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An Economic Analysis of Corn Yield, Corn Profitability, and Risk at the Edge of the Corn Belt

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This study investigates the recent evolution of corn yield, with a special focus on the tradeoff between corn profitability and risk. The analysis relies on time-series data from Wisconsin experimental farms at the edge of the Corn Belt. An econometric model of corn yield, corn grain moisture, and corn profitability is specified. Both conditional means and conditional variances are estimated for different sites in Wisconsin. The empirical analysis shows the changes in corn yield and profit over time and across space. The evidence suggests that yield trends are due mostly to technical progress, with smaller effects generated by climate change. On average, corn yield and profitability have improved faster in northern Wisconsin than in the Corn Belt. However, risk has also increased faster. Results show that the choice of corn hybrid maturity makes it easier to manage risk in the Corn Belt than in northern Wisconsin.

Key words: climate, corn, crop yield, farm profitability, management practices, risk, technology

Introduction

Many factors influence the evolution of agricultural productivity. First, a substantial amount of research has focused on climate change and its effects on crop yields (e.g., Adams et al.; Baker, Rushy, and Skaggs; Houghton and Woodwell; Thompson 1969, 1975, 1986, 1988). These effects involve changes in yield trend as well as yield variability. Second, there is strong evidence showing rapid technological change has contributed to a significant increase in average yield over time (e.g., Baker, Rushy, and Skaggs; Ramirez). Thompson (1975, 1986) and Cardwell found that only a small portion of yield trends can be attributed to evolving weather patterns in recent years. This stresses the important effects of technological progress on yield and crop productivity. However, there is also evidence of a significant increase in yield variability over the last few decades (e.g., Thompson 1988; Ramirez). Part of this increase has been attributed to climatic changes (Baker, Rushy, and Skaggs), which suggests farmers are now exposed to greater production uncertainty. There is a need to investigate farmers' changing risk exposure and to reassess farm management strategies dealing with production risk.

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Accumulations of greenhouse gases (particularly CO_2) contribute to climatic changes and global warming (Houghton and Woodwell; U.S. Department of Commerce/NOAA). The effects of global warming on agricultural productivity have generated much interest. Mendelsohn, Nordhaus, and Shaw found evidence showing global warming (through generation of both higher temperatures and higher precipitations) would be harmful to the traditional U.S. grain-producing regions (such as the Corn Belt) while benefiting the northern fringe of the United States. Thus climatic changes have differential impacts across regions, suggesting a need to investigate how agricultural productivity has recently changed over space.

This study investigates the recent evolution of corn yield, with a special focus on the tradeoff between corn profitability and risk. Our analysis relies on time-series data from Wisconsin experimental farms at the edge of the Corn Belt for the period 1974–1997. An econometric model of corn yield, corn grain moisture, and corn profitability is specified for three different sites in Wisconsin. The analysis provides useful insights on the economics and uncertainty of corn production in the northern Corn Belt and the northern fringe of the United States, reflecting the effects of changes in climate as well as technology.

We focus on an ex ante analysis at planting time, when the farmer does not know the weather conditions during the growing season. In this context, corn yield is treated as a random variable, conditional on decisions made at planting time. We analyze the effects of choosing corn hybrid maturity on corn yield, corn grain moisture at harvest, and corn profitability. The choice of hybrid maturity is an important management tool for dealing with production uncertainty. For example, for a given length of the growing season, planting longer (shorter) season hybrids tends to increase (decrease) expected yield, but also increases (decreases) production risk. These effects can vary across sites (e.g., with changes in the corn growing season). Effects also vary over time due to technological progress and climate change. An important objective of this research is to evaluate the effectiveness of choosing corn hybrid maturity as a risk management tool, and to observe how this effectiveness has varied both over time and across sites.

Evaluated ex ante at planting time, corn yield, corn grain moisture at harvest, and corn profitability are random variables that depend on weather patterns during the growing season. Thus, there is a need to specify and estimate their respective distribution functions, conditional on technology, climate, and the choice of corn hybrid maturity. This can be done using biophysical models of corn yield, which evaluate the effects of weather on corn growth (Runge; Coelho and Dale; Dixon et al.; Kaufmann and Snell).

Alternatively, econometric methods can be used to estimate the distribution functions more directly (Nelson and Preckel; Kaylen, Wade, and Frank; Gallagher; Goodwin and Ker; Ramirez). As noted by Goodwin and Ker, and by Ramirez, these distribution functions can be complex. Here, we rely on central-moment measurements. Following Antle, and Antle and Goodger, this method provides a flexible and convenient basis for evaluating the effects of risk on production decisions. It gives the framework for estimating conditional means and conditional variances of the relevant variables over time and at different Wisconsin sites.

The remainder of the article is organized as follows. We first develop a model of decision making under uncertainty and review the moment-based representation of the uncertainty under risk aversion. The data and application to corn at the edge of the Corn Belt are then considered, followed by a presentation of the empirical analysis. The empirical analysis demonstrates how corn yield and profit have changed over time, and how they are affected by the choice of corn hybrid maturity across sites. The evidence suggests yield trends are due mostly to technical progress, with smaller effects generated by climate change. Based on our results, corn yield and corn profitability have improved faster in northern Wisconsin than in the Corn Belt. However, risk has also increased faster. Further, we found that the choice of corn hybrid maturity makes it easier to manage risk in the Corn Belt than in northern Wisconsin. Concluding remarks are presented in the final section.

Decision Making Under Uncertainty

Consider a farm producing under uncertainty. Under technology t, farm profit is represented by the stochastic function $\pi(\mathbf{x}, t, \mathbf{e})$, where $\mathbf{x}$ is an $(n \times 1)$ vector of inputs and $\mathbf{e}$ is a vector of uncontrollable factors that are not known to the decision maker at the time $\mathbf{x}$ is chosen. The vector $\mathbf{e}$ is treated as a random vector with a given probability distribution G. It includes the unpredictable effects of weather on farm production. In this context, the influence of input choice $\mathbf{x}$ on farm profit depends on both weather effects $\mathbf{e}$ and technology t.

Assume that inputs are chosen to maximize the expected utility of profit, $EU(\pi) = \int U(\pi)\, dG$, where E is the expectation operator based on the information available at the time decisions are made. The von Neumann-Morgenstern utility function $U(\pi)$ represents the risk preferences of the decision maker, with $\partial U/\partial \pi > 0$.[1] Thus, we assume that farm decision making is represented by the following optimization problem:

$$(1) \qquad \mathbf{x}^*(t) \text{ solves } \max_{\mathbf{x}} \{EU[\pi(\mathbf{x}, t, \mathbf{e})]\}.$$

Making (1) empirically tractable requires information about the expected utility $EU(\pi)$. A convenient approach is to rely on the moments of stochastic profit π. Let $\mu_{1\pi}(\mathbf{x}, t) = E\pi(\mathbf{x}, t, \mathbf{e}) = \int \pi(\mathbf{x}, t, \mathbf{e})\, dG(\mathbf{e})$ the mean profit or first moment of profit. Then, assuming differentiability, expanding $U(\pi)$ in an mth-order Taylor series about $\mu_{1\pi}$ and taking expectation gives

$$(2) \qquad \begin{aligned} EU(\pi) &\approx U(\mu_{1\pi}) + \sum_{i=2}^{m} \left[\frac{1}{i!} \frac{\partial^i U}{\partial \pi^i} (\mu_{1\pi}) \cdot E\left[(\pi - \mu_{1\pi})^i\right] \right] \\ &= U(\mu_{1\pi}) + \sum_{i=2}^{m} \left[\frac{1}{i!} \frac{\partial^i U}{\partial \pi^i} (\mu_{1\pi}) \cdot \mu_{i\pi} \right], \end{aligned}$$

where $\mu_{i\pi}(\mathbf{x}, t) = E[(\pi(\mathbf{x}, t, \mathbf{e}) - \mu_{1\pi}(\mathbf{x}, t))^i]$ is the ith central moment of π $\{i = 2, \ldots, m\}$. Equation (2) shows how expected utility depends on mean profit $\mu_{1\pi}(\mathbf{x}, t)$, on the variance of profit $\mu_{2\pi}(\mathbf{x}, t)$, on the skewness of profit $\mu_{3\pi}(\mathbf{x}, t)$, etc. In turn, each moment of profit depends on the input decision $\mathbf{x}$ and on technology t. Note that equation (2) applies under very general conditions. It requires only that the first m moments of π are finite. As such, it allows for many probability distribution functions for the random variables $\mathbf{e}$, thus providing a flexible representation of the uncertainty.

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[1] A linear function $U(\pi)$ would represent risk neutrality, while risk aversion implies that $U(\pi)$ is a concave function (Pratt).

Under risk neutrality, the utility function $U(\pi)$ is linear, and maximizing (2) reduces to maximizing expected profit $\mu_{1\pi}(\mathbf{x}, t) = E\pi(\mathbf{x}, t, \mathbf{e})$. However, there is strong empirical evidence suggesting most farmers are risk averse (Young; Lin, Dean, and Moore; Saha, Shumway, and Talpaz; Chavas and Holt). Under risk aversion, $\partial^2 U/\partial\pi^2 < 0$ means that the variance of profit $\mu_{2\pi}$ becomes relevant in (1), indicating a need to estimate the moments of profit $\mu_{i\pi}(\mathbf{x}, t)$ $\{i = 1, 2, ..., m\}$. This can be done by specifying a parametric form for each $\mu_{i\pi}$ and estimating the corresponding parameters. Let $\mu_{i\pi} = f_i(\mathbf{x}, t, \beta_i)$, where β_i is a vector of parameters representing the effects of $\mathbf{x}$ and t on the ith moment of profit $\mu_{i\pi}$ $\{i = 1, 2, ..., m\}$. Then, consider the econometric model

$$\pi = f_1(\mathbf{x}, t, \beta_1) + v_{1\pi}, \tag{3}$$

where $v_{1\pi}$ is an error term distributed with mean zero, $E(v_{1\pi}) = 0$. Assume that we obtain a sample of observations on profit π and on the variables $(\mathbf{x}, t)$. Then, treating $(\mathbf{x}, t)$ as exogenous variables, equation (3) is a standard regression model where the parameters β_1 can be consistently estimated by the least squares method. Let $\beta_1^{\mathbf{e}}$ be the least squares estimator of β_1 in (3), giving $v_{1\pi}^{\mathbf{e}} = \pi - f_1(\mathbf{x}, t, \beta_1^{\mathbf{e}})$ as the least squares residual. Because $\beta_1^{\mathbf{e}}$ is a consistent estimator of β_1, it follows that $v_{1\pi}^{\mathbf{e}}$ is a consistent estimator of $v_{1\pi}$.

Using (3), we obtain $E[(v_{1\pi})^i] = E[(\pi - \mu_{1\pi})^i] = \mu_{i\pi}$. It follows that $(v_{1\pi})^i = f_i(\mathbf{x}, t, \beta_i) + v_{i\pi}$, where $v_{i\pi}$ is an error term distributed with mean zero, $E(v_{i\pi}) = 0$, and $i \geq 2$. This suggests the following model specification:

$$(v_{1\pi}^{\mathbf{e}})^i = f_i(\mathbf{x}, t, \beta_i) + v_{i\pi}, \quad i \geq 2. \tag{4}$$

Again, assuming a sample of observations on profit π and on the exogenous variables $(\mathbf{x}, t)$, consider (4) as a regression model and let $\beta_i^{\mathbf{e}}$ be the least squares estimator of β_i in (4). Because $v_{1\pi}^{\mathbf{e}}$ is a consistent estimator of $v_{1\pi}$, it follows that $\beta_i^{\mathbf{e}}$ is a consistent estimator of β_i in (4), where $i \geq 2$ (Antle).

Thus, the least squares estimation of (3) and (4) gives consistent estimates of the central moments of profit, including mean profit $\mu_{1\pi} = f_1(\mathbf{x}, t, \beta_1^{\mathbf{e}})$, and the variance of profit $\mu_{2\pi} = f_2(\mathbf{x}, t, \beta_2^{\mathbf{e}})$. This provides a framework for the empirical investigation of the distribution of profit as it changes with technology t and the input choices $\mathbf{x}$. Under risk neutrality, expression (1) implies the input choice $\mathbf{x}$ would be chosen so as to maximize expected profit $E(\pi) = f_1(\mathbf{x}, t, \beta_1^{\mathbf{e}})$. Alternatively, under risk aversion, production decisions in (1) would take into consideration both mean profit $f_1(\mathbf{x}, t, \beta_1^{\mathbf{e}})$, and the variance of profit $f_2(\mathbf{x}, t, \beta_2^{\mathbf{e}})$. If we restrict our attention only to these first two moments, then risk aversion will imply some tradeoff between expected profit and the variance of profit (Meyer).

Under risk aversion, the decision maker will always choose to obtain the highest possible expected profit for a given variance, or the smallest possible variance for a given expected profit (Anderson, Dillon, and Hardaker). This defines the "mean-variance frontier" or, equivalently, a "mean-standard deviation" frontier. Without information on the exact risk preferences of the decision maker, the optimal decision in (1) will be a point on this frontier. Under risk neutrality, it would correspond to the point where the expected profit is the largest possible. Under extreme risk aversion, it would correspond to the point where the variance (or standard deviation) of profit is the smallest possible (which is typically associated with lower expected profit). Under intermediate situations, it would trade off increases in expected profit with decreases in variance (or standard deviation) depending on the degree of risk aversion of the decision maker.

It is often of interest to know in more detail how input choice $\mathbf{x}$, technology t, and uncertainty $\mathbf{e}$ affect farm profit π. These effects can take place through outputs and/or inputs. On the output side, these effects can be represented by a stochastic production function: $y = y(\mathbf{x}, t, \mathbf{e})$, where y denotes farm output, and $\mathbf{e}$ represents the effects of production uncertainty (e.g., weather) on agricultural production. On the input side, cost effects can be represented by a stochastic function: $C = C(\mathbf{x}, t, \mathbf{e})$, which allows cost to vary with input choice $\mathbf{x}$, technology t, and production uncertainty $\mathbf{e}$ (e.g., weather).[2] Denoting by p the price of output y, then farm profit is specified as $\pi(\mathbf{x}, t, \mathbf{e}) = py(\mathbf{x}, t, \mathbf{e}) - C(\mathbf{x}, t, \mathbf{e})$.

Based on the above discussion, we decompose the effects of $(\mathbf{x}, t, \mathbf{e})$ on farm profit π into two effects: (*a*) production effects through the production function $y(\mathbf{x}, t, \mathbf{e})$, and (*b*) cost effects through the function $C(\mathbf{x}, t, \mathbf{e})$.[3] Both functions are stochastic because they depend on the random variables $\mathbf{e}$. Like the profit function π, they can each be represented by their central moments—mean, variance, etc. The empirical analysis of these moments can be conducted in a manner similar to the approach discussed above for the profit function. In particular, the central moments of the production function $y(\mathbf{x}, t, \mathbf{e})$ can be parameterized as $E(y) = \mu_{1y} = g_1(\mathbf{x}, t, \alpha_1)$ for average production, $E[(y - \mu_{1y})^2] = \mu_{2y} = g_2(\mathbf{x}, t, \alpha_2)$ for the variance of production, and so forth. Furthermore, given sample data on output y, and the variables $(\mathbf{x}, t)$ are treated as exogenous variables, the functions $g_i(\mathbf{x}, t, \alpha_i)$ $\{i = 1, 2, \ldots, m\}$ can be consistently estimated by standard econometric methods. Similarly, the central moments of the function $C(\mathbf{x}, t, \mathbf{e})$ can be parameterized as $E(C) = \mu_{1c} = h_1(\mathbf{x}, t, \gamma_1)$ for expected cost, $E[(C - \mu_{1c})^2] = \mu_{2c} = h_2(\mathbf{x}, t, \gamma_2)$ for the variance of cost, etc. Again, given appropriate sample data, the functions $h_i(\mathbf{x}, t, \gamma_i)$ $\{i = 1, 2, \ldots, m\}$ can be consistently estimated using standard econometric methods. This procedure can provide useful insights on the effects of management practices on crop yield, agricultural productivity, cost, farm profitability, and risk exposure.

While least squares estimation provides consistent estimates of the parameters of the conditional moments [e.g., in (3) and (4)], it will be of interest to test hypotheses about these parameters. In general, the conditional-moment specifications suggest the presence of heteroskedasticity (Just and Pope; Yang, Koo, and Wilson). This factor must be taken into consideration when conducting hypothesis testing. We address this issue by implementing the procedure proposed by White, which gives consistent estimates of the standard errors in the presence of general heteroskedasticity. This estimation and testing procedure is applied in the investigation of corn production, discussed in the next section.

An Application to Corn

The effects of technology and climatic changes on corn yield have been the subjects of much research. These effects are particularly interesting at the edge of the Corn Belt, where it is well known that corn production has a large comparative advantage. Corn is grown in this region under a broad range of economic and climatic scenarios. However,

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[2] Note that this allows for cost to depend directly on output y [e.g., $c(y, \mathbf{x}, t, \mathbf{e})$]. An example is the case of storage and drying cost considered below, cost that varies with output. In this case, after substituting the stochastic production function $y = y(\mathbf{x}, t, \mathbf{e})$, we obtain $C(\mathbf{x}, t, \mathbf{e}) = c(y(\mathbf{x}, t, \mathbf{e}), \mathbf{x}, t, \mathbf{e})$.

[3] For simplicity, we focus our attention on production and cost uncertainty. This neglects the possible effects of price uncertainty. Incorporating price risk into the analysis would be straightforward. This is not done here given our focus on weather and technology effects.

Table 1. Description of Data: Annual Experimental Observations, 1972–1997

Wisconsin Research Station Site (Location)	No. of Observ.	Average Yield (bu./acre)	Average Moisture (%)	Relative Maturity (*RM*) (days)	
				Min.	Max.
Arlington (South)	2,484	166.3	25.9	85	120
Marshfield (North Central)	1,591	119.5	27.5	75	110
Spooner (North)	2,335	109.0	27.9	70	110

changing technology and weather patterns can have significant effects on corn production in more marginal areas around the Corn Belt. Indeed, such changes can contribute to either expanding or contracting the region where corn is profitably grown, depending on how they affect corn yield, production cost, and risk exposure.

In this analysis, we investigate the effects of changing technology and weather patterns using corn production data generated from several research stations in Wisconsin. The stations in southern Wisconsin are located in the northern Corn Belt, but the research stations in central or northern Wisconsin are not located in traditional corn-producing regions. As one moves north in Wisconsin, the length of the growing season gets shorter, it becomes more difficult for corn grain to reach maturity before the first frost, and corn yields tend to decline. However, farmers can deal with the reduced growing season by planting shorter-season corn hybrids. These hybrids face a higher probability of reaching maturity before the end of the growing season and have lower drying costs, but generate lower expected yield. This tradeoff and its evolution over the last few decades are evaluated empirically below using the approach discussed in the previous section.

The data were generated from long-term studies of corn yields conducted by the University of Wisconsin Agricultural Experiment Station (AES). The data set used for our analysis was obtained from agronomic trials designed to measure corn hybrid performance. The trials evaluated yield and grain moisture for a large selection of corn hybrids. Since 1972, the experiment has been conducted at several agricultural research locations throughout Wisconsin. The experiment controlled for other input conditions by using similar cultural practices at each site. As a result, yield variations in each location are due to the choice of hybrid maturity, to genetic improvements, and to uncontrollable factors (in particular, weather effects). The data set from the AES trials provides the basis for evaluating the changing distribution of corn yield. To the extent that agronomic trials represent situations similar to farm conditions, the findings can help farmers decide which hybrid maturity to choose at planting time.

The data set consists of 26 years (1972–1997) of yield and relative maturity (RM) information. Corn hybrid maturity is measured using the "Minnesota relative maturity rating," a standardized index (measured in days) characterizing each hybrid. The data are summarized in table 1 for three research stations: Arlington (in south Wisconsin), Marshfield (in north central Wisconsin), and Spooner (in northern Wisconsin). It reports the number of observations, average yield (bushels/acre), average corn moisture at harvest (%), and the range of maturity ratings (*RM*) for each location. The number of observations varies across sites. For example, the Arlington station has 2,484 observations, while Marshfield has 1,591 observations. Note that the expected yield over the sample period decreases as one moves north. In contrast, average corn moisture is distributed evenly across sites, except in the northern region where it is higher. Relative maturity ranges from 85 to 120 days in the south, and from 70 to 110 days in the north, reflecting the different climatic conditions experienced at the sites.

Empirical Results

The empirical analysis focuses on three issues. First, the determinants of the distribution of corn yield are investigated. Second, the factors affecting the moisture of corn grain at harvest are analyzed. Cost is also affected, since drying cost increases with corn grain moisture. Third, the distribution of profit and its evolution (both over time and across space) are examined.

Analysis of the Mean and Variance of Corn Yield

The implications of technology and uncertainty for agricultural production are examined here. Our analysis focuses on corn yield.[4] As discussed in the earlier section on decision making under uncertainty, we estimate the factors influencing both the mean and variance of corn yield. First, we consider the stochastic production function representing corn yield, $y = g_1(\mathbf{x}, t, \alpha_1) + v_{1y}$, where v_{1y} is an error term distributed with mean zero. The expected yield function $g_1(\cdot)$ is specified and estimated as a linear function of relative maturity (RM), the square of relative maturity (RM^2), and a time trend (T). Introducing RM^2 allows for a nonlinear relationship between relative maturity and expected corn yield. The time trend T captures two effects: the impact of technological change (e.g., genetic progress) on yield (Cardwell), as well as the impact of climatic change (Baker, Rushy, and Skaggs; Mendelsohn, Nordhaus, and Shaw). Attempting to assess these two effects separately is addressed below. The error term v_{1y} accounts for unobserved weather effects and other uncontrollable factors affecting corn yield. Note that while using least squares estimation gives consistent estimates, it involves a possible heteroskedasticity problem (Yang, Koo, and Wilson). As noted previously, we adopt White's method, which provides consistent estimates of the standard errors under heteroskedasticity.[5]

Second, in order to examine the effects of relative maturity on the risk associated with corn production, we consider the variance of yield $\mu_{2y} = g_2(\mathbf{x}, t, \alpha_2) + v_{2y}$. Following the approach discussed earlier, we specify and estimate the variance of corn yield as a linear function of relative maturity (RM) and a time trend (T).

The regression results are presented in table 2 for the three selected Wisconsin sites. The Arlington site (South) represents the growing conditions in the northern area of the Corn Belt. The Marshfield (North Central) and Spooner (North) sites are outside the Corn Belt, and represent increasingly difficult conditions for corn production due to a shorter growing season.

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[4] At the farm level, this amounts to treating corn acreage as given. Then, corn production is simply corn yield multiplied by corn acreage. The effects of climate change on corn acreage are not explored in our study. This appears to be a good topic for further research.

[5] Note that there may also be nonzero covariance in the error terms across observations. While this would not affect the consistency of the parameter estimates reported below, it would influence their efficiency (meaning that standard errors of the parameters may be upward biased).

Table 2. Estimated Relationship Between Yield and Relative Maturity at the Three Wisconsin Sites

(A) Expected Yield = $g_1(RM, RM^2, T)$

Site	No. of Observ.	Parameter: Constant	RM	RM^2	T	R^2
Arlington	2,484	-77.98 (98.35)	3.58* (1.879)	-0.014 (0.0089)	1.84*** (0.073)	0.245
Marshfield	1,591	-140.30 (85.35)	4.91*** (1.884)	-0.026** (0.010)	1.89*** (0.080)	0.249
Spooner	2,335	-540.76*** (90.25)	13.93*** (2.116)	-0.078*** (0.012)	2.19*** (0.086)	0.232

(B) Variance of Yield = $g_2(RM, T)$

Site	No. of Observ.	Parameter: Constant	RM	T	R^2
Arlington	2,484	-785.18*** (276.60)	11.795*** (2.59)	3.155 (2.607)	0.0094
Marshfield	1,591	-21.75 (259.57)	5.599* (2.955)	7.684*** (2.061)	0.0110
Spooner	2,335	-530.72 (350.39)	13.808*** (4.068)	8.777*** (2.879)	0.0075

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.

The coefficient estimates in the expected yield equation [table 2(A)] have anticipated signs and a high level of significance. The model explains about 25% of the variation in corn yields. This low R^2 value is due to the important effects of unpredictable weather variations captured in the error term. Note that this is appropriate for ex ante analysis, where production decisions (e.g., the choice of relative maturity) are made at planting time when relevant weather conditions during the growing season are still unknown. The coefficients associated with *RM* are all statistically significant. At all three sites, we find a positive relationship between relative maturity and corn yield, confirming the conventional wisdom widely shared by agronomists—i.e., short-season hybrids tend to produce lower expected yield. Moreover, we also identify a nonlinear and concave relationship between relative maturity and expected corn yield. The relative maturity length which maximizes expected yield at Arlington, Marshfield, and Spooner is calculated as 125.9, 96.0, and 89.0 days, respectively. These values imply that, in the south, risk-neutral farmers would plant long-season corn hybrids. As one moves north, the calculated *RM* value decreases, reflecting the shorter growing season.

The coefficients of the time trend (T) are all statistically significant at the 1% level. They are positive, indicating expected corn yield increases over time. T measures the joint effects of climate change and productivity growth due to genetic and technology improvements. Note that the magnitude of the time trend effects increases as one moves north. The average annual output increase at Arlington is 1.84 bushels/acre, whereas it is 2.19 bushels/acre at Spooner.

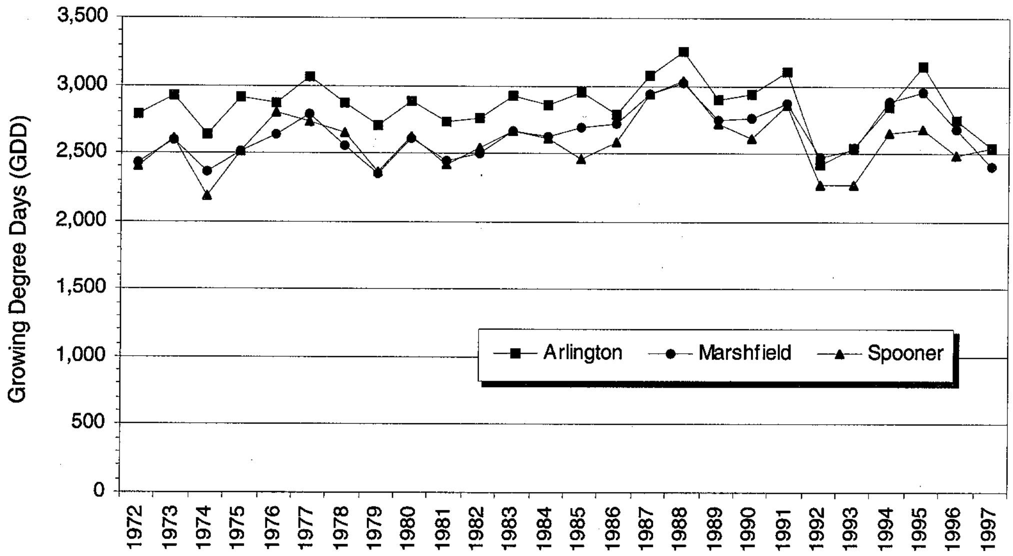

Figure 1. Annual data on growing degree days (GDD) for the three Wisconsin sites (1972–1997, April–October)

Table 2(B) reports estimation results for the variance of yield. The R^2 is fairly low, implying a large part of the variance remains unexplained. However, the variance of yield tends to increase over time. While not significant in Arlington, this effect becomes more positive and significant as one moves north—confirming that technological and climatic changes have increased production risk for corn at the edge of the Corn Belt.

While these results show significant increases in both the mean and variance of yield over time, can we assess how much is due to technological change versus climate change? To answer this question, consider the evolution of growing degree days (GDD) reported in figure 1 for Arlington, Marshfield, and Spooner. GDD is a temperature-based index[6] commonly used as a summary measure of the length of the growing season for corn. Figure 1 shows how the GDD index fluctuates over time as well as across space.

A trend analysis of GDD over the period 1972–1997 is reported in table 3. Three regression equations (each employing *GDD* as a dependent variable and time trend T as an independent variable) were estimated using a seemingly unrelated regression (SUR) method to account for the possible contemporaneous correlation between unexplained variations in GDD across locations. Table 3 shows a positive and significant trend in GDD for Marshfield, but no significant trend for Arlington or Spooner. Thus, for Arlington and Spooner, there is no strong evidence of a longer growing season (as measured by GDD). For these stations, this weak evidence of global warming effects suggests that most of the yield trends could be attributed to technological change.

The results for Marshfield indicate an average annual increase in GDD of 10.15°F, showing a significant lengthening of the growing season of 0.37% per year—a finding consistent with beneficial effects of global warming in the northern fringe of the United

[6] For a given location and growing season, the GDD index for corn is defined as $GDD = \Sigma_i\{(1/2)[\max(T\min_i, 50) + \min(T\max_i, 86)] - 50\}$, where $T\min_i$ ($T\max_i$) is the minimal (maximal) temperature on day i (in degree F). It reflects the absence of appreciable corn growth for temperatures below 50°F or above 86°F.

Table 3. Seemingly Unrelated Regression Analysis of Growing Degree Days (GDD) at the Three Wisconsin Sites, 1972–1997 [$GDD = f(T)$]

Site	No. of Observ.	Parameter		R^2
		Constant	T	
Arlington	25	2,877.40*** (75.79)	−1.817 (4.91)	0.0052
Marshfield	25	2,508.48*** (67.18)	10.150** (4.35)	0.1388
Spooner	25	2,541.56*** (79.44)	3.326 (5.14)	0.0158

Notes: Double and triple asterisks (*) denote significance at the 5% and 1% levels, respectively. Numbers in parentheses are standard errors.

States (Mendelsohn, Nordhaus, and Shaw). This can be compared with the annual yield increase of +1.89 bushels/acre/year (or +1.14%/year) reported for Marshfield in table 2(A). Therefore, to the extent that GDD increases are expected to generate proportional changes in expected corn yield, about 32% of productivity gains in Marshfield would be attributed to a longer growing season. The remaining 68% of productivity gain may be associated with technological change.[7] In agreement with earlier results reported by Thompson (1975, 1986) and Cardwell, our findings indicate only a small proportion of yield trend can be attributed to evolving weather patterns. Thus, for all three sites, technological progress seems the dominant factor influencing productivity trends in corn production.

If the above conclusion is correct, the results presented in table 2(A) reveal technological progress in corn production (e.g., genetic progress in the form of new hybrids) has improved faster in the marginal corn production areas compared to the Corn Belt. This finding is consistent with the observed expansion of corn production outside the Corn Belt over the last few decades. More specifically, the development of new hybrids has allowed farmers to grow corn relatively more profitably outside the traditional Corn Belt (Cardwell).

Next, we evaluate the role of climatic change on production risk. We would like to determine whether the length of the growing season has become more unpredictable. For that purpose, we investigate the variance of the error term in the GDD regression reported in table 3. We test whether this variance is higher in the second half of the sample (compared to the first half). The corresponding F-statistic is 4.18, 2.23, and 1.79 for Arlington, Marshfield, and Spooner, respectively. With (12, 12) degrees of freedom and a 5% significance level, the critical value for the F-test is 3.28. This shows a significant increase in the variance of GDD for Arlington, but no significant change for Marshfield or Spooner.

Thus, for Marshfield and Spooner, there is no strong evidence that the length of the growing season has become more unpredictable; i.e., at these stations, it is not clear whether global warming is contributing to increasing corn yield uncertainty. Never-

[7] It should be noted, however, that there might be other factors which potentially explain the proportion of the trend not associated with weather patterns. Including other factors in the model would require a more refined analysis of how technological change affects yield variations. This appears to be a good topic for further research.

theless, significant increases in yield risk are reported in table 2(B) for Marshfield and Spooner. To the extent that they are not associated with climatic fluctuations, such changes can be attributed to changing technology; along with higher expected yields, improved technologies also bring an increased exposure to production risk (for example, improved short-season hybrids with better average yield but more sensitivity to weather shocks).

The findings differ in the northern Corn Belt (Arlington). At the Arlington site, the variance test result indicates a significant increase in the unpredictability of the length of the growing season. Consistent with Baker, Rushy, and Skaggs, our investigation found global warming may contribute to production uncertainty. Yet, as seen from table 2(B), while the variance of yield has increased over time in Arlington, this effect is not statistically significant. How can we explain that this significant increase in weather variability is associated with no significant changes in yield variation? One possible explanation can be offered: In Arlington, technological change may have counterbalanced the exposure to production risk. For example, new long-season corn hybrids may be less sensitive to some weather shocks. In this context, our results could be interpreted as indirect evidence showing technological change may have contributed to reducing exposure to production risk in the Corn Belt. Thus, for all three sites, technological progress seems an important factor influencing corn production uncertainty. The results presented in table 2(B) indicate global warming and technological change appear to interact with each other as they affect production risk, but in a way that varies across regions.

Finally, in table 2(B), the relationship between relative maturity and variance of yield is found to be statistically significant and positive, suggesting a tradeoff between expected yield increases and risk. For example, a larger *RM* value tends to increase yields, but it also increases production risk (as measured by the variance of yield). By stressing the role of risk, this tradeoff can make farmers' ex ante production decisions more complex. We explore this issue in more detail below.

Analysis of the Mean and Variance of Corn Moisture

Next, we examine the changes in corn grain moisture at harvest. Corn grain moisture is affected both by weather conditions toward the end of the growing season and by the choice of hybrid maturity. Expected moisture and variance of moisture equations are specified and are estimated econometrically. Results are reported in table 4 for the Arlington, Marshfield, and Spooner sites.

The expected moisture equation is specified as a linear function of relative maturity *RM* and its square, RM^2 [see table 4(A)].[8] This allows for a nonlinear relationship between *RM* and moisture. The coefficients associated with relative maturity are all statistically significant except the *RM* term at the Marshfield site. Even though the selected sites do not share the same pattern of quadratic relation between *RM* and moisture (concave relationship for Arlington and convex relationship for the others), they all show positive relationships between *RM* and moisture in the range of the data.

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[8] Note that the moisture equation does not include a time trend. This is justified based on a priori agronomic information. The calculation of RM depends on the moisture of hybrids tested against standard hybrids. As a result, one can expect a stable relationship between moisture and RM. In addition, inclusion of a time trend in the moisture equation yielded insignificant coefficient estimates for RM variables, which is not consistent with a priori agronomic information.

Table 4. Estimated Relationship Between Corn Moisture and Relative Maturity at the Three Wisconsin Sites

(A) Expected Moisture = $h_1(RM, RM^2)$

Site	No. of Observ.	Parameter			R^2
		Constant	RM	RM^2	
Arlington	2,484	-41.14** (16.72)	0.937*** (0.319)	-0.0029* (0.0015)	0.155
Marshfield	1,591	53.50** (25.69)	-0.811 (0.570)	0.0057* (0.0032)	0.071
Spooner	2,335	-59.69*** (20.49)	-1.110** (0.482)	0.0086*** (0.0028)	0.094

(B) Variance of Moisture = $h_2(RM)$

Site	No. of Observ.	Parameter		R^2
		Constant	RM	
Arlington	2,484	-33.804*** (8.73)	0.499*** (0.083)	0.0094
Marshfield	1,591	-46.540*** (17.70)	0.876*** (0.199)	0.0189
Spooner	2,335	-38.606** (19.67)	0.894*** (0.235)	0.0071

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.

This means that increasing relative maturity tends to increase expected moisture in all three sites. The coefficient of RM^2 and its significance suggest the degree of nonlinearity becomes more important as one moves north. In particular, the convex relationship between RM and expected moisture implies the (positive) marginal impact of RM on expected moisture becomes greater as one gets further away from the Corn Belt toward shorter growing seasons.

The variance of moisture is specified as a linear function of relative maturity RM. The corresponding estimation results are reported in table 4(B) for the three sites. The coefficients of RM are all statistically significant at the 1% level. Within the range of the data, they show a positive relationship between relative maturity and the variance of corn moisture. The increasing magnitude of these coefficients as one moves north reveals that the impact of RM on the variability of corn moisture increases as one moves away from the Corn Belt toward shorter growing seasons.

Analysis of the Mean and Variance of Income

Finally, we explore the implications of technology and uncertainty on income from corn production. Since cultural practices are similar across plots at a given location, we measure income as corn revenue minus drying cost, all on a per acre basis. Income uncertainty involves both production uncertainty and uncertainty in the cost of drying (which depends on the moisture of corn grain at harvest). Corn price is assumed to be

\$2 per bushel.[9] The drying cost varies depending on corn moisture at harvest as well as farm type. We consider three farm types: a *livestock farm* where corn is fed directly to livestock, a grain farm using *on-farm drying* facilities, and a grain farm relying on *commercial drying*. On a livestock farm, drying costs are zero and corn moisture variations have no impact on income. In contrast, corn drying affects cost under commercial drying, with a drying cost of 0.03¢ per bushel per percentage moisture in excess of 15.5%. On-farm drying represents an intermediate situation, with a drying cost of 0.015¢ per bushel per percentage moisture in excess of 15.5%.

Expected income and its variance are specified and estimated as discussed previously. The econometric results are presented in table 5. Table 5(A) summarizes the estimation results for expected income by farm type and by location (Arlington, Marshfield, and Spooner). The results are consistent with those obtained in the analysis of expected yield (see table 2 and the related discussion). For example, the coefficients associated with relative maturity *RM* and time trend *T* are statistically significant (except the square of *RM* for Arlington for a livestock farm) and have expected signs. Following the analysis of the mean and variance of corn yield, summarized above, these coefficients confirm that technological change has contributed to increases in expected corn profitability over time, with the rate of increase being faster as one moves north. However, the patterns of variance in corn profitability become more complex. For example, only in northern Wisconsin (Spooner) does profit risk increase significantly over time for all farm types. The rate of increase is largest for the Spooner farm using commercial drying, and smallest for the livestock farm. In the other two locations, the results vary across farm types, emphasizing the significant role of drying cost. This stresses the need for analysts to go beyond yield effects in the investigation of how technology and climate affect the economics of corn production.

The results in table 5(A) enable us to examine these relationships by farm type. For each site, we calculated the *RM* value that maximizes expected income (corresponding to a risk-neutral farmer). At Arlington this equals 125.9 for the livestock farm, 110.9 for on-farm drying, and 98.7 for commercial drying. The respective values at Marshfield are 96.0, 90.1 and 84.9, and at Spooner are 89.0, 87.3, and 85.3. Therefore, as one moves north, the drying cost effects are important, and maximum expected profit is achieved at a lower value of *RM*. In addition, the fact that these *RM* values tend to decline as drying cost increases (particularly in the south) confirms the significant role played by drying cost.

Based on these findings, under commercial drying, switching to a lower maturity rating provides farmers an opportunity to reduce their drying cost and to increase expected profit. But how would that affect the farmer's risk exposure? If this plan involves greater production risk, then a risk-averse farmer would choose a different production plan, provided the costs associated with risk increase offset the benefits associated with expected profit increase. Indeed, as seen in table 5(B), there is a statistically significant and *positive* relationship between the variance of income (risk) and relative maturity *RM*. The effects of drying cost on expected income and variance of income by location and by farm type are discussed next.

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[9] The analysis was also conducted under alternative corn-price scenarios. While higher corn price increased corn profitability, the empirical findings presented below were found to be fairly robust to the corn-price scenario.

Table 5. Estimated Relationship Between Profit and Relative Maturity at the Three Wisconsin Sites

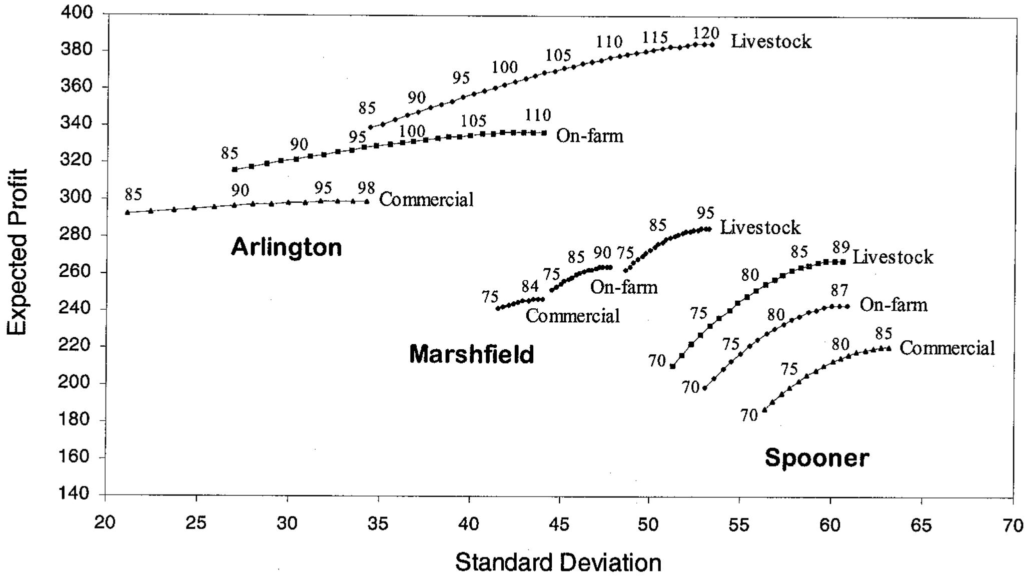
(A) Expected Profit = $f_1(RM, RM^2, T)$

Site	Farm Type	Parameter: Constant	RM	RM^2	T	R^2
Arlington	Livestock	-155.96 (196.70)	7.151* (3.758)	-0.0284 (0.018)	3.688*** (0.145)	0.245
	On-farm	-116.53 (185.64)	7.039** (3.548)	-0.032* (0.017)	2.534*** (0.146)	0.136
	Commercial	-77.108 (182.90)	6.928** (3.50)	-0.035** (0.017)	1.380*** (0.153)	0.048
Marshfield	Livestock	-280.60 (170.71)	9.816*** (3.77)	-0.051** (0.021)	3.771*** (0.160)	0.249
	On-farm	-274.27* (163.39)	9.805*** (3.602)	-0.054*** (0.020)	3.868*** (0.147)	0.253
	Commercial	-267.94 (164.51)	9.794** (3.627)	-0.058*** (0.020)	3.965*** (0.142)	0.249
Spooner	Livestock	-1,081.50*** (178.20)	27.850*** (4.19)	-0.156*** (0.025)	4.373*** (0.163)	0.232
	On-farm	-988.56*** (172.70)	26.110*** (4.05)	-0.149*** (0.024)	4.130*** (0.154)	0.215
	Commercial	-915.63*** (171.30)	24.370*** (4.012)	-0.143*** (0.024)	3.880*** (0.151)	0.192

(B) Variance of Profit = $f_2(RM, T)$

Site	Farm Type	Parameter: Constant	RM	T	R^2
Arlington	Livestock	-3,140.70*** (1,106.6)	47.183*** (10.37)	12.62 (10.43)	0.0094
	On-farm	-3,106.70*** (1,057.5)	48.425*** (9.95)	-11.29 (10.80)	0.0099
	Commercial	-3,709.60*** (1,114.4)	56.210*** (10.58)	-24.93** (11.87)	0.0133
Marshfield	Livestock	-86.99 (1,038.3)	22.400* (11.82)	30.74*** (8.243)	0.0110
	On-farm	261.01 (955.76)	19.830* (10.86)	9.52 (7.782)	0.0037
	Commercial	161.20 (953.37)	23.570** (10.84)	-8.06 (8.334)	0.0028
Spooner	Livestock	-2,122.90 (1,410.5)	55.230*** (16.27)	35.11*** (11.51)	0.0075
	On-farm	-2,392.50 (1,413.2)	52.510*** (16.45)	61.14*** (10.59)	0.0127
	Commercial	-2,967.90** (1,507.8)	54.480*** (17.61)	92.92*** (10.28)	0.0218

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard errors.



Note: Numbers above each frontier denote maturity days.

Figure 2. Expected profit-standard deviation frontiers for the three Wisconsin sites (with T set at 1997 level)

Tradeoff Between Expected Income and Risk

The expected income-standard deviation frontiers are shown in figure 2. These frontiers illustrate the tradeoff that exists between per acre expected income and risk (represented by the standard deviation of income) by location and by farm type, for different relative maturity ratings. Figure 2 is constructed from the information reported in table 5, with the time trend value T set at its 1997 level (the most recent year in the data set). A move along each frontier is obtained by changing corn hybrids and their associated *RM* ratings (expressed in days). The positive slope of the frontier functions indicates that expected income cannot increase without also increasing risk. Alternatively, risk cannot be reduced without sacrificing expected income.

In the northern Corn Belt (represented by the Arlington site), the growing season is longer. There, the tradeoff between risk and expected return varies across farm types. Indeed, each farm exhibits a different slope of its frontier function. The livestock farm shows a relatively large tradeoff between expected return and risk, whereas the tradeoff is less pronounced under commercial drying. This means that, under commercial drying, risk can be reduced without much reduction in expected profit by choosing hybrids with lower relative maturity. For example, even a moderately risk-averse farmer would choose a low RM to avoid risk while not sacrificing much in expected profit. On the other hand, for a livestock farm, the mean profit-risk tradeoff is more significant, and the choice of relative maturity would depend on farmers' risk preferences. For example, a risk-averse farmer would have incentive to plant hybrids with low relative maturity (e.g., RM = 85). But a risk-neutral farmer would choose an RM of 120 because this production plan substantially increases expected profit. These large differences among farm types originate from drying cost differentials. When there is no drying cost (as with the livestock farm), planting a high RM produces both higher expected profit and higher risk. Alternatively, when drying cost becomes significant (as under commercial drying), using a high RM hybrid has only a modest effect on expected net return while significantly increasing the farmer's risk exposure.

In contrast, under a short growing season, Spooner (in northern Wisconsin) shows much more significant tradeoff between risk and expected return. This is illustrated by a much steeper mean-standard deviation frontier in figure 2. Also, figure 2 shows the mean-standard deviation frontiers have a similar shape for all Spooner farm types, indicating similar risk tradeoff across farm types. In this case, risk-neutral farmers have an incentive to use long-season hybrids for all farm types. But, across all drying cost scenarios, risk-averse farmers have an incentive to switch to short-season hybrids as a means of reducing significantly their risk exposure.

Finally, the results obtained in north central Wisconsin (Marshfield) are intermediate between the other two sites. The risk tradeoff is not as pronounced as in the north, but is more pronounced than in the south. These findings stress the role of risk management in corn production, especially as one moves away from the Corn Belt toward the northern fringe of the United States. Our results emphasize the role of choosing corn hybrids and their relative maturity as a means of managing risk. They also reveal that risk exposure can vary significantly both across sites and across farm types. Consequently, risk management strategies are expected to differ depending on the location and the farm type, as well as on the decision maker's degree of risk aversion.

Concluding Remarks

This study has investigated the recent evolution of corn yield focusing on the tradeoff between corn profitability and risk. The analysis relied on time-series data from Wisconsin research stations and farm test sites at the edge of the Corn Belt. Both conditional means and conditional variances for corn yield, corn grain moisture, and corn profitability were specified and estimated for different sites in Wisconsin.

The empirical analysis demonstrates how corn yield and profit have changed over time, and how they are affected by the choice of corn hybrid maturity across sites. The results indicate that, on average, corn yield and profitability have improved faster in northern Wisconsin than in the Corn Belt, suggesting a slow northward expansion of the Corn Belt. However, we also found that both yield risk and profit uncertainty have increased faster in northern Wisconsin than in the Corn Belt. Our empirical results show the choice of corn hybrid maturity makes it easier to manage risk in the Corn Belt than in northern Wisconsin. Thus, the tradeoff between risk and expected return appears to be site specific.

Finally, our investigation points to the importance of drying costs. While higher drying cost tends to reduce expected profit, it also makes reducing risk easier through switching to shorter-season hybrids. This finding identifies the need for adapting risk management strategies to both the location and type of farm. Our analysis stresses the increased importance of risk management in response to climatic and technological change.

Although there is strong evidence that both technological progress (Cardwell) and climate change (Baker, Rushy, and Skaggs; Mendelsohn, Nordhaus, and Shaw) affect the economics of corn production, our results identify technological change as the dominant factor. In northern Wisconsin, we find large productivity gains, but such gains are also associated with significant increases in production risk. This contrasts with the Corn Belt, where productivity gains are positive but smaller. There, we find indirect evidence that technological change may have contributed to reducing exposure to production risk (e.g., new long-season hybrids exhibiting less sensitivity to adverse weather shocks). This seems particularly relevant in a context where global warming contributes to increasing weather uncertainty. Indeed, the development of new agricultural technologies can create new options to deal with climate changes. Future research might benefit from more in-depth analysis of these important issues.

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