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Technological Change and Risk Management:

An Application to the Economics of Corn Production

by

Kwansoo Kim

and

Jean-Paul Chavas*

Abstract: The paper investigates the linkages between technological change and production risk, with an application to corn. The effects of technology on risk exposure are characterized based on the properties of the risk premium. We define technological progress to be risk-increasing (risk-decreasing) if it increases (decreases) the relative risk premium. The analysis is applied to panel data from Wisconsin research stations. Conditional moments (including mean, variance and skewness) of corn yield, grain moisture and corn profit are estimated for different sites. We investigate how the trade-off between expected return and the risk premium varies over time and over space. The empirical results indicate that technological progress contributes to reducing the exposure to risk as well as downside risk in corn production, although this effect varies across sites. They also stress the role of the relative maturity of corn hybrid as a means of managing risk.

Keywords: technological change, production risk, downside risk, corn.

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* Respectively, Research Associate and Professor, Department of Agricultural and Applied Economics, University of Wisconsin, Madison, WI 53706. We would like to thank J. Lauer for providing the data, and R. Klemme for making this research possible. This project was funded by a Hatch grant from the College of Agricultural and Life Sciences, University of Wisconsin, Madison.

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1. Introduction

Technological change has contributed to large increases in agricultural productivity (e.g., Ball et al.; Brennan; Masters et al.; Byerlee). Besides improving productivity, technological change has also affected production risk (e.g., Antle and Crissman; Binswanger and Barah). While genetic improvements have increased mean crop yields, they have also affected yield variability. For example, while the green revolution generated increases in both mean and variance of yield, Traxler et al. found that the post-green revolution era exhibited both slower mean yield growth and declining yield risk. This latter effect can be attributed in part to genetic improvements targeted to improved pest and disease resistance.

The interest in risk issues is motivated by the empirical evidence that most farmers are risk averse (e.g., Lin et al.; Binswanger; Antle, 1987; Saha et al.). It suggests that technological change can also generate benefits by reducing the farmers' exposure to production risk. In addition, the empirical evidence indicates that most farmers exhibit decreasing absolute risk aversion (DARA) (e.g., Binswanger; Chavas and Holt). This implies that farmers are averse to "downside risk" (Antle, 1987). Intuitively, this means that farmers are especially averse to being exposed to unexpectedly low returns (e.g., due to crop failure). This has motivated research on the role of downside risk in risk management, including the "safety first" approach (e.g., Roumasset). Much research has analyzed agricultural risk. This includes the mean-variance investigation of input effects (e.g., Just and Pope), and technology (e.g., Traxler et al.). Yet, the influence of technological change on downside risk exposure (e.g., on the probability of crop failure) remains poorly understood. There is a need to refine our understanding of the linkages between technological change and exposure to risk and downside risk in agriculture, with implications for the cost of private risk bearing.

There is evidence of a significant increase in yield variability over the last few decades (e.g., Thompson; Ramirez). Part of this increase appears due to climate changes (Baker et al.) suggesting that farmers are now facing greater production uncertainty. With accumulations of greenhouse gases (e.g., CO_2) contributing to global warming (IPCC; Houghton and Woodwell; NOAA), climatic changes have implications for farmers' risk exposure. Considering that the impacts of climate change are region-specific (IPCC), it is of interest to examine how the linkages between climate, technology and production risk vary across regions.

This study presents an economic analysis of risk exposure in corn production and corn profitability at the edge of the Corn Belt. Following Antle (1983) and Antle and Goodger, our analysis of production risk involves a moment-based approach. We extend the mean-variance analysis presented in Just and Pope, and Traxler et al. by also examining the third central moment (the skewness) of the relevant random variables. Under risk aversion, decision makers are adversely affected by a higher variance of returns. And under downside risk aversion, the welfare of decision makers is positively (negatively) affected by an increase (decrease) in skewness of returns. This paper examines the effects of technological change on the mean, variance and skewness of corn yield and corn profitability, as they evolve under technological progress. Relying on Pratt's risk premium (as a measure of the cost of private risk bearing), we define technological progress to be risk-increasing (risk-decreasing) if it increases (decreases) the relative risk premium. We investigate empirically the tradeoff between risk (measured by both second and third central moments) and expected profit, with a special focus on the degree of farmers' exposure to downside risk.

The analysis is applied to corn yield and corn profitability using time series data (1974-1997) from several research stations in Wisconsin. The panel structure of the data enables us to investigate the implications of risk (including downside risk) associated with corn profitability on farmers' welfare over time and across space. Econometric estimates are obtained for the first three central moments (mean, variance, and skewness) of the distribution of corn yield, corn

moisture, and corn profit. The empirical evidence shows how the trade off between expected return and risk has evolved over time and across sites. Our results indicate that technological progress has contributed to reducing risk exposure, although such effects vary across space. They also stress the importance of relative maturity of corn hybrid as a means of managing production risk. Finally, they document the role and evolution of downside risk exposure, and its implications for the cost of risk.

This paper is organized as follows. Section 2 presents a conceptual framework of decision making under risk. Under the expected utility model, we analyze the effects of technology and input use on production risk, profitability. We use the properties of the relative risk premium to characterize the effects of technology on risk exposure. We also rely on a moment-based approach to approximate the risk premium. This guides our econometric specification for empirical research. The data and application of the model to corn are discussed in section 4. Sections 5 and 6 present the empirical analysis. We analyze how the choice of corn hybrid maturity affects corn yield and corn profitability, focusing on its effects on expected value, variance as well as skewness. Corn hybrid maturity is found to have statistically significant effects on production risk. This implies that the choice of hybrid maturity is an important risk management tool for farmers. We also find evidence that technological change contributes to a significant reduction in risk exposure through its effects on the variance as well as skewness of profit. In other words, besides increasing yield, technological progress also lower farmers' exposure to both risk and downside risk. However, these effects are found to vary between farm types and across space. Finally, concluding remarks are presented in section 7.

2. Conceptual Framework

Consider a farm producing $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_n)$, a vector of outputs under uncertainty. Under technology t, farm production of output Y_i is represented by the stochastic functions $Y_i =$

$A_i \cdot y_i(\mathbf{x_i}, t, \mathbf{e})$, where A_i is the acreage of the i-th commodity, $y_i(\cdot)$ is the corresponding production per acre, $\mathbf{x_i}$ is a vector of inputs used to produce y_i, and $\mathbf{e}$ is a vector of stochastic factors that are not known to the decision maker at the time when the input decisions are made. The vector of stochastic factors $\mathbf{e}$ is treated as a random variable with a given probability distribution G. The vector $\mathbf{e}$ includes unpredictable weather effects as well as the effects of pest and diseases on farm production. Similarly, under technology t, farm production cost in producing the i-th commodity is represented by the stochastic function $[A_i \cdot C_i(\mathbf{x_i}, t, \mathbf{e})]$, where $C_i(\mathbf{x_i}, t, \mathbf{e})$ is the cost per acre, depending of input choices $\mathbf{x_i}$, technology t, and production uncertainty $\mathbf{e}$. Note that this allows for cost to depend directly on yield, e.g., $C_i = c_i(y_i(\mathbf{x_i}, t, \mathbf{e}), \mathbf{x_i}, t, \mathbf{e})$. Examples of ex post costs that vary with output include storage cost and drying cost. By denoting p_i the price of output Y_i, total profit associated with farm activities $\mathbf{Y}$ is

$$\pi = \sum_{i=1}^{n} \{A_i \cdot [p_i \cdot y_i(\mathbf{x_i}, t, \mathbf{e}) - C_i(\mathbf{x_i}, t, \mathbf{e})]\}, \tag{1}$$

subject to $\sum_{i=1}^{n} A_i = A$, where A denotes total acreage available for farm production. The price of output, p_i, can also introduce a stochastic market environment in the analysis. This allows for price and weather uncertainty, as well as technology effects in production decisions. Assume that inputs are chosen to maximize the expect utility of profit $EU(\pi)$, 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 $\partial U/\partial \pi > 0$. Then, we can characterize farm decision-making by the optimization problem: Max $\{EU(\pi)\}$, where profit π is given in (1). The cost of private risk bearing can be measured by the sure amount R satisfying

$$EU(\pi) = U[E(\pi) - R], \tag{2}$$

where $[E(\pi) - R]$ is the certainty equivalent of profit (Pratt). The value R defined in (2) is the risk premium measuring the largest amount of money the decision maker is willing to pay to replace

the random variable π by its expected value $E(\pi)$. It is a monetary measure of the implicit cost of private risk bearing. In this context, for non-degenerate risk, risk aversion implies that $R > 0$, i.e. that the decision maker always prefers a riskless world. This corresponds to a concave utility function: $\partial^2 U/\partial\pi^2 < 0$ (Pratt).

From equation (2), maximizing expected utility is equivalent to maximizing the certainty equivalent, $E[\pi(\mathbf{x}, t, \cdot)] - R(\mathbf{x}, t)$. In general, the certainty equivalent, $E[\pi(\mathbf{x}, t, \cdot)] - R(\mathbf{x}, t)$, depends on input use $\mathbf{x}$ and technology t. Of particular interest are the effects of input use $\mathbf{x}$ and technology t on risk exposure. An input x is said to be risk-increasing (risk-decreasing) if $\partial R(\mathbf{x}, t)/\partial x > 0$ (< 0), i.e. if it increases (decreases) the cost of private risk bearing (e.g., Ramaswami). Assuming an interior solution, and using the first-order necessary condition $\partial[E(\pi)-R]/\partial x = 0$, this can be expressed equivalently through the effects on the relative risk premium: $R(x, t)/[E(\pi(x, t, \cdot) - R(x, t)]$. In other words, at the optimum, input x is risk-increasing (risk-decreasing) if it tends to increase (decrease) the relative risk premium: $\dfrac{\partial\left[\dfrac{R(\mathbf{x},t)}{E(\pi(\mathbf{x},t,\cdot)) - R(\mathbf{x},t)}\right]}{\partial x} > 0$ (< 0).

In a similar fashion, we propose to investigate the effects of technological change on risk exposure. We consider the case of technological progress associated with an increase in the technology index t, such that $\partial[E(\pi(\mathbf{x}, t, \cdot) - R(\mathbf{x}, t)]/\partial t > 0$.

Definition: Under risk aversion (where $R > 0$), technological progress is said to be risk-increasing (risk-decreasing) if $\dfrac{\partial\left[\dfrac{R(\mathbf{x},t)}{E(\pi(\mathbf{x},t,\cdot)) - R(\mathbf{x},t)}\right]}{\partial t} > 0$ (< 0).

Assuming that $E(\pi) > 0$, $E(\pi) - R > 0$, and $R > 0$, this definition implies that technological progress is risk-increasing (risk decreasing) if $\partial \ln[R(\mathbf{x}, t)]/\partial t > (<) \partial \ln[E\pi(\mathbf{x}, t)]/\partial t$, i.e., if

technological progress tends to increase the risk premium relatively more (less) than expected return. Note that this characterization of linkages between technology and risk exposure depends on risk preferences as they influence the cost of private risk bearing R. This suggests a need to assess the risk premium R.

While R can always be obtained as an implicit solution to equation (2), this requires knowing both the utility function $U(\pi)$ and the probability distribution of π. Given the empirical difficulties in obtaining this information, it will be useful to develop some simple approximation to R. Under differentiability, take a first order Taylor series expansion on the right-hand side of (2) with respect to R, and a m-th order Taylor series expansion on the left-hand side of (2) with respect to π. In the neighborhood of the riskless case (where $\pi = E(\pi)$), this gives the following approximation to the risk premium R

$$R \cong \frac{1}{U^1} \cdot \left[-\sum_{j=2}^{m} \frac{U^j}{j!} \cdot E[\pi - E(\pi)]^j \right], \tag{3}$$

where $U^j = \frac{\partial^j U}{\partial \pi^j}(E(\pi))$ is the j-th derivative of U with respect to profit π, evaluated at $E(\pi)$, j = 1, …, m, m ≥ 2. Note that $E[\pi - E(\pi)]^j$ is the j-th central moment of π. Thus, expression (3) provides an approximate measure of the risk premium as a function of the first m central moments of profit. This starts with the variance of π (when j = 2), but it can also include higher moments (e.g., skewness when j = 3). This provides a framework to assess the relative importance of each moment in the cost of risk. Under risk neutrality, the utility function $U(\pi)$ is linear, the risk premium R is zero, and maximizing (2) reduces to maximizing the sum of expected profit $E[\sum_{i=1}^{n} \pi_i(\mathbf{x_i}, t, \mathbf{e})]$. However, under risk aversion, $\partial^2 U/\partial \pi^2 < 0$ (Pratt), implying that the risk premium R tends to increase with the variance of profit. And under downside risk aversion, $\partial^3 U/\partial \pi^3 > 0$, implying that the third central moment becomes relevant: decision-makers prefer a positive skewness as it reduces their exposure to downside risk (e.g., Antle, 1987).

The model just presented is quite general: it includes multiple sources of uncertainty associated with different productions. However, one may sometimes want to focus on the uncertainty associated with a particular production. This is the empirical case presented below, where we focus on corn production. In this case, we want to adapt the above analysis. For that purpose, assume that we want to focus on the first commodity (i = 1). Let $\pi = \sum_{i=1}^{n} [A_i \cdot \pi_i]$, where $\pi_i = p_i \cdot y_i(\mathbf{x_i}, t, \mathbf{e_i}) - C_i(\mathbf{x_i}, t, \mathbf{e_i})$ denotes profit per acre of the i-th commodity. Note that $(\sum_{i=1}^{n} \varepsilon_i)^j = \sum \frac{j!}{j_1!j_2!...j_n!} \varepsilon_1^{j_1} \cdot \varepsilon_2^{j_2} \cdots \varepsilon_n^{j_n}$, where $j_1, j_2, \ldots, j_n$ are non-negative integers satisfying $\sum_{i=1}^{n} j_i = j$.

Letting $\varepsilon_i = [A_i \cdot (\pi_i - E(\pi_i))]$, it follows that the risk premium R can be approximated by

$$R \cong \frac{1}{U^1} \cdot \left[- \sum_{j=2}^{m} \frac{U^j}{j!} \cdot [A_1^j \cdot \mu_{j\pi} + \delta_j] \right], \qquad (3')$$

where $\mu_{j\pi} = E[(\pi_1 - E(\pi_1))^j]$ is the j-th central moment of profit per acre of the first commodity, π_1, and $\delta_j = \sum_{j_i<j} \frac{j!}{j_1!j_2!...j_n!} \varepsilon_1^{j_1} \cdot \varepsilon_2^{j_2} \cdots \varepsilon_n^{j_n}$, j = 2, …, m. Expression (3') relates the risk premium R to the first m central moments of π_1, while the δ_j's account for the effects of risky returns associated with other production activities. It follows that the certainty equivalent of profit can be approximated as

$$E(\pi) - R \cong \sum_{i=1}^{n} [A_i \cdot E(\pi_i)] - \frac{1}{U^1} \cdot \left[- \sum_{j=2}^{m} \frac{U^j}{j!} \cdot [A_1^j \cdot \mu_{j\pi} + \delta_j] \right]. \qquad (4)$$

Equation (4) identifies the components of the certainty equivalent directly associated with the first commodity. They are: $A_1 \cdot \mu_1 - \frac{1}{U^1} \cdot \left[- \sum_{j=2}^{m} \frac{U^j}{j!} \cdot [A_1^j \cdot \mu_{j\pi}] \right]$, where $\mu_1 = E(\pi_1)$. This shows the direct effects of the first m moments of the distribution of profit π_1, $\mu_{j\pi}$, j = 1, …, m, on the certainty equivalent. Note that equation (4) applies under very general conditions. It only

requires that the first m moments of π are finite. As such, it allows for many probability distribution functions for the random variables **e**, thus providing a flexible representation of the uncertainty.

3. Econometric Specification

This section discusses the econometric specification used below in our empirical investigation of the distribution of corn yield, moisture and profit. Let $\mu_{1\pi}(\mathbf{x_1}, t) = E\pi_1(\mathbf{x_1}, t, \mathbf{e})$ denote the mean profit or first moment of profit per acre of the first commodity. And let $\mu_{j\pi}(\mathbf{x_1}, t) = E[(\pi_1(\mathbf{x_1}, t, \mathbf{e}) - \mu_{1\pi}(\mathbf{x_1}, t))^j]$ be the j-th central moment of π_1, j = 2, …, m, conditional on input decisions $\mathbf{x_1}$ and on technology t. Equation (4) shows how the certainty equivalent of profit depends on the mean profit $\mu_{1\pi}(\mathbf{x_1}, t)$, on the variance of profit, $\mu_{2\pi}(\mathbf{x_1}, t)$, on the skewness of profit $\mu_{3\pi}(\mathbf{x_1}, t)$, etc., and on other interaction effects across activities. This suggests a need to estimate the moments of profit $\mu_{j\pi}(\mathbf{x_1}, t)$, j = 1, 2, 3…. For that purpose, we specify a parametric form for each $\mu_{j\pi}$ and estimate the corresponding parameters. Let $\mu_{j\pi} = f_j(\mathbf{x_1}, t, \mathbf{b_j})$, where $\mathbf{b_j}$ is a vector of parameters representing the effects of $\mathbf{x_1}$ and t on the j-th moment of profit $\mu_{j\pi}$, j = 1, 2, 3 …. Then, consider the econometric model

$$\pi_1 = f_1(\mathbf{x_1}, t, \mathbf{b_1}) + v_{1\pi} \tag{5}$$

where $v_{1\pi}$ is an error term distributed with mean zero, $E(v_{1\pi}) = 0$. Then, treating $(\mathbf{x_1}, t)$ as exogenous variables, equation (5) represents a standard regression model where the parameters $\mathbf{b_1}$ can be consistently estimated by the least squares method. Let $\mathbf{b_1}^{LS}$ be the least squares estimator of $\mathbf{b_1}$ in (5), giving the least squares residual $v_{1\pi}^{LS} = \pi_1 - f_1(\mathbf{x_1}, t, \mathbf{b_1}^{LS})$. Consider the following model specification

$$(v_{1\pi}^{LS})^2 = f_2(\mathbf{x_1}, t, \mathbf{b_2}) + v_{2\pi}. \tag{6}$$

Then, the least squares estimation of (6) gives $\mathbf{b_2}^{e}$, a consistent estimator of $\mathbf{b_2}$ (Antle, 1983). It follows that $f_2(\mathbf{x_1}, t, \mathbf{b_2}^{e})$ is a consistent estimator of $Var(v_{1\pi})$. In the presence of

heteroscedasticity, this provides a basis for re-estimating equation (5) by generalized least squares. The resulting estimator $\mathbf{b_1}^{GLS}$ is consistent, asymptotically efficient, and asymptotically normal. This provides the estimator of expected profit reported below. Next, define $v_{1\pi}^{GLS} = \pi_1 - f_1(\mathbf{x_1}, t, \mathbf{b_1}^{GLS})$ and consider

$$(v_{1\pi}^{GLS})^j = f_j(\mathbf{x_1}, t, \mathbf{b_j}) + v_{j\pi}, j \geq 2, \qquad (6')$$

Since $v_{1\pi}^{GLS}$ is a consistent estimator of $v_{1\pi}$, it follows that the least squares estimator of $\mathbf{b_j}$ in (6') is consistent and asymptotically normal for $j \geq 2$ (Antle, 1983; Antle and Goodger). However, noting that $Var(v_{j\pi}) = f_{2j} - (f_j)^2$, the standard errors of $\mathbf{b_j}$ need to be corrected for heteroscedasticity. For that purpose, we implement the procedure proposed by White to obtain consistent estimates of the standard errors of $\mathbf{b_j}$ in (6'). This provides the empirical framework used below in the investigation of the distribution of profit (measured through its mean, variance, and skewness) as it changes with technology t and the input choices $\mathbf{x_1}$.

Farm profit π_1 is a function of input choice $\mathbf{x_1}$, technology t, and uncertainty $\mathbf{e}$. As indicated in equation (1), it will be of interest to decompose the effects of $(\mathbf{x_1}, t, \mathbf{e})$ on farm profit π_1 into two main effects: (i) production effects through the production function $y_1(\mathbf{x_1}, t, \mathbf{e})$; and (ii) cost effects through the cost function $C_1(\mathbf{x_1}, t, \mathbf{e})$.[1] Both functions are stochastic because they depend on the random variables $\mathbf{e}$. Following the moment-based approach, they can each be represented by their central moments: mean, variance, skewness, etc. The empirical analysis of these moments can be conducted in a way similar to the approach just discussed for the profit function. For example, the central moments of the production function $y_1(\mathbf{x_1}, t, \mathbf{e})$ can be parameterized as $E(y_1) = \mu_{1y} = g_1(\mathbf{x_1}, t, \mathbf{a_1})$ for the expected value of yield, $E[(y_1 - \mu_{1y})^2] = \mu_{2y} = g_2(\mathbf{x_1}, t, \mathbf{a_2})$ for the variance of yield, $E[(y_1 - \mu_{1y})^3] = \mu_{3y} = g_3(\mathbf{x_1}, t, \mathbf{a_3})$ for the skewness of yield, etc. Following the estimation method discussed above, the parameters of the functions $g_j(\mathbf{x_1}, t, \mathbf{a_j})$, $j = 1, 2, \ldots$, can be consistently estimated. Similarly, the central moments of the function $C_1(\mathbf{x_1}, t, \mathbf{e})$ can be parameterized as $E(C_1) = \mu_{1c} = h_1(\mathbf{x_1}, t, \mathbf{g_1})$ for expected cost, $E[(C_1 - \mu_{1c})^2] = \mu_{2c}$

$= h_2(\mathbf{x_1}, t, \mathbf{g_2})$ for the variance of cost, $E[(C_1 - \mu_{1c})^3] = \mu_{3c} = h_3(\mathbf{x_1}, t, \mathbf{g_3})$ for the skewness of cost, etc. Again, the parameters of the functions $h_j(\mathbf{x_1}, t, \mathbf{g_j})$, j = 1, 2, …, can be consistently estimated as discussed above.

4. An Application to Corn

We apply the conceptual framework developed in the previous sections to corn production, with a focus on the risk implications of production uncertainty. In particular, we examine the effects of technology and climate change at the edge of Corn Belt. First, Mendelsohn et al. has argued that the effects of climatic change are expected to be more significant in marginal areas around the Corn Belt. Second, characterizing the implications of technological change at the edge of the Corn Belt allows us to examine the differential effects of technological change on corn production over space.

Our analysis relies on corn production and cost data obtained from three research stations in Wisconsin: Arlington, Marshfield and Spooner. The Arlington research station is in Southern Wisconsin, Spooner is in Northern Wisconsin, while Marshfield is in Central Wisconsin. The Arlington station is located in the Northern Corn Belt. As such, the data from Arlington provide information on the effects of technology and climatic changes on corn production and costs in the Corn Belt. In contrast, Marshfield and Spooner are outside the Corn Belt. This means that the data from Marshfield and Spooner provide useful information on technology and climate effects in more marginal areas for corn production.

As one moves north in Wisconsin, corn yields decline as the length of the growing season gets shorter. To deal with this shorter growing season, farmers in Northern Wisconsin plant short-season corn hybrids for at least two reasons: 1/ they give a higher probability of reaching maturity before the end of the growing season; and 2/ they require lower drying costs. These trade-offs are evaluated below. The data set consists of 24 years (1974-1997) of yield and relative

maturity[2] (RM) information generated from long-term studies of corn yields conducted by the University of Wisconsin Agricultural Experiment Station. These agronomic trial studies were designed to measure corn hybrid performance. They measured yield and grain moisture for a range of corn hybrids. Because other inputs (including cultural practices) were uniformly administrated during the experiment at each site, yield variations in each location are mainly due to the choice of hybrid maturity, genetic improvements and uncontrollable factors (mainly weather effects). This provides a basis of evaluating the evolution of the distribution of corn yield and cost over time and across space.

Table 1 summarizes the data for the Arlington, Marshfield and Spooner research stations. Number of observations (N), average GDD (Growing Degree Days)[3] and its standard deviation, average yield (bu/acre), average corn moisture at harvest (percent) and the range of maturity rating (RM) for each location are presented. As expected, as one moves north, average GDD declines. Below, we will examine the evolution of GDD as a proxy measure of climate change. The average yield over the sample period decreases as one moves north. Relative maturity ranges from 85 to 120 in the south, and from 70 to 110 in the north, reflecting the different climatic conditions.

5. Estimation Results

Focusing on the first three central moments of the distribution of corn yield, corn moisture, GDDs (Growing Degree Days) and corn profit, this section presents an empirical investigation of (i) the determinants of the distribution of corn yield, (ii) the distribution of GDDs and its trend, (iii) the factors affecting the moisture of corn grain at harvest, and (iv) the distribution of corn profit and its evolution (both over time and across space).

5.1. Mean, variance, and skewness of corn yield

As discussed in section 3, we estimate the factors influencing the mean, variance, and skewness of corn yield. First, we consider the stochastic production function representing corn yield, $y_1 = g_1(\mathbf{x}_1, t, \mathbf{a}_1) + v_{1y}$, 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). The introduction of RM^2 allows for possible nonlinear relationship between relative maturity and corn yield. The time trend T captures two effects: the impact of technological change (e.g., genetic progress)[4] on yield (Cardwell), as well as the impact of climatic change (Baker et al.; Mendelsohn et al.). The error term v_{1y} accounts for unobserved weather effects and other uncontrollable factors affecting corn yield.

Second, we consider the variance of yield: $\mu_{2y} = g_2(\mathbf{x}_1, t, \mathbf{a}_2) + v_{2y}$. We specify and estimate the variance of corn yield as a linear function of relative maturity (RM) and a time trend (T). Third, we investigate the skewness of yield: $\mu_{3y} = g_3(\mathbf{x}_1, t, \mathbf{a}_3) + v_{3y}$. This function is estimated using a linear specification with relative maturity (RM) and a time trend (T) as explanatory variables.

The econometric results are reported in Table 2. From Table 2-A, the coefficient estimates in the expected yield equation have anticipated signs and a high level of significance. First, the coefficients associated with RM are all statistically significant. In all three sites, we find a positive and concave relationship between relative maturity and corn yield: long season hybrids tend to produce higher expected yield. Second, the coefficients of time trend (T) are all statistically significant at the 1% level. The positive signs of the coefficients indicate that expected corn yield increases over time. As discussed, this measures the joint effects of climate change and productivity growth due to genetic and technological improvements. It is noted that

the magnitude of the time trend effects increases as one moves north, identifying slightly heterogeneous effects of technology and climate changes on expected corn yield.

Table 2-B reports estimation results for the variance of yield. The fairly low R^2 value suggests that 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 positive and significant as one moves north. This suggests that technological and climatic changes have increased production risk for corn at the edge of the Corn Belt (but possibly not within the Corn Belt).

The estimation results for the skewness of yield is reported in Table 2-C. We found no evidence of statistically significant relationship between relative maturity and the skewness of yield. While the choice of relative maturity is relevant in dealing with production risk (as measured by the variance of yield), it suggests that RM choice does not affect exposure to downside yield uncertainty. At Arlington, positive and significant time trend suggests that technology and climate changes tend to increase the skewness of yield. This implies that exposure to downside yield risk has declined over time at Arlington. However, these effects are not statistically significant outside the Corn Belt (Marshfield and Spooner).

Next, we investigate the nature of the exposure to downside yield risk. For that purpose, we tested the null hypothesis that the yield distribution is symmetric, using a Wald statistic. The skewness coefficient measuring symmetry of the distribution is defined as $\beta_1 = (f_3)^2/(f_2)^3$, where f_i is the i-th central moment of yield (Greene, p310). Under the null hypothesis of symmetry ($\beta_1 = 0$), the test statistic $W = N \cdot (\beta_1^e/6)$ is distributed $\chi^2(1)$. We tested for symmetry at each site for different values of RM and at different time periods. For Arlington and Marshfield, the test results imply that, in most cases, the null hypothesis of symmetry is rejected at the 5 percent significance level. The test results then provide evidence that the distribution of yield is skewed to the left (corresponding to a significant exposure to downside risk) in Arlington and Marshfield.

As one moves north (Spooner), the null is rejected regardless of the maturity length of corn hybrids. Thus, in general, we find evidence that the distribution of yield is skewed to the left, implying a significant exposure to downside yield risk. However, one exception is at Arlington, where we failed to reject the null for medium-season hybrids in the 1990s, while we rejected the null for the same hybrids in the 1970s and the 1980s. This indicates that yield skewness has changed and that the exposure to downside risk has declined over time in Arlington.

5.2. Technological change versus climatic change

The estimation results discussed in the previous section show some significant increases in the mean, variance and skewness of yield over time. The joint effects of technology and climate changes on the mean, variance and skewness of corn yield (captured by the time trend T), appear to vary across sites. A question of interest is whether we can assess how much of these are due to technological change versus climate change.

To address this question, we consider the evolution of the distributions of Growing Degree Days (GDD) at each site. Since GDD is a temperature-based index providing a summary measure of the length of the growing season for corn, we use it as a proxy for climate change. Using the moment-based approach discussed in section 3, the mean, variance and skewness of GDD are estimated as a linear function of a time trend. The results are presented in Table 3 for Arlington, Marshfield and Spooner. As indicated in Table 3-A, the coefficient of the time trend (T) in mean GDD equation is positive and statistically significant for Marshfield. However, it is not statistically significant for Arlington and 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.[5] For Marshfield, we find strong evidence of a longer growing season. This is consistent with beneficial effects of global warming in the northern fringe of the U.S. (Mendelsohn et al.). On the other hand, as indicated in Table 2-A, we also find strong

evidence of joint effects of technology and climate changes on productivity gain. Then, how much of productivity gain at Marshfield can be attributed to technological improvement? Compared with the annual yield increase of +1.87 bu/acre/year (+1.13 %/year), 0.42% per year increase in growing season (associated with an average annual increase in GDD of 11.45°F) is reported in Table 3-A. To the extent that GDD increases are expected to generate proportional changes in expected corn yield, this suggests that about 37 percent of productivity gain in Marshfield would be attributed to a longer growing season. This would suggest that 63 percent of productivity gain may be associated with technological change. In a way consistent with Thompson (1975, 1986) and Cardwell, this indicates that 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.

Next, we evaluate the impact of climatic change on production risk (as measured by the variance of corn yield). Table 3-B reports that the coefficient of the time trend (T) in the variance of GDD equation is positive and statistically significant for Arlington and Marshfield. This suggests that the growing season has become more unpredictable at Arlington and Marshfield. However, the time trend effect is not statistically significant at Spooner. Thus, at Spooner, there is no strong evidence that the length of the growing season has become more unpredictable. This suggests that, at the edge of the Corn Belt, it is not clear whether global warming is contributing to increased corn yield uncertainty. Yet, significant increases in yield risk have been reported in Table 2-B for Spooner. To the extent that they are not associated with climatic fluctuations, such changes can be attributed to changing technology. This indicates that, along with higher expected yields, improved technologies also bring an increased exposure to production risk (e.g., improved short-season hybrids with better average yield but more sensitivity to weather shocks). In contrast, in the Corn Belt (Arlington), we find a significant increase in the unpredictability of the length of the growing season. Yet, as indicated in Table 2-B, there is no statistical evidence that the variance of yield has increased over time in Arlington. These two findings suggest that

technological progress in Arlington has contributed to reducing exposure to production risk in the Corn Belt. This shows that technological progress interacts with production risk in different ways across regions.

Finally, we inquire about the effects of climatic change on exposure to downside production risk. This involves an investigation of the skewness of GDD. As indicated in Table 3-C, we find no statistical evidence that the skewness of GDD has changed over time. To the extent that the time trend captures climate change, this suggests that the impact of climate change on exposure to downside risk remains unchanged. Yet, we found statistically significant increase in the skewness of corn yield at Arlington. We interpret this to mean that, at Arlington, most of the reduction in downside risk can be attributed to technological progress (e.g., due to new hybrids that are more resistant to pests and diseases). In all cases, we conclude that technological progress seems the dominant factor influencing the evolving distribution of corn yield.

5.3. Mean, variance, and skewness of corn moisture

This section explores corn grain moisture at harvest. Since the cost of drying depends on the moisture of corn grain at harvest, we examine the factors affecting the uncertainty involved in drying cost. Expected moisture, variance of moisture, and skewness of moisture are specified and estimated. The estimation results are reported in Table 4 for each site. Mean, variance and skewness of moisture equations are specified as a linear function of relative maturity RM and a time trend T. Including a time trend allows us to examine the effects of technology and climatic changes on the evolution of moisture over time.

As indicated in Table 4-A, the effects of RM on mean corn grain moisture are positive and become significant as one moves north. The variance of moisture also exhibits a positive relationship with RM, suggesting that the risk associated with the unpredictability of corn grain moisture increases with corn hybrid maturity. This relationship seems to become more important as one moves north. As indicated in Table 4-C, we find strong evidence of a statistically

significant and positive relationship between RM and the skewness of corn moisture at Arlington and Marshfield. This suggests that planting a longer season corn hybrid increases the odds of facing high moisture corn at harvest time.

Next, we evaluate the evolution of the distribution of corn grain moisture. First, at Arlington, the coefficient of the time trend in the expected moisture equation is positive and statistically significant. This means that technological progress and climatic change tend to increase expected moisture, thereby increasing drying costs. With no evidence of changes in climatic trend (Table 3-A), this suggests that most of these effects can be attributed to technological progress at Arlington. However, as indicated by the statistically significant and negative relationship between time trend and the skewness of moisture (Table 4-C), technological progress contributes to lowering the odds of facing high moisture corn at harvest (which would reduce drying cost). At Marshfield and Spooner, we find no strong evidence of time trend effects on either expected moisture or skewness of moisture. However, note that these sites show statistically significant relationships between time trend and the variance of moisture.

5.4. Mean, variance, and skewness of corn profit

Finally, we explore the implications of technology and uncertainty on corn profit. We measure corn profit as corn revenue minus drying cost on a per acre basis. Corn price is assumed to be $2.00 per bushel.[6] 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 with no drying; a grain farm using on-farm drying facilities; and a grain farm relying on commercial drying.[7] The expected value of profit, its variance and its skewness are specified and estimated as discussed in section 3. 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 associated discussion). For example, the coefficients

associated with relative maturity RM and time trend T are statistically significant (except RM^2 at Arlington for a livestock farm) and have expected signs. They indicate 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, it is only in Northern Wisconsin (Spooner) that profit risk increases significantly over time for all farm types. The rate of increase is largest for the farm using commercial drying, and smallest for the livestock farm. In the other locations, the results vary across farms types, indicating the significant role of drying cost.

Using the econometric results presented in Table 5-A, we evaluated the RM value that maximizes expected profit. This corresponds to a risk neutral scenario. At Arlington the optimal RM equals 125.9 for the livestock farm, 110.9 for on-farm drying, and 98.7 for commercial drying. These values are 96.0, 90.1 and 84.9 at Marshfield, and 89.0, 87.3 and 85.3 at Spooner, respectively for livestock farm, on-farm drying and commercial drying. This shows that, as one moves north, the drying cost effects are important, and maximum expected profit is achieved at lower value of RM. These results indicate that, under commercial drying, switching to lower maturity rating provides farmers an opportunity to reduce their drying cost and to increase expected profit.

Next, we evaluate the farmer's risk exposure. Table 5-B reports statistically significant and positive relationship between the variance of profit and relative maturity RM. This suggests a trade-off between expected profit and the variance of profit. Table 5-C shows no significant RM effects on the skewness of profit. This suggests that RM is not an effective means of controlling downside risk. Yet, a Wald test statistic suggests that, in general, the distribution of corn profit is not symmetrically distributed. For example, at Arlington and Spooner relative skewness values indicate that the distribution of profit is skewed to the left, implying the presence of a significant exposure to downside risk. However, in Arlington, we find that the exposure to downside risk has decreased over time.

6. Economic Implications

This section discusses the economic implications of our econometric estimates. First, we explore whether relative maturity is a risk-increasing or risk-decreasing input. We also investigate the relationships between technological progress and risk exposure. Second, we examine the relationship between expected corn profit and the cost of risk (as measured by the risk premium), and its evolution over time and across space. Finally, we decompose the risk premium into two parts: one due to the second moment and the other due to the third moment of corn profit. This provides some insights on the relative role of variance versus downside risk exposure (as captured by the third moment) in the evaluation of the cost of risk.

6.1 Technology, relative maturity and risk

The cost of private risk bearing was defined by the risk premium R in equation (2) and approximated by equation (3) or (3'). From equation (3'), the risk premium per acre of corn can be approximated by

$$R_1 \cong \frac{1}{A_1 \cdot U^1} \cdot \left[- \sum_{j=2}^{m} \frac{U^j}{j!} \cdot [A_1^j \cdot \mu_{j\pi}] \right], \qquad (7)$$

where $\mu_{j\pi}$ is the j-th central moment of corn profit per acre, π_1. Expression (7) shows that the risk premium depends on the first m moments of π_1 as well as risk preferences U. We have information about the first three central moments of π_1 (see Table 5). To make use of (7) to evaluate the cost of risk, we need to know the decision maker's risk preferences. Below, we present results obtained assuming that the decision maker's risk preferences exhibit Constant Relative Risk Aversion (CRRA), with utility function $U(\pi) = \pi^{1-\lambda}$, $\lambda > 0$ being the relative risk aversion coefficient (Pratt). Note that this is consistent with risk aversion ($U^2 < 0$), decreasing absolute risk aversion (see Pratt), as well as downside risk aversion ($U^3 > 0$). Given the empirical

evidence that most farmers are risk averse (Lin et al.; Binswanger; Antle, 1987; Saha et al.) as well as downside risk averse (e.g., Binswanger; Chavas and Holt), this risk preference specification seems reasonable. For the purpose of illustration, the results presented below correspond to a CRRA coefficient $\lambda = 2$.[8]

Using the approximate risk premium given in (7), we first examine the relationship between relative maturity (RM) and the cost of risk. Evaluated at 1997, we calculated the change in the risk premium R_1 due to a change in relative maturity (RM). We found that, regardless of sites and farm types, the risk premium R_1 increased with a longer maturity corn hybrid. This implies that relative maturity is a risk-increasing input: a longer relative maturity involves a higher cost of risk.

In a similar fashion, we explored the relationship between technological change and risk. In section 2, we defined technological progress to be risk-increasing (or risk-decreasing) depending on its impact on the relative risk premium. We used expression (7) to evaluate the relative risk premium comparing 1975 with 1994, for each location and each farm type. With one exception (commercial farm in Spooner), we found that the relative risk premium was lower in the 1995 than in the 1975. We interpret this as strong evidence that technological progress has been risk-decreasing. This is consistent with the results reported in Table 5.

Next, we examine whether these findings are statistically meaningful. First, we tested the null hypothesis that RM input has no effect on the risk premium. This is done by calculating the change in the risk premium due to a change in RM, and bootstrapping its distribution. The null hypothesis that RM has no effect on the risk premium was tested for each farm type and each site. Using a 5 percent significance level, we strongly rejected the null hypothesis for each farm type at Arlington as well as Spooner. This provides statistical evidence that choosing a lower RM is a risk-reducing strategy. At Marshfield, we also rejected the null hypothesis for on-farm storage and commercial farm. Again, this provides evidence that short season hybrids generate a lower risk premium. However, we failed to reject the null hypothesis for the livestock farm at

Marshfield (with a p-value of 0.197). This shows that risk exposure varies across sites. It also illustrates the importance of drying cost in the evaluation of risk management strategies.

Second, we examined the statistical significance of the time trend T on the relative risk premium. The null hypothesis is that the relative risk premium has not changed over time. Again we used (7) to bootstrap the distribution of the change in the relative risk premium between 1975 and 1994. Using a 5 percent significance level, the null hypothesis is strongly rejected for all farm types and all RM at Arlington and Marshfield. We interpret this as strong statistical evidence that technological progress is risk-reducing at Arlington and Marshfield. However, the tests results differ for a commercial farm at Spooner. The p-values were 0.32, 0.779, 0.755 and 0.651 for RM = 70, 75, 80, 90, respectively, indicating that we fail to reject the null hypothesis at Spooner. This suggests that the linkages between technological change and risk exposure vary across sites as well as across farm types. These issues are further discussed next.

6.2. Trade-off between expected profit and risk premium

The trade-offs between expected profit and the risk premium (obtained from equation (7)) are reported in Figures 1-a, 1-b, 1-c by farm type for Arlington, Marshfield and Spooner, respectively. They summarize the effects of drying cost and technological progress on the expected profit and risk premium by location and by farm type. They also show the evolution of the relationship between expected profit and risk premium between the 1970s and the 1990s. Each point is obtained by changing corn hybrids and their associated RM ratings (expressed in days). The slope of the lines shows how expected corn profit and risk premium relate to each other. For example, the positive slope of frontier functions indicates that expected income cannot be increased without also increasing the risk premium. Alternatively, the risk premium cannot be reduced without sacrificing expected income.

In the Corn Belt (represented by the Arlington site), the growing season is longer. Each farm type exhibits a different slope of its frontier function. For example, the livestock farm shows relatively large trade-off between expected return and risk premium, whereas the trade-off is less pronounced under commercial drying. This means that, under commercial drying, the risk premium can be reduced without much reduction in expected profit by choosing hybrids with lower relative maturity RM. The relationship indicates that technological progress has allowed farmers to significantly reduce their risk premium without much reduction in expected return.

In contrast, under a short growing season, Spooner (in Northern Wisconsin) shows different linkages between technological change and the trade-off between risk premium and expected return. There, technological progress has not allowed farmers to reduce their risk premium without significant reduction in expected return. Finally, the results obtained in Central Wisconsin (Marshfield) are intermediate between the other two sites. The risk premium trade-off is not as pronounced as in the north, but more pronounced than in the south.

6.3. Decomposition of the cost of risk

This section presents a more detailed analysis of the risk premium. We decompose the risk premium into its components due to variance versus skewness. Again, this relies on equation (7), which relates the risk premium to the second and third central moments of corn profit.

The decomposition of the risk premium into its second and third moment effects is presented in Figures 2-a, 2-b, 2-c by farm type for different sites. In each figure, the horizontal axis represents the cost of risk due to the second moment, while the vertical axis measures the cost of risk due to the third moment. For all sites and all farm types, a large part of the risk premium is attributed to second moment effects. This is particularly true at Arlington. For example, the variance effects consist of 67% (when RM = 85) to 91% (when RM = 120) of the risk premium in commercial farm. Each figure shows the relative effectiveness of RM and farm type as risk management tools affecting the risk premium.

In the Corn Belt (Arlington) where the growing season is longer, lower relative maturity RM significantly reduces the cost of risk due to variance. However, this cannot be achieved without increasing the cost of downside risk exposure. Risk exposure is more prominent for the commercial farm in the 1970s. In the 1990s, however, a commercial farm has the least exposure to risk attributable to both variance and downside risk. This suggests that technological progress has contributed to reducing risk associated with the unpredictability of corn grain moisture. For the other two farm types, risk improvements also exist, but they are smaller.

Interestingly, under a short growing season, Spooner (in Northern Wisconsin) shows different evolution patterns of second and third moment effects. In particular, Figure 2-c indicates that, for a commercial farm, technological improvement has shifted the expected return-risk premium frontier to the northeast direction (as compared to southwest in Arlington). This means that, in Spooner, technology has weakened farmers' ability to manage risk (especially downside risk) in a commercial farm (where drying cost significantly affect the variability of corn profit). As one moves north, the third moment effects appear important in evaluating risk of corn-growing farmers. This illustrates the complex interactions between technological progress and risk exposure over space.

7. Summary and Conclusions

This paper has investigated the distribution of corn yield, grain moisture and profit, with a focus on the effects of technology and climate changes on the evolution of trade-off between corn profitability and risk. It used panel data from Wisconsin research stations, covering sites from the Corn Belt to the Northern fringe of the U.S. Using a moment-based approach, our empirical analysis examined conditional means, variances and skewness for corn yield, moisture and profit in different sites in Wisconsin. It shows how corn yield, moisture and profit have evolved over time, and how technology and climate change have affected them across sites.

We found evidence that technology and climate changes have increased production risk in Central and Northern Wisconsin. But our results also show that, in Southern Wisconsin (in the Corn Belt), these changes have increased the skewness of corn yield and contributed to reducing exposure to downside risk and to lowering the cost of risk. While we found some evidence of climatic changes, such effects appear to be dominated by the impact of technological change. Thus, our findings indicate that technological progress has provided improved means of dealing with risk in the Corn Belt. This can be attributed in part to genetic improvements targeted to improved pest and disease resistance. However, we want to stress that such benefits are found to vary across sites.

Our analysis has stressed the role of risk management in corn production. It has emphasized the importance of choosing corn hybrids and their relative maturity as a means of managing risk. Also, it highlighted the role of technological progress in risk exposure. The analysis of risk premium and expected profit showed that technology and exposure to risk and downside risk can interact, and that such effects vary over space. It illustrated the role of downside risk exposure in the assessment of technological change in agriculture. Further research is needed to evaluate production uncertainty issues for different commodities and in different locations.

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Table 1. Description of Data

Location		N[a]	GDD		Average Yield (bu/acre)	Average Moisture (%)	Relative Maturity (RM) (days)	
			Mean	Standard Deviation			Min.	Max.
South	Arlington	2484	2852.9	191.9	166.3	25.9	85	120
Central	Marshfield	1591	2645.5	186.6	119.5	27.5	75	110
North	Spooner	2335	2586.5	202.2	109.0	27.9	70	110

[a] N denotes the number of observations.

Table 2. Estimated relationship between yield and RM in Wisconsin

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

Location	N	Parameter				R^2
		Constant	RM	RM^2	T	
Arlington	2484	-73.51 (100.32)	3.48 (1.904)*	-0.014 (0.009)	1.86 (0.068)***	0.252
Marshfield	1591	-148.80 (89.40)	5.10 (1.967)***	-0.026 (0.011)**	1.87 (0.092)***	0.250
Spooner	2335	-531.02 (90.28)***	13.70 (2.124)***	-0.077 (0.012)***	2.18 (0.085)***	0.234

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

Location	N	Parameter			R^2
		Constant	RM	T	
Arlington	2484	-788.71 (276.3)***	11.795 (2.59)***	3.425 (2.60)	0.0088
Marshfield	1591	-25.48 (259.9)	5.631 (2.96)*	7.753 (2.06)***	0.010
Spooner	2335	-533.80 (350.6)	13.841 (4.07)***	8.80 (2.88)***	0.0067

C- Skewness of Yield = g_3(RM, T)

Location	N	Parameter			R^2
		Constant	RM	T	
Arlington	2484	-17109 (18890)	78.29 (174.04)	451.51 (182.37)**	0.0033
Marshfield	1591	-19848 (15715)	256.14 (179.1)	-47.15 (102.9)	0.0001
Spooner	2335	2427.8 (24331)	-102.92 (283.09)	45.22 (185.66)	0.0001

Note: Standard errors are provided in parentheses. N denotes the number of observations. The symbols *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Table 3. Estimated relationship between Growing Degree Days (GDD) and T in Wisconsin

A- Expected GDD = $d_1(T)$

Location	N	Parameter		R^2
		Constant	T	
Arlington	25	2868.5 (59.67)***	-1.126 (4.84)	0.0023
Marshfield	25	2500.99 (51.62)***	11.45 (4.12)**	0.212
Spooner	25	2535.58 (75.69)***	3.742 (5.33)	0.0201

B- Variance of GDD = $d_2(T)$

Location	N	Parameter		R^2
		Constant	T	
Arlington	25	-815.67 (9597)	2885.5 (1055)***	0.1654
Marshfield	25	3299.17 (9213)	1963.4 (959.3)**	0.1328
Spooner	25	30518* (16020)	654.83 (1235.3)	0.0092

C- Skewness of GDD = $d_3(T)$

Location	N	Parameter		R^2
		Constant	T	
Arlington	25	2577741 (3637943)	-251988 (531405)	0.0075
Marshfield	25	4278078 (3953626)	-407019 (456373)	0.0046
Spooner	25	-1258625 (6631540)	116721 (533661)	0.0014

Note: Standard errors are provided in parentheses. N denotes the number of observations. The symbols *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Table 4. Estimated relationship between corn moisture and RM in Wisconsin

A- Expected Moisture = h_1(RM, T)

Location	N	Parameter			R^2
		Constant	RM	T	
Arlington	2484	-11.46 (1.35)***	0.309 (0.013)***	0.323 (0.011)***	0.371
Marshfield	1591	0.439 (1.838)	0.341 (0.021)***	-0.295 (0.020)*	0.183
Spooner	2335	-2.278 (2.014)***	0.362 (0.024)***	-0.024 (0.0178)	0.091

B- Variance of Moisture = h_2(RM, T)

Location	N	Parameter			R^2
		Constant	RM	T	
Arlington	2484	-42.63 (8.07)***	0.535 (0.083)***	0.023 (0.089)	0.020
Marshfield	1591	-77.65 (15.82)***	1.271 (0.192)***	-0.668 (0.159)***	0.045
Spooner	2335	-83.37 (21.47)***	1.156 (0.250)***	1.491 (0.162)***	0.040

C- Skewness of Moisture = h_3(RM, T)

Location	N	Parameter			R^2
		Constant	RM	T	
Arlington	2484	-210.55 (119.7)*	2.613 (1.287)**	-3.106 (1.327)**	0.0073
Marshfield	1591	-723.50 (260.8)**	8.601 (3.190)***	-1.185 (2.397)	0.0097
Spooner	2335	-133.26 (421.6)	1.468 (4.884)	4.915 (2.981)	0.0002

Note: Standard errors are provided in parentheses. N denotes the number of observations. The symbols *, ** and *** denote statistical significance at 10, 5 and 1% levels, respectively.

Table 5. Estimated relationship between profit and RM in Wisconsin

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

Location	Farm Type	Parameter				R^2
		Constant	RM	RM^2	T	
Arlington	Livestock	-147.03 (200.65)	6.972 (3.808)*	-0.0275 (0.018)	3.731 (0.136)***	0.252
	On-farm	-127.76 (193.28)	7.263 (3.669)**	-0.033 (0.017)*	2.498 (0.131)***	0.134
	Commercial	-105.43 (194.35)	7.493 (3.692)**	-0.038 (0.017)**	1.285 (0.132)***	0.042
Marshfield	Livestock	-297.61 (178.80)*	10.215 (3.93)***	-0.053 (0.021)**	3.748 (0.185)***	0.249
	On-farm	-284.66 (173.79)	10.039 (3.822)***	-0.055 (0.021)***	3.860 (0.179)***	0.252
	Commercial	-277.49 (174.87)	9.999 (3.845)***	-0.058 (0.021)***	3.944 (0.179)***	0.247
Spooner	Livestock	-1062.0 (180.56)***	27.41 (4.25)***	-0.153 (0.025)***	4.357 (0.170)***	0.234
	On-farm	-972.10 (176.77)***	25.51 (4.16)***	-0.146 (0.024)***	4.10 (0.165)***	0.218
	Commercial	-880.47 (177.62)***	23.58 (4.18)***	-0.138 (0.024)***	3.83 (0.165)***	0.196

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

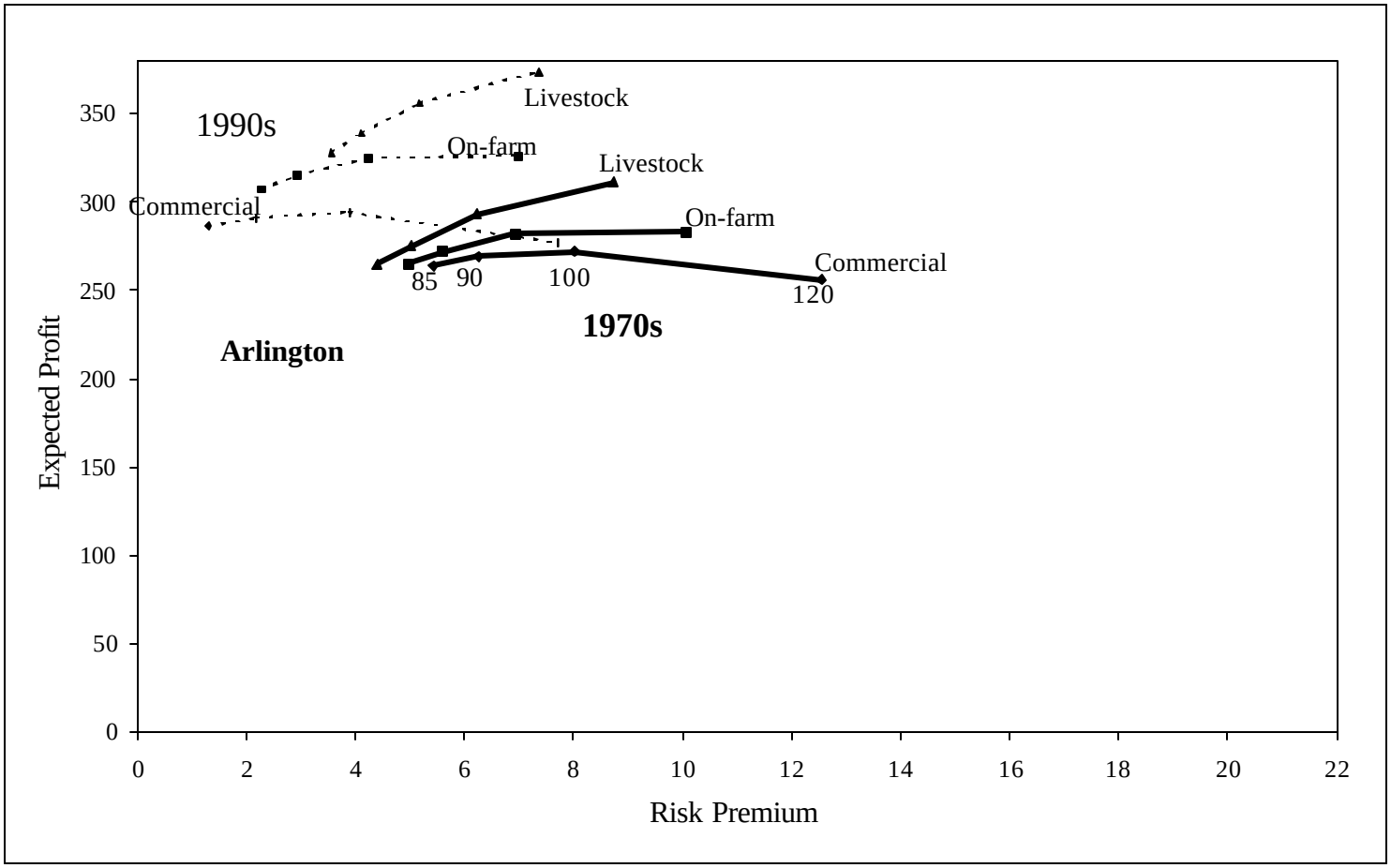
Location	Farm Type	Parameter			R^2
		Constant	RM	T	
Arlington	Livestock	-3154.8 (1105.1)***	47.18 (10.36)***	13.70 (10.39)	0.0088
	On-farm	-3091.6 (1059.5)***	48.42 (9.97)***	-12.34 (10.84)	0.0091
	Commercial	-3661.2 (1122.04)***	56.17 (10.65)***	-28.15 (12.0)**	0.0130
Marshfield	Livestock	-101.95 (1039.8)	22.52 (11.83)*	31.01 (8.25)***	0.0098
	On-farm	254.29 (956.31)	19.90 (10.87)*	9.53 (7.78)	0.0025
	Commercial	146.55 (953.02)	23.76 (10.83)**	-8.33 (8.33)	0.0015
Spooner	Livestock	-2135.2 (1402.4)	55.36 (16.28)***	35.20 (11.53)***	0.0067
	On-farm	-2412.7 (1412.9)	52.72 (16.45)***	61.36 (10.61)***	0.0120
	Commercial	-2999.4 (1505.1)**	54.78 (17.58)***	93.34 (10.28)***	0.0213

C- Skewness of Profit = f_2(RM, T)

Location	Farm Type	Parameter			R^2
		Constant	RM	T	
Arlington	Livestock	-136871 (151125)	626.35 (1392.3)	3612.1 (1458.9)**	0.0033
	On-farm	-218213 (142750)	1083.2 (1315.5)	6485.9 (1524.4)***	0.0129
	Commercial	-298163 (154627)**	1508.3 (1449.4)	9280.6 (1731.5)***	0.0214
Marshfield	Livestock	-158785 (125725)	2049.1 (1432.9)	-377.18 (823.18)	0.0001
	On-farm	-35596 (109204)	833.25 (1245.3)	-1955.9 (741.6)***	0.0004
	Commercial	108668 (107465)	-579.60 (1228.6)	-3065.0 (809.9)***	0.0039
Spooner	Livestock	21982 (194650)	-823.34 (2264.7)	361.76 (1485.3)	0.0001
	On-farm	38721 (198032)	-352.67 (2309.6)	-2296.2 (1334.8)	0.0007
	Commercial	36328 (220540)	327.78 (2528.9)	-4421.0 (1338.0)***	0.0012

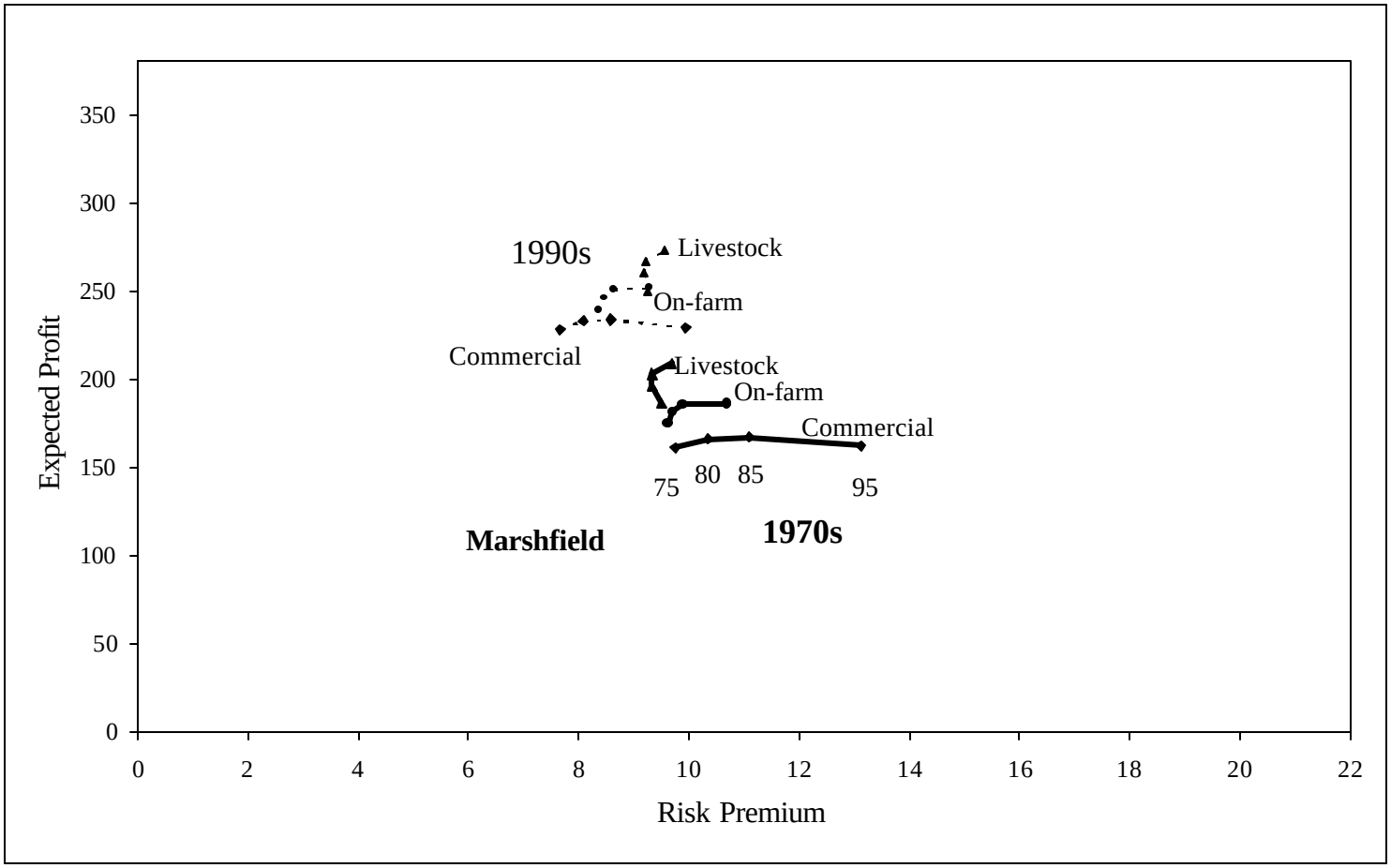
Note: Standard errors of the parameter estimates are in parentheses.

Figure 1-a. Expected profit and risk premium at Arlington



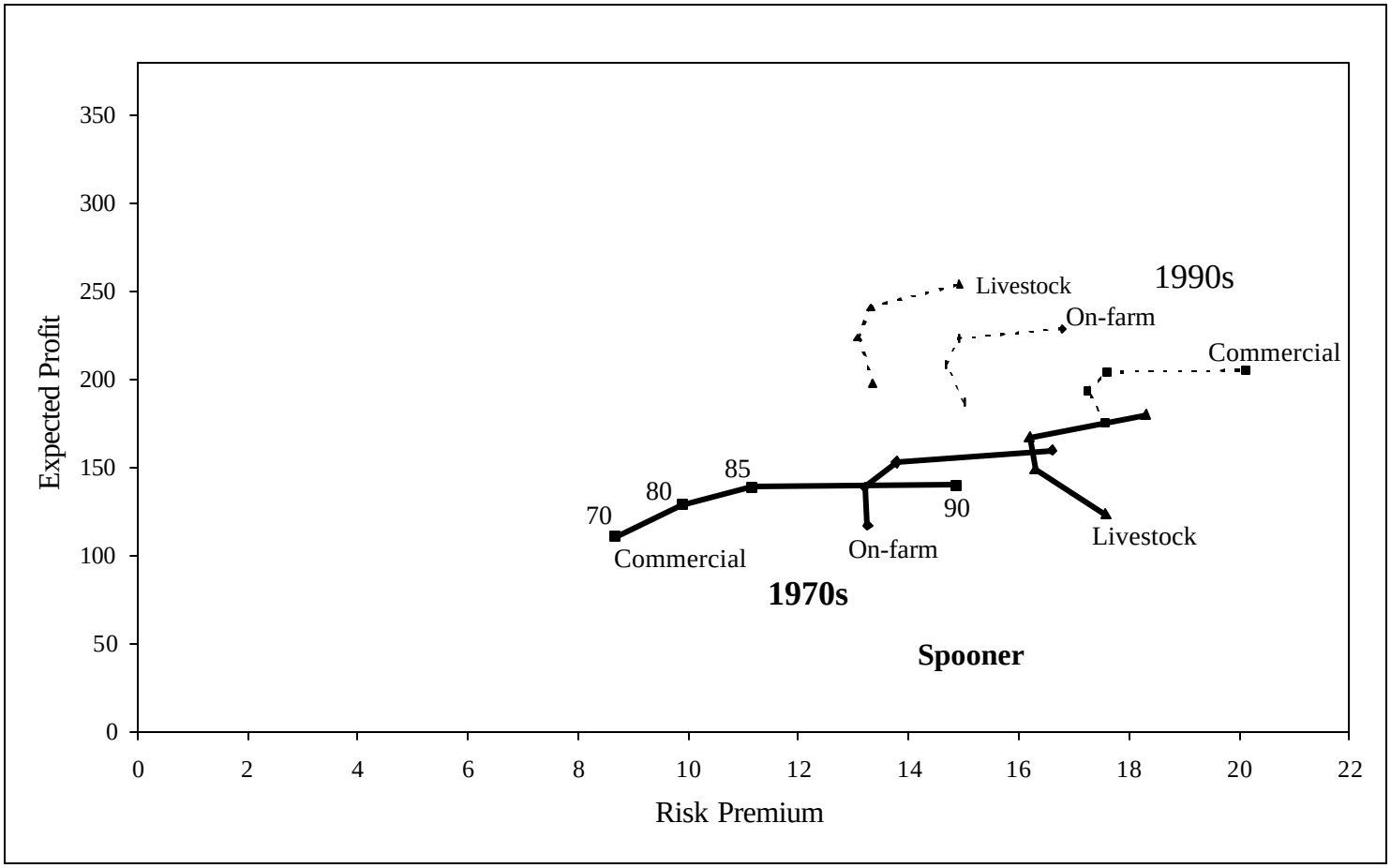
Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Figure 1-b. Expected profit and risk premium at Marshfield



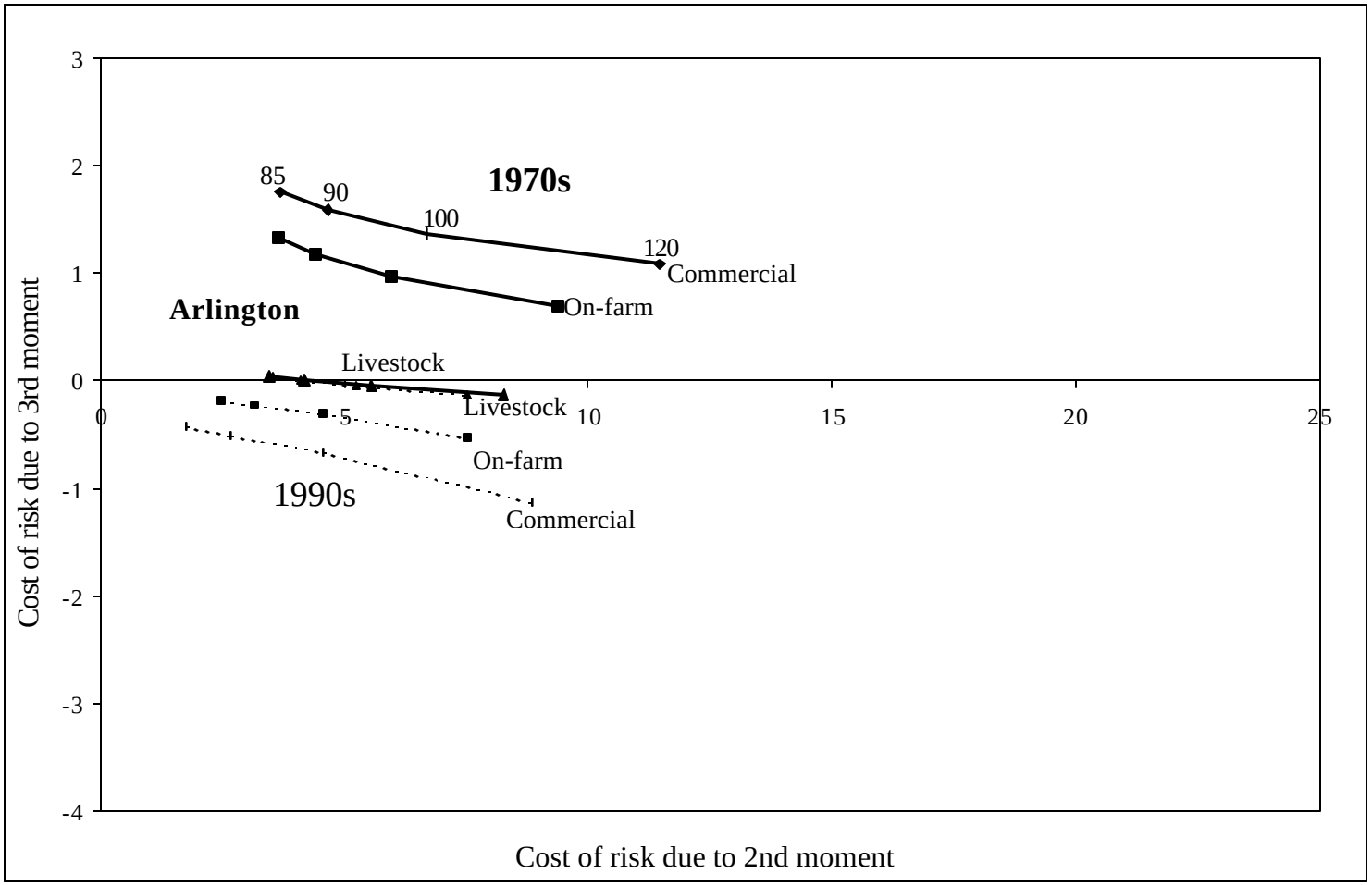
Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Figure 1-c. Expected profit and risk premium at Spooner



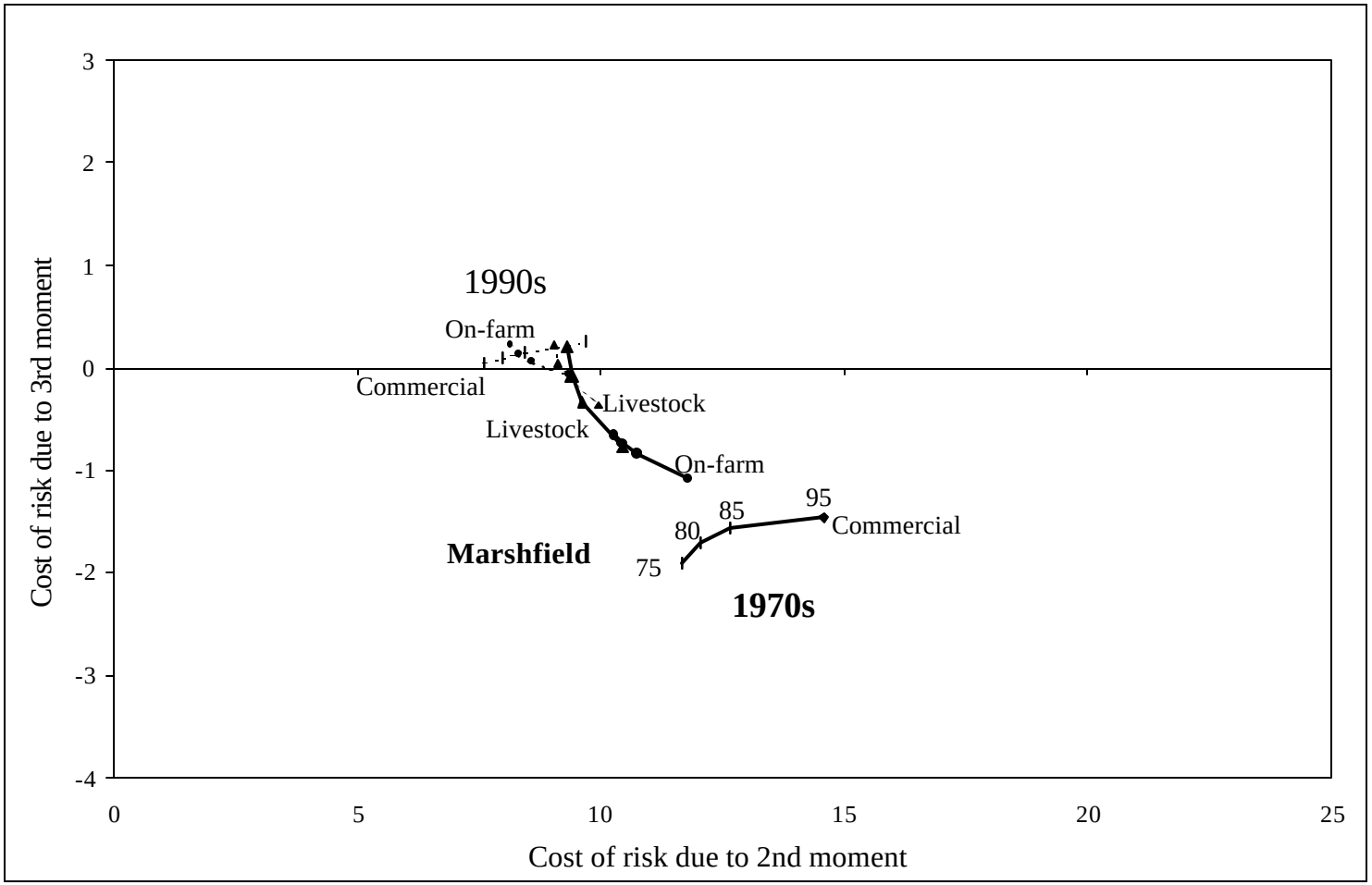
Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Figure 2-a. Cost of risk due to second and third moments at Arlington



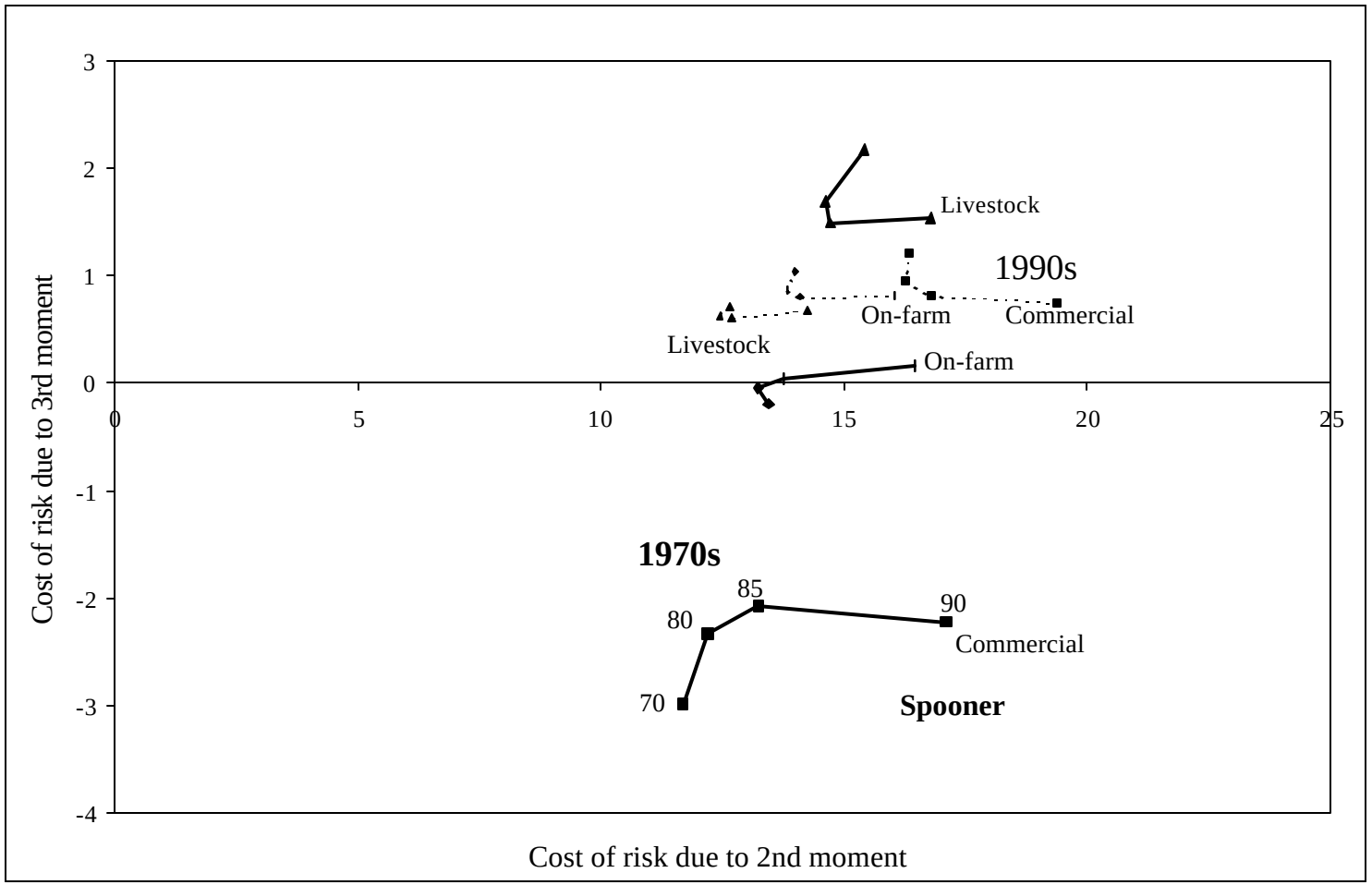
Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Figure 2-b. Cost of risk due to second and third moments at Marshfield



Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Figure 2-c. Cost of risk due to second and third moments at Spooner



Note: Numbers above each frontier denote maturity days. Unit of measurement: $/acre.

Footnotes

[1] 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.

[2] Corn relative maturity is measured using the "Minnesota relative maturity rating", a standardized index characterizing the number of days it typically takes each corn hybrid to reach maturity.

[3] GDD is a temperature-based index commonly used as a summary measure of the length of the growing season for corn. For example, for a given location and growing season, the GDD index for corn is defined as $GDD = \sum_i \{(1/2)[\max(Tmin_i, 50) + \min(Tmax_i, 86)] - 50\}$, where $Tmin_i$ ($Tmax_i$) 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.

[4] More informative measures of technology can possibly replace time trend. For example, genetic improvements can be directly measured by different hybrids applied. However, it is not included in our analysis. This is because the number of hybrids is very large and the hybrids change over time in our data. For example, some of the hybrids used in the early part of the sample are no longer present in the later part. This makes it difficult to find any simple way of incorporating the hybrid information in our analysis beyond their relative maturity rating, RM.

[5] This requires the impacts of other factors that potentially explain the proportion of the time trend not associated with weather patterns to be not significant. Including other factors in the model would require a more refined analysis of how technological change affects yield variations.

[6] Thus, the analysis presented below neglects price uncertainty. The sensitivity of our results to the price scenario was evaluated. While higher corn price increased corn profitability, the empirical findings presented below were found to be fairly robust to the corn-price scenario.

[7] On a livestock farm, drying cost 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 cent per bushel per percentage moisture in excess of 15.5 percent. On-farm drying represents an intermediate situation, where a drying cost of 0.015 cent per bushel per percentage moisture in excess of 15.5 percent.

[8] A sensitivity analysis was conducted on the relative risk aversion coefficient λ. We investigated the following scenarios: $\lambda = 1, 2, 3, 6$. Although the quantitative results varied depending on the choice of λ, we found fairly similar qualitative results across scenarios.