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An Economic Analysis of Risk, Management, and Agricultural Technology

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This paper uses conditional quantile regression to analyze the effects of genetically modified (GM) seed technology and management on production risk in agriculture, with an application to the distribution of corn yield in Wisconsin. Using the certainty equivalent (CE) as a welfare measure, our analysis decomposes the welfare effects of risk, management, and agricultural technology into two parts: mean effects and risk premium (measuring the cost of risk). We document how biotechnology and management interact to improve agricultural productivity and reduce farm risk exposure. For corn, we find that GM European Corn Borer (GM-ECB) technology consistently increases *CE* (the increase ranging from +4.6% to +11.8%) and that a significant part of this increase can come from risk reduction. We also show that the benefits of the GM-ECB biotechnology are heterogeneous: they vary significantly across regions as well as across management schemes.

Key words: corn yield, GM, management, risk

Introduction

Agricultural production is exposed to much risk: both weather shocks and unpredictable pest damages can have large effects on farm production (e.g., Antle, 2010; Antle and Goodger, 1984; Goodwin and Ker, 1998; Just and Pope, 1979, 2002; Lin, Dean, and Moore, 1974). For example, the 2012 drought in the U.S. Corn Belt contributed to a 20–30% reduction in corn yield (USDA Economic Research Service, 2014). Such uncertainty creates significant challenges in the design and implementation of technology and management schemes that aim to reduce exposure to agricultural risk. Evaluating these schemes requires the assessment of three important steps: (i) the extent and nature of risk exposure; (ii) the potential of management schemes to reduce risk; and (iii) the welfare effects of risk (as measured by the cost of risk), reflecting the combined effects of risk exposure and risk aversion. Typically, the cost of risk varies with technology and management decisions. The choice of technology and management can provide options to reduce agricultural risk exposure and improve food security. Of special interest is the impact of biotechnology on agricultural productivity (e.g., Qaim, 2009; Benbrook, 2012). This paper evaluates the economic linkages among management, technology, risk exposure, and the cost of risk, with an application to corn yield.

Since risk can be measured by probabilities, the assessment of risk involves evaluating the probability distribution of risky events. As technology and management also influence risk exposure, the probability distribution of production varies with management decisions. In this context, several approaches have been used in the empirical assessment of risk exposure (see Saastamoinen, 2013, for a review). A first approach has been to rely on variance as a measure of risk exposure and has

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supported investigations of how the variance of output varies with production decisions (e.g., Just and Pope, 1979). For example, inputs that increase output variance are said to be "risk-increasing" (e.g., fertilizer), while those that reduce output variance are "risk-decreasing" (e.g., irrigation and pest control). While variance provides a convenient measure of risk exposure, it has significant limitations. Most decision makers express special concerns about exposure to "downside risk," or unfavorable risky events located in the lower tail of the payoff distribution (e.g., Antle, 1983, 2010; Binswanger, 1981; Menezes, Geiss, and Tressler, 1980; Roy, 1952; Weitzman, 2009; Shi, Chavas, and Lauer, 2013). The variance (the second central moment) cannot measure this type of risk, as it does not distinguish between "downside risk" and "upside risk." To address this issue, other moment-based measures have been proposed, including using higher moments such as skewness or kurtosis (e.g., Antle, 1983; Antle and Goodger, 1984).[1] Alternatively, "partial moments" have also been used to measure exposure to unfavorable events (e.g., "lower partial moment" capturing exposure to risk only below some reference point; see Antle, 2010).

More generally, risk exposure can be assessed by estimating the distribution function of the relevant random variables. In agriculture, the evaluation of the distribution function of crop yield has been of special interest (e.g., Day, 1965).[2] The evaluation can be done using econometric methods, either by specifying and estimating a parametric distribution function or by relying on more flexible nonparametric methods (e.g., Atwood, Shaik, and Watts, 2003; Goodwin and Ker, 1998; Ker and Coble, 2003; Ozaki, Goodwin, and Shirota, 2008; Tack, Harri, and Coble, 2012). An alternative approach is to rely on quantile regression, a quantile function being defined as the inverse of a distribution function (Koenker and Bassett, 1978; Koenker, 2005). Conditional quantile regression is appropriate for our purpose: it is a semi-nonparametric method that can be used to evaluate the effects of management and technology on risk exposure. The method is parametric in the sense that parameters specify the linkages among explanatory variables and each quantile of the underlying distribution function. This is particularly useful in analyzing and conducting hypothesis testing about the effects of management and technology across different quantiles of the distribution. But the method is nonparametric in the sense that it allows the regression parameters to vary across quantiles. As such, conditional quantile regression provides a flexible way to estimate the distribution of agricultural production risk and to examine the role played by technology and production decisions in risk management. This method applies to general conditional distributions, including distribution functions exhibiting ill-defined moments.[3] And, as illustrated below, it provides a good empirical basis to investigate the welfare implications of risk exposure under alternative risk management strategies.

This paper assesses production risk in agriculture using quantile regression, with an application to the distribution of corn yield and its determinants. In particular, we are interested in evaluating the impact of biotechnology on agricultural productivity. Our analysis focuses on genetically modified (GM) corn hybrids[4] containing the Bt gene against the European Corn Borer (GM-ECB).[5] We investigate the joint effects of GM-ECB biotechnology and farm management on the distribution

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[1] Skewness (reflecting the third central moment) measures possible asymmetries in the distribution of production risk, while kurtosis (reflecting the fourth central moment) captures the possible existence of "thick tails" in the probability function.

[2] Risk analysis can be done equivalently using the probability density function. Indeed, for continuous random variables, the probability density function is just the derivative of the associated distribution function.

[3] Examples of distribution functions that exhibit infinite moments include the Cauchy distribution and the Pareto distribution. As such, conditional quantile regression applies under more general conditions than the moment-based approaches proposed by Antle (1983); Antle (2010); or Tack, Harri, and Coble (2012).

[4] GM seeds include genes that have been transferred (through genetic engineering) from different species. This contrasts with traditional seeds that have been obtained through traditional breeding, in which genetic selection is restricted to genes already present within the same species. Since their introduction in 1996, GM corn hybrids have been rapidly adopted on U.S. farms, with an adoption rate reaching 90% in 2013 (USDA National Agricultural Statistics Service, 2014). GM hybrids include both insect resistant (Bt) and herbicide tolerant hybrids, either as individual traits or stacked traits.

[5] The ECB (European Corn Borer) is a major pest that can generate significant yield losses to corn production. The GM-ECB corn is a variety of transgenic corn that includes a gene from *Bacillus thuringiensis* (Bt). The Bt gene induces the corn plant to produce a toxin that kills the corn borer, thus greatly reducing the damages caused the corn borer.

of corn yield and document how GM-ECB biotechnology and management interact in improving agricultural productivity and reducing farm risk exposure. Under the expected utility model, we use the certainty equivalent (CE) as a welfare measure, decomposing welfare effects into two parts: mean effects and the Arrow-Pratt risk premium (measuring the cost of risk). We show how quantile regression can be used to assess risk exposure and welfare under alternative technology and management choices.

With an application to experimental data on corn yield in Wisconsin, we study how GM-ECB has contributed to significant increases in corn yield and reductions in risk exposure in agriculture. Compared to the conventional hybrids, we find that GM-ECB corn consistently increases *CE* (the increase ranging from +4.6% to +11.8%). Stressing the importance of risk, we show that a significant part of this increase can come from risk reduction. We document the presence of significant interaction effects between GM-ECB corn and management. We find that GM-ECB corn behaves as a substitute for crop rotation. We also show that the benefits of GM-ECB are heterogeneous: they vary significantly across regions as well as across management schemes.

Evaluating the Role of Risk

Consider a production process represented by the production function $y(\boldsymbol{x}, \boldsymbol{v})$, where y is output, $\boldsymbol{x} = (x_1, \ldots, x_m)$ is a vector of inputs (e.g., technology, management), and $\boldsymbol{v}$ is a vector of non-controllable shocks (e.g., weather shocks). A decision maker chooses inputs $\boldsymbol{x}$ *ex ante* (i.e., before $\boldsymbol{v}$ is observed). Thus, $\boldsymbol{v}$ represents production risk. We treat v as random variables and assume that the decision maker evaluates her risk exposure by assessing the probability distribution of $\boldsymbol{v}$ conditional on input choice $\boldsymbol{x}$. Then the conditional distribution function of $y(\boldsymbol{x}, \boldsymbol{v})$ is defined as $F(c|\boldsymbol{x}) = \text{Prob}[y(\boldsymbol{x}, \boldsymbol{v}) \leq c]$. Note that the conditional output mean $M(\boldsymbol{x}) = \int y dF(y|\boldsymbol{x})$ reflects the effects of inputs $\boldsymbol{x}$ on expected output.

We are interested in evaluating the productivity implications of alternative management choices, $\boldsymbol{x}$. Under the expected utility model, assume that the decision maker has preferences represented by the utility function

$$EU(y(\boldsymbol{x}, \boldsymbol{v})) - V(\boldsymbol{x}), \tag{1}$$

where $EU(y)$ is the expectation operator defined as $EU(y) = \int U(y) dF(y|\cdot)$, $U(y)$ is a utility function representing risk preferences, and $V(\boldsymbol{x})$ reflects the disutility of $\boldsymbol{x}$. In equation (1), the management decisions, $\boldsymbol{x}$, have two effects: they influence the distribution of output y, as captured by $EU(y(\boldsymbol{x}, \boldsymbol{v}))$, but they come at a cost, denoted by $V(\boldsymbol{x})$ in equation (1).[6] We assume that the utility function $U(y)$ in equation (1) is strictly increasing in y. The welfare of the decision maker depends on mean output, $M(\boldsymbol{x})$. When the decision maker is risk averse, her welfare and decisions depend in general on her risk exposure as represented by the distribution function $F(c|\boldsymbol{x})$. Following Pratt (1964), the decision maker is risk averse if $U(y)$ is concave in y. In general, the risk premium (reflecting the cost of risk measured in units of y) is the sure amount $R(\boldsymbol{x})$ satisfying

$$EU(y(\boldsymbol{x}, \boldsymbol{v})) = U[M(\boldsymbol{x}) - R(\boldsymbol{x})], \tag{2a}$$

or

$$R(\boldsymbol{x}) = M(\boldsymbol{x}) - U^{-1} EU(y(\boldsymbol{x}, \boldsymbol{v})). \tag{2b}$$

It follows from equation (2a) that $[EU(y(\boldsymbol{x}, \boldsymbol{v})) - V(\boldsymbol{x})] = U[M(\boldsymbol{x}) - R(\boldsymbol{x})] - V(\boldsymbol{x})$, which is a monotonic function of the certainty equivalent

$$CE(\boldsymbol{x}) = M(\boldsymbol{x}) - R(\boldsymbol{x}) = U^{-1} EU(y(\boldsymbol{x}, \boldsymbol{v})). \tag{3}$$

[6] Equation (1) assumes that the utility cost of management, $V(\boldsymbol{x})$, is known and shows up in additive form. As such, it should be kept in mind that $EU(y(\boldsymbol{x}, \boldsymbol{v}))$ in equation (1) reflects only the *ex ante* gross benefit of $\boldsymbol{x}$.

The certainty equivalent $CE(\boldsymbol{x})$ defined in equation (3) includes two terms: mean output, $M(\boldsymbol{x})$, minus the risk premium, $R(\boldsymbol{x})$, measuring the implicit cost of risk. As such, $CE(\boldsymbol{x})$ in equation (3) is a risk-adjusted welfare measure for the producer, evaluated in units of y. Both $M(\boldsymbol{x})$ and $R(\boldsymbol{x})$ depend on risk exposure as measured by the distribution function $F(y|\boldsymbol{x})$. The empirical evaluation of $F(y|\boldsymbol{x})$ will be discussed below. The cost of risk $R(\boldsymbol{x})$ depends on both risk exposure and risk preferences represented by $U(y)$.

To illustrate the role of risk preferences, consider the case of constant relative risk aversion (CRRA) where the utility function is $U(y) = y^{1-r}/(1-r)$, r being the Arrow-Pratt relative risk aversion coefficient (Arrow, 1965; Pratt, 1964). Then the risk premium in equation (2b) becomes

$$(4) \qquad R(\boldsymbol{x}) = M(\boldsymbol{x}) - [(1-r)EU]^{1/(1-r)},$$

where $EU = \int [y^{1-r}/(1-r)]dF(y|\boldsymbol{x})$, and the certainty equivalent in equation (3) becomes

$$(5) \qquad CE(\boldsymbol{x}) = [(1-r)EU]^{1/(1-r)}.$$

Equations (4) and (5) give two convenient measures: $R(\boldsymbol{x})$ in equation (4) evaluates the cost of risk, while the certainty equivalent $CE(\boldsymbol{x})$ in equation (5) is a risk-adjusted welfare measure for the producer. Importantly, they both depend on the management decisions, $\boldsymbol{x}$. As such, equations (2)–(3) or (4)–(5) provide a basis to study the role of management choices and their effects on productivity and welfare.

A Quantile-Based Assessment of Risk

As noted above, under a given management decision $\boldsymbol{x}$, risk can be assessed by evaluating the conditional distribution $F(c|\boldsymbol{x}) = \text{Prob}[y(\boldsymbol{x},\boldsymbol{v}) \leq c]$. For a given k, $0 < k < 1$, the quantile of y is defined as the inverse of the distribution function: $Q(k,\boldsymbol{x}) = \inf\{y : F(y|\boldsymbol{x}) \geq k\}$. Intuitively, conditional on $\boldsymbol{x}$, the quantile $Q(k,\boldsymbol{x})$ is the production level that can be attained with probability k. As a special case, the conditional median of y occurs when $k = 0.5$ and is given by $Q(0.5,\boldsymbol{x})$.

Conditional on management decisions $\boldsymbol{x}$, assume that the quantile functions are linear in the parameters and take the form

$$(6) \qquad Q(k,\boldsymbol{x}) = \boldsymbol{z}(\boldsymbol{x})\boldsymbol{\beta}_k,$$

where $\boldsymbol{z}(\boldsymbol{x})$ is a $(1 \times m)$ vector (possibly nonlinear functions of $\boldsymbol{x}$) and $\boldsymbol{\beta}_k$ is a $(m \times 1)$ vector of parameters. Then, we can proceed to use data on $(y, \boldsymbol{z}(\boldsymbol{x}))$ to estimate the parameters $\boldsymbol{\beta}_k$ (Koenker, 2005). Conditional on $\boldsymbol{x}$, the quantile functions $Q(k,\boldsymbol{x})$ in equation (6) provide a basis to evaluate risk exposure (as measured by the associated distribution function). Consider a sample of n observations on $(y, \boldsymbol{z}(\boldsymbol{x}))$. Denote the ith observation by $(y_i, \boldsymbol{z}(\boldsymbol{x}_i))$, $i \in \boldsymbol{N} \equiv \{1, \ldots, n\}$. For a given $k \in (0,1)$ and following Koenker (2005), the quantile regression estimate of $\boldsymbol{\beta}_k$ is

$$(7) \qquad \boldsymbol{\beta}_{k^e} \in \text{argmin}_{\beta} \sum_{i \in \boldsymbol{N}} \rho_k(y_i - \boldsymbol{z}(\boldsymbol{x}_i)\boldsymbol{\beta}),$$

where $\rho_k(w) \equiv w[k - I(w)]$ and $I(w) = \left\{ \begin{array}{c} 1 \\ 0 \end{array} \right\}$ when $w \left\{ \begin{array}{c} < \\ \geq \end{array} \right\} 0$. As discussed in Koenker (2005), the quantile estimator $\boldsymbol{\beta}_{k^e}$ in equation (7) is a minimum-distance estimator that can be obtained by solving simple linear programming problems. And under some regularity conditions, Koenker (2005, pp. 119–121) showed that $\boldsymbol{\beta}_{k^e}$ in equation (7) is a consistent estimator of $\boldsymbol{\beta}_k$ with asymptotic normal distribution given by

$$(8a) \qquad \sqrt{n}[\boldsymbol{\beta}_{k^e} - \boldsymbol{\beta}_k] \xrightarrow{d} N[0, k(1-k)D_1^{-1}D_0D_1^{-1}],$$

where $D_0 = \lim_{n\to\infty}[\sum_{i\in \boldsymbol{N}}[\boldsymbol{z}(\boldsymbol{x}_i)'\boldsymbol{z}(\boldsymbol{x}_i)]/n]$ and $D_1 = \lim_{n\to\infty}[\sum_{i\in \boldsymbol{N}}[f_i\boldsymbol{z}(\boldsymbol{x}_i)'\boldsymbol{z}(\boldsymbol{x}_i)]/n]$ are positive definite matrices and $f_i = \partial F/\partial y$ is the conditional density function associated with the ith observation. The asymptotic covariance matrix of $\boldsymbol{\beta}_{k^e}$ and $\boldsymbol{\beta}_{k'^e}$ is

(8b) $$\mathrm{ACov}(\sqrt{n}\boldsymbol{\beta}_{k^e}, \sqrt{n}\boldsymbol{\beta}_{k'^e}) \to [\min(k,k') - kk']D_1^{-1}D_0D_1^{-1}.$$

Equations (6) and (7) provide a basis to estimate the quantiles $Q^e(k,\boldsymbol{x}) = [\boldsymbol{z}(\boldsymbol{x})\boldsymbol{\beta}_{k^e}]$ for different values of k and different management strategies $\boldsymbol{x}$. In turn, this gives an estimate of the underlying distribution function under alternative management decisions. Equations (8a) and (8b) provide a statistical basis to test hypotheses about the factors in $\boldsymbol{x}$ affecting the distribution of risk facing the decision maker. In our empirical analysis, the explanatory variables, $\boldsymbol{x}$, in equation (6) include location, managerial inputs, and technology. Finally, as illustrated below, the estimated distribution function can be used to evaluate mean yield $M(x)$, risk premium $R(\boldsymbol{x})$, and certainty equivalent $CE(\boldsymbol{x})$ as given in equations (2)–(3) or (4)–(5).

An Application

To illustrate the usefulness of our proposed quantile approach in evaluating production risk and technology, we use plot-level field experiment data on corn yield. The use of experimental data is well suited for our investigation of the effects of management and technology on risk exposure.[7] Our analysis relies on plot-level field experiments conducted by the University of Wisconsin (UW) at seven sites in the state of Wisconsin. Each site has roughly 800 to 1,000 plots. Hybrids being tested are assigned to each plot randomly. These plots are managed similarly to neighboring commercial fields. The seven sites are grouped into two sets. The first set includes three sites located in the U.S. Corn Belt in southern Wisconsin: Arlington, Janesville, and Lancaster. These sites face similar agro-climatic environments and favorable growing conditions for corn. The second set includes four sites located in central Wisconsin at the northern edge of the U.S. Corn Belt: Chippewa Falls, Marshfield, Valders, and Seymour. While these sites face similar agro-climatic conditions, they must cope with a shorter growing season that is less favorable to corn production. Given their relative position in Wisconsin, we call the first region the "Southern region" and the second region the "Central region."[8]

We present an empirical analysis of the determinants of corn yield, with a focus on the interaction effects of GM technology, management, and production risk. Our analysis focuses on two regions ("Southern" and "Central") from UW experiment fields for the following reasons: 1) the data are all from field experiments designed and managed by the University of Wisconsin in a consistent way, allowing yield comparisons across regions and years; and 2) the data can support investigating how the effects of technology and management on agricultural productivity and risk varying across geographic regions with different agro-climatic conditions.

For the purpose of evaluating the role of GM technology and its interaction effects with other inputs, we conduct the analysis using data from 1990 to 2010 to allow for enough pre- and post-technology time effects, as the commercialization of GM corn hybrids started in 1996.

There are currently two major groups of GM traits in the corn hybrid market: those that provide insect resistance and those that provide herbicide tolerance. These traits are present in the seeds

[7] The plot-level field experiments were conducted using farm management practices commonly used on Wisconsin farms. The experiments provided detailed information on the effects of crop rotation and technology on corn yield. Importantly, such information is not readily available from current farm survey data. Thus, relying on plot-level yield data allowed us to develop a refined investigation of the effects of crop rotation and technology on risk exposure (as reported below). Given current data availability, we believe that this analysis could not be performed from other data sources.

[8] Shi, Chavas, and Lauer (2013) analyzed a similar data set using a moment-based approach. Our approach is new and more general in several ways. First, a moment-based approach may not provide sufficient statistics for the underlying distribution. In contrast, our estimation of conditional quantiles is equivalent to estimating the distribution function. Second, the welfare analysis presented by Shi, Chavas, and Lauer (2013) is based on Taylor series approximations obtained in the neighborhood of the riskless case. In contrast, the welfare analysis presented in this paper does not involve any approximation. Third, our analysis goes beyond Shi, Chavas, and Lauer (2013) by examining how the effects of technology and management can vary across agro-climatic regions.

Table 1. Summary Statistics

Variable	Region	Mean	Minimum	Maximum
Corn yield (bushels per acre)	Southern	200.10	43.9	289.80
	Central	181.10	30.7	289.80
Crop rotation: after corn (*pcorn*)	Southern	0.26	0	1
	Central	0.26	0	1
Crop rotation: after alfalfa (*palfalfa*)	Southern	0.04	0	1
	Central	0.06	0	1
Crop rotation: after wheat (*pwheat*)	Southern	0.02	0	1
	Central	0.02	0	1
Crop rotation: after soybean (benchmark)	Southern	0.68	0	1
	Central	0.59	0	1
Plant density (1,000 plants per acre)	South	28.42	21.48	32.32
	Central	28.54	18.25	33.41

Notes: The number of observations is 8,023 for the Southern region (7,657 for conventional and 1,366 for GM-ECB single traited) and 8,273 for the Central region (7,225 for conventional and 1,048 for GM-ECB single traited). One bushel of corn is equal to 25.40 kg. and 1 acre is equal to 0.4047 hectare.

either alone or stacked together with up to eight different traits. Of all these different traited GM seeds, the single insect-resistance trait controlling the European Corn Borer (GM-ECB) has demonstrated market success ever since its introduction to the market in 1996. The success of GM-ECB trait suggests that farmers have obtained real benefits from this technology. In order to understand where the benefits come from, we examine and compare the GM-ECB single-trait seeds performance relative to conventional hybrids over time and across regions.

Effects of Management and Technology

The quantile parameters $\boldsymbol{\beta}_k$ were estimated for both conventional and GM-ECB single-traited corn hybrids. We focus on three sets of factors: GM-ECB technology, management, and the effects of other technological change over time. Hence, the explanatory variables, $\boldsymbol{x}$, include the GM-ECB technology dummy, a time trend (capturing other technological change), the location dummy (capturing local agro-climatic conditions), and management variables (including crop rotation and plant density). Crop rotation has been used by farmers for thousands of years as a way to deal with infestation and soil fertility restoration (e.g., Bullock, 1992). Studies have also suggested that most of the historical increases in U.S. corn yield are due to increases in plant density (Duvick, 2005; Stanger and Lauer, 2006).

We allow all parameters $\boldsymbol{\beta}_k$ to vary between conventional hybrids and GM-ECB hybrids. We also introduce interaction effects between GM-ECB trait and crop rotation and between GM-ECB trait and plant density. By doing so, the effects of GM-ECB trait are allowed to vary over time and to change with crop rotations as well as plant density.

Our empirical analysis uses UW experimental field data on corn yield. In those experimental fields, management practices were typical of those used on farms practicing rainfed agriculture. A total of 4,748 corn hybrids have been tested at these sites from 1990 to 2010. Some hybrids were tested in multiple locations and/or for multiple years. In total there were 8,023 usable observations on corn yield (measured in bushels per acre) for a single hybrid at a single location for a single year from the Southern region (7,657 for conventional and 1,366 for GM-ECB single traited) and 8,273 from the Central region (7,225 for conventional and 1,048 for GM-ECB single traited).

Table 1 presents the summary statistics of the corn hybrids from the Southern and Central regions, respectively. Corn yield is on average higher in the Southern region (at 200.1 bushels per acre) than in the Central region (at 181.1). The crop rotation patterns are similar between the two regions. However, the Southern region tends to have slightly more corn after soybean (at 67.9%) than the Central region (at 58.8%). Both regions have limited corn-after-wheat or corn-after-alfalfa crop-rotation practices. Plant density is also similar in both regions, with an average of around 28,000 plants per acre.

A number of statistical tests were performed on the econometric model. First, we tested whether the regression parameters for year, corn-after-corn (denoted as *pcorn*), and plant density were the same across the two regions.[9] There is strong evidence that corn productivity differs between the two regions. On that basis, the analysis proceeds to analyze each region separately (Southern and Central).

Second, we tested whether the regression parameters were the same for conventional and GM-ECB single-traited hybrids. As far as corn yield is concerned, we strongly reject the null hypothesis that GM-ECB technology and conventional technology are the same.

Third, we tested whether the regression parameters were the same across the quantiles ($k = 0.1,\ 0.2,\ \ldots,\ 0.9$). Again, there is strong statistical evidence that the parameters $\boldsymbol{\beta}_k$ change across quantiles. These results help justify our quantile approach. They show that it would be inappropriate to assume that the regression parameters are constant across quantiles (as done in a standard regression analysis).

Results for selected quantiles ($k = 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9$) are presented for both technologies (conventional and GM-ECB single-traited) in table 2 for the Southern region and in table 3 for the Central region. Most parameters are statistically significant. In particular, the time trend variables (measured as $Yr = (\text{year} - 2000)$) are often positive and statistically significant for the conventional technology, reflecting the rapid rate of technical change in corn production over the last two decades. For the GM-ECB technology, the additional time trend effects are negative and statistically significant. However, the GM-ECB dummy variables are positive and outweigh partially the coefficient of the time trend variable in the upper tail. The results suggest that GM-ECB seeds outperform the conventional seeds as a whole for the high yielding group, yet the advantage of the GM-ECB over the conventional decreased over time. We tested the null hypothesis that the management variables (crop rotation and plant density) have no effect on corn yield. In all cases, we strongly reject the null hypotheses for both technologies, providing strong evidence of the important role of management. Moreover, many interaction effects between time trend and the management variables (density and *pcorn*) are statistically significant for both technologies, indicating that the productivity effects of management have changed over time. In addition, the results reported in tables 2 and 3 document how these effects can vary across quantiles and hybrids as well as across regions.

For the Southern region, table 2 shows that density has a positive effect on corn yield in the year 2000 (when $yr = 0$), while *pcorn* (corn-after-corn rotation) has a negative effect for both conventional and GM-ECB hybrids and across quantiles. After 2000 (when $yr > 0$), the effect of density became weaker for conventional but stronger for GM-ECB, and the negative effect of *pcorn* became weaker for GM-ECB, especially in the upper quantile of the distribution. These results document different responses of corn yield to management both over time and across hybrids.

For the Central region, table 3 shows slightly different patterns in yield response. In the year 2000, the positive effect of density on yield remains but only for conventional hybrids and in the upper quantile of the distribution. The effect of *pcorn* remains negative for both conventional and GM-ECB—but only in the upper quantile—and is positive for GM-ECB in the lower quantile. After 2000, the positive effect of density became stronger, especially in the lower quantile, and the negative impact of *pcorn* becomes stronger in the upper quantile for conventional but weaker for GM-ECB. Corn yield response to technology and management seems to vary across agro-climatic sites.

To examine the effects of GM-ECB technology and its interactions with management, the estimated model was simulated to obtain the distribution function of corn yield under alternative

[9] The test we are using here and later is a Wald test. All test statistics are significant at 1% level.

Table 2. Parameter Estimates of the *k*th Quantile of Corn Yield, Southern Region

Variable	$k = 0.1$	$k = 0.2$	$k = 0.3$	$k = 0.5$	$k = 0.7$	$k = 0.8$	$k = 0.9$
Intercept	16.42*	30.78***	42.56***	46.64***	42.25***	41.01***	46.78***
Yr = year - 2000	37.94***	38.20***	36.63***	33.01***	25.95***	23.75***	24.24***
pcorn	−13.35***	−14.82***	−11.63***	−11.40***	−8.43***	−8.24***	−7.92***
palfalfa	41.30***	42.51***	44.41***	48.80***	46.71***	44.51***	38.33***
pwheat[a]	19.17***	18.01***	14.66***	11.45***	4.72**	3.06**	−1.95
Janesville	8.07***	7.51***	5.44***	6.63***	5.52***	5.54***	3.83***
Lancaster	−12.61***	−12.00***	−11.14***	−0.29	7.05***	9.05***	12.27***
Density	5.67***	5.45***	5.28***	5.45***	6.01***	6.26***	6.38***
Yr × density	−1.26***	−1.27***	−1.22***	−1.09***	−0.86***	−0.79***	−0.81***
Yr × *pcorn*	0.29	−0.32	−0.09	0.26	1.12***	1.48***	1.65***
ECB	−69.73**	−34.91	−4.65	13.42	56.05***	92.76***	101.55***
ECB × Yr	−56.19***	−68.59***	−83.28***	−72.27***	−52.98***	−50.12***	−51.59***
ECB × *pcorn*	11.70***	6.42*	−1.20	−5.58	−7.53*	−7.93***	−14.16***
ECB × *palfalfa*	−39.08***	−27.03	−28.43***	−20.23***	−15.64	−18.89***	−12.77***
ECB × Janesville	−6.57***	−5.37***	−3.11	−1.16	0.81	−0.03	5.87**
ECB × Lancaster	12.03***	12.79***	18.55***	19.45***	13.17***	10.57***	9.72***
ECB × Density	2.84***	1.63	0.55	−0.16	−1.78**	−3.01***	−3.34***
ECB × Yr × density	1.87***	2.29***	2.77***	2.41***	1.77***	1.67***	1.70***
ECB × Yr × *pcorn*	0.82	2.00**	2.81***	3.40***	2.08**	1.96***	2.93***

Notes: ECB is a dummy variable satisfying ECB = 1 for GM-ECB and ECB = 0 for conventional. There are 6,657 observations for conventional (ECB = 0) and 1,366 observations for GM-ECB (ECB = 1). Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

[a] In the Southern region, the rotation *pwheat* (corn after wheat) is observed only for conventional (ECB = 0).

Table 3. Parameter Estimates of the *k*th Quantile of Corn Yield, Central Region

Variable	$k = 0.1$	$k = 0.2$	$k = 0.3$	$k = 0.5$	$k = 0.7$	$k = 0.8$	$k = 0.9$
Intercept	232.51***	221.87***	188.30***	151.07***	141.98***	127.97***	119.04***
Yr = year - 2000	−55.08***	−43.50***	−29.62***	−15.05***	−4.24	0.47	−1.94
pcorn	−11.25***	1.50	−1.75	−5.59***	−8.53***	−12.37***	−14.24***
Seymour	7.31***	0.36	−1.31	−1.34	−0.17	1.47	1.84
Marshfield	3.31	−5.57***	−6.90***	−1.11	0.36	3.99***	5.24***
Valders	−1.45	−7.52***	−6.49***	−4.77***	0.24	5.81***	11.00***
Density	−4.50***	−3.33***	−1.62***	0.31	1.13***	1.90***	2.53***
Yr × density	1.95**	1.58***	1.11***	0.61***	0.23**	0.05	0.14
Yr × *pcorn*	−0.81*	0.26	−0.42	−1.18***	−1.05***	−0.86***	−0.72**
ECB	−132.00**	−136.72***	−55.11	31.92	−18.46	55.51	100.32**
ECB × Yr	−3.94	−12.31	−23.88	−25.91***	−9.81	−21.18	−16.98
ECB × *pcorn*	25.69*	20.50***	19.59***	11.07***	0.63	0.91	−1.96
ECB × Seymour	24.73***	28.27***	25.77***	20.87***	22.45***	20.64***	22.47***
ECB × Marshfield	25.27***	32.92***	26.05***	8.62**	7.13	1.16	0.79
ECB × Valders	33.39***	45.62***	42.83***	35.52***	22.66***	9.15***	−1.50
ECB × Density	4.56*	4.20***	1.41	−1.32	0.67	−1.81	−3.37**
ECB × yr × density	0.07	0.34	0.73	0.78**	0.21	0.62	0.47
ECB × yr × *pcorn*	−1.16	−2.77*	−1.61	1.55	4.01***	4.95***	5.52***

Notes: ECB is a dummy variable satisfying ECB = 1 for GM-ECB and ECB = 0 for conventional. There are 6,225 observations for conventional (ECB = 0) and 1,048 observations for GM-ECB (ECB = 1). Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 4. Estimates of Mean Yield, Certainty Equivalent (CE) and the Cost of the Risk under Selected Scenarios, bu/acre

Scenarios	Conventional		GM-ECB		Difference: GM-ECB – Conventional	
	South	Central	South	Central	South	Central
Corn after soybean						
Mean yield	215.77	153.34	223.96	151.52	8.19	−1.82
Risk premium	1.91	16.55	0.72	8.47	−1.19	−8.08
CE	213.86	136.79	223.24	143.04	9.38	6.25
Corn after corn						
Mean yield	204.77	145.62	212.84	151.39	8.07	5.77
Risk premium	4.04	18.71	0.26	9.41	−3.78	−9.30
CE	200.72	126.91	212.57	141.98	11.85	15.07
Corn after soybean, high density						
Mean yield	224.97	152.81	232.77	152.67	7.80	−0.14
Risk premium	1.71	19.39	0.42	8.56	−1.29	−10.83
CE	223.26	133.42	232.35	144.11	9.09	10.69

Notes: The scenarios are evaluated at the year 2000, a plant density of 30.7 for the base case, and a higher density of 32.20 (corresponding to a 5% increase compared to the base case). The risk premium and certainty equivalent are obtained using equations (4)–(5) and a relative risk aversion coefficient of $r = 2$. The scenarios are for corn grown in Arlington in the southern region and in Chippewa Falls in the central region.

scenarios.[10] We consider the following situations: years 2000 and 2005; two crop rotations: corn after soybean (treated as the base case) and corn after corn (*pcorn*); and two plant densities (measured in 1,000 plants per acre): 30.7 (treated as the base case) and a higher density of 32.20 (corresponding to a 5% increase compared to the base case). The year 2000 was chosen as the base year for our simulation because it was in the middle of our study period. The years 2000 and 2005 are the fifth and the tenth years since the commercialization of GM crops, while our study period covers fifteen years of GM crop production. Finally, all simulations are for Arlington in the Southern region, and for Chippewa Falls in the Central region. The simulated distribution functions are presented in figures 1–4.

Figure 1 shows the effect of technology (conventional versus GM-ECB) on the distribution of corn yield in the Southern region in 2000 and 2005. It illustrates three points. First, between 2000 and 2005, the distribution of corn yield shifted to the right, reflecting a general improvement in productivity across all quantiles. Second, compared to conventional hybrids, GM-ECB hybrids reduce exposure to downside risk, generating a much stronger right shift of the yield distribution in the lower quantiles (with little shift in the upper quantiles). Third, the effects of hybrid types on corn yield are much stronger than the effects of time. The last result indicates that biotechnology has been a major driver of improved corn productivity over the last decade.

Figure 2 shows similar results for the Central region, but a notable difference between figures 1 and 2 is in the spread of the yield distributions. The Central region exhibits both lower mean yield and higher yield variability (including higher exposure to downside risk) than the Southern region.

Figure 3 illustrates the effects of crop rotation on the distribution of corn yield in the Southern region and generates two important findings. First, *pcorn* tends to have a negative effect on corn yield, especially in the lower quantiles of the distribution (e.g., see figure 3 in 2005). Second, these effects are becoming smaller for GM-ECB than for conventional hybrids (see figure 3 comparing

[10] While the estimates reported in tables 2 and 3 are for a few selected quantiles, the simulations reported below are based on estimates for all quantiles where the distribution function has a jump. The simulation exercises generate estimated distribution functions of corn yield under alternative scenarios (as reported in figures 1–4). These distribution functions are also used in the welfare evaluation reported in table 4.

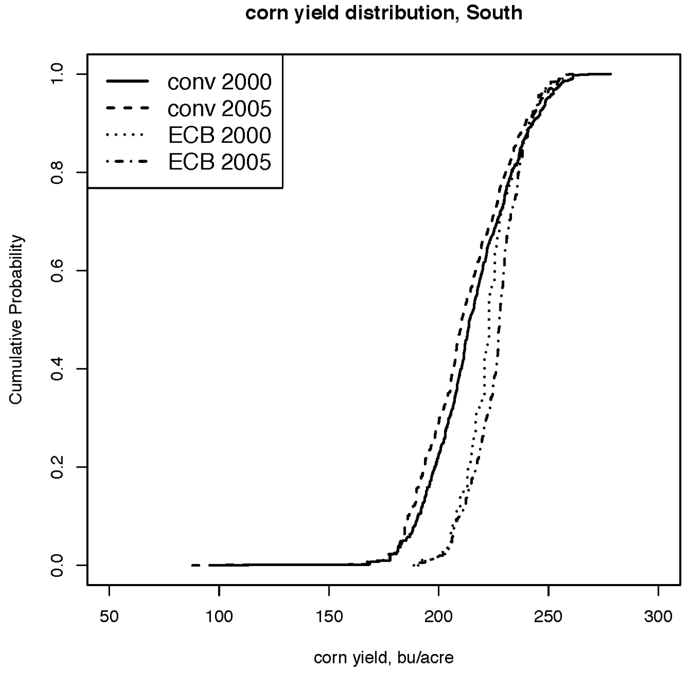


Figure 1. Effects of Technology on the Distribution of Corn Yield, Southern Region

Notes: Distribution of corn yield in southern Wisconsin under alternative scenarios. Corn yield is measured in bushels per acre. The scenarios include corn grown in Arlington in two years: 2000 and 2005; and two types of seeds: conventional seeds (conv) and seeds with GM-ECB genes (ECB).

2000 and 2005). It seems that the GM-ECB trait is a substitute for crop rotation: the negative effects of continuous corn on yield become smaller when GM-ECB hybrid is used. When both crop rotation and GM-ECB provide alternative ways to control some pest populations, they behave as substitutes in the corn production process.

Figure 4 shows the impact of plant density on the distribution of corn yield in the Southern region. Higher plant density is a major contributor to both increasing mean yield and reducing exposure to downside risk. Such effects are strong and becoming stronger over time for GM-ECB hybrids. Figure 4 indicates the presence of synergy between biotechnology and plant density as they affect corn productivity. By improving pest control, GM-ECB hybrids make it possible to obtain greater productivity from higher plant density.

Next, we evaluate the welfare implications of our analysis. We use equations (4)–(5) to estimate the mean yield, the risk premium, and the associated certainty equivalent under alternative technology and management practices. The analysis is conducted under cosntant relative risk aversion (CRRA), with utility function $U(y) = y^{1-r}/(1-r)$, where r is the Arrow-Pratt relative risk aversion coefficient. Previous studies have suggested that the degree of risk aversion varies across individuals, with r typically being in the range from 0 (risk neutrality) to 5 (a high degree of risk aversion) (Gollier, 2001). Below, for illustration purpose, we assume a relative risk aversion coefficient $r = 2$, corresponding to moderate risk aversion.[11]

Evaluated in the year 2000, the welfare simulation results are reported in table 4. First, compared to conventional hybrids, GM-ECB hybrids generate a consistently higher mean yield in the Southern region: +8.19 bu/acre for corn-after-soybean, +8.07 bu/acre for corn-after-corn, and +7.80 bu/acre

[11] We also conducted the analysis under alternative risk preferences (e.g., reflecting different degrees of risk aversion). As expected, the cost of risk was found to increase (decrease) when the decision maker became more (less) risk averse.

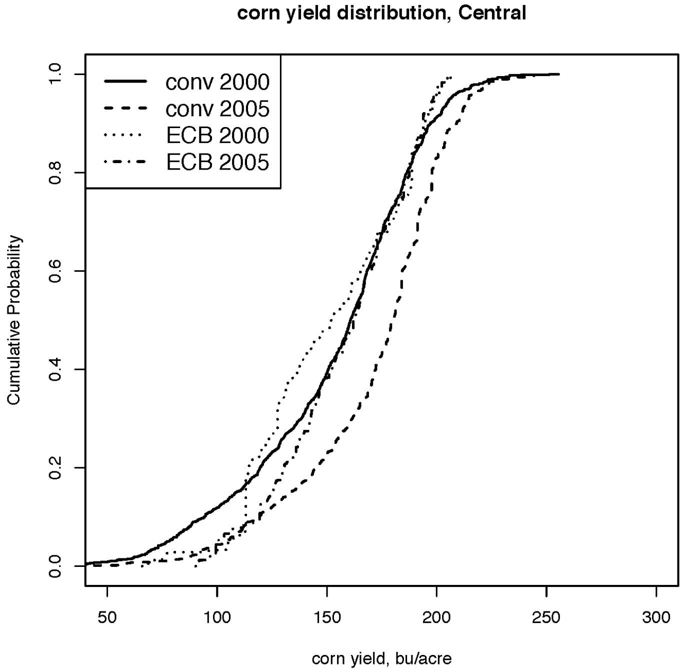


Figure 2. Effects of Technology on the Distribution of Corn Yield, Central Region

Notes: Distribution of corn yield in central Wisconsin under alternative scenarios. Corn yield is measured in bushels per acre. The scenarios include corn grown in Chippewa Falls in two years: 2000 and 2005; and two types of seeds: conventional seeds (conv) and seeds with GM-ECB genes (ECB).

under high density. But these results are mixed in the Central region: GM-ECB hybrids increase yield only under the corn-after-corn rotation (+5.77 bu/acre). The productivity effects of bioetchnology vary across regions.

Second, the risk premium (measuring the cost of risk) is found to vary across technology, management, and regions. The risk premium goes from 0.26 bu/acre under corn-after-corn GM-ECB hybrids in the Southern region to 19.39 bu/acre in corn-after-soybean conventional hybrids in the Central region. In general, the cost of risk is higher under corn-after-corn, for conventional hybrids, and in the Central region. Alternatively, it is smaller under corn-after-soybean, for GM-ECB hybrids, and in the Southern region. The results indicate that the corn-after-soybean rotation and GM-ECB hybrids have similar risk effects: they behave as substitutes by providing alternative ways to reduce yield damages caused by the corn borer. The risk effects also vary across regions. The Central region exhibits a a higher risk premium, which reflects the fact that agro-climatic conditions are more favorable for corn production in the Southern region.

Third, our analysis illustrates the important role of risk. For example, table 4 shows that switching from conventional to GM-ECB hybrids under corn-after-corn in the Central region reduces the risk premium from 18.71 bu/acre to 9.41 bu/acre. In this case, the risk benefit (amounting to 9.30 bu/acre) exceeds the associated gain in mean yield (+5.77 bu/acre). As noted above, the risk benefit is due in large part to a reduction in downside risk exposure. This result documents that a major part of the benefits from a new technology can come from its implied reduction in risk exposure. In this case, GM-ECB hybrids provides enhanced control of pest damages, thus reducing exposure to both risk and downside risk.

Finally, table 4 presents the welfare effects of both technology and management (as measured by the certainty equivalent *CE*) to show that GM-ECB hybrids contribute to improving welfare. Compared to conventional hybrids, GM-ECB hybrids consistently increase *CE* between +6.25

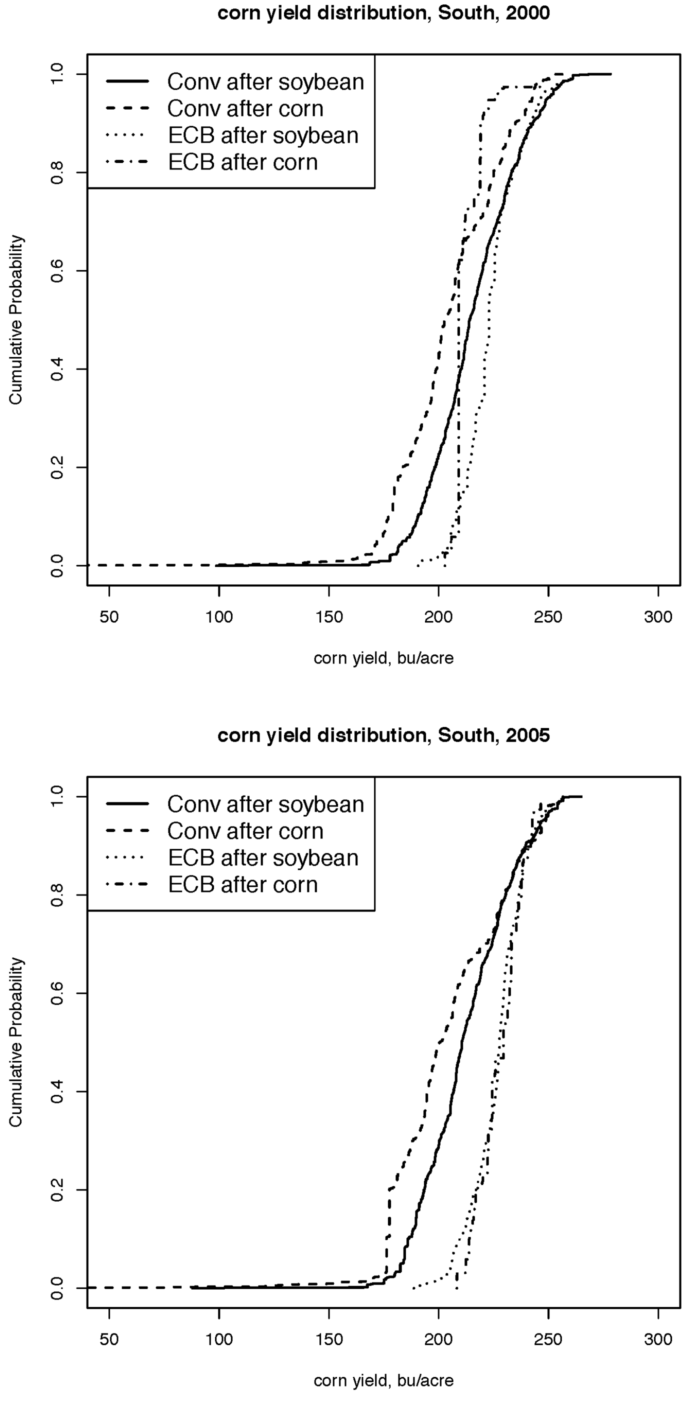
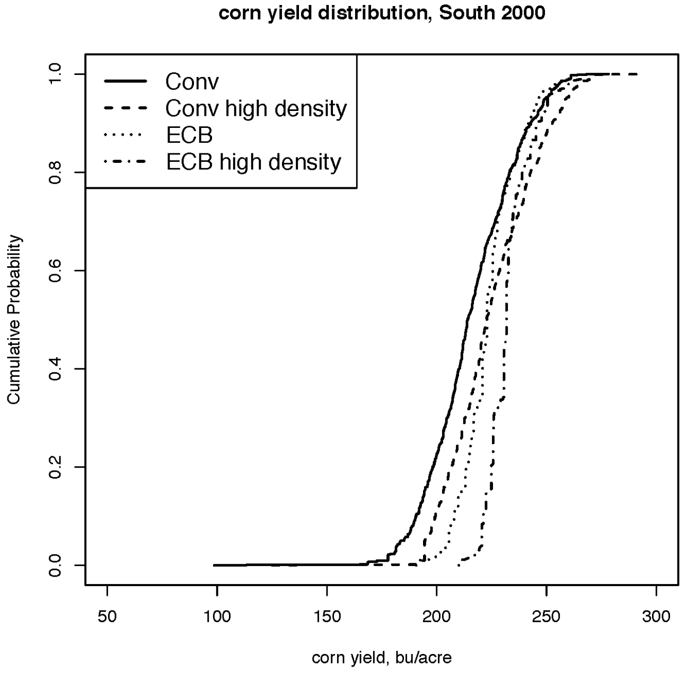


Figure 3. Effects of Crop Rotation on the Distribution of Corn Yield, Southern Region

Notes: Distribution of corn yield in southern Wisconsin under alternative scenarios. Corn yield is measured in bushels per acre. The scenarios include corn grown in Arlington in two years: 2000 and 2005; two types of seeds: conventional seeds (conv) and seeds with GM-ECB genes (ECB); and two types of crop rotation: corn after soybean ("after soybean") and corn after corn ("after corn").



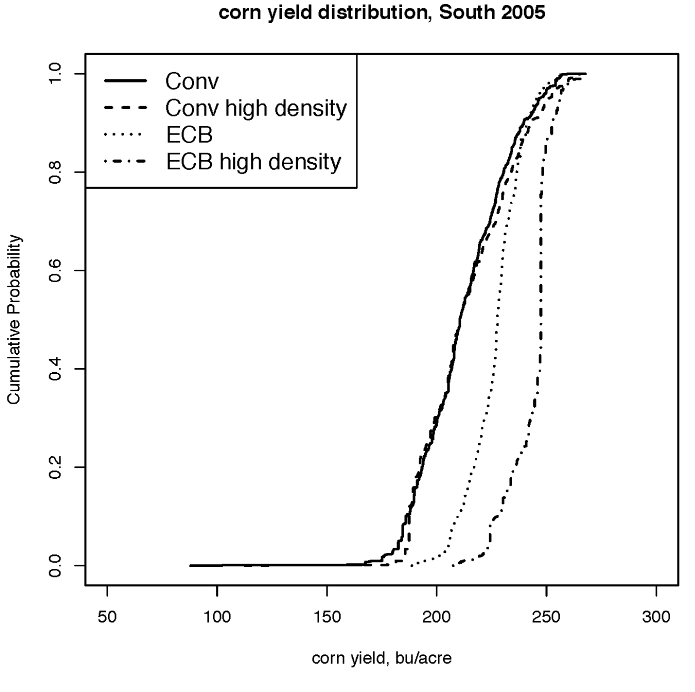


Figure 4. Effects of Plant Density on the Distribution of Corn Yield, Southern Region

Notes: Distribution of corn yield in southern Wisconsin under alternative scenarios. Corn yield is measured in bushels per acre. The scenarios include corn grown in Arlington in two years: 2000 and 2005; two types of seeds: conventional seeds (conv) and seeds with GM-ECB genes (ECB); and two plant densities: 30,700 plants per acre (treated as the base case) and a higher density of 32,200 plants per acre ("high density").

bu/acre (or +4.6%) in corn-after-soybean in the Central region to +15.07 bu/acre (or +11.8%) in corn-after-corn in the Central region. These results document significant welfare gains from GM-ECB trait technology. But the sources of gains vary across regions. For corn-after-soybean, welfare gains come mostly from improvement in mean yield in the Southern region but from reduction in risk exposure in the Central region. In addition, the benefit of GM-ECB trait can also vary with management and tends to be larger under corn-after-corn rotation. For example, table 4 shows that, in the Central region, the GM-ECB hybrids increase the certainty equivalent *CE* by +6.25 bu/acre under corn-after-soybean but by +15.07 bu/acre under corn-after-corn. Our results document how both technology and management affect agricultural productivity and welfare under risk.

Conclusion

This paper uses quantile regression to assess production risk in agriculture, with an application to the distribution of corn yield. Using experimental farm data from Wisconsin, we investigated the joint effects of biotechnology and farm management on the distribution of corn yield. The analysis documented how biotechnology and management interact in improving agricultural productivity and reducing farm risk exposure. We used the certainty equivalent *CE* as a welfare measure, decomposing welfare effects into two parts: mean effects and risk premium (measuring the cost of risk). We found that GM-ECB hybrids consistently increase *CE* and documented that a significant part of the farm benefit from GM-ECB trait technology can come from a reduction in risk exposure. The analysis indicates how biotechnology can contribute to both increasing mean yield and reducing risk exposure. Thus, biotechnology offers good prospects to improve future agricultural productivity under changing climatic conditions. But we also showed that the effects of biotechnology are heterogeneous: they can vary significantly across regions as well as across management schemes. For example, as far as corn productivity is concerned, our analysis showed that GM-ECB corn hybrids behave as a substitute for crop rotation.

Our paper has illustrated the usefulness of quantile regression in the economic assessment of production risk in agriculture, with implications for management, technology, and welfare. Yet further refinements are possible. First, while our approach provides a basis to evaluate the role of risk, additional investigations are needed to explore the cost of downside risk (e.g., risk associated with catastrophic events). Second, our approach has focused on the role of farm management and technology on risk exposure. It could be extended to explore the role of risk-transfer mechanisms (e.g., crop insurance) in risk management. Third, quantile regression appears to be a useful tool to analyze the linkages between agricultural risk management, technology, and climate change. Finally, while our paper has focused on the factors affecting the distribution of corn yield in Wisconsin, our approach could be used to investigate agricultural risk facing different crops in different regions. These appear to be good topics for future research.

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