Journal of Agricultural and Resource Economics, 19(1): 69–77

Kansas Wheat Yield Risk Measures and Aggregation: A Meta-Analysis Approach

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A meta-analysis approach to prediction of farm level yield risk from county level yield series is applied to Kansas wheat yields. A nonlinear relationship between county level and farm level yield risk is found, which indicates that yield risk increases at an increasing rate as the number of acres in the risk measure decreases. County level yield variability should be adjusted upward by approximately .1% for each percent difference in county acreage and average farm acreage within the county. The meta-analysis approach is shown to be promising for the prediction of farm level yield risk when farm level information is difficult to obtain.

Key words: meta-analysis, risk measurement, wheat production, yield risk.

Introduction

Over the past 25 years, there have been many developments in the theory of individual producer behavior under uncertainty. Beginning with the works of Baron, Sandmo, and Holthausen and continuing with more recent papers by Antle, Just and Zilberman, and Meyer, to name a few, our understanding of the important theoretical aspects of risky decision making has made significant progress.

Several problems remain, however, in moving toward empirical implementation of this work. Some of these relate to the measurement of risk attitudes, while others are concerned with the definition and measurement of the risk itself. One important issue related to the latter is the general lack of sufficient data needed to measure the yield risk faced by individual producers. Collection of these data at the farm level is expensive or the data are impossible to obtain, while yield data at more aggregated levels are readily available from the U.S. Department of Agriculture (USDA) Crop Reporting Service data series and, now, from a comprehensive dataset compiled by the S-232 Regional Research Project and maintained by National Crop Insurance Services (NCIS) in Overland Park, Kansas.

Yield Risk and Aggregation

That farm level yield variability should be greater than variability measures at a more aggregate level is intuitively obvious. "Variability of production and income on single farms is greater than for the state (or county) because fluctuations tend to be averaged out as large numbers of farms are aggregated together into a single statistic" (Heady, Kehrberg, and Jebe, p. 634). The question is, *how much* greater should farm level yield variability measures be relative to the measures readily available? The sketchy evidence

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This is Maine Agricultural and Forestry Experiment Station Publication No. 1779.

The authors would like to thank members of the S-232 Regional Research Project, especially George Patrick, and also Larry Held and two anonymous reviewers for valuable comments on previous drafts. All remaining errors are the responsibility of the authors.

Table 1. Summary of Past Studies which Include Farm Level and County Level Yield Risk Measures

Study/(State)	Crop	Time Period	Std. Dev. Farm[a]	Std. Dev. County[a]	Std. Dev. Ratio Farm/Co.	Acres Ratio Farm/Co.[b]
Eisgruber and Schuman (IN)	Corn	1948–60	12.6	6.8	1.9	.00077
	Soybeans		5.2	2.6	2.0	.00144
	Wheat		7.7	4.8	1.6	.00142
	Oats		13.9	10.0	1.4	.00134
Carter and Dean (CA)	Sugar Beets	1938–57	3.1	1.5	2.0	.03268
Debrah and Hall (KY)	Corn	1974–82	18.6	11.6	1.6	.00319
	Soybeans		6.1	2.5	2.4	.00984
	Wheat		9.2	3.5	2.7	.00262
	Burley Tobacco		5.8	2.1	2.8	.00162

[a] All yield series had a linear trend removed.
[b] Ratios of harvested acres were computed at the middle year of the time series (U.S. Department of Agriculture).

from past studies where farm level yield risk measures were compared to measures based upon some aggregate unit would seem to indicate that the effect of aggregation on yield risk measures may depend upon the crop, the geographic area, and the time period in question (table 1).

The number of acres of the crop on a farm also may be an important variable influencing yield variability on the farm since this is a form of aggregation even though it is still at the farm level. Many of the factors affecting crop yield in any season are spatially spotty, such as pest infestations and even summer showers. One part of a farm may experience pest pressure and/or water stress, while other parts do not. Also, there can be significant variation in soil on a farm and different soils result in different yield responses to weather conditions. The larger the number of acres on the farm, the more likely that these effects will be "averaged out," resulting in lower yield variability.

This notion is similar to the theory underlying farm portfolio selection, where the choice of farm enterprises affects overall farm level risk by reducing the unsystematic or diversifiable risk (see Collins and Barry, or Turvey, Driver, and Baker, for example). In farm portfolio selection, the decision maker allocates portions of acreage to different enterprises with less than perfectly correlated yields, which results in lower overall yield (and income) risk. This theory can be extended to the choice of farm size, if an acre of land is thought of as a separate enterprise, or asset, whose yield is not perfectly correlated with the other acres on the farm. Thus, as more acres are added to the farm portfolio, farm level yield variability should decline. Moreover, standard portfolio theory suggests that, if acres behave as separate assets as described above, yield variability should decline rapidly at first as more acres are added and then decline more slowly above a certain acreage. This relationship between portfolio risk and the number of assets in the portfolio is described in most finance texts (Levy and Sarnat, for example) and is depicted in figure 1.

Given the above reasoning, the question remains as to whether the reduction in risk as more acres are added occurs in a regular pattern upon which we can capitalize in predicting farm level yield risk. The purpose of this research is to investigate empirically whether the more aggregated data series can be adjusted in a systematic way to reflect the yield risk faced by producers at the farm level. Without compiling new data at the farm level for each application, there are two ways to approach this investigation using existing data. First, one could attempt to describe what has been reported in the literature about yield variability at various levels of aggregation in the conventional way. The results of this might be a table of results and a verbal description that might include some summary statistics, such as in table 1. The second way to attempt to discover an appropriate adjustment is to perform a meta-analysis of the existing information.

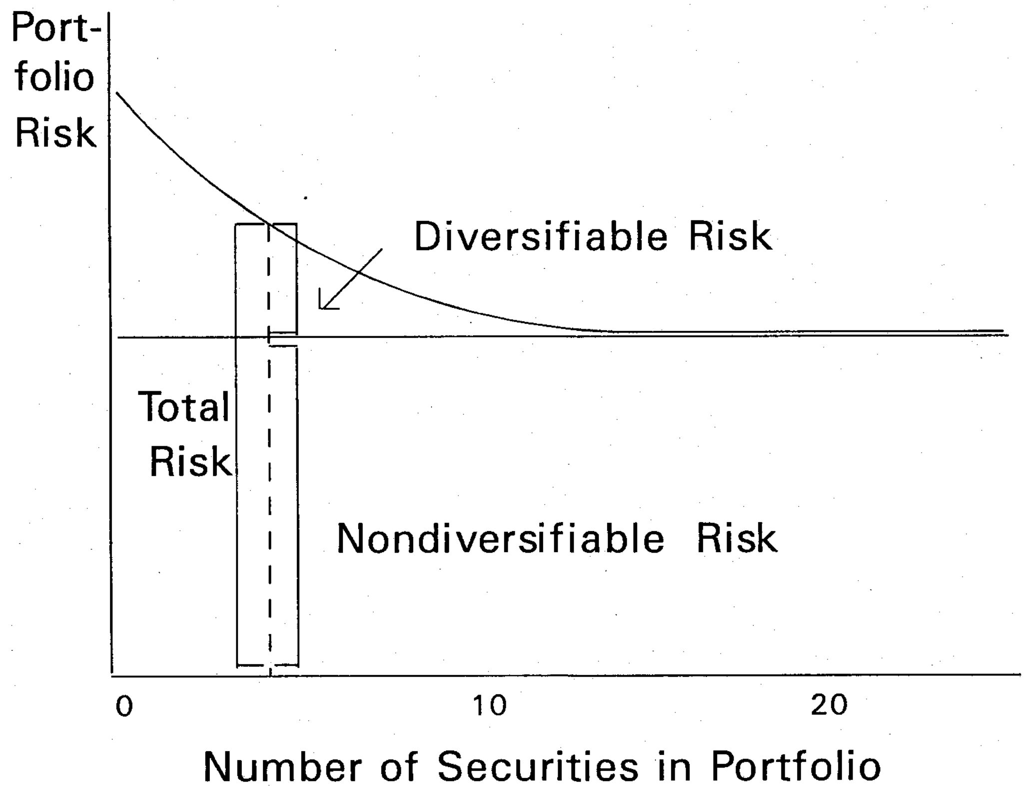

Figure 1. Relationship between portfolio size and risk

Meta-Analysis

A meta-analysis is, essentially, an analysis of analyses. It is an attempt to cumulate research findings in a more formal, statistical way so that, if there is some systematic, underlying "weight of evidence" in the research to date, it is more likely to be discovered. Meta-analysis can be performed across a number of studies, on multiple findings within one study, or both at once (Hunter, Schmidt, and Jackson). It uses any one of a number of standard statistical procedures, including regression, to summarize the cumulative meaning of the results of past work on a particular subject. The basic assumption underlying a meta-analysis is that each study result is an observation that can be thought of as one data point in a larger dataset containing all possible observations, given the true relationship under study. The first meta-analyses were performed in the areas of medicine and psychology and generally were concerned with cumulating correlations across a group of experiments performed by different researchers on the same subject (Glass, McGraw, and Smith). It has been used to cumulate the research findings in such diverse areas as treatment of migraine and tension headaches (Blanchard et al.) to teaching style and pupil achievement (Cohen).

The two major questions posed by meta-analysts are: (*a*) Is the effect of factor *X* on outcome *Y* significant? and (*b*) What is the size of the effect of factor *X* on outcome *Y*? Answering these questions through a descriptive review of existing literature can lead to startling errors. Hunter, Schmidt, and Jackson describe an experiment they conducted in which a group of study outcomes was generated from an underlying distribution and factor levels randomly assigned to each study result. The outcomes were then presented to several researchers in tabular form, and they were asked to summarize the study results. None of the researchers came close to the true mean effect, and some concluded that several factors contributed significantly to the results that were, in fact, randomly assigned to each study outcome! However, descriptive literature review is still the most popular way to summarize research findings today. Meta-analysis, while still a controversial approach, seems to hold promise for the cumulation of research results.

One method of meta-analysis, which can answer both of the above questions simultaneously (and is surely the method most familiar to economists) is least squares regression of the study outcomes on various characteristics of the studies, such as study location, time, type of subject (students, general public, hospital patients, etc.), and published or unpublished work. Meta-analysis using regression techniques has been employed in marketing research to analyze differences in consumer response to external stimuli, such as price, advertising, etc. (Farley and Lehmann). More recently, Smith and Kaoru used it to cumulate the findings of the numerous studies of user benefits from recreation sites that employed the travel cost method of estimating value. One of their stated purposes was to determine if the current practice of adjusting the results of one or more existing studies and using them to value a particular resource that has not been studied (called benefits transfer) is valid. Their method was to regress the real consumer surplus per unit of use on several characteristics of the recreation site studies, several behavioral assumptions (such as how the opportunity cost of time is handled in the study), and several researcher judgments (such as the functional form or estimator used). They used as the dependent variable consumer surplus measures from several studies, including multiple estimates reported within one study in several cases. They found that many factors under the researchers' control, in addition to site characteristics, significantly affected the consumer surplus measure. They therefore concluded that caution should be used when transferring benefits from existing studies to another recreation site.

Our study is similar in purpose to the Smith and Kaoru study. We are investigating the potential existence of an adjustment procedure that could be used to adjust aggregated yield variability information to reflect the variability faced by farmers. In this initial analysis, we perform a meta-analysis of within-study results to avoid potential statistical problems of cumulating over time and space and to eliminate across-study effects so that we can concentrate on the question of developing an appropriate adjustment procedure. It is a meta-analysis in the sense that the variability measures generated under various assumptions about land tenure and type of trend removal are used as observations in a cumulative regression analysis, rather than considered separately.

Wheat Yield Data

As a preliminary effort, the analysis was limited to dryland wheat in Kansas. Data from the Kansas Farm Management Associations were organized for analysis. Only farms which had grown wheat for 16 consecutive years (1973 to 1988) were selected. The farm management data contain information on rented wheat acres and production, owned wheat acres and production, and total wheat acres and production. After sorting, 339 farms had a complete series of wheat production. Of these, 171 had a complete series of wheat on owned acres, and 221 had a complete series of wheat on rented acres. Some farms had complete series on rented, owned, and then the total acreage. We included in the analysis every complete series, whether rented, owned, or total.

Several methods of detrending the data were explored. Since farm yield variability can be substantial, particularly over a short period of time, detrending methods must be considered carefully so that overfitting does not occur. If a higher-order time trend is removed from the series or if the trend is tailored too closely to an individual (capturing the results of some intended yield changes in response to changing economic conditions), it may result in an underestimate of the true risk faced by the farmer. In the limit, one could theoretically choose a polynomial time trend that would exactly fit the observed data, thus eliminating all the residual risk. On the other hand, it is also possible to overestimate the risk by not accounting for technological advance at all if it has occurred.

Table 2. Farm Level Wheat Yield Variability Measures Calculated Without Removing Trend

	Type of Farm		
	Owned Dryland Wheat ($N = 171$)	Rented Dryland Wheat ($N = 221$)	Total Dryland Wheat ($N = 339$)
Mean of Means	35.20	34.19	34.42
Mean of Std. Dev.	9.25	8.73	8.72
Min. Std. Dev.	3.55	4.62	3.20
Max. Std. Dev.	18.38	25.81	19.38
Mean of Coeff. of Var.	26.68	26.04	25.77

The appropriate amount of detrending will depend on the crop in question and the time period over which measurement takes place, as well as the best judgment of the researcher.

Three measures of yield variability were calculated. First, standard deviations were calculated with no time trend removed. The means of the standard deviations calculated without trend removal for three categories of wheat are shown in table 2. For dryland wheat, the means of the standard deviations range from 8.72 to 9.25. These are likely overestimates of the variability since no trend, accounting for technical change, is removed. Second, standard deviations were calculated as residuals from regressions of individual farm yields on a linear time trend. The means of the standard deviations calculated in this fashion are presented in table 3. For dryland wheat, the means of the standard deviations range from 8.36 to 8.87. This measure has the potential for overfitting the data and thus underestimating the variability of yields. Examination of the trends indicates that the mean of the individual trends for the farms ranged from .25 to .30 bushels per year increase in yield. However, the range of individual trends removed from farm data was from -1.07 to 1.88 bushels per year. These trends provide some indication of the overfitting that can occur by allowing individual trends to be removed from each farm yield series. Finally, a common trend was removed from all the data from all the farms. Variability around this trend was then measured. As shown in table 4, the means of standard deviations ranged from 8.62 to 9.15 after removal of the common trend. This method could be viewed as a compromise approach, given that a common trend is removed. However, this common trend is more than some farmers are experiencing and less than others are experiencing. As indicated by the means of the standard deviations, this method provided estimates of variability which generally fall between those of the other two methods.

The same detrending methods were used on the county yield variability series. County

Table 3. Farm Level Wheat Yield Variability Measures Calculated After Individual Trends Were Removed

	Type of Farm		
	Owned Dryland Wheat ($N = 171$)	Rented Dryland Wheat ($N = 221$)	Total Dryland Wheat ($N = 339$)
Mean of Std. Dev. of Resid.	8.87	8.41	8.36
Min. of Std. Dev. of Resid.	3.21	4.25	3.15
Max. of Std. Dev. of Resid.	17.61	25.51	19.89
Mean of Indiv. Trends Removed	.30	.25	.28
Min. of Indiv. Trend	-1.00	$-.96$	-1.07
Max. of Indiv. Trend	1.83	1.68	1.88

Table 4. Farm Level Wheat Yield Variability Measures Calculated After Removing a Common Trend

	Type of Farm		
	Owned Dryland Wheat ($N = 171$)	Rented Dryland Wheat ($N = 221$)	Total Dryland Wheat ($N = 339$)
Mean of Std. Dev. of Resid.	9.15	8.66	8.62
Min. of Std. Dev. of Resid.	3.21	4.60	3.25
Max. of Std. Dev. of Resid.	18.03	26.02	19.90
Common Trend	.30	.25	.28

yields from 1973 to 1987 were used for the analysis. The results of the different detrending procedures on the county yields are presented in table 5. They are more aggregated than the farm series and so differences between detrending methods are smaller. Even so, there was some slight reduction in variability when individual trends were removed.

Information on the range of acres for the different aggregation levels is provided in table 6. The mean of the mean acres per farm ranged from 202 to 408 and the range of the means across all farm observations was from 21 to 2,388 acres. The mean acres for counties ranged from 2,600 to 462,000. There was a small gap between the acreage of the largest farm and the smallest county.

Meta-Analysis Results

A dataset was created which contained 2,193 observations. The dataset included 731 farm observations with the corresponding county information using no detrending, 731 observations detrending each farm and county series individually, and 731 observations removing a common trend from the farm series and a common trend from the county series. A meta-analysis using the dataset described above was then performed in an attempt to identify a procedure to adjust county yield variability to the farm level. The function that was estimated using various functional forms was:

$$SDF = f(SDC, ACR, RAIN, D1, D2),$$

where SDF is the standard deviation of the farm yield series, SDC is the standard deviation of the county (where the farm is located) yield series, ACR represents the measure of acres of wheat on the farm, $RAIN$ is the average rainfall in the county where the farm is located, $D1$ is a dummy indicating individual trends were removed from each series, and $D2$ is a dummy indicating a common trend was removed from the farm series and a common trend was removed from the county series. The estimates of the regression models are shown in table 7. Three estimates are included using different specifications of farm acreage and one in which all variables are in natural logs.

The positive, significant coefficients on the county variability factor suggest that, at any

Table 5. Yield Variability Measures for 105 County Yield Series

	No Trend Removed	Individual Trends Removed	Common Trend Removed
Mean of Std. Dev. of Resid.	6.862	6.627	6.862
Min. of Std. Dev. of Resid.	4.128	4.127	4.127
Max. of Std. Dev. of Resid.	9.893	9.749	9.881

Table 6. Acres of Wheat Production per Farm and County

	Mean Owned Acres per Farm	Mean Rented Acres per Farm	Mean Total Acres per Farm	Mean Acres per County
Mean	202	323	408	112,858
Min.	21	35	30	2,600
Max.	1,052	1,359	2,388	462,000

relative farm size, farm level variability will be higher in counties where variability is higher in general. This is as expected. The rainfall variable suggests that higher rainfall areas experience lower yield variability at a given farm size. Thus, yields likely would be more variable for a given farm size in the western part of Kansas than in the eastern part.

The dummy variables indicate that the adjustment from county to farm level depends on the detrending technique used. $D1$ indicates that if individual trends are removed from both farm and county data, the standard deviation of farm yield is a statistically significant amount lower than when no trend is removed. $D2$ shows that there is no significant difference between no trend removal and removing a common trend from all farms and from all counties.

The estimated coefficients on *ACR* confirm the relationship between acres of wheat on a farm and variability of yield. Larger wheat acreage is associated with lower variability of wheat yield. The curvilinear forms with wheat acreage in reciprocal and log form show slightly improved R^2s, supporting a curvilinear relationship between size and yield variability with variability decreasing quickly at first and then slower as size increases. The log-linear form also supports the hypothesis of a significant, curvilinear relationship.

Results and Conclusions

Meta-analysis of farm and county yield variability has allowed estimates of farm level yield variability from farm data and county data. The results of the analysis are quite interesting. Higher county level variability is associated with greater farm level yield

Table 7. Coefficients and Standard Errors from Regression Analyses of Farm Yield Variability

	Logged Dependent Var.	Untransformed Dependent Var.		
Parameter	Acres in Log Linear Form	Acres in Linear Form	Acres in Reciprocal Form	Acres in Log Linear Form
Intercept	2.58***	6.71***	5.68***	11.71***
	(.11)	(.33)	(.24)	(.51)
SDC	.49***	.71***	.69***	.68***
	(.02)	(.03)	(.03)	(.03)
ACR	−.11***	−.002***	117.41***	−.88***
	(.01)	(.0001)	(7.66)	(.06)
RAIN	−.22***	−.052***	−.061***	−.073***
	(.02)	(.008)	(.007)	(.008)
*D*1	−.03**	−.23*	−.23*	−.23*
	(.01)	(.10)	(.10)	(.10)
*D*2	−.01	−.09	−.09	−.09
	(.33)	(.10)	(.10)	(.10)
R^2	.33	.26	.28	.29

Note: Single, double, and triple asterisks (*) indicate significance at the .05, .01, and .001 levels, respectively.

variability, higher rainfall is associated with lower yield variability, and the detrending assumption may significantly affect the estimated relationship between farm and county yield variability. The most important result is that greater wheat acreage is associated with lower yield variability, and that the variability appears to be decreasing at a decreasing rate consistent with the hypothesis that farm acres can be thought of as separate, not perfectly correlated assets. Thus, increased farm size results in large gains in risk efficiency at smaller acreages, but as farm size increases, the marginal decrease in variability diminishes. This result also implies that estimates of farm level yield risk based upon more aggregated yield measures will depend upon the relative magnitudes of the acreages involved at the farm level and at the more aggregated level.

The adjustment factors, based on the regression results above, are the acre elasticities of variability ($\partial SDF/\partial ACR$, estimated at the data means, where appropriate). With a common trend removed, the mean farm level yield variability based on total acres is 8.62 (table 4), and the mean farm level total acres is 408 (table 6). Using these data means, the elasticities are $-.11$ for the log-linear form, $-.09$ for the acres in linear form, $-.03$ for the acres in reciprocal form, and $-.10$ for the acres in log form. Although the elasticity calculated using the reciprocal form of acres is significantly lower, the weight of the evidence suggests that the standard deviation of yield increases by approximately .1% for every 1% decrease in total acres. This adjustment factor can be used to estimate farm level yield variability by finding the percentage difference between the average farm level acreage within a county and the county acreage, and then adjusting the county level standard deviation upward using the adjustment factor.

The data necessary to make this adjustment are relatively accessible from various USDA data series and would not require farm level yield data. For example, using the adjustment parameter above and the mean county level and farm level acreages (from table 6) of 112,858 and 408, respectively, the predicted farm level standard deviation is 7.57. The calculation using the adjustment parameter alone results in about a 12% error (7.57 compared to the calculated standard deviation of total dryland wheat with a common trend removed of 8.62 in table 4). Given the extreme amount of extrapolation involved in going from acreage of 112,858 to one of only 408, this seems to be a rather small error. A more precise estimate could be obtained for a specific county/farm combination, at slightly higher information cost, by using the complete regression results presented here. Both methods are superior to using a rule-of-thumb approach, such as assuming farm level variability to be two to three times the variability at the county level.

While the results of this study appear promising, more work needs to be done across other crops and in different regions of the country. The next step would be to see if the adjustment factor performs well in another region of the country where a farm level wheat yield series is available. If so, then an across-crop and region meta-analysis could be performed using all available farm level yield data series. While lack of data may impede progress in this area, these relationships would provide valuable information for farm level risk work and, thus, additional effort seems justified.

[*Received August 1992; final revision received January 1994.*]

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