoption rate over 2000-2004 (see figures 2 and 3).[10]

Moving forward, crop-specific GM adoption rates are the result of a combination of factors including seed availability or supply by the private seed industry, prices of GM- and non-GM seed, and local pest pressure. Moreover, each year the seed industry presents farmers with a revised set of available varieties, adding some new ones with enhanced performance attributes and deleting others that have become obsolete due to later R&D advances, erosion of pest resistance or/and poor sales. Hence, the GM adoption decision by any one farmer is complex, and then the adoption rate at the state level is an average rate over all farmers' decisions on the target crop planted. Hence, crop-specific GM adoption rates are a combination of factors weighing on both the supply and demand for seed. Later, we will examine the endogeneity of GM crop adoption rates.

Third, consider an indicator for knowledge stocks created by public agricultural research that might impact farm production at the state level. Huffman and Evenson (2006a), Huffman (2010), and others have shown that public agricultural research capital is a major factor explaining agricultural productivity at the state level. Also, Huffman and Evenson (1989) have shown that public agricultural research capital also affected outputs supplied and inputs demanded for cash grain farmers in state aggregate data. Based on these findings, we expect the stock of public agricultural research to affect production decisions of farmers in Midwestern States in this study.

Alternative measures of the stock of public agricultural research are possible. However, Huffman and Evenson (1989, 2006a), Huffman (2010) and others have had considerable success using a stock of public agricultural research created from public agricultural research undertaken

[10] Moreover, our graphing procedure produces estimates of GM adoption rates that are similar to those for GM corn in Iowa, Minnesota, and Ohio that are reported by Alston et al. (2010, pp. 252). They took the NASSA data on adoption rates by state in 2000 and worked backward using rough proprietary data on state-specific adoption rates.

by the USDA and Land-Grant System in the various states to explain state agricultural productivity. Public agricultural research is widely approximated by real expenditures on research by the USDA-ARS and ERS, and by the state agricultural experiment stations (SAESs), and veterinary medicine colleges (VMCs) that have an agricultural productivity focus (see for details Huffman 2010). Critical data for this effort are reported by the USDA's Current Research Information System (CRIS). The public agricultural research stock for each state is then derived by first allowing a two-year gestation period of no impacts followed by 31 years of first rising, then constant and finally declining weights, ending at zero. The timing weight pattern is approximated by a trapezoid (figure 4) and applied to annual real agricultural research expenditures by state to obtain research stocks. The resulting stock of public agricultural research is interpreted as a proxy for the "true" public agricultural research stock. This variable is constructed so that current production problems facing farmers do not affect the current stock of public agricultural research, which reduces endogenous regressor problems.[11]

We do not choose timing weights by Alston et al. (2010) because they apply an implausible methodology that ignores important advances in the construction of public agricultural research stocks by others over the past four decades. For example, (a) they assume public SAES research and Extension are perfect substitutes and have the same lag pattern in affecting productivity, which is a dubious assumption and distorts the structure of the weights. Since the mid-1970s, the standard has been to separate research and extension. (b) They use a gross measure of public agricultural research expenditures to construct research stock variables, even though a considerable amount of public agricultural research is on commodities and research problem areas that have no impact on agricultural productivity, e.g., research on recreation, rural

[11] See Khanna et al. (1994) for a discussion of the public- good perspective of public agricultural research and public provision of this good.

and community development, food science and human nutrition, family studies, and other types of post-harvest research. Huffman and Evenson have netted out these non-productivity oriented research expenditures (see Huffman 2010). (c) They treat the research by the USDA as being undertaken only by the Agricultural Research Services (ARS) and ignore all of the research of the Economic Research Service (ERS). Moreover, they treat the research of ARS as if it were undertaken in Washington, DC, and then spilling over to all 48 states, even though the USDA had moved its research facilities to state locations to be close to local production problems by the late 1930s. Data reported in the CRIS *Inventory of Agricultural Research* contradict their assumption. In our study, we exclude public agricultural extension as a quasi-fixed factor because data are not available over the latter years of the study period.

Farmers are assumed to know preseason precipitations when they make production plans and modify these plans accordingly, but of course, they do not know the actually weather that will be realized over an upcoming growing and harvesting season . For example, if the spring is unusually wet, farmers may shift some of their intended corn planting to soybeans, which are planted later in the spring. In Midwestern States, "preseason" precipitation is defined as falling over October through March before spring planting. Preseason precipitation for each state and year is measured in inches of water equivalent over October to the end of March before each growing season, and then expressed relative to the 30-year average precipitation over October to March for each state.

Minnesota, Wisconsin and Michigan lie north of the Corn Belt States and have a significantly shorter growing season. Dairying and wheat production are also more prevalent there, and dairying is quite labor intensive relative to other livestock production. Also, the northern half of these states consists of poor quality land for commercial farming (Huffman and Evenson 2006,

p. 271; USDA 1957, p. 535-552). Hence, we allow for some differences in the technology of farming for Lake States relative to Corn Belt States.

For expected prices of outputs and variable inputs, we use expected prices at planning or planting time. Implementing this procedure is complicated by the fact that some crop and livestock production plans are made at different times of the year, and that production cycles differ in length. The production of milk from dairy cows and eggs from hens is roughly a continuous process. However, the production cycle for meat and poultry varies roughly from three months with broilers, five months for swine, to two years from the birth of beef calves to the date of slaughter of the fattened steers and heifers.[12] To economize on work to obtain an expected livestock output price index, we chose to use the index of prices received by farmers for livestock and livestock products that is available in the state agricultural production accounts of ERS. Moreover, this livestock output price index has the major advantage of matching the livestock output quantity index of ERS, which we are also using (Ball et al. 2010).

For (variable) inputs, we also assume that expected prices at planning time are reflected in actual prices paid by farmers (or their opportunity cost in a few cases). We note that farmers frequently contract for materials before planting time. Price indexes for our (variable) input groups are reported in the state agricultural accounts of ERS and match up with our input quantity indexes (Ball et al. 2010).

Corn, soybean and wheat outputs are defined narrowly, and this opens up new possibilities for an approximation to farmers' expected prices for these outputs at planning time.[13] For

[12] Although futures' market prices exist for some livestock and livestock products, they do not exist for all, and it would be difficult to construct a meaningful weighted price index with a mixture of futures' and actual prices received. We do recognize that our particular choice of a livestock price index may contain measurement error.

[13] In an earlier step, we experimented with using the actual crop price data reported in the state accounts of ERS (Ball et al. 2010), which represents prices received by farmers in a given calendar year, including adjusting upward for actual farm program payments received. At this stage, we were using a single composite crop indicator and used

example, Huffman and Evenson (1989) successfully used commodity-specific futures market prices adjusted for state-specific basis to examine state aggregate farm production decisions on feed grains, wheat, and soybeans of cash grain farms.

Here, we follow Huffman and Evenson (1989) and use commodity-specific futures market prices at planning/planting time for the harvest date, adjusted for the state-specific basis for corn, soybean, and wheat. Average closing futures market prices in the planning month for the harvest date are the average of the Thursday closing prices in the planning month for the harvest month futures contract. The planning month is April for corn, soybean, and spring wheat, but August of the previous year for winter wheat. The best match of available data for harvest-month futures contracts is December for corn, November for soybeans, and July for spring and winter wheat. The state-specific basis reflects largely transportation (but also storage) costs associated with getting the grain/beans from farms to a river terminal market. The basis is 25 percent to 35 percent higher for soybean than corn, and the basis trends upward over time due to rising transportation costs.

All quantity and price indexes for inputs and outputs are expressed relative to the corresponding quantity and price index for Alabama in 1996 (Ball et al. 2010).

The Econometric Model

To obtain the empirical specification of the equations (2) and (2′), we define wheat as the numeraire commodity (y_0) and the expected price of wheat becomes the numeraire price (P_0). Table 1 contains a list of the key variables, and symbolic definitions and sample means and standard deviations for these variables.

In the econometric model, we add a zero mean random disturbance term to the nine output supply and input demand equations, or μ_{ilt} ,i = specific supply or demand equation, l = state, t =

ERS's price index from the state agricultural accounts. When we fitted this production system, we obtained poor results.

year. The variable d_1 takes a value of 1 if a state is a Lake State (Minnesota, Wisconsin or Michigan) and 0 otherwise and is included in the empirical specification of output supply and variable input demand equations.

We include a linear time trend and first-order autocorrelation to control for likely time-series process issues. The time trend controls for omitted variables that are correlated with time, e.g., change over time in the organizational structure of livestock production in Midwestern optimal farm size, and share of corn harvested that is sold for out-of-state uses, such as for exports. It also ensures that the means of all series are not trended. In annual aggregate time series data, we can expect some spillover of shocks (μ_{it}) from one period to the next (Enders 2010; Greene 2003). Hence, we allow for first-order autocorrelation by reparameterizing the nine output supply and input demand equations as follows:

$$Y_{it} = X_{it}\delta_i + \varphi d_{1\text{it}} + \gamma\, t + \mu_{it},\ i = 1, \ldots 9;\ t = 1, \ldots 45. \qquad (12)$$

Given that output supply and input demand equations contain cross-equation restrictions, all equations must receive the same auto-regressive transformation in the final estimation (Barten 1969). Hence, define $\mu_{it} = \rho\, \mu_{it\text{-}1} + \varepsilon_{it}$ where ε_{it} is uniformly distributed with a zero mean, variance σ_i^2 (allowing for heteroscedasticity across equations), and is uncorrelated over time.

To obtain an estimate of ρ we first fitted equation (12) without regard to cross-equation restrictions. We then collected the residuals from all nine equations together and use them to estimate one single value for ρ, which is 0.620 with a t-value of 115. Under plausible assumptions, there is a 99.9 percent probability that the random confidence interval ($0.48 \leq \rho \leq 0.76$) covers the true parameter. Moreover, this confidence interval does not include and, in fact, is far away from one, so a unit root of the production system *with trend* is highly unlikely.

Using $\hat{\rho} = 0.620$, equation (12) is then transformed into a nine-equation model that is expressed as pseudo first-differences:

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

The production system (13) is then estimated in a straight forward way as a quasi-differenced-seemingly-unrelated (SUR) regression model *with cross-equation restrictions imposed* (Greene 2008, Zellner 1962, Barten 1969).

The Empirical Results

The estimated coefficients and *t*- or *z*-values for the non-numeraire equations are reported in table 2, and for the numeraire (wheat) supply equation are reported in table 3. The set of estimated coefficients displayed in tables 2 and 3 provide new evidence of the structure of farm production in Midwestern States over 1960-2004. There are 344 observations per equation and nine equations, or 3,096 total observations, and a total of 135 different coefficients being estimated after imposing cross-equation restrictions. A quick check of table 2 shows that the estimated α_{ii}'s are positive as expected, except for livestock where the coefficient is not significantly different from zero. All of these estimated coefficients with positive signs are significantly different from zero at the 5 percent level.

Turning to variable d_1 in the non-numeraire equations, the supply of corn and soybeans is significantly less and of livestock and wheat (with the latter coefficient being 1.642) is significantly greater in the Lake States than in the Corn Belt States, other things equal. Also, the quantity of labor and "other materials" demanded are substantially larger and of farm capital and energy are slightly larger in the Lake States than the Corn Belt States. These results are also consistent with the lake states engaging in more labor-intensive agriculture, especially dairy, and in wheat production. The quantity of farm chemicals is significantly lower in the Lake States than Corn Belt States, largely reflecting the fact that livestock manure is a more important source of

soil nutrients than commercial fertilizer there. In addition, the system of equations has significant trend effects, except for farm energy and chemical inputs and soybean output.[14]

Estimates of Supply and Demand Elasticities. The responsiveness of farms to (expected) prices of outputs and inputs is an important part of behavior and reveals new information about the structure of production. The own-price and cross-price elasticities for the four outputs and five (variable) inputs are obtained by evaluating equation (3) using estimated coefficients from table 2 and 3 and 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, except for livestock. The negative own-price effect for livestock can be rationalized by thinking of the farmers responding to an increase in livestock prices by marketing animals at lighter weights or building breeding-stock inventories, i.e., our model does not capture the dynamics of the livestock production very well. Among the outputs, the own-price elasticity of supply for wheat is largest, 0.81, for corn is moderate, 0.32, and for soybeans is smallest, 0.13. Hence, the elasticity of supply of major crops produced in Midwestern States is substantial. Among inputs, the own-price elasticity of demand for farm chemicals is largest, -0.69, and followed by farm energy, -0.37 and "other materials, -0.28. The other (variable) inputs have somewhat smaller own-price elasticities; -0.09 for farm capital services and -0.04 for farm labor.

The cross-price elasticities for (variable) inputs provide insights on which pairs are substitutes and which are complements (table 4). Farm capital services and farm labor, energy and chemicals are substitutes, and capital services and "other materials" are complements. Farm labor is a strong substitute for "other materials" and weak substitute for farm capital services and energy but a complement with farm chemicals. Farm energy is a substitute for farm chemicals, capital services, and labor but a complement for "other materials." Farm chemicals are a substitute for

[14] At the sample mean of the data, the estimated coefficient of trend in the numeraire or wheat equation is -0.020.

farm energy, "other materials," and capital services but a complement with farm labor. "Other materials" are a substitute for farm chemicals and labor but a complement for farm energy and "other materials."

We expect an increase in the price of an input to generally reduce the supply of outputs, but not all supply effects need to be negative. An increase in the price of farm capital services (labor) reduces the supply of corn and soybeans but increases the supply of wheat and livestock (table 4). An increase in the price of farm energy reduces the supply of wheat, corn, soybean, and livestock. An increase in the price of "other materials" reduces the supply of wheat, corn, soybean and livestock but increases the supply of wheat. Hence, 14 of 20 input-price effects on outputs supplied are negative.

An interesting feature of our model of production is that we have estimates of the cross-price supply elasticities. An increase in the price of soybeans decreases the supply of corn and wheat, suggesting trade-offs among crop outputs along the transformation frontier. However, this increase in price of soybeans also increases the supply of livestock. An increase in the expected price of corn decreases the supply of wheat but increases the supply of soybeans and livestock. The impact of the price of corn on the supply of livestock can be rationalized as follows: a higher expected price of corn leading farmers to sell-off feeder livestock earlier or reduce livestock herd sizes. An increase in the price of wheat reduces the supply of soybean, corn, and livestock. Consistent with these cross-price effects representing trade-offs, 7 of the 12 output cross-price elasticities are negative. The other outcomes suggest some type of complementariness. Turing to the impact of output prices on input demand, an increase in expected output prices increases the quantity demanded for almost all of the inputs; 14 of 20 elasticities of input demand with respect to output prices, which is as expected.

We also examined the performance of a closely related product system. We tried instrumenting land and GM-soybean and GM-corn adoption rates by using the one-year lagged value of each of these variables and then re-estimating.[15] If the estimated coefficients with the instrumented variable are similar to those in the original results, this may be interpreted as supporting exogeneity. If they change significantly, this is evidence against exogeneity (Greene 2003). When we instrumented with the one-year lagged land variable and GM-soybean and corn adoption rates, the estimated coefficients were similar. The main difference is that the own-price elasticity of supply of wheat is a little larger when we use these one-year lagged variables. This is expected because much of the wheat grown in the Midwest is winter wheat. Tests reported in the next section of the paper also support the simpler production system; not using lagged values of fixed factors.[16]

Impacts of z_l on Quantities Supplied and Demanded. Tables 2 and 3 show that an increase in available land increases the supply of all outputs and demand for all inputs. An increase in the adoption rate for GM-soybean varieties significantly reduces the demand for farm energy and increases the supply of soybeans but other effects are small. An increase in the GM-corn adoption rate significantly reduces the demand for farm capital services and labor (at 10% level) but reduces the supply of wheat. Other effects are small and statistically weaker. An increase in public agricultural research increases the supply of all outputs and the demand for all inputs. Larger preseason precipitation reduces the supply of corn and increased the demand for farm capital services, but other effects are relatively weak.

Shadow-Values of z_l. Estimates of the shadow-value of (quasi-) fixed factors are obtained using equations (4), estimates of coefficients from tables 2 and 3 and sample mean values of the

[15] These are plausible but not perfect instruments. We don't have a long list of potential instruments, and any set can be questioned.

[16] These additional results are available from the authors upon request.

variables from table 1, which results in a state average value. They show that the shadow-value of a unit of farmland is $1.67 per dollar of land services (in 1996 prices). This number is substantially larger than one, and supports our hypothesis that land is a quasi-fixed and not a variable input. It also suggests that the conversion of farmland to nonfarm uses has been at a significant cost to the agriculture sector in the Midwest.

An increase in the adoption rate for GM-soybean varieties (and displacement of non-GM soybean varieties) by one percentage point has a shadow-value of about $32 million (in 1996 prices) per year per state. This is an estimate of the benefits from switching from non-GM soybean to GM-soybean varieties. When we convert this to average value per acre of harvested soybeans over 1996-2004, we obtain a value of $5.70 dollars (1996 prices) per acre. This shadow-value is roughly equal to the herbicide-tolerant technology fee (in 1996 prices) on HT seed soybeans in effect over 1996-2004. However, our measure of profit does not account for the benefit to farmers from GM soybeans due to ease of use of the technology, wide window of effective application, and low level of management skill requirement (Fernandez-Cornejo 2008). Moreover, over the GM-technology period, the acres of soybeans harvested in the Midwest region grew relative to corn acreage harvested—from 11 percent fewer soybean acres than corn in 1996 to only 2 percent less in 2004 (USDA-NASS).

The shadow-value of the GM-corn variety adoption rate is substantially larger than for the GM-soybean adoption rate. The shadow-value of increasing the GM-corn variety adoption rate by one percentage point is $270 million (1996 prices) per year per state or roughly an average of $47.40 per acre. This value is much larger than the GM-technology fee on GM-hybrid seed corn over 1996-2004 of roughly $10-12 per acre (for two traits) and is consistent with the fact that the frequency of use of GM-corn varieties has risen rapidly over 2004-2007 (figure 3). We conclude that treating the GM soybean and corn adoption rates as quasi-fixed is a reasonable approximation

to reality, given their shadow-value seems to be different from the technology fee on GM seeds and that the GM-corn and soybean adoption rates have not peaked in 2004.

The shadow-value of a unit ($1 million) increase in public agricultural research capital is $207 million per year (in 1996 prices or $126 million in 1984 prices). These benefits are distributed over a 35-year period as in figure 6 and imply a 72 percent marginal real internal rate of return. This rate of return falls with the 75-25 percentile range on the real rates of return to public agricultural research reported by Huffman and Evenson (2006, p. 294-295).[17] Hence, public funds invested in agricultural research in the Midwest have provided a large rate of return; one that is very large relative to alternative public sector investments in these states.

The shadow-value of one inch of preseason precipitation is also positive—roughly $49 million per year per state (in 1996 prices).

Bias Effects of Quasi-Fixed Factors. When z_l changes, it might cause neutral effects on inputs demanded and outputs supply, but more likely is a non-neutral or biased effect. The estimates of the bias effects (impact on optimal cost or revenue shares) of (quasi-) fixed factors are obtained by evaluating equations (9), (10) and, (11) using estimated coefficients from tables 2 and 3 and sample mean values of the variables from table 1. The magnitude of bias effects is in general small for inputs but larger in some cases for outputs (see table 5). Additional land biases optimal cost shares toward farm energy, "other materials," chemicals and capital services but against farm labor. Additional land also biases optimal revenue shares strongly toward wheat and modestly toward soybeans but against livestock and corn.

Increasing the GM-soybean varieties adoption rate biases optimal input shares toward farm chemicals as expected, and toward farm labor but against farm capital services, energy and "other

[17] This analysis assumes that a marginal increase in public agricultural research capital leaves soybean, corn, wheat and livestock output prices and farm capital service, labor, energy, chemical and "other material" input prices unchanged.

materials." It also biases optimal revenue shares toward wheat and livestock and away from corn but has no effect on the optimal revenue share for soybeans. The adoption of GM-corn varieties biases optimal input cost shares toward "other materials," farm energy, and chemicals but against farm capital services and labor. Surprisingly, it also biases optimal revenue shares toward wheat and away from corn, soybean, and livestock.

An increase in public agricultural-research-capital biases input shares strongly toward farm chemicals and "other materials," which are major purchased inputs of Midwestern farmers, but against farm labor, capital services, and energy. It also biases optimal revenue shares strongly toward wheat and moderately toward corn but against soybean and livestock.

Overall, it is seems surprising that the adoption of GM-soybean (corn) varieties has not biased optimal revenue shares toward soybean (corn) output. However, on the input side, the bias effects are more in line with expectations. An increase in the GM-soybean variety adoption rate biases optimal input cost shares toward agricultural chemicals. However, the adoption of GM-corn strongly biases optimal input cost shares toward farm chemicals and "other materials." The increase in the share for farm chemicals may be a reflection of farmers spending more on additional fertilizer and *Roundup* with GM-corn varieties than is saved from application of less insecticide when planting *Bt*-corn varieties.

Conclusions

This paper provides new empirical evidence about the structure of agriculture production in the US Midwest over 1960-2004, a region known for its productive rain-fed farmland and production of corn, soybeans, and livestock and, to a lesser extent, wheat. The new estimates of supply elasticities for wheat, corn and soybeans vary in size but overall show farmers to be quite responsive to expected output price changes. On the input side, farmers are shown to be quite responsive to the prices of farm chemicals, energy, and "other materials," but the price elasticities

of demand for farm capital services and labor are shown to be somewhat smaller. A majority of input-price cross elasticities are positive, but not all. For example, farm capital services and "other materials" are complementary with labor. Among cross-price elasticities for outputs, a majority are negative.

Adjustments in (quasi-) fixed factors are shown to shift the output supply and input demand functions and to bias the composition of outputs produced and variable inputs used. A higher GM-soybean adoption rate (or displacement of non-GM varieties) reduces significantly the demand for farm energy and biases optimal input cost shares toward farm chemicals. A higher adoption rates for GM corn significantly reduces the demand for farm capital services and labor and biases optimal input cost shares toward farm chemicals. Hence, both GM-soybean and corn variety adoption bias optimal input-cost shares toward farm chemicals and the measure is small but of exactly the same size.

Investments in public agricultural research are shown to increase the supply of farm outputs and demand for farm inputs in the Midwest, and hence, to have many effects on the structure of farm production. In particular, an increase in the stock of public agricultural research increases significantly the supply of soybeans, corn, wheat and livestock and demand for farm capital services, labor, energy, chemicals and "other materials." An increase in public agricultural research also biases optimal input costs share toward farm chemicals and "other materials" but away for farm labor, capital, and energy. Moreover, these changes occur in such a way that aggregate farm profit increases and the real rate of return from marginal investments in public agricultural research in the Midwest over the study period is quite large, at 72 percent.

We have eight years of data on GM corn and soybean variety adoption by Midwestern farmers. As data for later years becomes available and GM corn and soybean adoption rates move closer, new research will examine the impacts on farmers' production decisions.

References

Alston, J.M., M.A. Andersen, J.S. James and P.G. Pardey. *Persistence Pays*: *U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending.* New York, NY: Springer 2010.

Antle, J. "The Structure of U.S. Agricultural Technology, 1910-1978." *American Journal of Agricultural Economics* 66(1984):414-21.

Bairam, E.I. (Ed.) *Production and Cost Functions*: *Specification, Measurement and Applications.* Aldershot, U.K, 1998, pp. 68-106.

Ball, V.E., S.L. Wang and R. Nehring. "Agricultural Productivity in the United States: Data Documentation and Methods." 2010. Available at: http://www.ers.usda.gov/data/agproductivity/methods.htm

Ball, V.E. "Modeling Supply Response in a Multiproduct Framework." *American Journal of Agricultural Economics* 70(1988):813-25.

Ball, V.E., F. Gollop, A. Kelly-Hawke, and G. Swinand. "Patterns of Productivity Growth in the U.S. Farm Sector: Linking State and Aggregate Models." *American Journal of Agricultural Economics* 81(1999):164-79.

Ball, V.E. and G.W. Norton. *Agricultural Productivity: Measurement and Sources of Growth*. Kluwer Academic Press, 2002.

Barten, A.P. "Maximum Likelihood Estimation of a Complete System of Demand Equations." *European Economic Review* 1(1969):7-73.

Chambers, R.G. *Applied Production Analysis-A Dual Approach*. New York, NY: Cambridge University Press, 1988, pp. 120-290.

Chambers, R.G., R. Fare, S. Grosskopf and M. Vardanyan, "Generalized Quadratic Revenue Functions." University of Maryland, Department of Agricultural and Resource Economics, Working Paper, August 2008.

Clark, J.S. and C.E. Youngblood. "Estimating Duality Models with Biased Technical Change: A Time Series Approach." *American Journal of Agricultural Economics* 74(May 1992):353-60.

Diewert, W.E. "An Application of Shephard Duality Theorem, A Generalized Leontief Production Function." *Journal of Political Economy* 79(1971):481-507.

Diewert, W.E. "Functional Forms for Revenue and Factor Requirement Functions." *International Economic Review* 15(1974):481-507.

Enders, W. *Applied Econometric Time Series.* Hoboken, NJ: John Wiley & Sons, Inc. 2010.

ERS (Economic Research Service). "1996 FAIR Act Frames Farm Policy for 7 Years." *Agricultural Outlook Supplement*, April 1996.

ERS. "Adoption of Genetically Engineered Crops in the U.S." A Data Set Product of the U.S. Department of Agriculture, 2008. Available at: http://www.ers.usda/data/biotechcrops/

Evenson, R.E. "Economic Impacts of Agricultural Research and Extension." In B.L. Gardner and G. Rausser, Eds., *Handbook of Agricultural Economics*, Vol. 1A. New York, NY: North-Holland, 2001, pp. 574-628.

Fernandez-Cornejo, J. "The Seed Industry in U.S. Agriculture: An Exploration of Data and Information on Crop Seed Markets, Regulation, Industry Structure, and Research and Development. *Agricultural Information Bulletin No.* 786 (AIB786), Jan. 2004.

Fernandez-Cornejo, J. "The Impact of Adoption of Genetically Engineered Crops on Yields, Pesticide Use and Economic Returns in the USA." Presented at the Farm Foundation Conference on Biotechnology, Washington, D.C., Jan. 16, 2008.

Fernandez-Cornejo, J. and M. Caswell. "The First Decade of Genetically Engineered Crops in the United States." USDA-ERS, *Economic Information Bulletin*, No. 11, April 2006.

Fernandez-Cornejo, J. and W.D. McBride. "Genetically engineered Crops for Pest Management in U.S. Agriculture: Farm-Level Effects." *Agricultural Information Economics Report* No. 786, April 2000.

Fernandez-Cornejo, J. and W.D. McBride. "Adoption of Bioengineered Crops." *Agricultural Economics Report* No. 810, May 2002.

Fuss, M and D.L. McFadden. *A Dual Approach to Theory and Applications*. Vol. 1. The Theory of Production. Amsterdam, The Netherlands: Elsevier North Holland, 1978.

Greene, W.H. *Econometric Analysis*. 5th ed. Upper Saddle River, NJ: Prentice Hall 2003.

Greene, W.H. "Econometric Analysis of Panel Data." Department of Economics, Stern School of Business, New York University, 2008.

Griliches, Z. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25(1957):501-522.

Griliches, Z. "Hybrid Corn and the Economics of Innovation." *Science* 132(1960):275-280.

Hamilton, J.D. *Time Series Analysis.* Princeton, NJ: Princeton University Press, 1994.

Huffman, W.E. "Measuring Public Agricultural Research Capital and Its Contribution to State Agricultural Productivity." Iowa State University, Department of Economics Working Paper #09022, Aug. 2010.

Huffman, W.E. "Technology and Innovation in World Agriculture: Prospects for 2010-2019." Iowa State University, Department of Economics, Working Paper #09007, April 2009.

Huffman, W.E. "Contributions of Public and Private R&D to Biotechnology Innovation." In *Genetically Modified Food and Global Welfare*, C. Carter, G. Moschini and I. Sheldon, Eds., Bingley, UK: Emerald Publishing Group forthcoming.

Huffman, W.E. and R.E. Evenson. "Supply and Demand Functions for Multiproduct U.S. Cash Grain Farms: Biases Caused by Research and Other Policies." *American Journal of Agricultural Economics* 71(1989):761-73.

Huffman, W.E. and R.E. Evenson. *Science for Agriculture*: *A Long-Term Perspective*. Ames, IA: Iowa State University Press 1993.

Huffman, W.E. and R.E. Evenson. "Structural and Productivity Change in U.S. Agriculture, 1950-1982. *Agricultural Economics* 24(2001):127-147.

Huffman, W.E. and R.E. Evenson. *Science for Agriculture*: *A Long-Term Perspective*. Ames, IA: Blackwell Publishing 2006.

Huffman, W.E., V.E. Ball, M. Gopinath, and A. Somwaru. "Public R&D and Infrastructure Policies: Effects on Cost of Midwestern Agriculture." *Agricultural Productivity: Measurement and Sources of Growth*. Kluwer Academic Press, 2002. pp. 167-83.

Hutchinson, W.D., E.C. Burkness, P.D. Mitchell, R.D. Moon, T.W. Leslie, S.J. Fleischer, M. Abrahamson, K.L. Hamilton, K.L. Steffey, M.E. Gray, R.L. Hellmich, L.V. Kaster, T.E. Hunt, R.J. Wright, K. Pecinovsky, T.L Rabaey, B.R. Flood and E.S. Raun. "Areawide Supression of European Corn Borer with Bt Maize Reaps Savings to Non.-Bt Maize Growers." *Science* 330(Oct. 8, 2010):222-225.

Karagiannis, G. and G.J. Mergos. "Total Factor Productivity Growth and Technical Change in a Profit Function Framework." *Journal of Productivity Analysis* 14(2000):31-51.

Khanna, J., W.E. Huffman and T. Sandler. "Agricultural Research Expenditures in the United States: A Public Goods Perspective," *Review of Economics and Statistics*, 76(May 1994):267-277.

Lau, L.J. "A Characterization of the Normalized Restricted Profit Function." *Journal of Economic Theory* 12(1976):131-63.

Lim, H. and C.R. Shumway. "Technical Change and Model Specification: U.S. Agricultural Production." *American Journal of Agricultural Economics* 79(1997):543-54.

McKay, L., D. Lawrence, and C. Vlastuin. "Profit, Output Supply, Input Demand Functions for Multiproduct Firms: The Case of Australian Agriculture." *International Economic Review* 24(1983): 323-39.

Mundlak, Y. “Production and Supply.” In B.L. Gardner and G. Rausser, *Handbook of Agricultural Economics,* Vol 1A (*Agricultural Production*), New York, NY: North Holland, 2001, pp. 1-85.

Nadiri, M.I. “Producers Theory.” *Handbook of Mathematical Economics*. Vol. 2, K.J. Arrow and M.D. Intriligator, Eds. New York, NY: North-Holland Publishing Co., 1982.

Nelson, C.R. and C. I. Plosser. “Trends and Random Walks in Macroeconomic Analysis.” *Journal of Monetary Economics*. 10(1982):139-62.

NRC (National Research Council, Committee on the Impact of Biotechnology on Farm-Level Economics and Sustainability). *The Impact of Biotechnology on Farm-Level Economics and Sustainability*. Washington, DC: The National Academies Press 2010.

Runge, C.F. and B. Ryan. “The Economic Status and Performance of Plant Biotechnology in 2003: Adoption, Research and Development in the United States.” A study prepared for The Council for Biotechnology Information (CBI), Washington, DC. 2003.

Sexton, Steven and David Zilberman. “Land for Food and Fuel Production: The Role of Agricultural Biotechnology.” In Agricultural Economics, J. Zivin and J. Perloff, Editors, Chicago, IL: The University of Chicago Press, 2011.

Shumway, C.R. “Supply, Demand, and Technology in a Multiproduct Industry: Texas Field Crops.” *American Journal of Agricultural Economics* 65(1983):748-60.

Shumway, C.R., R.R. Saez, and P.E. Gottret. “Multiproduct Supply and Input Demand in U.S. Agriculture.” *American Journal of Agricultural Economics* 70(1988):330-37.

Shumway, C.R., and H. Lim. “Functional Form and U.S. Agricultural Production Elasticities.” *American Journal of Agricultural Economics* 18(1993):266-76.

Taylor, R.D., E.A. DeVuyst and W. Koo. “Potential Impacts of GM Wheat on United States and Northern Plains Wheat Trade.” North Dakota State University, Center for Agricultural Policy and Trade Studies, Department of Agribusiness and Applied Economics, Agribusiness & Applied Economics Report No. 515, May 2003.

USDA. *The Year Book of Agriculture 1957: Soils*. Washington, DC: U.S. Government Printing Office 1957.

Wikipedia, “Atrazine.” 2011. Available at: http://en.wikipedia.org/wiki/Atrazine

Wilson, W.E., E.L. Janzen and B.L. Dahl. “Issues in Development and Adoption of Genetically Modified (GM) Wheat.” *AgBioForum* Vol. 6, No. 3(2003):1-20

Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press, 2002.

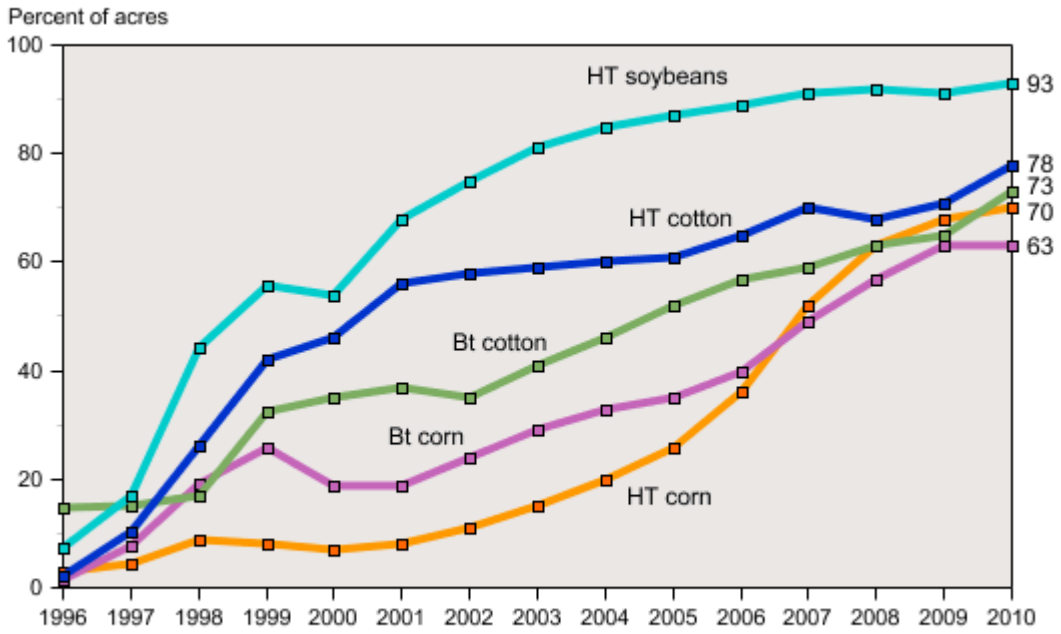
Yee, J. "Assessing Rates of Return to Public and Private Agricultural Research." *Journal of Agricultural Economic Research* 44(1992):35-41.

Yee, J., W.E. Huffman, E. Wallace., M. Ahearn, and D. Newton. "Sources of Agricultural Productivity Growth at the State Level, 1960-1993." *Agricultural Productivity: Measurement and Sources of Growth*. Kluwer Academic Press, 2002, pp. 185-210.

Zellner, A. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistically Association* 57(1962):348-368.

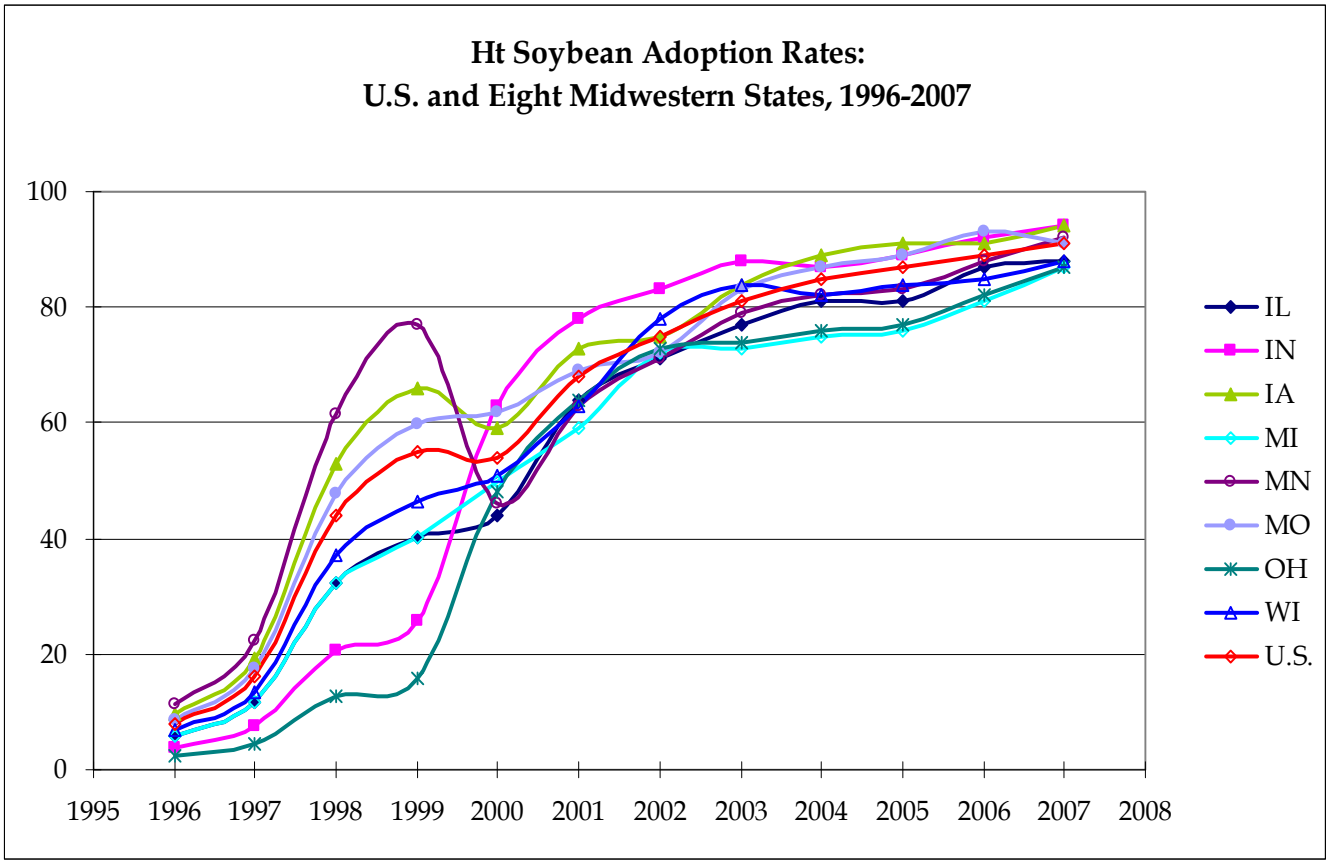
Zilberman, D. "The Economics of Pesticide Usage." Department of Agricultural and Resource Economics, University of California Berkeley, 2004. Available at: http://are.berkeley.edu/%7Ezilber/

Figure 1. Percent Adoption of GM Corn, Cotton and Soybean Varieties in the United States, by Trait Type, 1996-2010



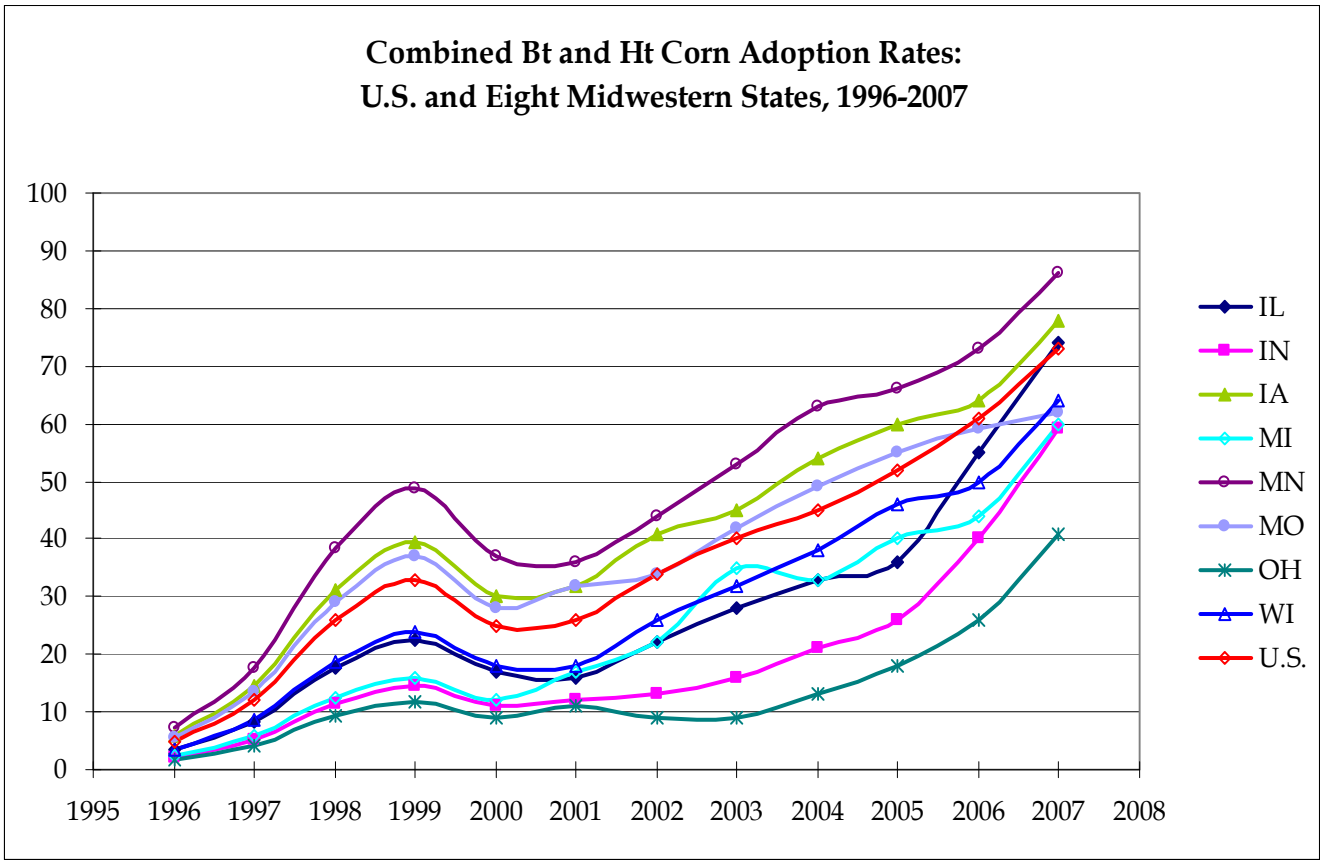
Note: Data for each crop category include varieties with both HT and *Bt*(stacked traits.
Source: USDA 2010

Figure 2



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

Figure 3



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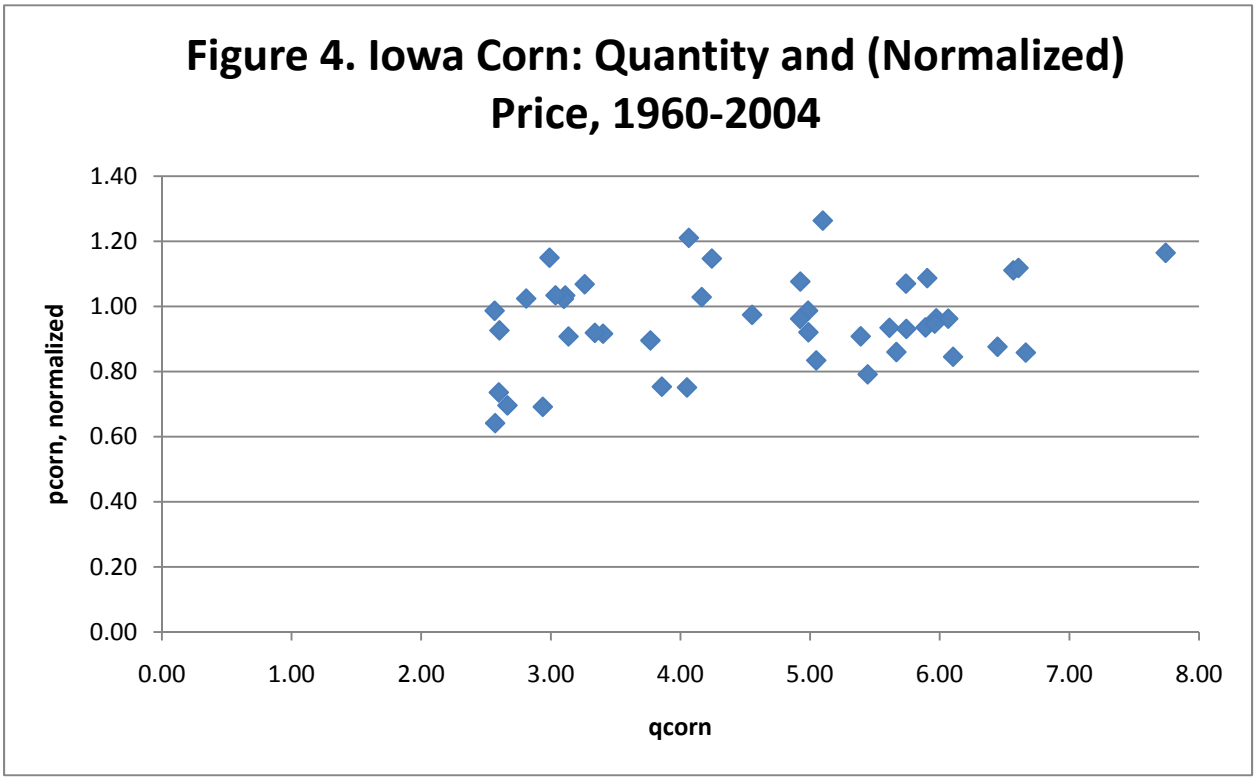
Figure 4. Iowa Corn: Quantity and (Normalized) Price, 1960-2004
pcorn, normalized
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
qcorn

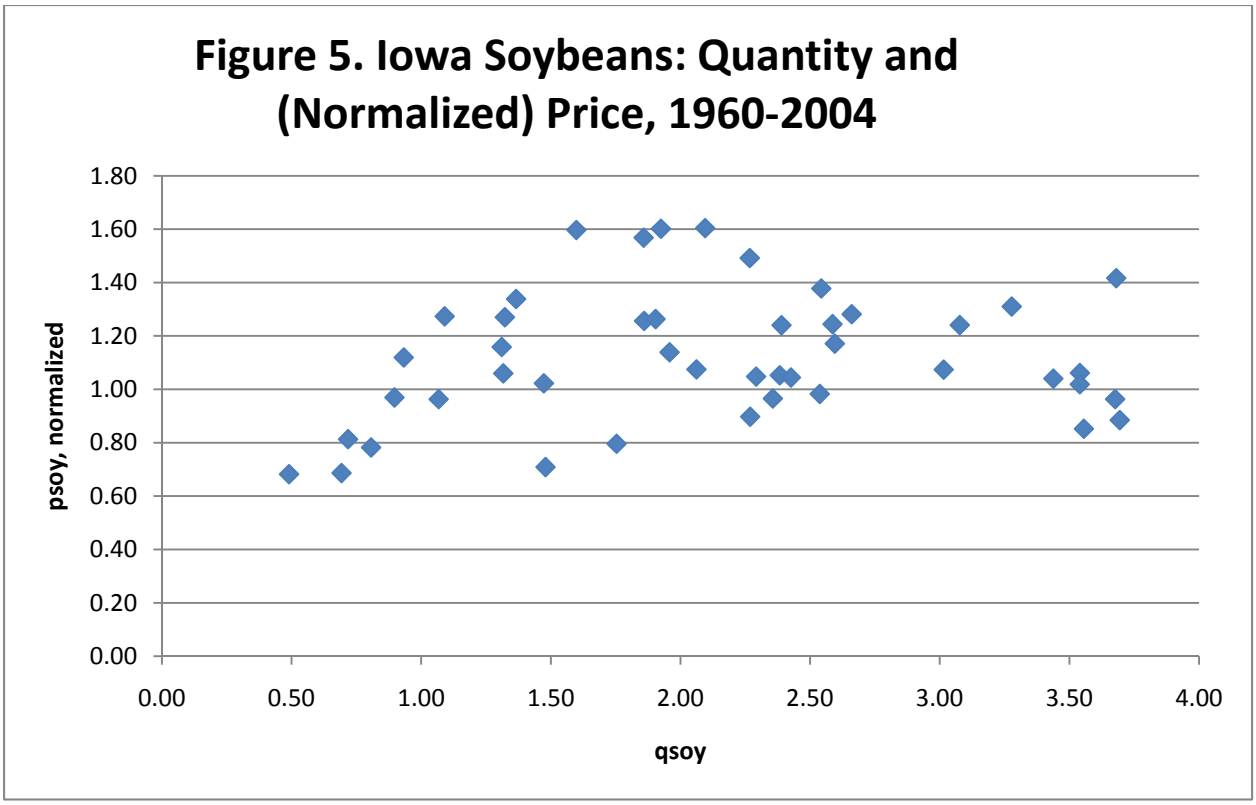
Figure 5. Iowa Soybeans: Quantity and (Normalized) Price, 1960-2004
psoy, normalized
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
0.00
0.50
1.00
1.50
2.00
2.50
3.00
3.50
4.00
qsoy

Figure 6. Public Agricultural Research Timing Weights

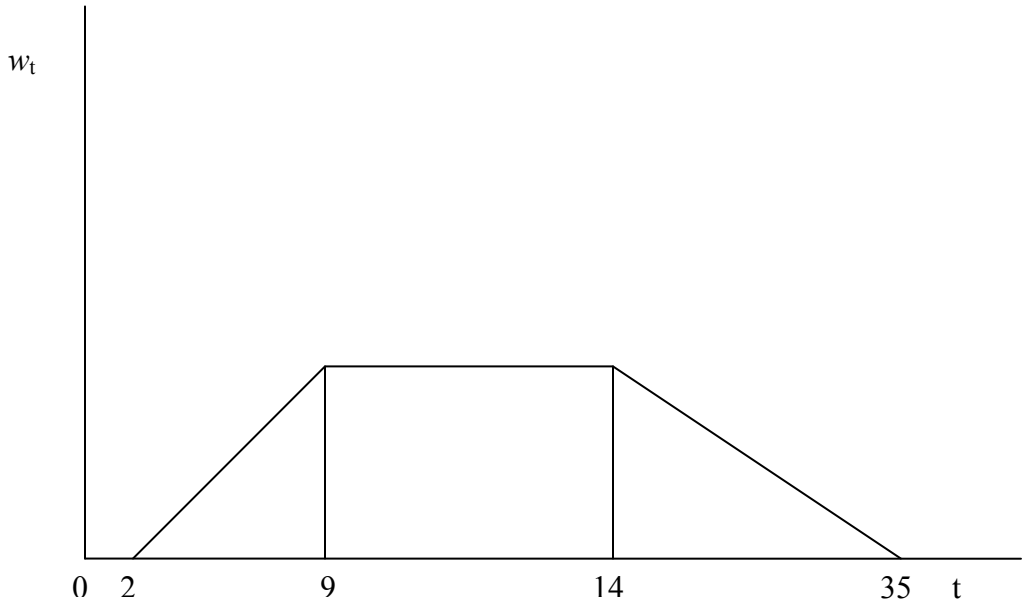

Table 1. Variable Names and Summary Statistics for US Agriculture in Eight Midwestern States, 1960-2004

Variables	Mean	St.Dev
Quantities[1]		
Wheat Output (y_0)	0.18	0.14
Soybean Output (y_s)	1.11	0.90
Corn Output (y_c)	2.05	1.63
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]		
Wheat Output (P_0)	numeraire	
Soybean Output (p_s)	1.09	0.24
Corn Output (p_c)	0.95	0.16
Livestock Output (p_v)	1.28	0.39
Capital Services (p_k)	1.03	0.44
Labor (p_h)	0.81	0.54
Energy (p_e)	1.25	0.39
Farm Chemicals (p_a)	1.14	0.30
Other Materials (p_m)	1.53	0.38
Profit (Π)		
Revenue (Π_R)	7.369	
Cost (Π_C)	9.715	
Quasi-Fixed Factors		
Land (z_l)[3]	0.87	0.24
GM Soybean Adoption Rate (z_s)	0.11	0.24
GM Corn Adoption Rate (z_c)	0.04	0.11
Public Ag Research (z_r)[4]	30.05	10.71
Preseason Precipitation (z_p)[5]	0.00	2.49
Lake States, $d1$ = 1 if Lake State and 0 otherwise	0.38	

[1]Value $1,000,000,000 in 1996 prices of Alabama

[2] Expected wheat price in nominal relative to Alabama wheat price in 1996.

[3]Value $1,000,000,000 in 1996 prices in Alabama

[4]$1,000,000 in 1996 prices of Alabama

[5]Deviation from 30-year norms or means by state

Table 2. Estimation of a System of Output Supply and Input Demand Equations with Cross-Equation Symmetry Restrictions (SUR Model with Cross-Equation Restrictions and a Single First-Order Autoregressive Process): Eight Midwestern States, 1960-2004 (absolute value asymptotic *t*-or *z*-values in parentheses; N = 43x8 = 344 observations per equation)[1]

	Output Supply Equations			Input Demand Equations				
Variables	**Soybean**	**Corn**	**Livestock**	**Capital**	**Labor**	**Energy**	**Farm Chemical**	**Other Materials**
Normalized Prices:								
Soybean (p_s)	0.129	-0.289	0.163	-0.060	-0.066	-0.001	0.072	-0.011
	(1.90)	(3.35)	(2.88)	(1.40)	(1.58)	(0.09)	(2.24)	(0.20)
Corn (p_c)	-0.289	0.692	0.493	-0.206	-0.100	-0.049	-0.199	-0.157
	(3.35)	(3.88)	(5.09)	(2.98)	(1.26)	(3.24)	(3.96)	(1.67)
Livestock (p_v)	0.163	0.493	-0.072	0.064	0.111	-0.015	-0.055	-0.335
	(2.88)	(5.09)	(0.67)	(1.40)	(1.81)	(1.53)	(1.73)	(4.78)
Capital (p_k)	-0.060	-0.206	0.064	0.147	-0.004	-0.017	-0.052	0.069
	(1.40)	(2.98)	(1.40)	(2.63)	(0.14)	(1.26)	(1.61)	(1.50)
Labor (p_h)	-0.067	-0.100	0.111	-0.004	0.179	-0.014	0.028	-0.099
	(1.58)	(1.26)	(1.81)	(0.14)	(3.36)	(2.17)	(1.24)	(2.08)
Energy (p_e)	- 0.001	-0.049	-0.015	-0.017	-0.014	0.086	-0.021	0.024
	(0.09)	(3.24)	(1.53)	(1.26)	(2.17)	(8.34)	(2.30)	(2.35)
Farm Chemical (p_a)	0.072	-0.199	-0.055	-0.052	0.028	-0.021	0.411	-0.134
	(2.24)	(3.96)	(1.73)	(1.61)	(1.24)	(2.30)	(11.58)	(4.05)
Other Materials (p_m)	-0.011	-0.159	-0.335	0.069	-0.099	0.024	-0.134	0.457
	(0.20)	(1.67)	(4.78)	(1.50)	(2.08)	(2.35)	(4.05)	(6.03)
Fixed Factors:								
Land (z_l)	1.786	2.783	2.447	-1.400	-2.543	-0.301	-0.669	-2.728
	(10.53)	(6.38)	(7.60)	(13.52)	(9.30)	(15.85)	(10.50)	(12.40)
GM Soybean Adoption (z_s)	0.061	-0.107	0.235	0.126	0.459	0.062	0.050	0.119
	(0.24)	(0.17)	(0.50)	(0.81)	(1.24)	(2.18)	(0.51)	(0.37)
GM Corn Adoption (z_c)	-0.128	-0.037	-0.377	0.870	1.280	0.047	0.140	0.060
	(0.27)	(0.03)	(0.42)	(2.96)	(1.67)	(0.87)	(0.77)	(0.10)
Public Research (z_r)	0.042	0.137	0.123	-0.024	-0.024	-0.005	-0.021	-0.069
	(6.56)	(8.36)	(10.19)	(6.22)	(2.32)	(6.95)	(8.57)	(8.32)
Preseason Precipitation (z_p)	-0.002	-0.023	-0.002	-0.005	-0.010	0.001	0.002	-0.003
	(0.37)	(1.82)	(0.23)	(1.64)	(1.31)	(1.00)	(0.98)	(0.52)
Dummy($d1$) – Lake States	-0.635	-0.759	0.787	-0.150	-1.073	-0.040	0.129	-0.509
	(8.06)	(3.75)	(5.28)	(3.11)	(8.48)	(4.50)	(4.34)	(4.98)
Time (t)	0.004	-0.037	-0.089	0.015	0.090	0.000	-0.003	0.040
	(1.67)	(2.46)	(8.05)	(4.06)	(9.57)	(0.46)	(1.48)	(5.27)
Intercept	-0.643	-1.297	-0.368	0.018	-0.969	-0.040	0.196	0.443
	(8.74)	(7.04)	(2.84)	(0.37)	(8.38)	(4.50)	(6.57)	(4.66)

Table 3. Estimate of the Numeraire (Wheat Output) Equation with Cross-Equation Restrictions (to coefficients in Table 2)

Variable	Coefficient	t-value	Variable	Coefficient	t-value
z_l	-1.650	2.06	$.5(p_h)^2$	0.179	3.36
z_r	-0.036	2.54	$p_h p_e$	-0.014	2.17
z_s	-0.556	0.42	$p_h p_a$	0.028	1.24
z_c	1.430	0.52	$p_h p_m$	-0.009	2.08
z_p	-0.001	1.43	$.5(p_e)^2$	0.086	8.34
$d1$	-0.885	5.09	$p_e p_a$	-0.021	2.30
t	0.032	2.98	$p_e p_m$	0.024	2.35
$.5(p_s)^2$	0.129	1.90	$.5(p_a)^2$	0.411	11.58
$p_s p_c$	-0.289	3.35	$p_a p_m$	-0.134	4.05
$p_s p_v$	0.163	2.88	$.5(p_m)^2$	0.460	6.03
$p_s p_k$	-0.060	1.40	$.5(z_l)^2$	2.582	1.09
$p_s p_h$	-0.066	1.58	$z_l z_r$	0.080	1.84
$p_s p_e$	0.001	0.09	$z_l z_s$	0.174	0.15
$p_s p_a$	-0.072	2.24	$z_l z_c$	-3.078	1.21
$p_s p_m$	-0.011	0.20	$z_l z_p$	-0.010	0.73
$.5(p_c)^2$	0.692	3.88	$z_l d1$	2.012	5.14
$p_c p_v$	0.493	5.09	$z_l t$	-0.013	0.39
$p_c p_k$	-0.206	2.98	$.5(z_r)^2$	0.0003	0.21
$p_c p_h$	-0.100	1.26	$z_r z_s$	0.011	0.29
$p_c p_e$	-0.049	3.24	$z_r z_c$	0.072	1.96
$p_c p_a$	-0.199	3.96	$z_r z_p$	0.0004	0.62
$P_c p_m$	-0.159	1.67	$z_r d1$	0.009	0.36
$.5(p_v)^2$	-0.072	0.67	$z_r t$	-0.001	0.94
$p_v p_k$	0.064	1.40	$.5(z_s)^2$	-3.680	1.79
$p_v p_h$	0.110	1.81	$z_s z_c$	3.482	1.17
$p_v p_e$	-0.015	1.53	$z_s z_p$	-0.446	1.21
$p_v p_a$	-0.055	1.73	$z_s d1$	-0.376	0.62
$p_v p_m$	-0.335	4.78	$z_s t$	0.070	0.82
$.5(p_k)^2$	0.147	2.63	$.5(z_c)^2$	0.469	0.08
$p_k p_h$	-0.004	0.14	$z_c z_p$	1.065	1.28
$p_k p_e$	-0.017	1.26	$z_c d1$	0.757	0.44
$p_k p_a$	-0.052	1.61	$z_c t$	-0.182	1.01
$p_k p_m$	0.069	1.50	$.5(z_p)^2$	-0.001	2.00
			$z_p d1$	0.010	1.15
			$z_p t$	0.0002	0.38
			$.5t^2$	-0.0004	1.31
			$td1$	0.023	1.19
			Intercept	0.499	3.07

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

	Elasticity w.r.t. prices of:								
Quantity	Capital	Labor	Energy	Farm Chemical	Other Materials	Soybean	Corn	Wheat	Livestock
Inputs									
Capital	-0.089	0.002	0.014	0.039	-0.069	0.043	0.128	-0.007	-0.053
	(2.63)	(0.14)	(1.26)	(1.61)	(1.50)	(1.40)	(2.89)		(1.40)
Labor	0.001	-0.037	0.004	-0.008	0.039	0.019	0.025	-0.006	-0.036
	(0.14)	(3.36)	(2.17)	(1.24)	(2.08)	(1.58)	(1.26)		(1.81)
Energy	0.062	0.039	-0.371	0.084	-0.125	0.003	0.161	0.082	0.065
	(1.26)	(2.17)	(8.37)	(2.30)	(2.35)	(0.93)	(3.25)		(1.53)
Farm Chemical	0.080	-0.034	0.039	-0.694	0.302	-0.117	0.281	0.040	0.103
	(1.61)	(1.24)	(2.30)	(11.58)	(4.05)	(2.24)	(3.96)		(1.73)
Other Materials	-0.028	0.032	-0.012	0.061	-0.277	0.005	0.060	-0.010	0.170
	(1.51)	(2.08)	(2.35)	(4.05)	(6.03)	(0.20)	(1.67)		(4.78)
Outputs									
Soybean	-0.056	-0.048	-0.001	0.074	-0.015	0.128	-0.248	-0.021	0.188
	(1.40)	(1.58)	(0.09)	(2.24)	(1.20)	(1.90)	(2.92)		(2.88)
Corn	-0.103	-0.039	-0.030	-0.111	-0.118	-0.154	0.321	-0.073	0.307
	(2.98)	(1.26)	(3.25)	(3.96)	(1.67)	(3.35)	(2.90)		(5.09)
Wheat	0.060	0.104	-0.164	-0.140	0.219	0.114	-0.792	0.810	-0.861
Livestock	0.021	0.028	-0.006	-0.020	-0.162	0.057	0.149	-0.039	-0.029
	(1.40)	(1.81)	(1.53)	(1.73)	(4.78)	(2.88)	(5.09)		(0.67)

[1] Elasticities are obtained by evaluating equation (3) at the sample mean value of the variables from Table 1 and using coefficient estimates taken from Tables 2 and 3. The reported *t*- or *z*-values in parentheses (absolute value), conditional on sample mean values of prices and quantities, yield for non-numeraire outcomes the same values as for the estimated coefficient. Given the extremely complex numeraire (wheat) supply equation, no *t*- or *z*-value is reported for the price elasticities associated with the wheat supply equation.

07-14-10

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	GM-Soybean Adoption Rate	GM-Corn Adoption Rate	Public Ag Research	Factor-Cost or Revenue Shares
Inputs					
Capital	0.003	-0.004	-0.036	-0.080	0.163
Labor	-0.221	0.005	-0.010	-0.372	0.324
Energy	0.116	-0.001	0.007	-0.036	0.037
Farm Chemical	0.071	0.003	0.003	0.365	0.080
Other Materials	0.155	-0.002	0.022	0.267	0.395
Outputs					
Soybean	0.166	0.000	-0.019	-0.440	0.164
Corn	-0.055	-0.005	-0.008	0.427	0.264
Livestock	-0.557	0.001	-0.019	-0.401	0.547
Wheat	11.898	0.028	0.648	7.269	0.024

[1] Evaluation of equation (9), (10) and (11) is at sample mean values of the variables from Table 1 and using estimated coefficients from Tables 2 and 3.