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Preface

Agricultural Finance Review (*AFR*) provides a forum for discussion of research, extension, and teaching issues in agricultural finance. This publication contains articles contributed by scholars in the field and refereed by peers.

Volume 43 was the first to be published at Cornell University. The previous 42 volumes were published by the United States Department of Agriculture. *AFR* was begun in 1938 by Norman J. Wall and Fred L. Garlock, whose professional careers helped shape early agricultural finance research. Professional interest in agricultural finance has continued to grow over the years, involving more people and a greater diversity in research topics, methods of analysis, and degree of sophistication. We are pleased to be a part of that continuing development. We invite your suggestions for improvement.

AFR was originally an annual publication. Starting with volume 61, Spring and Fall issues are published. The *AFR* web page can be accessed at http://afr.aem.cornell.edu/. Abstracts of current issues and pdf files of back issues since 1995 are available.

The effectiveness of this publication depends on its support by agricultural finance professionals. We especially express thanks to those reviewers listed below. Grateful appreciation is also expressed to the W. I. Myers endowment for partial financial support. Thanks are also due to Faye Butts for receiving, acknowledging, and monitoring manuscripts, and Judith Harrison for technical editing.

Manuscripts will be accepted at any time.

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Credit Score Migration Analysis of Farm Businesses: Conditioning on Business Cycles and Migration Trends

Jill M. Phillips and Ani L. Katchova

Abstract

This study examines credit score migration rates of farm businesses, testing whether migration probabilities differ across business cycles. Results suggest that agricultural credit ratings are more likely to improve during expansions and deteriorate during recessions. The analysis also tests whether agricultural credit ratings depend on the previous period migration trends. The findings show that credit score ratings exhibit trend reversal where upgrades (downgrades) are more likely to be followed by downgrades (upgrades).

Key words: business cycle, credit migration, migration trend, path dependence, rating drift, trend reversal

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Migration analysis, a probability-based measurement concept of changes in credit risk, has been used to analyze the effects that business cycles and rating drift have on bond ratings (Bangia et al., 2002; Lando and Skodeberg, 2002; Nickell, Perraudin, and Varotto, 2000). Our study conducts similar migration analysis by conditioning migration rates of farm businesses on business cycles and testing for path dependence. Such analysis presents agricultural lenders with valuable insight into modifications to be implemented in their own internal credit risk rating models.

Migration analysis of bond ratings has revealed that transition probabilities are highest for retaining the current rating, decrease as distance between classes increases, and exhibit a higher tendency to downgrade than upgrade.[1] Recent bond studies have shown that transition probabilities are significantly affected by type of industry, geographical location of company, and macroeconomic business cycles (Bangia et al., 2002; Nickell, Perraudin, and Varotto, 2000).

Migration studies have also tested for the presence of rating drift in risk ratings of bonds. A key assumption in migration analysis, known as the Markov property of independence, is that the probability of a bond or loan moving to any state during this period is independent of any outcomes in previous periods (Bangia et al., 2002;

[1] A retention rate is defined as the probability of staying in the same credit class.

Saunders and Allen, 2002). The presence of path dependence implies the bond's current rating is dependent on previous rating changes, a clear violation of this assumption. Path dependence can be rating drift or momentum, where downgrades (upgrades) are more likely to be followed by downgrades (upgrades), and trend reversal, where downgrades (upgrades) are more likely to be followed by upgrades (downgrades). Studies by Bangia et al. (2002) and Lando and Skodeberg (2002) found rating drift was present in bond ratings; in particular, bonds that downgraded in the previous period were more likely to downgrade in the next period, while results on upgrade momentum were less conclusive.

Estimation of migration rates for agricultural loans is complicated by the lack of data on historic loan credit ratings (Barry, 2001). In the absence of actual lender loan data, several agricultural finance studies have applied migration analysis to farm-level data. Barry, Escalante, and Ellinger (2002); Escalante et al. (2001); and Katchova and Barry (2005, forthcoming) applied migration analysis to farm businesses in Illinois. These studies utilized the Illinois Farm Business Farm Management Association data set, although different time periods were analyzed in each study. Unlike the aforementioned finance studies, these agricultural finance studies estimated a single unconditional transition matrix, without testing whether these migration probabilities differ depending on business cycles and migration trends.

In addition, the previous agricultural finance studies utilized a credit score model as a proxy for credit risk, a tool often employed by agricultural lenders. While a credit score model is useful for estimating borrower creditworthiness, it is generally not the only method employed by lenders in determining credit risk. Lenders analyze financial, nonfinancial, and character traits of the farm business and operator in internal credit risk rating models. Thus, studies that employ a credit scoring model to measure migration rates of farm businesses, as our study does, may not capture the true credit risk of agricultural loans as effectively as do lenders' internal credit rating tools. Nevertheless, farm business performance, as measured by a credit score model, plays a very vital and critical role in the lender's determination of borrower credit capacity.

If rating drift is present in the credit score ratings of farm businesses, there could be serious implications for agricultural lenders. If downgrade momentum is present, then loans that deteriorated in credit quality in previous periods are more likely than other loans to downgrade during future periods, all other factors being the same. Awareness of downgrade momentum would allow lenders to more carefully scrutinize loans that downgraded in credit quality in previous periods, and better direct monitoring resources toward loans more likely to further deteriorate in the future. On the other hand, if trend reversal is present in agricultural loans, implications for agricultural lenders may not be as serious. Thus, a need exists to identify whether migration rates of farm businesses display path dependence, and if so, whether rating drift or trend reversal is present.

This study builds on previous agricultural finance studies by applying additional migration analysis to farm-level data. Farm-level data for 1985–2002 are utilized from the Illinois Farm Business Farm Management Association to derive annual migration rates based on farmers' calculated credit scores. We calculate a single unconditional transition matrix for the entire sample and test for differences in migration rates by conditioning on the business cycle. In addition, migration analysis is employed to test for a violation of the Markov property of independence or the presence of path dependence in credit score ratings of farm businesses. The remaining sections explain the measurement approaches, illustrate the theories of credit score migration and trend analysis, address data issues, define the business cycles, present the results, and summarize the conclusions.

Credit Score Migration Rates

Credit score migration analysis considers changes in a farm business's credit quality over time. The changes are summarized across years and farm businesses to produce transition probabilities. Transition probabilities represent the probability of a farm business retaining the same credit score rating or migrating to a different credit score class during a specific time period. Transition probabilities are calculated as follows:

$$(1) \quad p_{ij} = \frac{n_{ij}}{n_i}.$$

Given that there are n_i farm businesses in a given rating class i at the beginning of the year and that out of this group, n_{ij} have migrated from class i to the class j, the one-year transition rate is estimated as p_{ij} (Lando and Skodeberg, 2002).

In this study, we test whether the Markov property of independence is violated for farm businesses. Path dependence hypothesizes that preceding changes in credit rating hold information about the direction of future rating changes. Rating drift, a form of path dependence, has three characteristics—direction, magnitude, and distance.

To determine if a farm business's previous change in risk rating will influence the change in risk rating from this period to the next period, analysis of three consecutive years of risk ratings is necessary. Consider a risk rating system with five risk classes, i = 1 to 5, where class 1 (with credit score = 1) represents the lowest risk farm businesses and class 5 represents the highest risk farm businesses.

Assume a farm business's risk rating places it in class i in year t - 1, changes to class (i + 1) in year t, and then changes to class (i + 2) in year t + 1. The initial change, from class i to class (i + 1), is a downgrade. This initial change, from year t - 1 to year t, is the basis for the migration trend measurement, and this farm business is placed in the downward trend matrix. If the initial change is an upgrade credit score rating, then the farm business is placed in the upward trend matrix. When the farm business retains its current rating from year t - 1 to year t, the farm business is placed in the no-trend matrix.

If a downgrade momentum is present in the sample, an initial downgrade in credit quality would be followed by another downgrade from year t to year t + 1. The opposite is true of upgrade momentum: an upgrade in risk rating would be followed by another upgrade in credit quality. The other case of path dependence, trend reversal, will have upgrades more likely to be followed by downgrades and less likely to be followed by upgrades, and vice versa. Figure 1 presents a simplified illustration of the patterns of upgrades and downgrades over the required three-year period.

Conditional Credit Score Migration

Previous agricultural finance studies assumed that transition probabilities are the same across all years, independent of factors such as business cycles and migration trends, while our hypothesis is that transition probabilities differ across business cycles and migration trends. To test this hypothesis, we first calculate the unconditional transition probabilities, p_{ij}, according to equation (1). Conditional transition probabilities, p_{ij}^c, are then calculated for the business cycles and migration trends. Transition probabilities are calculated separately for farm businesses during the years of expansion and recession, which produces a conditional transition matrix for each cycle. Our hypothesis for testing for the effect of business cycle is as follows:

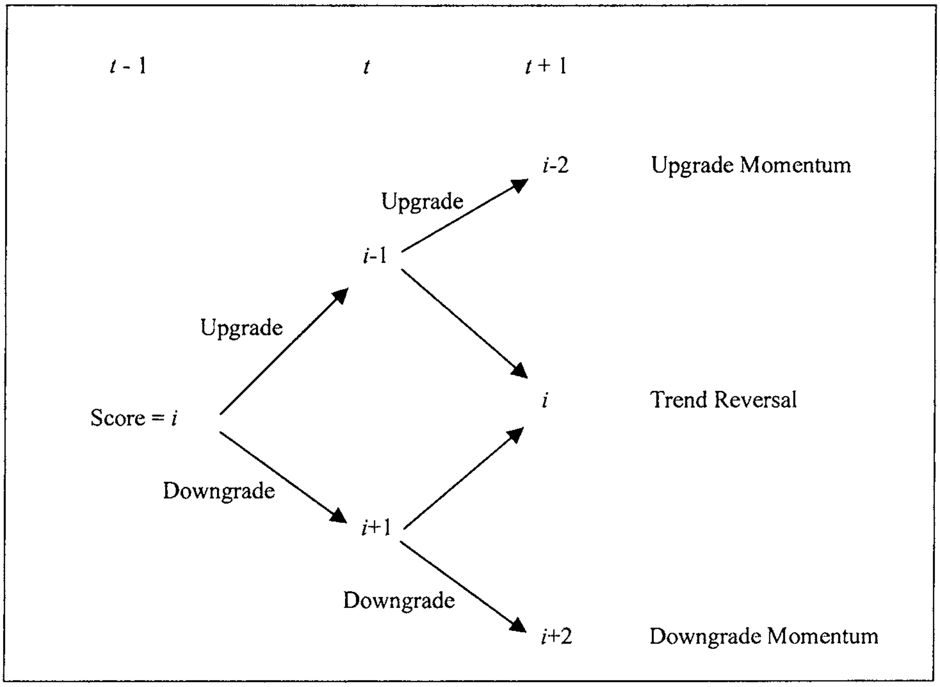

Figure 1. Simplified Illustration of Migration Trends

(2) H_0: $p_{ij} = p^c_{ij}$(expansion) $= p^c_{ij}$(recession);

H_a: $p_{ij} \neq p^c_{ij}$(expansion) or

$p_{ij} \neq p^c_{ij}$(recession).

In the case of migration trends, there are three conditional matrices—downward trend, upward trend, and no trend—based on the initial change in a farm business's credit rating. Our hypothesis for testing for the violation of the Markov property of independence is:

(3) H_0: p_{ij}(upgrade) $= p^c_{ij}$(upgrade|upgrade)

$= p^c_{ij}$(upgrade|downgrade)

$= p^c_{ij}$(upgrade|no trend);

H_a: At least one $p^c_{ij} \neq p_{ij}$.

To determine if the unconditional transition matrix is different from the conditional business cycle matrices and migration trends matrices, t-statistics are computed equal to the difference between the conditional probabilities and the unconditional probabilities divided by the standard errors of the conditional probabilities. We follow Nickell, Perraudin, and Varotto (2000) in calculating the standard errors of the conditional probabilities and the t-statistics:

(4) $se(p^c_{ij}) = \sqrt{\dfrac{p^c_{ij}(1 - p^c_{ij})}{n_i}}$ and

(5) $t = \dfrac{p_{ij} - p^c_{ij}}{se(p^c_{ij})}$.

If these probabilities are significantly different via the t-statistics test, the unconditional matrix is not the most accurate measure of credit migration, and conditional migration analysis should be employed. In the case of path dependence, significantly different t-statistics imply that the Markov property of independence is violated for the specific sample period. If path dependence is not present in credit migration of farm businesses, a pattern of systematic upgrades or downgrades will not be observable in the transition probabilities.

While Nickell, Perraudin, and Varotto (2000) evaluate differences between transition matrices using cell-by-cell *t*-test comparisons, two finance studies (Jafry and Schuermann, 2003; and Schuermann and Jafry, 2003) suggest an alternative approach where matrices are compared using an overall singular value measure. Transition matrices are diagonally-dominant (with high probabilities concentrated on the diagonal), which implies little migration. Since we are interested in the amount of migration, a mobility matrix $\tilde{\mathbf{P}}$ is calculated by subtracting the identity matrix $\mathbf{I}$ from the transition matrix $\mathbf{P}$ (with elements p_{ij}):

(6) $\tilde{\mathbf{P}} = \mathbf{P} - \mathbf{I}.$

The identity matrix represents a static matrix with no migration; thus the mobility matrix represents only the dynamic part of the original transition matrix. Using the mobility matrix, the singular values of $\tilde{\mathbf{P}}$ are calculated:

(7) $\mathbf{S}(\tilde{\mathbf{P}}) = \sqrt{\text{eig}(\tilde{\mathbf{P}}'\tilde{\mathbf{P}})}\ ,$

where eig(·) are the eigenvalues of a matrix. The average of the singular values of the mobility matrix,

$$\overline{\mathbf{S}(\tilde{\mathbf{P}})},$$

approximates the average probability of migration across all credit classes (Jafry and Schuermann, 2003). The unconditional and conditional matrices can be compared using the singular value metric:

(8) $m(\tilde{\mathbf{P}}, \tilde{\mathbf{P}}^c) = \overline{\mathbf{S}(\tilde{\mathbf{P}})} - \overline{\mathbf{S}(\tilde{\mathbf{P}}^c)}\ .$

We need to know if the singular value metric $m(\tilde{\mathbf{P}}, \tilde{\mathbf{P}}^c)$, based on the overall difference in the probabilities between the two matrices, is significantly different from zero. We use 1,000 bootstrap samples from the original data to estimate a confidence interval for the metric. The null hypothesis that the conditional and unconditional matrices are equal will be rejected if zero is outside the 95% confidence interval for the singular value metric.

Measurement Approaches

In order to calculate migration rates, one must first classify farm businesses by creditworthiness using a risk rating instrument. Bonds are assigned risk rating categories by the rating companies such as Moody's and Standard & Poor's. Thus, bonds transition between rating categories as they are reevaluated by the rating companies.

Zech and Pederson (2003) used linear and logistic analysis to decipher the factors that predict actual farm profitability and debt repayment ability of Minnesota farms. They found the rate of asset turnover and family living expenses to be strong predictors of farm performance, and the debt-to-asset ratio to be a strong predictor of repayment ability over several time periods. Using measurements of profitability, repayment capacity, and a credit scoring model to classify farm businesses by credit risk, Barry, Escalante, and Ellinger (2002) found the credit score approach produced higher retention rates than the other classification approaches. Credit scoring models provide a more comprehensive evaluation of creditworthiness than a single measurement, by incorporating multiple financial factors into a composite index of credit risk, including measures of profitability and repayment capacity.

In this study, farm businesses are assigned credit scores based on the term loan credit scoring model developed by Splett et al. (1994). This model utilizes financial ratios recommended by the Farm Financial Standards Task Force (FFSTF) as explanatory variables, including one measure each of liquidity, solvency, profitability, repayment capacity, and financial efficiency, to sort farms into five uniform risk rating classes. Class 1 contains the lowest risk borrowers, while class 5 represents the highest risk borrowers.[2] The credit score used in this analysis differs from Splett et al. (1994) in that it defines new interval ranges for the repayment capacity measure since the intervals defined by Splett et al. resulted in heavy concentration of observations in the first class. The use of the credit score as a measurement tool and the use of the new interval ranges for the repayment capacity measure are consistent with the practices of previous agricultural finance studies (Barry, Escalante, and Ellinger, 2002; Escalante et al., 2001; Katchova and Barry, 2005, forthcoming).

While modern capital management studies (Barry, 2001; Basel Committee on Banking Supervision, 2003) suggest the use of more than five classes is ideal for measuring credit risk, there are pros and cons to such classification systems. More classes suggest increased homogeneity of loans within each class. On the downside, however, more classes lead to an increase in the probability of misclassification of loans, to a decrease in the retention rates, and can be hard to implement.[3]

For purposes of this study, migration analysis is measured by year-to-year transition probabilities. This is consistent with the finance literature (Bangia et al., 2002; Lando and Skodeberg, 2002; Nickell, Perraudin, and Varotto, 2000). Other agricultural finance studies (Barry, Escalante, and Ellinger, 2002; Escalante et al., 2001; Novak and LaDue, 1997) have also used three-year moving average measurements, which smooth a portion of the annual random movements in credit risk outcomes in order to differentiate the systematic movements from the random movements. To test for the effects of business cycles and the presence of path dependence, we need to capture annual changes in credit quality, since both business cycles and migration trends are defined on an annual basis. Therefore, this study's objectives limit the measurement of transition probabilities to one year.

Data Issues

This study employs annual farm-level data from the Illinois FBFM data set for 1985 to 2002. The FBFMA has annual membership of more than 6,500 farms; however, only a portion of these farms pass the field staff's rigorous process of certification of financial records.

The initial unconditional transition matrix is developed based on farm businesses with a minimum of two consecutive years of participation, and is compared to conditional transition matrices of the business cycles to test the effects of such cycles. To test for path dependence, an unconditional transition matrix is developed using only those farm businesses with a minimum of three consecutive years of participation. By selecting two consecutive years of data for the cycles analysis and three consecutive years of data for the migration trend analysis, we introduce survival bias.[4] This problem, however, is unavoidable given the measurement requirements of our study. Analysis of summary statistics for the two-year sample and three-year sample show the farms in each sample are similar in characteristics. The means and standard deviations for characteristics including

[2] This five-class credit scoring model does not include a class for farm businesses in default. Loans are often classified as in default when payments are 90 days or more past due, a variable that is unknown in our sample. Because farm-level data are utilized, and not lender loan data, the only measure of default available in the data is insolvency. Similar to Katchova and Barry (2005, forthcoming), we can define a default class for insolvent farm businesses and repeat the analysis. These results (available from the authors upon request) are almost identical to the results reported here.

[3] Analysis of a 10-class credit scoring model was performed by splitting each of the existing five classes in half. Results were generally consistent with the findings of the five-class analysis presented in this paper but are not included here. (Those results are available from the authors upon request.)

[4] Exclusion of a default class implies that all farm businesses "survive" in the migration analysis.

assets, liabilities, leverage, tenure, and total acres farmed are very similar. In addition, the percentages of downgrades, upgrades, and retentions in each sample are identical at 25%, 23%, and 52%. Based on these statistics, it seems the farm businesses that survive for at least three years have similar characteristics to those surviving a minimum of two years.

Earlier, finance literature was cited (Bangia et al., 2002; and Nickell, Perraudin, and Varotto, 2000) that suggests transition probabilities should be based on several conditioning factors, such as location of borrower, type of borrower, and business cycle. Nickell, Perraudin, and Varotto found the location of the bonded company or borrower to be of significance when they considered bonds of companies in different countries. Since the entire sample in our study is located in the state of Illinois, this analysis is not included here.

The same study also found bond transition probabilities differed across industries. While this hypothesis could easily be applied to agriculture by grouping farm businesses by type of production, our data set is limited in this regard. Illinois farms are predominantly involved in grain production, while livestock farms, diversified farms, and specialty farms make up a small portion of aggregate production. These trends are observed in the FBFMA data set where grain farms represent 86% of farms, while hog production is second at 7%, and dairy production third with 3%. The composition of our sample of mostly grain farms prevents us from conditioning migration analysis by type of production of farm business.[5]

[5] Previous agricultural finance studies (Barry, Escalante, and Ellinger, 2002; Escalante et al., 2001; and Katchova and Barry, 2005, forthcoming) utilizing the same data source (Illinois FBFM) analyzed migration rates for all farms, not just grain farms. In addition, migration analysis results are similar when our sample is restricted to grain farms (results are available from the authors upon request). Thus, our migration analysis includes all farm types, though we recognize the composition of farms in our sample is a limitation of this study.

Business Cycle Definitions

Bangia et al. (2002); and Nickell, Perraudin, and Varotto (2000) found year-to-year migration rates of bonds differed depending on corresponding national business cycles. Nickell, Perraudin, and Varotto (2000) studied migration analysis of international bonds by business cycle. They compared annual GDP levels across applicable countries to averages in order to determine the business cycle of each bond for each year. Bangia et al. defined the business cycle based on the definitions reported monthly by the National Bureau of Economic Research (NBER).

Bangia et al. (2002) suggest that the state of the economy, or business cycles, can serve as a proxy for measurement of the systematic risk of a firm's asset portfolio. In addition, Pederson, Stensland, and Fischer (1998) suggest macroeconomic policies directly and indirectly affect the agricultural industry, primarily through interest rates and exchange rates. Exchange rates affect exports and imports of agricultural products, while interest rates influence loan terms of agricultural loans. The underlying correlations between exchange rates, interest rates, and agricultural credit risks are driven by macroeconomic policies, while changes in economic cycles serve as indicators of shifts in the underlying macroeconomic policies and reflect changes in exchange rates and interest rates. For example, Bjornson (1995) found that expected lands returns were significantly affected by the business cycle effects of changing capital market risk premia and discount rates for the period 1961–1990. Results from their study suggest that agricultural asset performance and valuation should account for macroeconomic conditions and business cycles in addition to agricultural sector conditions.

In this study, we follow Bangia et al. (2002) and define the business cycles as *expansion* and *recession* based on the published reports of NBER. According to the NBER, the United States' economy was

Table 1. Unconditional Migration Probabilities (based on two consecutive years of data)

Current Year	Next Year					No. of Farm Obs.
	Class 1	Class 2	Class 3	Class 4	Class 5	
Class 1	75.48	16.78	6.19	1.43	0.12	5,941
Class 2	20.91	44.13	22.85	9.19	2.92	4,625
Class 3	7.71	23.25	42.33	16.85	9.87	4,125
Class 4	4.12	19.65	33.15	27.66	15.42	1,822
Class 5	0.48	11.00	35.22	21.72	31.58	1,045

Notes: The numbers in the table indicate the probability of moving from class *i* in the current year to class *j* in the next year, expressed as a percentage. This matrix is compared to the business cycle-conditioned migration matrices in Table 2.

in expansion during 1985–1989 and 1992–2000, while sustaining recessions from 1990–1991 and 2001. Though NBER has yet to release a report on the business cycle(s) experienced in 2002, we classify 2002 as a recession due to possible lag effects of the 2001 recession. For example, migration rates for changes in farm businesses' credit scores from 1988 to 1989 are included in the expansion cycle matrix, while changes from 1989 to 1990 are included in the recession cycle matrix.

Migration Results

The transition probabilities averaged across the full sample are exhibited in Table 1. Similar to previous agricultural finance studies (Barry, Escalante, and Ellinger, 2002; Escalante et al., 2001; Katchova and Barry, 2005, forthcoming), retention rates for classes 1, 2, and 3 are found to display the highest transition probabilities but are substantially lower than those exhibited by bond ratings. Retention rates, displayed along the diagonal of the matrix, represent the probability of a farm business remaining in the same credit score class for concurrent periods. The highest transition probability is 75.48%, signifying the probability of class 1 farm businesses retaining their credit score of 1 in the next period.

The transition probabilities usually exhibit greater tendency to move one class away from the current class in both directions and lower tendency to move more than one class from the current class. For example, as observed from Table 1, the likelihood of a farm business currently in class 3 migrating to class 4 is 16.85%, but the likelihood of the same class 3 farm business moving to class 5 is only 9.87%. Generally, the probabilities of a farm business migrating to a "near" class are higher than the probabilities of migrating to a "far" class. The singular value metric, unlike the cell-by-cell comparisons, takes into account near versus far migration.

Business Cycle Results

The results from the business cycle matrices are reported in Table 2. Based on two-tailed tests with a 95% confidence level, 14 of 25 transition probabilities observed during the expansion cycle and 18 of 25 transition probabilities observed during the recession cycle are found to be significantly different from those of the unconditional matrix (as shown in Table 1). Six of the 10 retention rates are significantly different from unconditional retention rates. The numbers in parentheses below the transition probabilities show the differences in the transition probabilities between the business cycle matrix and the unconditional matrix.

During the expansion cycle, some transition probabilities below the diagonal of retention rates in the matrix are higher than the unconditional matrix, while those above the diagonal are lower. For example,

Table 2. Business Cycle-Conditioned Migration Probabilities (based on two consecutive years of data)

Current Year	Next Year					No. of Farm Obs.
	Class 1	Class 2	Class 3	Class 4	Class 5	
Expansion: [a]						
Class 1	77.12*	16.05	5.42*	1.27	0.14	4,319
	(1.64)	(-0.73)	(-0.77)	(-0.16)	(0.02)	
Class 2	23.60*	44.62	21.28*	8.29	2.20*	3,364
	(2.69)	(0.49)	(-1.57)	(-0.90)	(-0.72)	
Class 3	9.22*	25.58*	41.67	14.66*	8.88	2,940
	(1.51)	(2.33)	(-0.66)	(-2.19)	(-0.99)	
Class 4	5.17	23.91*	33.96	24.14*	12.82*	1,334
	(1.05)	(4.26)	(0.81)	(-3.52)	(-2.60)	
Class 5	0.64	13.78*	39.03*	22.19	24.36*	784
	(0.16)	(2.78)	(3.81)	(0.47)	(-7.22)	
Recession: [b]						
Class 1	71.09*	18.74*	8.26*	1.85	0.06	1,622
	(-4.39)	(1.96)	(2.07)	(0.42)	(-0.06)	
Class 2	13.72*	42.82	27.04*	11.58*	4.84*	1,261
	(-7.19)	(-1.31)	(4.19)	(2.39)	(1.92)	
Class 3	3.97*	17.47*	43.97	22.28*	12.32*	1,185
	(-3.74)	(-5.78)	(1.64)	(5.43)	(2.45)	
Class 4	1.23*	7.99*	30.94	37.30*	22.54*	488
	(-2.89)	(-11.66)	(-2.21)	(9.64)	(7.12)	
Class 5	0.00	2.68*	23.75*	20.31	53.26*	261
	(-0.48)	(-8.32)	(-11.47)	(-1.41)	(21.68)	

Notes: An asterisk (*) denotes significance at a 95% confidence level (based on a two-tailed *t*-test). The numbers in parentheses indicate differences from the unconditional matrix in Table 1.

[a] Expansion cycles: 1985–1989, 1992–2000.

[b] Recession cycles: 1990–1991, 2001–2002.

the likelihood of a farm business currently in class 2 migrating up to class 1 in the next period is 2.69% higher in the expansion matrix than in the unconditional matrix. The opposite pattern is exhibited in the recession cycle matrix. Here, the likelihood of a farm business currently in class 2 migrating down to class 3 is 4.19% greater in the recession matrix than in the unconditional matrix.

Another striking result is the fluctuation in the retention rate of class 5, the highest risk class, across business cycles and the unconditional matrix. During expansion, the retention rate is 7.22% significantly lower than the unconditional retention rate. During recession, however, the retention rate for class 5 is 21.68% significantly higher than the unconditional retention rate. These results suggest farm businesses are more likely to improve during the expansion cycle and more likely to remain in high credit risk classes during recession. In particular, farm businesses in the high risk classes 4 and 5 are much more likely to retain or worsen their financial position and less likely to improve their financial position during recessions.[6] These farm businesses are more likely to improve their financial position during expansion periods by migrating away from the high risk classes.

[6] An increase in concentration in classes 4 and 5 during the recession cycle could be due to increases in default. Near-default farms would most likely be classified as high risk before exiting the sample.

Our results are consistent with those of previous finance studies, which examined significant differences in cell-by-cell transition probabilities. Nickell, Perraudin, and Varotto (2000) found that transition probabilities of bonds exhibited a higher tendency to upgrade during a business cycle peak (expansion) but a higher tendency to downgrade during a business cycle trough (recession). Bangia et al. (2002) also found the same pattern in transition probabilities of bonds, where bonds demonstrated a greater tendency to improve during a U.S. expansion cycle but a greater tendency to deteriorate during a U.S. recession cycle. The findings of Bangia et al. are especially relevant in comparison to our results, because both studies utilized the NBER cycle definitions for the business cycle.

In addition, matrices for the expansion and recession cycles were each compared to the unconditional matrix using the singular value metric. We calculated the mobility matrices by subtracting the identity matrix from the original matrices using equation (6). Symmetric $\{5 \times 5\}$ matrices were calculated as the transposed mobility matrices multiplied by the mobility matrices themselves. There are five eigenvalues corresponding to each symmetric matrix. One of these five eigenvalues is zero because each column in the mobility matrix is the sum of the rest of the columns, implying the matrices have a rank of 4 (Jafry and Schuermann, 2003). The singular values were estimated as the average of the eigenvalues of the mobility matrices according to equation (7). The singular value metric for each matrix is a number representing the average probability of migration across all credit classes.[7]

A bootstrap analysis with 1,000 replications was used to calculate 95% confidence intervals for the difference between the singular values for the unconditional matrix and those of the expansion (or recession) matrix. This process yielded confidence intervals of (-0.0273, -0.0269) for the difference between the unconditional and the expansion matrix and (0.0602, 0.0613) for the difference between the unconditional and the recession matrix. Because zero is outside of these confidence intervals, we conclude that overall the unconditional matrix is significantly different from the expansion and recession matrices. These results confirm the cell-by-cell conclusions that migration probabilities differ significantly in expansion and recession cycles.

Our results suggest farm businesses exhibit a greater tendency to upgrade when the national economy is in expansion and to downgrade when the economy is in recession than if we do not condition on the business cycle. Furthermore, the statistical significance of these results suggests the unconditional transition probabilities produce misleading results—supporting the hypothesis that macroeconomic conditions, as represented in this study by the business cycle, do affect the financial performance of farm businesses. Moreover, results lead us to conclude agricultural lenders should include macroeconomic factors, such as the business cycle, in migration analysis in order to minimize credit risk in their agricultural loan portfolios. Additionally, agricultural lenders need to be concerned about deteriorating loan quality during recession times.

Migration Trend Results

The full sample transition matrix is presented in Table 3. A new unconditional matrix must be calculated to test for path dependence because of the minimum requirement of three consecutive years of data, as opposed to Table 1, which is based on a minimum requirement of two consecutive years.

Table 4 shows the transition probabilities for downward trend, no trend, and upward trend, with the difference in transition

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[7] For example, the eigenvalues for the unconditional matrix are 0.86, 0.81, 0.53, 0.1, and 0, leading to an average migration probability of 57%.

Table 3. Unconditional Migration Probabilities (based on three consecutive years of data)

CURRENT	NEXT YEAR					No. of
YEAR	Class 1	Class 2	Class 3	Class 4	Class 5	Farm Obs.
Class 1	75.90	16.92	5.74	1.37	0.07	4,096
Class 2	20.74	45.18	22.42	8.97	2.69	3,154
Class 3	7.57	23.89	42.68	17.02	8.85	2,826
Class 4	4.09	18.57	34.07	28.48	14.79	1,271
Class 5	0.00	11.27	33.80	21.97	32.55	719

Notes: The numbers in the table indicate the probability of moving from class *i* in the current year to class *j* in the next year, expressed as a percentage. This matrix is compared to the trend-conditioned migration matrices in Table 4.

rates between the trend matrix and the unconditional matrix shown in parentheses below. Farm businesses in the downward trend (upward trend) matrix experienced downgrades (upgrades) during the previous period of migration analysis, while those in the no-trend matrix retained their credit score rating during the previous period of migration measurement. A two-tailed test with a 95% confidence level is employed to determine if any of the trend transition probabilities differ from those of the full sample.

The first noteworthy result is the number of significant probabilities present in the no-trend matrix. In previous studies, the no-trend matrix exhibited little significance when rating drift was present (Bangia et al., 2002). Thirteen out of 25 transition probabilities exhibited rates significantly different from those of the unconditional matrix. The retention rate of class 1 (81.45%) is 5.55% higher than in the unconditional matrix, while the retention rate for class 5 (48.55%) is 16% higher than that of the unconditional matrix. In fact, all of the retention rates are significantly higher than the unconditional retention rates. The significance found in the no-trend matrix implies a significant number of farm businesses maintain their credit score rating over a consecutive time period. The fact that farm businesses exhibiting no trend in the previous period are more likely to continue to retain their rating supports our hypothesis that the Markov property of independence is violated in our sample.

Second, the significant probabilities in the downward trend and upward trend matrices do not exhibit a pattern of rating drift, or momentum, as has been found in bond studies (Bangia et al., 2002; Lando and Skodeberg, 2002). The number of significant probabilities, however, indicates the Markov property of independence is violated. Instead of rating drift, the significant transition probabilities in the downward and upward trend matrices exhibit a pattern of trend reversal. For example, the transition probabilities for class 3 in the downward trend matrix are higher in lower risk classes and lower in the higher risk classes than the full sample. The probability of downgrading from class 3 to class 4 following a downgrade is 5.87% lower than the unconditional, while the probability of upgrading from class 3 to class 2 following a downgrade is 10.28% higher than the unconditional. Thus, farm businesses in class 3 that experienced a downgrade in credit quality last period are more likely to upgrade and less likely to further downgrade in credit quality over the next period.

The opposite pattern is represented in the upward trend matrix. The probability of upgrading from class 3 to class 2 following an upgrade is 8.82% lower than the unconditional, while the probability of downgrading from class 3 to class 4 is 10.45% higher than the unconditional. This finding demonstrates a pattern of trend reversal, whereby farm businesses are more likely to downgrade than upgrade

Table 4. Trend-Conditioned Migration Probabilities (based on three consecutive years of data)

CURRENT YEAR	NEXT YEAR Class 1	Class 2	Class 3	Class 4	Class 5	No. of Farm Obs.
Downward Trend:						
Class 1	—	—	—	—	—	
Class 2	41.14*	40.73*	11.30*	6.14*	0.70*	717
	(20.40)	(-4.45)	(-11.12)	(-2.83)	(-1.99)	
Class 3	17.40*	34.17*	32.50*	11.15*	4.79*	960
	(9.83)	(10.28)	(-10.18)	(-5.87)	(-4.06)	
Class 4	5.29	22.12*	34.62	24.64*	13.34	832
	(1.20)	(3.55)	(0.55)	(-3.84)	(-1.45)	
Class 5	0.55	13.00	37.73	21.25	27.47*	546
	(0.55)	(1.73)	(3.93)	(-0.72)	(-5.08)	
No Trend:						
Class 1	81.45*	12.50*	5.28	0.73*	0.03	3,143
	(5.55)	(-4.42)	(-0.46)	(-0.64)	(-0.04)	
Class 2	17.69*	48.82*	22.63	8.08	2.79	1,436
	(-3.05)	(3.64)	(0.21)	(-0.89)	(0.10)	
Class 3	3.11*	20.61*	50.97*	15.81	9.50	1,189
	(-4.46)	(-3.28)	(8.29)	(-1.21)	(0.65)	
Class 4	2.33*	15.28	30.23	37.54*	14.62	301
	(-1.76)	(-3.29)	(-3.84)	(9.06)	(-0.17)	
Class 5	0.00	5.78*	21.39*	24.28	48.55*	173
	(0.00)	(-5.49)	(-12.41)	(2.31)	(16.00)	
Upward Trend:						
Class 1	57.61*	31.48*	7.24	3.46*	0.21	953
	(-18.29)	(14.56)	(1.50)	(2.09)	(0.14)	
Class 2	10.49*	43.16	30.07*	12.19*	4.00*	1,001
	(-10.25)	(-2.02)	(7.65)	(3.22)	(1.31)	
Class 3	1.48*	15.07*	42.54	27.47*	13.44*	677
	(-6.09)	(-8.82)	(-0.14)	(10.45)	(4.59)	
Class 4	0.72*	4.35*	39.13	31.88	23.91*	138
	(-3.37)	(-14.22)	(5.06)	(3.40)	(9.12)	
Class 5	—	—	—	—	—	

Notes: An asterisk (*) denotes significance at a 95% confidence level (based on a two-tailed *t*-test). The numbers in parentheses indicate differences from the unconditional matrix in Table 3.

in credit quality following an upgrade in the previous period.

As with the business cycle, the overall singular value metric was used to test whether the transition matrices conditioned on previous trends were significantly different from the unconditional transition matrix. The confidence intervals for the difference between the unconditional matrix and the downward trend, no-trend, and upward trend matrices were (-0.0968, -0.0840), (0.0895, 0.0908), and (-0.0730, -0.0626), respectively. These results show significant differences between the probabilities in the unconditional and conditional matrices. In other words, credit migration is found to depend on the previous period trends.

Based on our results, the Markov property of independence is violated in our sample, and path dependence is found to exist. While results suggest path dependence is present, rating drift is not the form of path dependence present in the sample. Instead, the results indicate trend reversal of credit score ratings is present in our sample. The transition probabilities of the downward trend matrix are higher for migrating to lower risk classes, implying a downgrade in credit quality last period would more likely result in an upgrade in credit quality over the next period in comparison to an unconditional upgrade. The opposite pattern is present in the upward trend matrix, where the transition probabilities for migrating to higher risk classes are higher, implying an upgrade in credit risk last period would be more likely to be followed by a downgrade next period.

Bond ratings are determined by rating agencies, which utilize a complex, quantitative and qualitative judgmental process to rate bonds; however, in this study, farm businesses are measured by a credit scoring model. Agricultural lenders, though, use their own individualized internal risk rating models, similar to those of bond rating agencies, to risk rate agricultural borrowers. While agricultural lenders' internal models may include a credit scoring model, such a model is likely not their only risk rating tool. In addition, the rating drift studies utilized data on bond ratings, but our study employs farm-level data instead of loan-level data. Analysis of path dependence in agricultural borrowers may produce different results from those reported in our study of farm businesses. Based on these distinct differences, we cannot assess whether rating drift or trend reversal is present in agricultural borrowers, despite the fact that we find trend reversal present in our sample of farm businesses.

Summary and Concluding Remarks

The results of this study suggest agricultural lenders should employ credit risk migration analysis which determines transition probabilities across business cycles in order to fully evaluate the credit risk held in their agricultural loan portfolios. We have shown transition probabilities differ significantly across these business cycles when compared to the unconditional migration probabilities, the traditional migration analysis employed by lenders. In particular, the results from the cycles show farm businesses exhibit a higher tendency to downgrade (upgrade) than upgrade (downgrade) during recessions (expansions). Our findings are consistent with the results of finance studies (Bangia et al., 2002; Nickell, Perraudin, and Varotto, 2000), which found that bond ratings exhibit a higher tendency to downgrade in recession and upgrade in expansion.

We also found that the Markov property of independence is violated in our sample and that trend reversal of credit score ratings is present in farm businesses. This finding of trend reversal is in contradiction to the downward momentum found in bond ratings by finance studies (Bangia et al., 2002; and Lando and Skodeberg, 2002). Based on our sample and measurement process, we cannot determine whether trend reversal or rating drift is present in agricultural borrowers, though this study finds trend reversal to be present in a sample of farm businesses.

Further studies are warranted to determine if transition probabilities differ significantly across types of agricultural production and geographical locations of farm businesses and agricultural borrowers. Just as Splett et al. (1994) concluded lenders should develop credit score models for borrowers based on different structural characteristics, including loan structure and type of production, lenders need to condition migration analysis based on many of these same structural characteristics in order to better assess agricultural borrowers' credit risk. The lack of diversity among farm types in our data set prevented us from investigating migration analysis differences across farm types. A national data set or a regional data set encompassing multiple states would be most appropriate for such studies. In addition, our findings should be compared to studies that utilize lender loan-level data to verify our results.

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Determinants of Investments in Non-Farm Assets by Farm Households

Teresa Serra, Barry K. Goodwin, and Allen M. Featherstone

Abstract

Off-farm investment decisions of farm households are analyzed. Farm-level data for a sample of Kansas farms observed from 1994 through 2000 are utilized. A system of censored dependent variable models is estimated to investigate the factors that influence the composition of farm households' portfolios. The central question underlying the analysis is whether farm income variability influences off-farm investment decisions. Previous analyses on the determinants of non-farm investments have failed to consider the role of income variability. Results of this study indicate that higher farm income fluctuations increase the relevance of non-farm assets in the farm household portfolio, thus suggesting these assets are used as farm household income risk management tools.

Key words: farm income variability, off-farm investments, risk management

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The understanding of the determinants of farm households' off-farm investments is an issue of increasing relevance. The growing importance of this subject can be explained by at least two main factors: the tendency to decouple farm policies and the lack of analyses of off-farm assets held by farm households. The decoupling trend, which characterizes the evolution of farm policies in a number of countries, has largely resulted in a reduction in price support policies in favor of direct income support measures. Concerns have arisen that these changes may lead to an increase in farm households' income variability.

With the 1996 Federal Agriculture Improvement and Reform (FAIR) Act, and in an intention to decouple government payments from market prices, U.S. agricultural price support levels were reduced and production flexibility contracts (PFCs) were introduced. In addition, with the passage of the FAIR Act, producers were afforded much greater planting flexibility than under the old policy regime. The characteristics of the FAIR Act may have led not only to a direct increase in the variability of planted acreage, but also to an increase in the variability of market prices, thus raising farm revenue risk. As a result, in this new policy environment, farmers may have a higher need to manage farm income risk in order to keep relatively smooth income levels.

Several research papers have recognized that financial assets constitute sound diversification alternatives for farmers (see, e.g., Penson, 1972). As Young and Barry

(1987) explain, if financial assets have low or negative correlations with farm assets, non-farm asset holding can be an effective means of stabilizing the financial performance of farm household income.[1] Although U.S. agricultural policy has traditionally addressed farm household income risk through different tools such as crop insurance programs or commodity programs, non-farm investments have received little attention at the political level. More recently, however, consideration has been given to the possibility of using tax-deferred savings accounts as a farm risk management tool.[2] Effective diversification of farm households' investments would reduce the need to provide farmers with other policy measures that decrease farm household income variability, thus making it easier for policy makers to progressively dismantle highly distorting agricultural policies such as disaster assistance payments, in favor of more decoupled instruments.

As noted above, previous analyses of farm savings and off-farm investments have been limited by data availability and have mainly resorted to inferences on farm savings. The increasing availability of data on farm households' savings, such as the Federal Reserve Board's Survey of Consumer Finance (SCF) and the USDA's Agricultural Resource Management Survey (ARMS) database, has made it possible to study farm savings using actual data. Some analyses based on these sources have shown an increase in off-farm investments in recent years (Mishra and Morehart, 2001, 2002). The increasing relevance of these assets in the farm household portfolio makes the need to understand farm savings and investment decisions even more pressing.

While previous studies have identified a number of variables that explain the decision to invest in non-farm assets (as discussed more fully in the literature review section below), no previous analysis has considered the influence of farm income variability when modeling off-farm investments. We maintain, to the extent that farmers' preferences are not likely to be risk neutral (Chavas and Pope, 1985; Hansen and Singleton, 1983; Pope and Just, 1991) and that investments in non-farm assets can be used as a risk management strategy (Penson, 1972; Young and Barry, 1987), the influence of farm income variability on these investments should be explicitly considered.

The objective of this research is to model off-farm investment decisions, based on data from a sample of Kansas farms observed from 1994 to 2000, and explicitly consider the influence of farm income variability on these decisions. At the empirical level, we estimate a censored system of equations to assess the determinants of farm household investments in different types of assets such as retirement accounts, residence, liquid assets, salable stock, and other investments. Strong evidence that farm income variability influences non-farm investments is found.

Literature Review and Specification of Variables

As noted above, previous analyses of off-farm investments of farm households have been limited. Existing research has paid considerable attention to the desirability to invest in farm assets relative to non-farm assets, as well as to the optimal composition of a portfolio including both farm and non-farm assets. Overall, these previous studies have

[1] Opposite preferences exist as well. For example, agricultural assets are also attractive to non-farm investors, in terms of the relatively low systematic risk they can add to well-diversified portfolios (see, e.g., Barry, 1980; Sherrick, Irwin, and Forster, 1986; Moss, Featherstone, and Baker, 1987).

[2] Although the FAIR Act did not authorize any tax-deferred savings account program, it gave the Risk Management Agency the jurisdiction for such a policy and funded study on this issue. Policy deliberations that preceded the 2002 Act considered several versions of such farm savings accounts, though none were adopted in the legislation which eventually emerged from the deliberations.

concluded that farm assets should be included in most efficient portfolios (Sherrick, Irwin, and Forster, 1986; Moss, Featherstone, and Baker, 1987; Kaplan, 1985; Crisostomo and Featherstone, 1990). Farm assets have also been found to reduce risk in a well-diversified portfolio (Barry, 1980; Irwin, Forster, and Sherrick, 1988).

Notwithstanding the contribution of these previous analyses, little is known about non-farm assets held by farmers and the variables influencing these off-farm investments and types of investments. In a first study addressing this issue, Gustafson and Chama (1994) conducted a survey to identify the different types and sizes of financial assets held by North Dakota farmers. Their results suggest most farmers invest in low-risk financial assets which are primarily held for emergency and retirement reasons. Further, less than one-third of the farmers surveyed invested in common stocks, bonds, and mutual funds.

More recent analyses by Mishra and Morehart (2001, 2002) have identified a number of factors explaining the decision to invest in non-farm assets. These include individual characteristics of farm household members, family characteristics, farm production characteristics, farm households' financial situations, and location factors. However, no previous study has considered the influence of farm income variability when modeling off-farm investments. As argued above, if farmers are risk averse, and non-farm equities are seen as risk management tools, farm business risk as represented by farm income variability should influence farm household portfolio composition.

Following earlier analyses of off-farm investments (Mishra and Morehart, 2001, 2002; Cass and Stiglitz, 1972; Takayama, 1993; Monke, 1997; Young and Barry, 1987), we select the set of variables relevant to non-farm investment decisions. Unfortunately, farmers' degree of risk aversion cannot be directly observed. However, we do have information on the use of strategies to manage farm household income risk that can reveal farmers' risk preferences.

Specifically, these strategies are reflected in our analysis through the purchase of crop insurance by the farm, the diversification of farm business activities, and the reliance on off-farm income sources. While farm income risk can be reduced by purchasing crop insurance or by diversifying farm activities, non-farm income variables indicate a dependence of the farm family on off-farm work and non-farm assets possibly to meet consumption needs and perhaps to stabilize total farm household income. Farmers' response to risk might also shed light on farmers' risk preferences. The risk faced by farmers is captured through two variables that measure farm business' risk and non-farm risk. A detailed description of these variables, as well as the other explanatory variables included in the analysis, is provided below.

As noted above, households can respond to uncertain farm income in a number of different ways. They can work off the farm to secure a more stable source of income other than farm earnings, purchase crop insurance, use forward and future contracts, diversify farm activities, participate in government programs, reserve unused borrowing capacity, renegotiate loans, accumulate savings to draw on during difficult times, or invest in non-farm assets such as financial instruments.

To the extent that off-farm investments can be used as a tool to manage income risk, the influence of farm income variability on these investments should be considered. We measure farm income variability as the coefficient of variation of the farm's gross income over the preceding 10 years. The variability of non-farm investment returns should be taken into account as well. Unfortunately, this variable cannot be observed at the farm level.[3] Given this data limitation, it is assumed all farms, while having unique farm business risk, face the same off-farm risk. To reflect this issue, annual dummy variables are introduced, allowing risk to vary across time, but not across farms.

To the extent that farmers' risk preferences may be affected by wealth, we consider the household net worth influence on off-farm investment decisions. Following Mishra and Morehart (2001), a higher net worth is hypothesized to provide more financial resources to invest off the farm. It should also be noted that if farm households have decreasing absolute risk aversion (DARA) preferences, an increase in wealth should also lead to an increase in investments in risky assets, which would gain relative importance in the farm household portfolio (Cass and Stiglitz, 1972; Takayama, 1993). Initial wealth is defined here as the lagged sum of the household farm and non-farm net worth.

Previous analyses identify farm business characteristics as variables that may be relevant to the decision to hold off-farm assets in a farm household's portfolio. Following Goodwin and Mishra (2002), and as explained above, we include the ratio of farm insurance expenses to total farm operating expenses as one possible indicator of farmers' degree of risk aversion. The purchase of crop insurance represents one strategy to manage income risk. Thus it is hypothesized that as household risk aversion increases, the relative importance of using insurance increases as well. Of course, insurance participation may reflect many other factors, and so we are cautious in our interpretation of insurance purchases as an ideal indicator of risk preferences.

[3] While we have information on non-farm incomes of farm households, and while some of these income sources are related to non-farm assets, the fact that not all farms invest in non-farm assets precludes the use of these farm-level variables as good indicators of the variability of non-farm assets' returns.

Farm enterprise diversification can possibly be used as another tool to manage farm income risk. More farm diversification may result in a smoother stream of farm income and consequently may reduce the attractiveness of off-farm investments as alternative risk management strategies. Farm enterprise diversification is measured through the Herfindahl index, which is computed as follows:

$$H = 1 - \sum_{i=1}^{m} h_i^2,$$

where h_i is the share of total farm sales accounted for by enterprise i. Thus, higher values of the index indicate higher diversification levels.

Farm financial leverage, another farm business characteristic, is likely to influence savings. Previous analyses (e.g., Mishra and Morehart, 2001) have formulated the hypothesis that a higher degree of farm leverage may reduce the available resources to invest in non-farm assets. We measure farm financial leverage as the lagged value of the debt-to-asset ratio.

Off-farm investments are also likely to be associated with total farm acres, a measure of farm size. Larger farms may have more capital available for off-farm investments. However, it is also possible that the bigger farm incomes associated with larger farms may reduce the necessity of alternative non-farm income sources, and hence the need to invest in non-farm assets to complement farm household incomes.

It should also be considered that smaller farms are more likely to rely on off-farm jobs to meet their income needs (Barlett, 1991; Mishra and Goodwin, 1997), and that households with employment off the farm may have non-farm investments directly associated with these jobs (Mishra and Morehart, 2001). Operators of larger, commercial-scale, specialized farms may be more committed and less prone to work off the farm, which may make them more vulnerable to farm income fluctuations.[4] We measure total farm acres as the total (owned and rented) operated crop acres. Because a farmer's tenure position could have an influence on asset holdings, a variable measuring the proportion of operated crop acres which are rented is also included. While accumulating owned acreage could be one wealth-building strategy, the emphasis on non-farm investments could constitute an alternative net worth buildup approach.

Farm productivity relative to other farms may also influence off-farm investment decisions. Highly productive farms may be less likely to seek alternative non-farm income sources. Because farms generate multiple crops, we choose to represent farm relative productivity by taking an average over the preceding 10 years of the normalized yield across all crops on a farm. The normalized yield is the farm yield divided by the county-average yield. The mean ratio of total crops gross value to total crop production costs over the preceding 10 years is also included as an indicator of farm management performance. Higher values of this ratio may be associated with better farm management. Mishra and Morehart (2001) suggest that better farm managers may be more willing to explore off-farm investment opportunities relative to inferior managers.

Following previous research, government payments are also considered. The consumption of farm families has been shown to vary with farm income sources. Predictable income is often spent more promptly relative to more uncertain income (Carriker, Langemeier, Schroeder, and Featherstone, 1993; Monke, 1997). Hence, government payments, which are often predictable, may reduce farm household incentives to save, thus affecting off-farm investments. This hypothesis is supported by the finding of Mishra and Morehart (2002) that farms receiving government payments save less than those who do not. Mishra and Morehart also found that those farmers receiving program payments have more precautionary savings relative to those who do not. We choose to include farm expected government payments in the analysis, which are approximated by the amount of payments the farm received the preceding year.

As noted, farm income sources influence farm household savings. To address this issue, six variables are included which reflect the household gross income, classified into the following groups: wages, rents and royalties, dividends and interest, nontaxable income, other income, and farm gross income (excluding government payments). Nontaxable income includes different nontaxable income sources such as health insurance refunds, inheritance, disability income, or social security. "Other income" pools other taxable and nontaxable income sources such as non-farm business sales or oil leases. Income variables are introduced in the model with one lag. Those incomes linked to non-farm assets (i.e., rents and royalties, dividends and interest, and other income) are expressed as a rate (their value is divided by the total amount of non-farm assets held by the farm household).[5]

Family characteristics may also be relevant in assessing off-farm investments. The presence of dependent children in the household could alter the ability and will of the household to develop an off-farm job,[6] as well as the capacity and motivations of the household to save and invest. Individual household members' characteristics have also proven to be relevant explanatory variables of off-farm

[4] We thank an anonymous referee for suggesting this idea.

[5] We do not have information to allow an accurate computation of the returns derived from the different assets held by households.

[6] For more detailed information on this topic, interested readers are referred to Rosenfeld (1985); Furtan, Van Kooten, and Thompson (1985); Mishra and Goodwin (1997); Lass, Findeis, and Hallberg (1991); and Huffman (1980).

investments. Young farmers may be less risk averse and may undertake riskier investments relative to older farmers. Additionally, farmers may be less prone to invest in non-liquid assets as they approach retirement, when they are more likely to draw on savings. According to the life cycle theory, individuals will increase their work effort in earlier years in order to accumulate assets to draw on later in life. Many analyses of the farm household off-farm labor supply have found evidence in favor of the life cycle (Huffman, 1980; Sumner, 1982). Hence, we should expect farm households' savings to behave in accordance with this theory. Following previous studies, both farm operator's age and age squared are introduced to capture life-cycle effects.[7] Other individual characteristics such as education have also been found to influence off-farm investments (Mishra and Morehart, 2001). Unfortunately, due to data limitations, we are unable to introduce these variables in this analysis.

Constrained by data availability, this investigation considers as dependent variables five groups of non-farm assets that differ in terms of returns, safety, liquidity, tax status, and transactions costs: (a) non-farm cash, (b) residence, (c) salable stock (which includes investments in stocks and bonds), (d) retirement accounts, and (e) other non-farm investments. The dependent variables are measured as the proportion of the household total portfolio, which is comprised of both farm and non-farm assets, held in the off-farm investments considered.

Econometric Framework and Empirical Implementation

Off-farm investments can be expressed as a function of the exogenous factors selected in the previous section. This yields a system of demand equations for non-farm assets that can be expressed as:

$$(1)\quad \begin{cases} I_{1t} = f(\mathbf{X}_{1t}, \beta_1) \\ I_{2t} = f(\mathbf{X}_{2t}, \beta_2) \\ \vdots \\ I^{*}_{Zt} = f(\mathbf{X}_{Zt}, \beta_Z), \end{cases}$$

where I_{zt} symbolizes the proportion of the household portfolio invested in non-farm assets; $z = 1, 2, \ldots, Z$ represents each non-farm asset; $t = 1, 2, \ldots, N$ denotes each observation; $\mathbf{X}_z$ is a vector of explanatory variables; and β_z is a vector of parameters.

Because not every farm household invests in every off-farm asset considered, a censoring issue underlies the empirical model. To address this issue, the Shonkwiler and Yen (1999) estimation procedure for censored systems of equations is used. Consider our system of censored variables:

$$(2)\quad \mathbf{I}_{zt} = f(\mathbf{X}_{zt}, \beta_z).$$

Shonkwiler and Yen (1999) propose a two-step estimation procedure. In the first step, the discrete variable indicating a non-censored observation of $\mathbf{I}_{zt}(d(\mathbf{I}_{zt} > 0))$ is evaluated through a probit model of the form:

$$(3)\quad \mathbf{d}_{zt} = g(\mathbf{Z}_{zt}, \alpha_z),$$

where $\mathbf{Z}_{zt}$ represents a vector of exogenous variables,[8] and α_z is a vector of parameters. In the second step, the normal cumulative distribution function $\Phi(\mathbf{Z}'_{zt}\alpha_z)$ and the normal probability density function $\phi(\mathbf{Z}'_{zt}\alpha_z)$ derived from the probit model are used to construct correction terms in the system of equations (2) which can be rewritten as:

$$(4)\quad \mathbf{I}_{zt} = \Phi(\mathbf{Z}'_{zt}\alpha_z)f(\mathbf{X}_{zt}, \beta_z) + \delta_z\phi(\mathbf{Z}'_{zt}\alpha_z) + \xi_{zt},$$

[7] It should be noted here that we only observe farm operator's age, and not the spouse's age.

[8] In our empirical application, we define $\mathbf{Z}_{zt} = \mathbf{X}_{zt}$.

where δ_z is a vector of coefficients and ξ_{zt} represents a vector of error terms. Assuming a linear system of censored equations, equation (4) can be expressed as:

$$(5)\quad \mathbf{I}_{zt} = \Phi(\mathbf{Z}'_{zt}\alpha_z)\mathbf{X}'_{zt}\beta_z + \delta_z\phi(\mathbf{Z}'_{zt}\alpha_z) + \xi_{zt}.$$

Following Su and Yen (2000), it should be noted that parameter estimates derived from the Shonkwiler and Yen (1999) two-step method might disguise the actual effects of the explanatory variables. This would be especially true when a common variable is used in both the first and second stages of the estimation process. This common variable would affect the dependent variable not only through the index $\mathbf{X}'_{zt}\beta_z$, but also through the normal cumulative distribution function $\Phi(\mathbf{Z}'_{zt}\alpha_z)$ and the normal probability density function $\phi(\mathbf{Z}'_{zt}\alpha_z)$ derived from the probit model. To resolve this problem, we choose to compute the marginal effects and mainly rely on them for the interpretation of our results. Marginal effects are derived using the Su and Yen (2000) formulation and evaluated at the data means:

$$(6)\quad \frac{\partial \mathbf{E}[\mathbf{I}_{zt} / \mathbf{X}_{zt}, \mathbf{Z}_{zt}]}{\partial X_{zjt}} = \Phi(\mathbf{Z}'_{zt}\alpha_z)\beta_{zj} + \mathbf{X}'_{zt}\beta_z\phi(\mathbf{Z}'_{zt}\alpha_z)\alpha_{zj} - \delta_z(\mathbf{Z}'_{zt}\alpha_z)\phi(\mathbf{Z}'_{zt}\alpha_z)\alpha_{zj},$$

where j represents the explanatory variable whose marginal effect is being computed.

As Shonkwiler and Yen (1999) note, the error term derived from the second step of the method (ξ_{zt}) is heteroskedastic. In light of this problem, we use Monte Carlo bootstrapping procedures to derive consistent variance-covariance estimates for the parameters of the model. We utilize 1,000 pseudo-samples of the same size as the actual sample, drawn with replacement, to provide a sample of parameter estimates from which the parameter covariance matrix is estimated. For each pseudo-sample of data, the Shonkwiler and Yen two-step method is applied to estimate the parameters of the model. The covariance matrices are derived from the distribution of the replicated estimates generated in the bootstrap process. The standard errors of the marginal effects are also derived using the replicated marginal effects estimates from the bootstrapped samples.

The data used in this study were obtained from the Kansas Farm Management Associations. This information is collected from individual farms on an annual basis through a cooperative record-sharing, farm management, and tax preparation arrangement. Approximately 2,300 farms provide data annually to this database. The number of variables examined per farm has increased over time, reaching 990 beginning in 1999. These variables include farm financial and production data necessary to prepare federal and state tax statements, balance sheet, cash flow, and income statements, family living data such as expenditures, non-farm income, and non-farm investments. Unlike the ARMS data, farm identifiers allow a time series to be constructed for individual farms. Data from the USDA's National Agricultural Statistics Service (NASS) were also used to measure county average yields used in the computation of farm normalized yield.

Results

This analysis focuses on the decision to hold non-farm assets by a sample of Kansas farm households observed from 1994 to 2000.[9] Summary statistics for the variables of interest are presented in Table 1. Over the period of analysis (1994–2000), off-farm investments slightly increased their relative importance in the Kansas farm households' portfolios. While in 1994, non-farm assets represented around 10% of the households' portfolios, the average percentage reached 13% in 2000. Not all non-farm assets experienced the same evolution. Retirement accounts,

[9] Although our analysis was limited to the period 1994–2000, retrospective data were used to compute the lags needed to define our variables.

Table 1. Summary Statistics for Variables of Interest (N = 6,184)

Variable Name/Description	Mean	Std. Dev.
Retirement Accounts (as a proportion of the household portfolio)	0.0207160	0.0468350
Residence (as a proportion of the household portfolio)	0.0369856	0.0646718
Liquid Assets (as a proportion of the household portfolio)	0.0480518	0.0889508
Salable Stock (as a proportion of the household portfolio)	0.0150952	0.0491899
Other Investments (as a proportion of the household portfolio)	0.0024023	0.0146008
Farm Gross Income Coefficient of Variation (%)	52.5439225	32.7889646
Lagged Household Net Worth ($10,000s) [a]	50.4318330	45.3753059
Crop Insurance Expenses over *Total Farm Operating Expenses*	0.0170831	0.0201073
Farm Herfindahl Index	0.2554754	0.2149632
Lagged Debt-to-Asset Ratio (farm debts/farm assets)	0.2826446	0.2536818
Total Farm Operated Acres (10,000s of acres)	0.1082096	0.0858091
Proportion of Rented Acres	0.6075662	0.5944129
Mean Normalized Yields over Last 10 Years (individual yields/ county yields)	1.0145090	0.1499904
Mean Ratio of Gross Value of Crops to Total Crop Production Costs over Last 10 Years	1.8105575	1.2990810
Expected Farm Government Payments ($10,000s) [a]	2.0297786	2.2916425
Lagged Household Wages ($10,000s) [a]	0.9031792	1.4019024
Lagged Household Rents and Royalties as Percentage of Non-Farm Assets (%)	0.3302080	5.7319579
Lagged Household Dividends and Interest as Percentage of Total Assets (%)	0.1980504	4.1183235
Lagged Nontaxable Payments ($10,000s) [a]	0.4261666	1.8198653
Lagged Miscellaneous Income as Percentage of Total Assets (%)	2.7445048	69.1348836
Lagged Gross Farm Income ($10,000s) [a]	13.1206925	23.0085934
Farm Operator Dependents	2.9413001	1.4802431
Operator's Age	53.8392626	11.4638588

[a] Consumer Price Index deflated to constant 1993 dollars.

salable stock, and other investments registered the highest increases, while liquid assets reduced their weight in the farm households' portfolios.[10] The results of this research contribute to a better understanding of the evolution of these figures.

A censored system of equations is estimated to assess the composition of the farm household portfolio. Parameter estimates and summary statistics for the model are presented in Table 2. Marginal effects are presented in Table 3. As explained above, we mainly rely on marginal effects for the interpretation of our results, because parameter estimates derived from the Shonkwiler and Yen two-step method might be masking the actual effects of the explanatory variables.

Results suggest that highly variable farm incomes increase revenue-generating investments, as well as secure investments. Accordingly, an increase in farm income variability increases the relevance of financial assets (retirement accounts and salable stock) in the farm household portfolio. This result is

[10] These developments undoubtedly reflect the substantial increases in the values of stocks over this seven-year period.

Table 2. Parameter Estimates and Summary Statistics

Variable	Retirement Accounts	Residence	Liquid Assets	Salable Stock	Other Investments
Intercept	-0.21404	-0.17959	-0.01548	-0.07388	0.04416
	(0.37025)	(0.28105)	(0.10736)	(0.34180)	(0.12740)
Farm Gross Income Coefficient of Variation	0.00014*	0.00113**	0.00026**	0.00010	-0.00003
(%)	(0.00011)	(0.00061)	(0.00012)	(0.00032)	(0.00012)
Lagged Household Net Worth	0.00010	-0.00043**	0.00072**	0.00076	0.00016
($10,000s)	(0.00019)	(0.00017)	(0.00022)	(0.00066)	(0.00017)
Crop Insurance Expenses over *Total Farm*	0.34358	0.03508	0.26429	-0.06293	0.30404
Operating Expenses	(0.60450)	(0.22498)	(0.23633)	(0.55777)	(0.37427)
Farm Herfindahl Index	-0.03143	-0.04625**	-0.01618	0.01700	0.01560
	(0.05443)	(0.02535)	(0.01485)	(0.02415)	(0.01931)
Lagged Debt-to-Asset Ratio	-0.05784	0.10131**	0.01111	0.00857	0.00427
(farm debts/farm assets)	(0.05948)	(0.05688)	(0.01944)	(0.02210)	(0.03641)
Total Farm Operated Acres	-0.14338**	-0.07077	-0.28810**	-0.19304**	0.16545
(10,000s of acres)	(0.05217)	(0.07754)	(0.08606)	(0.06892)	(0.14513)
Proportion of Rented Acres	0.00413	0.01041	0.01247	0.00799	0.00778
	(0.01255)	(0.01375)	(0.01125)	(0.01094)	(0.01017)
Mean Normalized Yields over Last 10 Years	0.01593	-0.07252**	0.00474	-0.00784	0.03751
(individual yields/county yields)	(0.02096)	(0.03403)	(0.02101)	(0.05745)	(0.04967)
Mean Ratio of Gross Value of Crops to Total	0.00259	-0.00988*	0.00781**	0.01192*	-0.00500**
Crop Production Costs over Last 10 years	(0.00293)	(0.00751)	(0.00259)	(0.00804)	(0.00302)
Expected Farm Government Payments	-0.00031	-0.00362	-0.00484**	-0.00103	-0.00101
($10,000s)	(0.00327)	(0.00409)	(0.00255)	(0.00556)	(0.00241)
Lagged Household Wages ($10,000s)	0.00366	0.00790*	0.02094**	0.00211	0.00240
	(0.00673)	(0.00479)	(0.00708)	(0.00650)	(0.00348)
Lagged Household Rents and Royalties	-0.01220	-0.21927**	-0.00188	-0.00483	0.00095
as Percentage of Non-Farm Assets (%)	(0.01362)	(0.08682)	(0.00574)	(0.01155)	(0.02416)
Lagged Household Dividends and Interest	-0.12818	-0.34953	-0.02565	-0.04751	-0.00053
as Percentage of Total Assets (%)	(0.10110)	(0.40137)	(0.02517)	(0.04729)	(0.08796)
Lagged Nontaxable Payments ($10,000s)	0.00119	0.00409*	0.00263	0.00152	-0.00108
	(0.00306)	(0.00271)	(0.00213)	(0.00472)	(0.00289)
Lagged Miscellaneous Income as	-0.00332	-0.02503**	-0.00070**	-0.00385	0.00508
Percentage of Total Assets (%)	(0.00359)	(0.01375)	(0.00152)	(0.00450)	(0.01781)
Lagged Gross Farm Income ($10,000s)	-0.00062	-0.00040*	-0.00175**	0.00110	0.00025
	(0.00098)	(0.00026)	(0.00065)	(0.00151)	(0.00059)
Farm Operator Dependents	-0.00202	0.02384**	0.00278	0.00300	0.00422
	(0.00531)	(0.01436)	(0.00245)	(0.00493)	(0.00399)
Operator's Age	0.00845	-0.00206	-0.00694**	-0.00008	0.00367
	(0.00759)	(0.00309)	(0.00257)	(0.00363)	(0.00375)
Operator's Age Squared	-0.00007	0.00002	0.00007**	0.00001	0.00004
	(0.00007)	(0.00003)	(0.00002)	(0.00003)	(0.00004)
Dummy 1994	-0.03029	-0.05474*	0.12329**	-0.03426	0.23769
	(0.03649)	(0.03322)	(0.05141)	(0.05060)	(347.29385)
Dummy 1995	-0.00357	0.04751**	0.03398**	-0.00582	0.12162
	(0.01491)	(0.02797)	(0.01975)	(0.01602)	(3.20296)
Dummy 1996	-0.00584	0.02602*	0.03095*	-0.01034	0.09179
	(0.01558)	(0.01856)	(0.01926)	(0.01750)	(0.18187)
Dummy 1997	-0.00394	0.01515	0.03507*	-0.00768	0.09974
	(0.01087)	(0.01867)	(0.02136)	(0.01655)	(0.18323)

(continued . . .)

Table 2. Continued

Variable	Retirement Accounts	Residence	Liquid Assets	Salable Stock	Other Investments
Dummy 1998	-0.00579	0.01078	0.04282*	-0.00203	0.08525
	(0.01363)	(0.01838)	(0.02655)	(0.02027)	(0.16185)
Dummy 1999	-0.00160	0.01734	0.02310	0.00107	0.00661
	(0.01070)	(0.01813)	(0.01836)	(0.01701)	(0.02021)
Probability Distribution Function	0.04911	0.35500**	0.26606**	0.06791	-0.07953
	(0.22063)	(0.21527)	(0.14741)	(0.27088)	(0.13306)
R^2	0.1158	0.1687	0.1161	0.0893	0.0901
Objective Value = 4.977635					

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

consistent with findings reported by Young and Barry (1987) who concluded financial assets can constitute sound investment diversification alternatives for stabilizing the financial performance of farm businesses. Moreover, highly variable farm incomes motivate secure investments such as residential property and liquid assets. Marginal effects also suggest that off-farm risk, as measured through annual dummy variables (Table 3), exerts a relevant influence on the decision to invest off the farm. Estimated coefficients show that off-farm risk increases secure investments (residence and liquid assets), while reducing the relevance of risk-bearing assets (retirement accounts, salable stocks, and other investments).

In accord with the results of Mishra and Morehart (2001), our findings suggest a higher farm household net worth provides more financial resources to invest in non-farm equities. Coefficients representing total lagged household wealth are, with the exception of the residence equation, positive and statistically significant (Table 3). Conversely, the coefficient in the residence equation is negative and statistically different from zero. Hence, a greater farm household equity increases the relative importance of non-farm assets in the portfolio with the exception of residence, whose relative participation is diminished. This last result is not surprising, indicating the wealth elasticity of the demand for residence is low relative to the demand elasticity of other non-farm assets.

Per our earlier discussion, the ratio of crop insurance expenses to total farm operating expenses is considered as one possible indicator of farm risk preferences, and as a strategy to reduce farm household income risk. A higher value of this ratio is assumed to involve, among other things, a higher degree of risk aversion. Our estimates show that a higher aversion to risk may be motivating precautionary-type investments such as retirement accounts. The crop insurance ratio does not exert a statistically significant influence on the rest of non-farm equities. Coefficients representing farm business diversification are negative, and a majority are statistically significant. This result may be reflecting the fact that, while crop insurance purchases and off-farm investments are used as complementary risk management tools, diversification of farm enterprises is employed as an alternative mechanism to reduce income risk, thereby substituting for off-farm investments.

Contrary to findings reported by previous analyses (see, e.g., Mishra and Morehart, 2001), our results do not indicate that highly leveraged farms are necessarily less prone to invest in non-farm assets. An increase in farm leverage seems to be increasing the importance of residence and other investments in the household portfolio.

Table 3. Marginal Effects and Summary Statistics

Variable	Retirement Accounts	Residence	Liquid Assets	Salable Stock	Other Investments
Farm Gross Income Coefficient of Variation (%)	0.00006** (0.00003)	0.00017** (0.00003)	0.00019** (0.00005)	0.00003* (0.00002)	-0.000004 (0.00001)
Lagged Household Net Worth ($10,000s)	0.00005** (0.00002)	-0.00019** (0.00004)	0.00031** (0.00007)	0.00023** (0.00004)	0.00002* (0.00001)
Crop Insurance Expenses over *Total Farm Operating Expenses*	0.15578** (0.03201)	-0.03089 (0.04605)	0.01968 (0.05878)	-0.01818 (0.02730)	0.00416 (0.00808)
Farm Herfindahl Index	-0.01410** (0.00297)	-0.01521** (0.00413)	-0.00645 (0.00559)	-0.00521** (0.00317)	-0.00168** (0.00097)
Lagged Debt-to-Asset Ratio (farm debts/farm assets)	-0.02496** (0.00405)	0.01076** (0.00568)	0.00481 (0.00810)	0.00264 (0.00404)	0.00302** (0.00117)
Total Farm Operated Acres (10,000s of acres)	-0.05923** (0.01069)	-0.02649* (0.01629)	-0.13981** (0.02639)	-0.05964** (0.01351)	-0.00099 (0.00264)
Proportion of Rented Acres	0.00190 (0.00367)	0.00179 (0.00589)	0.00524 (0.00703)	0.00248 (0.00242)	0.00060 (0.00061)
Mean Normalized Yields over Last 10 Years (individual yields/county yields)	0.00633* (0.00440)	-0.02315** (0.00626)	0.00323 (0.00777)	-0.00254 (0.00476)	-0.00094 (0.00135)
Mean Ratio of Gross Value of Crops to Total Crop Production Costs over Last 10 years	0.00105** (0.00064)	-0.00161 (0.00130)	0.00107 (0.00142)	0.00367** (0.00215)	-0.00031* (0.00021)
Expected Farm Government Payments ($10,000s)	-0.00005 (0.00038)	-0.00059 (0.00068)	-0.00288** (0.00096)	-0.00031 (0.00041)	-0.00002 (0.00010)
Lagged Household Wages ($10,000s)	0.00167** (0.00048)	0.00131** (0.00057)	0.00641** (0.00113)	0.00067 (0.00064)	0.00018 (0.00021)
Lagged Household Rents and Royalties as Percentage of Non-Farm Assets (%)	-0.00522** (0.00263)	-0.06168** (0.01320)	-0.00086 (0.00230)	-0.00150 (0.00192)	-0.00006 (0.00155)
Lagged Household Dividends and Interest as Percentage of Total Assets (%)	-0.05438** (0.01094)	-0.11351* (0.07810)	-0.01283 (0.01094)	-0.01475** (0.00621)	-0.00504* (0.00330)
Lagged Nontaxable Payments ($10,000s)	0.00057* (0.00041)	0.00036 (0.00032)	-0.00002 (0.00057)	0.00049 (0.00047)	0.00012* (0.00008)
Lagged Miscellaneous Income as Percentage of Total Assets (%)	-0.00139* (0.00099)	-0.00823** (0.00340)	-0.00032 (0.00064)	-0.00119* (0.00077)	-0.00088** (0.00038)
Lagged Gross Farm Income ($10,000s)	-0.00028** (0.00004)	-0.00017** (0.00005)	-0.00066** (0.00010)	-0.00034** (0.00007)	-0.00006** (0.00002)
Farm Operator Dependents	-0.00095* (0.00061)	0.00317** (0.00069)	0.00194** (0.00080)	0.00093* (0.00058)	-0.00010 (0.00013)
Operator's Age	0.00369** (0.00047)	-0.00129** (0.00055)	-0.00331** (0.00086)	-0.00002 (0.00066)	0.00002 (0.00014)
Operator's Age Squared	-0.00003** (0.00000)	0.00001** (0.00001)	0.00004** (0.00001)	0.00000 (0.00001)	0.00000 (0.00000)
Dummy 1994	-0.01318** (0.00259)	-0.01054** (0.00384)	0.03412** (0.00483)	-0.01070** (0.00267)	0.00174 (26.66928)
Dummy 1995	-0.00122 (0.00263)	0.01009** (0.00351)	0.01044** (0.00526)	-0.00180 (0.00277)	-0.00501 (0.26059)
Dummy 1996	-0.00261 (0.00287)	0.00738** (0.00353)	0.00850* (0.00540)	-0.00321 (0.00278)	-0.00686** (0.00227)
Dummy 1997	-0.00157 (0.00259)	0.00291 (0.00332)	0.00903** (0.00508)	-0.00236 (0.00278)	-0.00579** (0.00133)
Dummy 1998	-0.00213 (0.00261)	0.00091 (0.00326)	0.00846** (0.00513)	-0.00060 (0.00270)	-0.00555** (0.00115)
Dummy 1999	-0.00062 (0.00252)	0.00204 (0.00292)	0.00404 (0.00487)	0.00036 (0.00254)	-0.00111** (0.00048)

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

This may suggest a risk-balancing strategy consisting of managing high farm financial risk via off-farm investments. The negative relationship between retirement accounts and financial leverage may be due to the fact that those farmers approaching retirement are likely to have paid off their farm loans and also to have a significant proportion of their portfolio invested in retirement accounts. The debt-to-asset ratio does not exert a statistically significant influence on salable stock and liquid assets.

As argued earlier, revenue-generating non-farm assets might be used as tools to complement farm incomes and manage farm business risk. Consistent with these findings, parameters representing farm size suggest that households running larger farms, which are likely to generate higher incomes, have less proportion of their wealth invested in non-farm assets. Another explanation for the negative relationship between farm size and off-farm investments may be that larger farms are more expansion-oriented, which might bring about financial constraints and limit diversity in investments.[11] A larger farm may also discourage household members from working off the farm. Consistent with this hypothesis, several previous analyses have found a negative correlation between off-farm jobs and farm acreage (Barlett, 1991; Mishra and Goodwin, 1997). Consequently, households running larger farms may be less likely to hold those financial assets associated with off-farm employment's fringe benefits, such as tax-deferred retirement accounts. Liquid assets are also reduced with farm size. A larger farm might reduce the risk perception of the household, which in turn might lead to a decrease in the amount of liquid assets held for emergency purposes. Contrary to our initial expectations, a farmer's tenure position does not have a statistically significant influence on off-farm investment decisions.

[11] This explanation was pointed out by an anonymous referee.

Our results suggest that farms with higher productivity are less likely to have higher portions of their portfolio invested in residence. More productive farms are likely to be wealthier. This fact, together with the probable low wealth elasticity of the demand for residence, helps to explain the negative influence of farm productivity on residential holdings. Results also indicate higher farm productivity is associated with higher investments in retirement accounts. Parameter estimates representing better farm managers (mean ratio of total gross value of crops to total crop production costs over the preceding 10 years) show that better managers are more likely to invest in retirement accounts and also in financial assets such as salable stock. These managers, however, are less likely to hold other off-farm investments.

Consistent with the findings of Monke (1997) and Mishra and Morehart (2002), our analysis shows that farm government payments have the potential to reduce household investments in non-farm assets. However, only the coefficient in the liquid assets equation is statistically different from zero. Based on the finding that government payments are not found to increase off-farm assets, government payments are perhaps reducing the household reliance on non-farm assets as an alternative source of income (Carriker et al., 1993). Government payments may also be lowering the perception of risk by farm families, and thus the motivation to manage this risk through non-farm investments.

In general, our results indicate that higher return rates from non-farm assets (rents, dividends and interest, and miscellaneous income) lower the relevance of all types of non-farm assets in the portfolio. Because non-farm investments may be used primarily to complement farm returns, a satisfactory return from these assets may allow Kansas farmers to invest a higher proportion of their wealth in the farm. This would reduce the weight of non-farm assets in the household portfolio.

Coefficients representing wages and nontaxable incomes such as social security suggest retained wages and non-taxable incomes are most often invested off the farm. It should be noted that the positive influence of wages on retirement accounts may be reflecting possible fringe benefits associated with off-farm jobs held by one or several household members. Our results also show that incomes derived from the farm business are mainly reinvested in the same business. Accordingly, an increase in farm gross income trims down the relevance of all non-farm investments in the household portfolio.

Coefficients representing the number of farm operators' dependents reveal that an increase in the number of dependents heightens the relevance of residence, liquid assets, and salable stock in the household portfolio. Retirement accounts are reduced with the presence of more dependents. No statistically significant effect of dependents on other investments is found. A larger family might necessitate a larger residence, which would be congruent with the positive and statistically significant parameter in the residence equation. The positive coefficient in the liquid assets equation may indicate a higher aversion to risk by larger families, which might motivate them to hold assets for emergency purposes such as liquid assets. Larger families are also found to have a higher portion of their portfolio invested in salable stock. This result might be consistent with larger families preferring to invest their savings in revenue-generating assets which are more easily convertible to liquid assets. In this sense, salable stock might be easier to cash than retirement accounts or other investments. The negative relationship between dependents and retirement accounts may signify that young farmers are likely to have more dependents, and also to have a smaller proportion of their portfolio invested in retirement accounts relative to older farmers.

In accordance with the life cycle theory, results suggest farm operator's age is a relevant variable when attempting to explain off-farm investments. Marginal effects representing a farm operator's age are statistically significant in the equations that explain retirement accounts, residence, and liquid assets. Operator's age does not exert a statistically significant influence on salable stock and other investments. The effects of operator age on retirement accounts have an inverted "U" shape, with peak investment age around 58.[12] Hence, after the age of 58, the relative importance of retirement accounts in the portfolio should begin to decrease. When operators reach their retirement age, they begin drawing on retirement accounts that will be progressively reduced. The relationship between age and residence assumes a "U" shape. The relative importance of residence in the farm household portfolio starts to increase after the age of 66. This is consistent with retirement accounts losing their holdings and thus causing other assets to increase their relative importance. It may also reflect the building of retirement homes by some households. According to our results, liquid assets' participation in the household portfolio starts to increase after 47 years of age. This is compatible with an increase of risk aversion associated with farm operator's age and the propensity of risk-averse agents to invest in liquid assets for emergency purposes.

Concluding Remarks

This study has analyzed the decisions to invest in non-farm assets by a sample of Kansas farm households observed from 1994 to 2000. A system of censored dependent variables was estimated to investigate the factors that influence the farm household portfolio composition.

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[12] This value, which was derived from coefficient estimates in Table 2, should be interpreted with care because, as noted above and as cautioned by Su and Yen (2000), estimated coefficients might be disguising the true effects of explanatory variables. Hence, peak ages computed using estimated coefficients may not be reliable.

The central question underlying the analysis was whether farm income variability influences off-farm investment decisions. Previous analyses on the determinants of off-farm assets, which are very scarce, have failed to model the influence of this variable on the decision to hold non-farm equities.

Consistent with findings reported by Young and Barry (1987), our results confirm that higher farm income fluctuations increase the relevance of financial assets in the farm household portfolio, thus suggesting these assets are used as household income risk management tools. Investments in secure investments are also used as a response to highly variable farm incomes. Our findings also indicate Kansas farms may use an alternative way to manage risk: the diversification of farm activities. Households running highly diversified farms are found to be less likely to have off-farm investments. On the other hand, farm insurance is found to be a complementary strategy to non-farm investments when managing income risk. Off-farm risk increases secure investments such as residence and liquid assets, while reducing the importance of risk-bearing non-farm equities.

Corroborating the hypothesis that farm households' economic decisions are influenced by wealth, those non-farm assets likely to have a high wealth elasticity of demand are found to increase their weight in the portfolio when household net worth increases. In accord with the results of Monke (1997) and Mishra and Morehart (2001, 2002), our estimates suggest that farm households expecting more farm government payments may be less likely to invest off the farm. Contrary to the findings of previous studies, bigger and more productive farms, which are more likely to generate more satisfactory incomes than smaller ones, are not observed to be more prone to hold non-farm assets. Better farm managers are more likely to explore off-farm investment alternatives and invest in retirement accounts and salable stock. Moreover, our findings do not confirm previous results that more leveraged farms are less likely to invest off the farm, which is congruent with a risk-balancing strategy.

Finally, in agreement with Monke (1997), our estimates likewise indicate that household income is invested differently depending on the source of this income and also on the return rates of the different investment alternatives. Farm operator's age and farm household size are also found to influence the off-farm portfolio composition of farm households.

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Rural Small Business Finance: Evidence from the 1998 Survey of Small Business Finances

Cole R. Gustafson

Abstract

The 1998 Survey of Small Business Finances provides robust information on the financing of small businesses, including an overview of the firms' organization, financial characteristics, and credit use. Information from the survey is used in this study to compare the financial characteristics of metro and rural small businesses. While many financial characteristics are similar, rural small businesses do own more land and depreciable assets, and have lower inventory and other current assets when compared to metro firms. Rural firms have relatively similar access to technology and financial services, although utilization varies. Both metro and rural small businesses rely on a wide variety of sources for financing; however, rural small businesses have significantly more mortgages, loans from shareholders, and other types of loans, but fewer credit cards. Use of nonparametric rank order statistical methods was required because normality assumptions were violated due to asymmetric distribution of small firms.

Key words: business, finances, rural, small business, survey

During revision of North Central Regional Research Project NC221, committee members identified rural business finance as one of four high-priority areas of future research. In the past, agricultural economists have emphasized agricultural finance from farm, agribusiness, and financial institution perspectives (Barry and Robison, 2002). Economists have explored many aspects of small business finance, in general (Petersen and Rajan, 1994). Western Regional Research Project W167 was organized to explore rural finance issues from the development perspective. However, those studies did not provide in-depth analyses of rural small business financial management, as their specific focus was on development finance and the appropriate role of public support programs. Moreover, the project was not renewed.

As Drabenstott and Meeker (1997) note, "Rural capital markets have not been widely studied, but many analysts believe that rural borrowers face less competitive markets, with fewer capital suppliers, and fewer financial products and services" (p. 1). Thus, a gap in rural small business finance research appears to exist at the present.

The purpose of this study is two-fold. A primary goal is to introduce newly available data from the 1998 Survey of Small Business Finances. This periodic Federal Reserve Bank survey provides robust information on the financing of small businesses, including an overview of the firms' organization, financial characteristics, and credit use. The survey

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is the most comprehensive source of such information; no other source provides the breadth and detail of information for a nationally representative sample of small businesses (Bitler, Robb, and Wolken, 2001). An appealing feature of this survey is the delineation of rural and metro respondents.[1] Research on rural small business finance has been difficult in the past due to data limitations. Hopefully, ready access to rural small business financial data will stimulate additional investigation on the performance of rural capital markets and small business finance. The second objective of this study is to present an overview of rural small business finance and delineate comparisons with metro small business firms.

The following section of this article describes the 1998 Survey of Small Business Finances, including the survey's history, content, sampling procedure utilized, and procedures for access. An overview of rural small business finance is then presented, with comparisons made to metro small business peers. Next, using data from the 1998 Survey of Small Business Finances, individual sections provide metro–rural comparisons of financial characteristics, financing sources, use of technology and financial services, and creditworthiness. Concluding remarks are given in the final section.

The Survey of Small Business Finances

The 1998 Survey of Small Business Finances (SSBF) was conducted by the Federal Reserve Bank and collects demographic and financial information from 3,561 for-profit, nonfinancial, nonfarm small businesses (less than 500 employees) who were in business in the United States at the end of 1998. The Federal Reserve Bank (FRB) has conducted similar surveys in 1987 and 1993.[2] Specific information collected in the survey includes the following:

- Demographic information on the owners and characteristics of the firm, including SIC, MSA, and Dun & Bradstreet industry classifications;
- Inventory of the firm's deposit and savings accounts, leases, credit lines, mortgages, loans, and other financial services (for each financial service, the supplier is identified);
- Characteristics of financial service suppliers, including type (e.g., bank, individual), method of conducting business, patronage, and reasons for choosing source;
- Experience in applying for credit in the past three years;
- Experience with trade credit and equity injections;
- Firm's income and balance sheet; and
- Credit history, credit scores for both firm and owners, and Herfindahl index of concentration.

The sample for the survey was drawn from the Dun & Bradstreet Market Identifier file, which represents approximately 93% of full-time business activity. Sampling was done according to a two-stage stratified random sample. In the second stage, small businesses with more than 20 employees and minority-owned firms were oversampled to ensure their numbers would be sufficient for statistical testing. An overall response rate of 33% was

[1] Documentation of the Survey refers to the distinction as urban and rural. However, the actual screening is on Census Metropolitan Statistical Areas (MSAs) which are defined as an area with more than 50,000 inhabitants. The term "urban" is generally reserved for areas exceeding 2,500 inhabitants. Thus, because the term "metro" is more exact, it is used in this study. Less inhabited areas will be referred to as "rural," a synonym for non-metro, since it is widely recognized within the profession. I am grateful to an anonymous reviewer who provided this clarification.

[2] Working papers, methodological documentation, codebooks, and full public data sets (SAS or PDF) are available at the FRB's online website at http://www.federalreserve.gov/pubs/oss/oss3/nssbftoc.htm.

obtained. Appropriate sample weights are included in the public data set.

In their assessment of financial services used by small businesses, based on data from the 1998 SSBF, Bitler, Robb, and Wolken (2001) summarize key survey findings. Over 83% of the small businesses had less than 10 employees, and over one-half were organized as sole proprietorships. The primary activity for 43% of the firms was business or professional services. Commercial banks were the primary supplier of financial services, and 55% of the small businesses reported having loans, capital leases, or lines of credit at year end. Trade credit was used by 60% of small businesses in 1998, but interest rates were quite high; 2% a month was not uncommon. Three-fourths of the firms used computers, primarily for accessing the internet, inventory management, and bookkeeping.

Data from this survey have been used to explore lending practices of rural banks involved in mergers (Walraven, 1999) and portfolio decisions of small agribusinesses (Holmes and Park, 2000). Walraven presents a table of summary statistics comparing demographic and financial characteristics of rural and metro small businesses. He concludes that rural small businesses are older, have greater sales and assets, experienced fewer business and personal bankruptcies, and have been denied trade credit less frequently.

Rural Small Business Finance

Historically, the financial performance of credit markets and small businesses in rural areas has been a topic of active professional discourse. At the center of the debate is whether or not gaps exist in rural financial markets. Based on a study of rural capital markets, Edelman (1997) notes: (a) rapid concentration of bank assets due to merger activity may limit lending to rural businesses; (b) financial market regulations impose greater costs to smaller lenders that are characteristic of rural communities; (c) rural borrowers with unique credit needs (large amount, start-up, unfamiliar venture) face greater difficulty obtaining credit; (d) rural equity markets are unorganized and virtually nonexistent; (e) rural infrastructure is difficult to finance; and (f) financing of housing construction and ownership is more difficult in rural areas.

Barkema and Drabenstott (2000) expand on the difficulties experienced by rural areas in maintaining fundamental physical and social infrastructure including roads, utilities, and educational and health services. They highlight the impending need to invest in digital communication infrastructure. Markley and McGee (1992) conducted several detailed case studies in Arkansas, Massachusetts, Michigan, and North Carolina, and found that credit gaps exist in all regions of the country, but are especially acute in rural areas. They offer several recommendations for improving the effectiveness of development finance programs that utilize public funds.

Other studies have not found significant shortfalls in rural small business financial markets. Surveys of small businesses in Arkansas (Lamberson and Johnson, 1992) and Illinois (Gruidl, 1991) found adequate availability of debt and equity capital. Shaffer and Pulver (1985) compared capital market performance in thinly and densely populated areas of Wisconsin, and concluded they functioned relatively well for small businesses in both locations. In a later study, Shaffer and Pulver (1990) found that availability of capital is not a widespread problem for rural nonfarm businesses, and no one type or stage of business had difficulty acquiring capital.

Two comprehensive assessments of rural small business finance were undertaken in 1997. First, the U.S. Department of Agriculture (USDA) published its assessment, *Credit in Rural America*. The report concluded that rural financial markets work reasonably well, but those with low incomes, low skills, and lack of collateral have particular problems with access to credit and financial services. The report goes on to state that any public financial market failures are neither endemic to nor epidemic in rural America. Therefore, policies which provide untargeted subsidies to a broad range of rural lenders or borrowers are unlikely to be cost-effective.

A conference organized by the Federal Reserve Bank of Kansas City came to a similar conclusion (Drabenstott and Meeker, 1997). Conference participants reviewed the importance of capital to the rural economy, discussed shortcomings in those markets, and identified opportunities to improve access to capital for rural borrowers. A consensus was that rural businesses have a smaller menu of products and often pay more for access to capital—due in part to the limited and declining supply of loanable funds, bank consolidation, and undeveloped equity markets in rural areas. Expanded secondary markets were identified as a source of increased liquidity, but development has been slow. Technology and globalization will likely diminish the geographical impediments in rural financial markets.

Also in 1997, the Rural Policy Research Institute (RUPRI) convened a rural finance taskforce. In its published background white paper, the taskforce reported most rural borrowers with relatively routine credit needs are well served by existing lenders. However, borrowers with large debt capital needs, borrowers needing debt capital for start-up businesses, and borrowers needing debt capital for businesses unfamiliar to their lenders can expect difficulties in obtaining the credit they request.

Past studies evaluating the performance of rural financial markets have not provided definitive assessments primarily because they relied on selected localized information, case studies, and anecdotal observations. Comprehensive financial survey information may alleviate these past shortcomings and provide the necessary quantitative data for statistical testing and extrapolation.

Financial Characteristics of Rural Small Businesses

In general, both metro and rural small businesses in the sample were strong financially (Table 1). On average, they were profitable, liquid, and solvent. Accounts receivable and inventory comprise nearly a third of total assets. Roughly 10% of assets are held in the form of cash. Land is a minor asset for most small businesses, whereas the average small business has a large investment in equipment. Trade financing in the form of accounts payable represents nearly a fourth of small business total financing.

An appealing feature of the SSBF for purposes of this study is the ability to distinguish between metro and rural small businesses who participated in the survey. Screening firms using the MSA/non-MSA variable yielded 2,782 metro and 779 rural firms, respectively. This sorting formed the basis for the following comparative analyses in this article.

Traditional parametric statistical analyses that compare the financial characteristics of metro and rural small businesses proved futile because the data violated assumptions of normality. A common feature of small business financial data is the presence of many small firms. The majority of firms contained in the data set are of relatively small size (as measured by either sales, total assets, or number of employees). However, larger firms are also present, but fewer in number, thus creating a long right tail when modeling the distribution function. Classifying the largest firms as outliers failed to restore normality. Further, no clear demarcation for selecting outliers was evident.

Initial *t*-tests of mean financial characteristics found few significant differences between metro and rural firms,

Table 1. Comparison of Financial Characteristics of Metro and Rural Small Businesses

	Metro (n = 2,782)		Rural (n = 779)	
Item	**Sample Weighted Mean**	**Standard Deviation**	**Sample Weighted Mean**	**Standard Deviation**
Income ($):				
Total sales	1,064,665	2.74E8	664,088	8.71E7
Other income	14,764	5.88E6	10,967	7.72E6
Cost of doing business	944,250	2.56E8	561,093	8.00E7
Corporate taxes paid	18,494	5.54E6	23,730	5.46E6
Assets ($):				
Cash on hand	44,212	1.16E7	30,497	1.12E7
Accounts receivable	104,155	2.54E7	49,470	8.93E6
Inventory	79,803	3.06E7	69,438***	2.06E7
Other current assets	32,734	1.40E7	21,076**	9.66E6
Investments	14,441	6.03E6	19,529	2.13E7
Land, book value	30,799	1.31E7	39,947**	1.15E7
Depreciable assets	115,259	3.05E7	122,520**	3.17E7
Total Assets:	426,710	8.05E7	356,711	6.44E7
Liabilities ($):				
Accounts payable	66,306	1.40E7	43,465	1.60E7
Current liabilities	38,431	1.29E7	20,710	7.50E7
Total Liabilities:	261,456	5.90E7	194,199	4.50E7
Financial Organization (%):				
Sole proprietor	47	N/A	58***	N/A
Partnership	5	N/A	5	N/A
Corporation	45	N/A	33***	N/A

Note: Double and triple asterisks (*) denote statistical significance based on the Wilcoxon nonparametric linear rank test at $p < 0.05$ and $p < 0.01$, respectively.

despite high statistical power as evidenced by a large number of observations and a sizable difference in mean values. Using Shapiro-Wilk and Kolmogorov-Smirnov tests, normality of the probability distribution function was readily rejected (SAS Institute, Inc., 1999). Efforts to transform the data into a normal distribution were unsuccessful. Therefore, the nonparametric Wilcoxon rank order method was used for statistical testing. Essentially, the Wilcoxon method determines whether two samples of financial data (metro vs. rural) have arisen from the same probability distribution function. Among linear rank statistics, Wilcoxon scores are locally most powerful for identifying location shifts of the distribution (SAS Institute, Inc.). While standard deviations are reported in the tables presented here, readers are advised against using traditional *t*-tests for significance tests due to nonnormality of data.[3]

Even with the more general Wilcoxon statistical test, rural and metro small business firms were found to have few differences in financial characteristics. As shown in Table 1, rural small businesses were found to have statistically lower levels of inventory and other current assets and

[3] In addition, a reviewer questioned the magnitude of the standard deviations, especially those of binary responses that range from 1–2. The deviations are high because sample weights ($w_i > 1$) are included in the calculation (SAS Institute, Inc., 1999).

higher levels of land and depreciable assets. All other financial characteristics, including sales, cost of doing business, corporate taxes paid, and liabilities, were not statistically different between metro and rural small businesses.

With respect to financial organization, the majority of firms are organized as sole proprietorships. Surprisingly, less than 6% of small businesses were organized as partnerships. Rural firms are significantly more likely to be organized as sole proprietorships as opposed to corporations. Rural firms may have access to fewer sources of equity capital.

Sources of Financing

Metro and rural small businesses both rely on a wide variety of sources for financing (Table 2). Surprisingly, rural firms utilize each source just as frequently and to the same degree as their metro counterparts.

Just about all metro and rural firms have a checking account with an average balance of $30,000. Savings accounts are far less frequent, with only 22% of firms reporting using one. Nearly half of metro and rural firms use an owner's or business credit card for transaction financing, although statistically, rural firms use both credit cards less frequently.

Firms in poor financial condition and those with limited access to capital often have multiple (split) credit lines to bridge their financial needs. The vast majority of metro and rural firms (over 80%) in this survey patronize one creditor. The average credit limit ranges from $140,470 for rural firms to $377,316 for metro firms, but the difference is not statistically significant. The actual amount borrowed on both lines is approximately one-half. The majority of these lines do require a guaranty, but not collateral.

Rural small businesses do rely more on mortgage financing as a source of capital than metro small businesses. The average balance of mortgages supporting rural small businesses is $160,686. Rural and metro small businesses utilize vehicle loans as a source of capital to the same extent (20% of firms). The average vehicle loan balance exceeds $25,000.

Neither metro nor rural small businesses utilize equipment financing extensively. Small business equipment is often so specialized with minimal salvage value that financing is difficult to obtain. Moreover, many small business equipment manufacturers may not have the financial capacity to offer financing programs.

Over one-fourth of rural and metro small businesses received loans from stockholders. Average loan size ranged from $108,573 for metro firms to $150,313 for rural firms. Rural firms statistically utilize other types of loans to a greater extent than do metro firms. This practice may be related to rural firms' relatively greater investment in land and depreciable assets. Moreover, the majority of rural firms are organized as sole proprietorships, and transactions costs associated with personal forms of credit (e.g., home equity loans, loans from relatives, etc.) may be lower for sole proprietors.

In addition, credit options in rural areas may be more limited. Consequently, rural firms would be expected to rely more heavily on mortgages, other loans, and larger stockholder loans than shorter-term financing such as credit cards, compared to metro small businesses. When financial services are limited, small business owners often draw on personal forms of credit to finance either investment or operations. Thus, reliance on mortgage, shareholder, and other loan types by rural small businesses could be construed as an indicator of inefficient financial markets in rural areas. If rural financial markets were as efficient as metro markets, rural small businesses would be provided with, and optimally use, a full range of financial products.

Table 2. Comparison of Financing Sources for Metro and Rural Small Businesses

	METRO (n = 2,782)		RURAL (n = 779)	
Item	**Sample Weighted Mean**	**Std. Dev.**	**Sample Weighted Mean**	**Std. Dev.**
Have checking account? (1 = yes, 2 = no)	1.05	9.01	1.07	9.51
If yes, average balance	$31,400	6.98E6	$29,096	7.77E6
Have savings account? (1 = yes, 2 = no)	1.77	16.23	1.78	15.27
If yes, average balance	$63,230	1.03E7	$35,819	3.32E6
Use owner's credit card for business? (1 = yes, 2 = no)	1.53	19.46	1.57**	18.28
If yes, average balance	$1,649	4.43E5	$1,011	3.11E5
Use business credit card? (1 = yes, 2 = no)	1.65	18.59	1.69**	17.03
If yes, average balance	$2,558	3.43E5	$1,255**	1.09E5
Have credit line(s)? (1 = yes, 2 = no)	1.19	17.94	1.10	17.33
If yes: Credit limit	$377,316	8.03E7	$140,470	1.73E7
Amount owed	$144,224	2.94E7	$68,834	1.16E7
Collateral required (1 = yes, 2 = no)	1.57	17.03	1.54	15.78
Guaranty required (1 = yes, 2 = no)	1.39	16.81	1.44	15.74
Any mortgages? (1 = yes, 2 = no)	1.89	12.21	1.78***	15.25
If yes, principal owed	$279,887	1.56E7	$160,686	2.34E7
Motor vehicle loan? (1 = yes, 2 = no)	1.80	15.70	1.79	15.07
If yes, principal owed	$25,254	6.10E6	$29,310	2.40E6
Equipment loan? (1 = yes, 2 = no)	1.91	11.31	1.88	12.19
If yes, principal owed	$81,480	1.20E7	$90,253	2.37E7
Any loans from stockholders? (1 = yes, 2 = no)	1.72	15.94	1.74	16.31
If yes, principal owed	$108,573	1.32E7	$150,313	2.57E7
Any other loans? (1 = yes, 2 = no)	1.91	11.46	1.86**	11.09
If yes, principal owed	$118,499	1.94E7	$82,275	1.12E7
Herfindahl Index: 1 = 0 < Herfindahl < 1,000 2 = 1,000 ≤ Herfindahl < 1,800 3 = 1,800 < Herfindahl	2.76	23.38	2.38***	13.47

Note: Double and triple asterisks (*) denote statistical significance based on the Wilcoxon nonparametric linear rank test at $p < 0.05$ and $p < 0.01$, respectively.

Financial markets are presumed to be most efficient when a large number of financial institutions compete against one another. A common measure of financial market competition is the Herfindahl index which is created by taking the percentage market shares of each firm in the market, squaring them, and summing. In this survey, rural small businesses operated in regions of statistically lower bank concentration as compared with metro small businesses. With more competition, banks have greater incentive to supply a breadth of financial products to risky small businesses. This lower concentration of banks does apparently lead to higher frequency or amounts of credit, as rural firms appear to utilize loan products equal to, or even to a greater degree than, metro firms. As described in the next section, access to financial services is also on par with metro small businesses.

Use of Technology and Financial Services

The majority of small businesses do use computers frequently for business purposes (Table 3). The most popular uses of a computer are for accounting/ bookkeeping, email, and general administration. However, use of computers for financial services such as PC banking and online credit applications is limited.

Table 3. Comparison of Use of Technology and Financial Services by Metro and Rural Small Businesses

	Metro (n = 2,782)		Rural (n = 779)	
Item	**Sample Weighted Mean**	**Std. Dev.**	**Sample Weighted Mean**	**Std. Dev.**
Computer used for business? (1 = yes, 2 = no)	1.21	15.86	1.35***	17.67
If yes, computer used for:				
PC banking	1.84	13.39	1.89**	14.00
Email	1.24	16.34	1.28	15.57
Internet sales	1.63	18.46	1.68	16.10
Credit applications online	1.94	8.55	1.95	7.66
Inventory management	1.60	18.71	1.54***	17.20
Administration	1.17	14.29	1.23***	14.42
Accounting/bookkeeping	1.17	14.30	1.18	14.31
Use financial service(s)? (1 = yes, 2 = no)				
Transactions services	1.58	19.23	1.62	17.98
Cash management services	1.94	8.82	1.96	7.58
Credit services	1.97	6.38	1.96**	7.58
Trade services	1.86	13.33	1.91	10.64
Brokerage services	1.95	8.21	1.97	6.42
Use trade credit?	1.38	18.97	1.37	17.83
If yes:				
% of purchases	69.11	1,226	71.14	1,160
Number of trade credit suppliers	25.37	4,442	19.06	2,832
% offering cash discount	20.51	1,199	28.00**	1,338
% balance paid after due date	31.67	1,622	29.02	1,504
Length of discount period (days)	13.97	537	14.20	606
Amount of discount (%)	1.46	125	2.41	70.5

Note: Double and triple asterisks (*) denote statistical significance based on the Wilcoxon nonparametric linear rank test at $p < 0.05$ and $p < 0.01$, respectively.

Computer usage among rural small businesses significantly lags behind metro firms. Rural firms are less likely to use computers for banking, email, internet sales, and administrative functions. Interestingly, rural firms utilize computers for inventory management more frequently compared to metro firms. Greater distance may preclude vendors from performing that function for them.

Rural and metro firms are frequent users of trade credit and periodic users of transactions services. However, few small businesses use other financial services for cash management, credit, or brokerage. Rural firms use a statistically higher rate of credit services, although use is infrequent.

With respect to trade credit, metro and rural small businesses purchase over two-thirds of their supplies on trade credit. Consequently, it is not surprising they report an average number of 20 trade credit suppliers. Rural firms are offered more frequent cash discounts (28%). Almost a third of both metro and rural small businesses report repayment of trade credit after the due date. The average length of discount is 14 days, and the average discount is 2.41% for rural firms and 1.46% for metro firms, although the difference is not statistically significant.

Creditworthiness

As measured by the Dun & Bradstreet credit score, rural small businesses possess statistically higher creditworthiness

Table 4. Comparison of Creditworthiness of Metro and Rural Small Businesses

	Metro (*n* = 2,782)		Rural (*n* = 779)	
Item	**Sample Weighted Mean**	**Std. Dev.**	**Sample Weighted Mean**	**Std. Dev.**
Dun & Bradstreet credit score (1 = low risk, 5 = high risk)	3.01	38.72	2.93**	36.04
Denied trade credit (1 = yes, 2 = no)	1.94	9.12	1.96	6.93
Bankrupt in past seven years (1 = yes, 2 = no)	1.95	6.07	1.97	5.69
Delinquent on business obligations (1 = yes, 2 = no)	1.32	34.15	1.26**	27.62
Didn't apply for mortgage loan fearing denial (1 = yes, 2 = no)	1.76	16.65	1.79**	14.96

Note: Double asterisks (*) denote statistical significance based on the Wilcoxon nonparametric linear rank test at $p < 0.05$.

compared to their metro counterparts (Table 4). Metro and rural firms appear to experience similar frequency of being denied trade credit and bankruptcy. Moreover, rural small businesses are statistically more likely to be delinquent on business obligations, but less reluctant to apply for mortgage loans for fear of being denied. Over 25% of rural small businesses reported being delinquent on business obligations.

Conclusions

The 1998 Survey of Small Business Finances provides robust information on the financing of small businesses, including an overview of the firms' organization, financial characteristics, and credit use. Information from the survey is used in this study to compare the financial characteristics of metro and rural small businesses. Nonparametric rank order statistical methods were required when comparing dollar values of metro and rural small businesses because normality assumptions were violated due to the high concentration of small firms.

On average, rural and metro small businesses were strong financially and profitable. Accounts receivable and inventory comprise nearly a third of total assets. Rural small businesses tended to have lower inventory and other current assets but higher levels of depreciable assets and land compared to metro small businesses. Most small businesses utilized computers, particularly for accounting/bookkeeping, administration, and email. Primary financial services are used for transactions and trade credit. Two-thirds of purchases involve trade credit from more than 20 trade credit suppliers, on average.

Both metro and rural small businesses rely on a wide variety of sources for financing, although rural small businesses have significantly more mortgages and other types of loans, but fewer credit cards. Whereas most metro small businesses were organized as either sole proprietorships or corporations, significantly more rural firms were organized as sole proprietorships. This, and their larger investment in fixed assets, may partially explain rural small businesses' greater reliance on mortgages and other types of loans for financial capital. Although lack of bank concentration in rural areas does not appear to stymie rural small business access to either loans or financial services, in general, rural small businesses do have less access to short-term credit and must rely on mortgages and other types of loans. Rural small businesses possess higher creditworthiness than their metro counterparts, but nearly one-fourth still report being delinquent on business obligations.

Preliminary results of the survey leave a number of unanswered researchable questions. First, it is unknown whether the lack of statistical difference between metro and rural firms is in fact due to few differences between the two groups, or whether high variation and nonnormal distributions of firm size within each group limit statistical power. Second, the results reflect only one observation in time, a period of relatively strong economic prosperity. Additional study utilizing either past or future survey results could provide more robust conclusions. Finally, a number of interesting financial differences characterizing rural small businesses (emphasis on longer term assets, more personal forms of finance, greater numbers organized as sole proprietorships, and higher use of computers for inventory management and administration) could be delineated with multivariate analysis to resolve unexplained relationships raised in this preliminary review of the data set.

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Risk Management Strategy Evaluation for Corn and Soybean Producers

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Abstract

Returns to a model farm are simulated to assess the impact of marketing and insurance risk management tools as measured by mean net returns and returns at 5% value-at-risk (VaR). Results indicate that revenue insurance strategies and strategies involving a combination of price and yield protection provide substantial downside revenue protection, while mean net returns only modestly differ from the benchmark harvest sale strategy when considering all years between 1986 and 2000.

Key words: crop insurance, marketing strategy, risk management

Managing revenue risk is important to crop producers, but choosing an appropriate risk management strategy is difficult because producers must evaluate many alternatives, including crop insurance products (yield insurance and revenue insurance), cash marketing opportunities (forward contracts acting as price insurance), and futures and options hedges. Recently, crop producers have had to evaluate new insurance products with which they were unfamiliar, and the premium subsidies for crop insurance have increased. In addition, the 2002 Farm Security and Rural Investment Act (FSRIA) has changed the risk environment facing crop producers as federal countercyclical payments have become a mechanism used to mitigate crop price risk.

Given the current risk environment, it is unclear whether one or more risk management alternatives may be used in a portfolio approach to reduce downside revenue risk. Downside risk involves both the likelihood and magnitude of low revenue outcomes located in the lower tail of a crop revenue distribution. Indeed, the likelihood of low revenue outcomes may actually increase due to the complicated interactions of some risk management tools.

This study examines the impact of crop insurance products used in conjunction with marketing alternatives on gross revenue distributions. Risk management strategies are evaluated based on expected revenues and on the extent to which the strategies reduce the occurrence of low revenue events. Results build on the work of Schnitkey, Sherrick, and Irwin (2003)

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who study the impact of multiple peril crop insurance on Illinois gross revenue distributions. The current study extends their results by considering a portfolio of mechanical marketing alternatives and insurance products, while broadening the array of insurance products, and including FSRIA countercyclical payments and loan rates.

The crop yields, cash prices, and subsidized insurance premiums in this study are for a specific locale—Carroll County, Indiana. A drawback of using a specific locale is that results may not apply to areas whose crop yield/cash price correlations are different from those of Carroll County. However, the example provides insights which are beneficial to crop producers, risk management professionals, and agricultural economists. More specifically, results suggest risk management alternatives do significantly reduce downside revenue risk. The greatest benefits are associated with revenue insurance products and synthetic revenue insurance strategies, which are a combination of yield insurance and a marketing strategy. Interestingly, results also suggest that the strategies with the greatest downside risk reduction potential do not necessarily decrease mean revenues when producers pay subsidized rates of insurance.[1]

The literature on risk management is extensive. This study focuses primarily on three areas: the risk and return of pre-harvest pricing for farmers, the risk-mitigating effects of crop insurance, and the complex interaction of marketing and crop insurance tools. The tradeoff between pre-harvest pricing and harvest time cash sales has been examined in prior studies. Wisner, Blue, and Baldwin (1998) simulated returns over variable costs for model farms in Iowa and Ohio over the period 1979 to 1996. They concluded the statistically best performing strategies resulted in mean annual returns considerably above variable costs and with coefficients of variation less than harvest time cash sales. These results are contrary to the efficient market hypothesis (Fama, 1991), which the authors attribute to differences in perceived and probable yields as well as the costs associated with information acquisition and use.

Economists have also argued that superior access to information or superior analytical ability can result in consistent trading profits (Grossman and Stiglitz, 1980). Zulauf and Irwin (1998) support this conclusion in an empirical study. Contrary to the findings of Wisner, Blue, and Baldwin (1998), Zulauf and Irwin found little empirical evidence that a price bias exists in pre-harvest futures markets, but suggest producers can benefit when using hedging strategies in conjunction with storage decisions. Zulauf et al. (2001) support this conclusion in an empirical study examining cash flow risk for Ohio corn farms. Pre-harvest pricing generated greater returns than harvest time cash sales, although the differences in returns were not statistically significant[2] and varied only modestly in percentage terms. In addition, the authors found a considerable cash flow risk associated with pre-harvest strategies due to margin risk and the initial cash outflow associated with implementing a pre-harvest strategy. Because pre-harvest returns were not significantly different from zero and cash flow risk was high, Zulauf et al. concluded that pre-harvest pricing is not likely to increase returns without the ability to time the market.

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[1] Care must be taken when interpreting this study's results that are specific to Indiana. As noted by a reviewer, a "natural hedge" exists in U.S. crop production. A natural hedge tends to smooth per acre crop revenues naturally—when yields are high, prices are low, and vice versa. The more highly correlated a farm's yields are with national prices, the stronger the natural hedge. A risk management tool's effectiveness in mitigating losses will vary according to the natural hedge found in a region; therefore, the results of this study are specific to areas which share the same natural hedge effect as central Indiana.

[2] The returns were not significantly different from zero at the 90% confidence level.

Other studies have focused on the risk-mitigating effects of crop insurance. Multiple peril crop insurance has been studied by a number of researchers.[3] A recent empirical evaluation of the use of crop insurance is a study by Philpot, Larson, and Stokes (2000), who simulated returns with various revenue insurance products under alternative risk-aversion levels. They concluded revenue insurance had little effect in limiting the variability of returns, but was effective in setting a floor price.

Very few investigations have modeled both crop insurance and marketing strategies in combination. Coble, Heifner, and Zuniga (2000) examined the relationship between selected crop and revenue insurance products and optimal hedging for a risk-averse corn producer. Their results suggest the higher coverage level insurance products decrease the effectiveness of hedging. Dhuyvetter and Kastens (1999) report similar results for a Kansas farm. They found little difference in average net revenues with insurance and hedging strategies. However, with respect to downside risk, there was strong evidence linking insurance products to higher minimum revenues. Furthermore, Dhuyvetter and Kastens argue that hedging decreases the advantage of Crop Revenue Coverage insurance over other insurance products in terms of mitigating revenue losses.

The current study provides an updated analysis of risk management strategies for a typical central Indiana farm. Specifically, 73 different strategies are evaluated in terms of mean revenues per acre and downside risk protection, and are compared against a harvest cash sale/no insurance benchmark. Strategy evaluation utilizes 2001 subsidized crop insurance premiums and explicitly considers combinations of crop insurance and pre-harvest marketing. Descriptions of the conceptual framework, the simulation process used to generate revenue distributions, and related data appear in the next sections.

[3] For a review of these studies, see Knight and Coble (1997) and Coble and Barnett (1998).

Conceptual Framework

A simple conceptual framework illustrates the manner in which crop insurance products and marketing alternatives impact revenue distributions for a representative farm. Following the recent work of Schnitkey, Sherrick, and Irwin (2003), and expanding the framework to consider additional marketing alternatives and insurance products, per acre revenues are defined for an individual crop as:

$$(1)\quad R = r_c + r_{i,j} + r_m + r_g,$$

where r_c represents cash revenues for the crop as it is sold at harvest; $r_{i,j}$ represents indemnity payments received for the crop using the ith insurance product at the jth coverage level; r_m denotes the proceeds from marketing alternatives including hedging with futures, options, and forward contracting; and r_g signifies the government payments received for growing the crop.

The following subsections consider each of the revenue components in turn.

Cash Market Sales

Revenues from cash market (r_c) are simply the product of the local harvest cash price (p_1) and the realized yield per acre (y). The realized yield is a random variable, as is the harvest price. The harvest price is jointly determined by two random variables as the difference between the harvest futures price (f_1) and the harvest local basis (b_1). Revenues from a cash market sale may then be written as:

$$(2)\quad r_c = (f_1 - b_1)y.$$

The revenue from cash market sales, as determined by equation (2), provides a useful benchmark for comparing various risk management alternatives.

Crop Insurance Indemnities

A number of insurance products at various coverage levels are considered in this study, including Actual Production History (APH), Group Risk Plan (GRP), Crop Revenue Coverage (CRC), Income Protection (IP), Group Risk Income Protection (GRIP), Revenue Assurance-Base Price (RA-BP) option, and Revenue Assurance-Harvest Price (RA-HP) option. Indemnity payment rules and calculations for the jth coverage level follow.

Actual Production History (APH)

Actual production history indemnities are based on yield triggers. Indemnities are calculated as:

$$(3.1)\quad r_{aph,j} = [p_{aph} * \max(0, y_{aph} * c_{aph,j} - y)] - x_{aph,j},$$

where p_{aph} is the indemnity price as determined by the Federal Crop Insurance Corporation (FCIC), y_{aph} is the APH yield, c_{aph} is the coverage level, and $x_{aph,j}$ is the premium paid for the insurance at the jth coverage level.

Group Risk Plan (GRP)

Group Risk Plan indemnities are also triggered by sufficiently low yields, but in this case the trigger is based on the county's realized yield (y_c) relative to its expected yield (y_{ec}):

$$(3.2)\quad r_{grp,j} = \max(0, w_{grp} * (y_{ec} * c_{grp,j} - y_c) / (y_{ec} * c_{grp,j})) - x_{grp,j},$$

where w_{grp} is the protection level, $c_{grp,j}$ is the coverage level, and $x_{grp,j}$ is the premium. The expression $(y_{ec} * c_{grp,j} * y_c)/(y_{ec} * c_{grp,j})$ is the percentage yield shortfall used to establish the indemnity payment.

The indemnities of the previously discussed products are triggered by yield shortfalls; the remaining insurance products in this study use indemnity triggers based on yield and price guarantees. In all revenue insurances, the Chicago Board of Trade (CBOT) futures prices,[4] not the actual prices received by a producer, are used to trigger and calculate indemnities. Consequently, revenue insurance does not protect producers against poor marketing decisions made in a cash market or against chronically low commodity prices.

Crop Revenue Coverage (CRC)

Crop Revenue Coverage insurance provides yield protection and price protection. The revenue guarantee in this insurance has an implied option because its price protection is based on the higher of a spring futures price (f_b) or a harvest price (f_h). The implied option found in the insurance allows the producer to protect the higher value of the crop whether it occurs in the spring or the fall. Indemnity payments are calculated as:

$$(3.3)\quad r_{crc,j} = \max(0, \max(f_b, f_h) * y_{aph} * c_{crc,j} - f_h * y) - x_{crc,j}.$$

Revenue Assurance (RA)

Revenue assurance provides a revenue guarantee which is calculated by multiplying the APH yield by the coverage

[4] The price used to calculate the revenue guarantee is calculated based on the average of futures prices, but the time period over which futures prices are averaged varies by insurance product. Using an example for corn, Crop Revenue Coverage insurance averages the closing prices for the December corn futures contract in February for the spring price guarantee, and the average closing price for the December corn futures contract in November for its harvest price. In contrast, the Revenue Assurance and Income Protection programs use different time periods for averaging the futures contract prices. The conceptual discussion treats the averaging time periods as if they were the same; however, the empirical model follows the averaging rules for each insurance product.

level and the price guarantee. Two price guarantees exist with revenue assurance: the Revenue Assurance-Base Price (RA-BP) option whose price is based on a spring futures price (f_b), and the Revenue Assurance-Harvest Price (RA-HP) whose pricing rule is similar to CRC's implied option. The RA-HP indemnity is calculated as:

$$(3.4)\quad r_{ra\text{-}hp} = \max(0, \max(f_b, f_h) * y_{aph} * c_{ra\text{-}hp,j} - f_h * y) - x_{ra\text{-}hp,j}.$$

The Revenue Assurance-Base Price (RA-BP) option differs because it uses only the spring futures price (f_b) when its indemnity payments are calculated:

$$(3.5)\quad r_{ra\text{-}bp} = \max(0, f_b * y_{aph} * c_{ra\text{-}bp} - f_h * y) - x_{ra\text{-}bp,j}.$$

Income Protection (IP)

The Income Protection insurance product calculates its indemnity similar to that of the Revenue Assurance-Base Price option, as follows:

$$(3.6)\quad r_{ip} = \max(0, (f_b * y_{aph} * c_{ip}) - f_h * y) - x_{ip,j}.$$

Marketing Alternatives

In addition to crop insurance products, producers may choose to use various pre-harvest marketing alternatives as risk management tools. Risk management alternatives examined in this study include hedging with futures, hedging with options, and forward contracts. In the case of forward contracts, marketing revenues are calculated as:

$$(4.1)\quad r_m = p_c * y_c,$$

where p_c is the quoted forward contract price in the spring, and y_c is the contract amount. Forward contract prices are assumed to be the spring quoted price for the harvest's nearby futures contract (e.g., December for corn futures) minus the historical basis. When the contracted quantity is greater than the realized yield ($y_c > y$), it is assumed the producer must purchase the shortfall at the harvest cash market price (p_1).

Producers might choose to manage their price risk using a short hedge in the futures market. The proceeds from this marketing strategy are written as:

$$(4.2)\quad r_m = (f_0 - f_1) * h - x_h.$$

Proceeds from short hedges in the futures market are the difference between the spring quoted price (f_0) and the harvest futures price (f_1) times the hedged quantity (h) minus the hedging costs (x_h). Hedging costs include brokerage charges and interest expense on margin accounts.

A final marketing alternative considered in the study is short hedges using put options on futures contracts. The proceeds from these option hedges are specified as:

$$(4.3)\quad r_m = \max(0, (f_g - f_h) * h) - x_{opt}.$$

Options hedges are exercised only if the futures price at harvest (f_h) is less than the strike price (f_s). Proceeds are the difference between the two multiplied by the hedging quantity minus the option premium, brokerage charges, and interest cost of the options hedge (x_{opt}).

Government Payments

Commodity producers receive financial assistance from the federal government as part of the Farm Security and Rural Investment Act (FSRIA) of 2002. Of the assistance outlined in the FSRIA,[5] loan deficiency payments and countercyclical payments are modeled in this study.

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[5] Producers also receive direct payments for producing program crops. These payments are fixed and unrelated to either the producer's actual production of the commodity or existing market prices. Consequently, direct payments are fixed and omitted from the analysis.

Total revenue received from the commodity programs (r_g) is the sum of the revenue from loan deficiency payments (r_{ldp}) and the countercyclical payment (r_{ccp}), where

(5.1) $r_{ldp} = \max(0, (p_{ldp} - p_l) * y)$,

and p_{ldp} is the loan rate and p_l is the harvest price.[6] Note that the loan deficiency payment is made on actual production, whereby an individual producer who suffers a yield shortfall is not protected from revenue losses unless the local harvest prices (p_l) increase substantially.

Countercyclical payments are based on the difference between a congressionally mandated target price (p_{tp}) and the national average price for the marketing year (p_s). If p_s is greater than p_{tp} minus the direct payment rate (dp), no countercyclical payment is made. However, if $p_s < (p_{tp} - dp)$, the countercyclical payment is denoted by:

(5.2) $r_{ccp} = ((p_{tp} - dp) - \max(p_s, p_{ldp})) * y_p$,

where y_p is the payment yield determined historically.

Empirical Procedure

Using the formulae found in equations (1)–(5), an empirical bootstrapping procedure generates revenue distributions for 73 different risk management strategies and for the benchmark, a cash sale at harvest. The study's unit of analysis is a 1,500-acre corn and soybean model farm located in Carroll County, Indiana. Revenue is defined according to equation (1), and is created via combinations of the alternatives found in equations (2)–(5). Fixed costs and variable production costs are assumed to be constant across all risk management scenarios. A listing of the marketing and crop insurance strategies evaluated in this study (either singly or in combination) is found in Table 1.

The model utilizes a historical bootstrapping procedure to simulate revenues.[7] A model iteration begins when a historical year is chosen at random from the period 1986 through 2001.[8] Once a year is selected, that year's actual cash market prices and futures contract prices, as well as that year's county corn and soybean yields, are drawn from the data set. The county yields are the base from which random farm-level yields are generated using the procedure described in a subsequent section. Farm-level yields and the selected year's prices are used to compute the farm's revenue for the benchmark strategy and under the 73 different risk management strategies. The model is iterated 1,000 times, and the resulting 1,000 revenue outcomes are collected, creating a revenue distribution for the benchmark strategy and each of the 73 risk management strategies.

Several criteria are available for evaluating and ranking risk management alternatives, including expected values, value-at-risk (VaR), Sharpe ratio, and stochastic dominance (Gloy and Baker, 2001). In addition, researchers have used willingness to pay (Wang et al., 1998), certainty equivalents (Hart and Babcock, 2001), and semivariance (Turvey and Nayak, 2003) when examining risk environments and risk management decisions. The current study evaluates gross revenue distributions based on expected values and 5% value-at-risk.

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[6] LDP payments are actually based on the posted county price, which closely follows the local harvest price.

[7] A historical bootstrap simulation procedure has limitations. The price/yield generation process which created the historical data is not stable over time. Thus, the generated revenue distributions are not created by an i.i.d. process, and it cannot be asserted that future price-yield combinations will follow historical patterns. However, the procedure does allow for a discussion of the relative merits and drawbacks of risk management alternatives, especially when the frame of reference is an individual farm.

[8] Because of data limitations for option premiums, price information is limited to the period 1986–2001.

Table 1. Risk Management Strategies Evaluated over the 1986–2001 Period

Risk Management Strategy	Description
INSURANCE PRODUCTS:	**Insurance**
Crop Insurance:	**Coverage Level**
▪ Actual Production History (APH) (100% price election)	65%, 75%, 85%
▪ Group Risk Plan (GRP) (100% maximum protection)	70%, 80%, 90%
▪ Group Risk Plan (GRP) (70% maximum protection)	70%, 80%, 90%
▪ Catastrophic Risk Protection (CAT)	50%
Revenue Insurance:	
▪ Crop Revenue Coverage (CRC)	65%, 75%, 85%
▪ Group Risk Income Protection (GRIP) (100% maximum protection)	70%, 80%, 90%
▪ Group Risk Income Protection (GRIP) (70% maximum protection)	70%, 80%, 90%
▪ Income Protection (IP)	65%, 75%, 85%
▪ Revenue Assurance-Base Price Option (RA-BP)	65%, 75%, 85%
▪ Revenue Assurance-Harvest Price Option (RA-HP)	65%, 75%, 85%
PRICING PRODUCTS:	**Percent of**
Market Hedging Strategies:	**Expected Production**
▪ Short Futures Hedge (March 15)	33%, 66%, 100%
▪ Short Futures Hedge (June 1)	33%, 66%, 100%
▪ Long Put Options Hedge (March 15)	33%, 66%, 100%
▪ Forward Contract (March 15)	33%, 66%, 100%
▪ Forward Contract (June 1)	33%, 66%, 100%
▪ Harvest Time Cash Sales (benchmark strategy)	N/A
	Insurance
Combination Strategies:	**Coverage Level**
▪ APH (100% price election) Corn Only & 66% Expected Production Short Futures Hedge Corn & Soybeans (March 15)	65%, 75%, 85%
▪ GRP (70% max protection) & 66% Expected Production Short Futures Hedge (March 15)	70%, 80%, 90%
▪ GRP (100% max protection) & 66% Expected Production Short Futures Hedge (June 1)	70%, 80%, 90%
▪ APH (100% price election) & 66% Expected Production Forward Contract (March 15)	65%, 75%, 85%
▪ APH (100% price election) & 66% Expected Production Forward Contract (June 1)	65%, 75%, 85%
▪ GRP (100% max protection) & 66% Expected Production Forward Contract (March 15)	70%, 80%, 90%
▪ GRP (100% max protection) Corn Only & CRC Soybeans Only	70%, 80%, 90% 65%, 75%, 85%
▪ APH (100% price election) & 66% Expected Production Put Option Hedge (March 15)	65%, 75%, 85%
▪ GRP (70% max protection) & 66% Expected Production Put Option Hedge (March 15)	70%, 80%, 90%

Value-at-risk (VaR) provides an intuitive measure of downside risk because it is concerned with the revenue outcomes in the lower tail of the gross revenue distribution. As an example, a strategy whose 5% VaR is $210 per acre indicates a 1-in-20 chance that simulated revenues will fall below $210 per acre. For a given probability level, a larger VaR is favored by all decision makers who prefer more wealth to less (Gloy and Baker, 2001). The VaR measure is useful for describing risk alternatives because it focuses on downside risk, and this risk is a primary concern for those who purchase or adopt risk management strategies. Previous studies using VaR to quantify downside risk include Manfredo and Leuthold (2001) and Schnitkey, Sherrick, and Irwin (2003).

As noted above, farm-level corn yields are created with county yields as a base. County-level yields for Carroll County, Indiana, were gathered from the U.S. Department of Agriculture/National Agricultural Statistics Service (USDA/NASS) statistical database. To calculate the 10-year moving average for APH, yield information from 1975 through 2001 was collected. County-level corn and soybean yields were detrended using 2001 as the reference year.

The farm-level corn yields are gathered from the APH database of the Risk Management Agency for the years 1985 through 1994, yielding 840 total observations.[9] Farm-level yields for corn are calculated from county detrended yield information using a regression equation plus a stochastic error. The regression equation is found in equation (6), in which the detrended county yield acts as an independent variable and the farm-level yield is the regressor:

(6) $$\textit{Farm Corn Yield}_{t,i} = -23.41 + 1.14 * (\textit{County Corn Yield}_t) + e_{i,1},$$
$$(5.27) \quad (0.04)$$

where t is the year and i is an index of farm observations.

An empirical distribution of regression errors based on equation (6) is used to compute the farm-level corn yield in each model iteration. Unfortunately, farm-level soybean yields are not included in the FCIC APH yield database, and farm-level soybean yields are generated from Carroll County soybean yields with a normally distributed error term.[10] Percentage errors were used in the analysis so that the relative risk is constant between historical years. The proportion of the difference between the variability of county and farm detrended yields is assumed to be the same for both corn and soybean yields.[11] Equation (7) describes farm-level soybean yields:

(7) $$\textit{Farm Soybean Yield}_{t,i} = \textit{County Soybean Yield}_t + e_{i,2}.$$

Corn and soybean yields tend to be highly correlated because they share similar production environments. The correlation of corn and soybean county yields was 0.66, which is highly significant for the 1975–2001 period. This correlation is incorporated into the simulation model when simulating farm-level corn and soybean yields.

Corn and soybean cash prices for the 1986–2001 period were gathered from a central Indiana terminal elevator. It was assumed cash marketing occurred on a single day of the year. For corn, the harvest time cash price was the Wednesday

[9] As noted by a reviewer, yields from the APH database may not be representative of the typical farm, as the farms in the database tend to have lower yields and higher yield variability.

[10] The error term is assumed to be distributed normally with a mean percentage error of 0.001265 and a standard deviation of 0.21593.

[11] For example, if the coefficients of variations of detrended county and farm corn yields are 12% and 18%, respectively, and the coefficient of detrended county soybean level is 10%, then the coefficient of variation of farm-level soybean yields would be 15%.

cash price closest to November 1 of each year, while the harvest time cash price for soybeans was the Wednesday cash price closest to October 1 of each year. Further, all production was assumed to be sold at this harvest time price for the respective randomly chosen, historical year.

Chicago Board of Trade (CBOT) December corn and November soybean futures prices were collected at three selected dates for each year over the 1986–2001 time period. The dates include an early spring futures contract price (March 15), a late spring futures contract price (June 1), and a harvest time futures price (November 1) for corn and (October 1) for soybeans.[12] The nearest at-the-money strike prices for closest Wednesdays to March 15, June 1, and October or November 1 were used to determine option strike price levels and option premiums. The springtime forward price for harvest delivery of both corn and soybeans was assumed to be $0.20 under the December corn and November soybean CBOT future contracts at the time of the quote.

Applicable commission and brokerage service fees were assumed to reflect current conditions. A 7.5% margin requirement was assumed for a producer's hedging account. At most brokerage services, margin accounts do not collect interest; therefore, the producer must sacrifice interest for the period of time the hedge is active. The annual interest rate charged for margin accounts was assumed to be 7% in this model.

Several assumptions were needed to evaluate the effect of risk management alternatives on revenues. For crop and revenue insurance products, only basic units are defined for all insurance products. Although some insurance products are not available in basic units (i.e., Income Protection insurance), it is computationally difficult to model more than one unit structure or to compare the results of one unit structure against another. The unit structure for this study is comprised of one 750-acre unit of corn and one 750-acre unit of soybeans, although results are presented on the basis of an acre of the corn/soybean rotation. Insurance premiums were computed using FCIC procedures.[13]

FCIC indemnity prices from 1986 through 2001 were used to determine the price for insurance. Maximum protection levels for Group Risk Plan (GRP) insurance were based on these FCIC prices, while maximum protection levels for Group Risk Income Protection (GRIP) insurance were based on applicable revenue insurance base prices. Accordingly, maximum protection levels for GRP and GRIP change with the respective year drawn with the year generator. In addition, indemnity payments for GRP and GRIP are not made until the National Agricultural Statistics Service releases county yield estimates, often occurring in March following the crop harvest. Because this model assumes all revenue and costs are associated with the current crop production year, GRP and GRIP indemnities are discounted four months at an assumed 7% interest rate. The discounting process reflects the cash value of indemnities in December.

[12] If the date of a specific futures price did not occur on a Wednesday, the closest Wednesday settlement price was used for all futures prices and options premiums.

[13] Prior to 2001, insurance premiums for Actual Production History (APH), Crop Revenue Coverage (CRC), and Revenue Assurance (RA) were based on actuarial tables created by the Risk Management Agency (RMA). In 2001 and beyond, the continuous rating model (CRM) will be utilized to determine premium rates for these insurances. With 2001 being the initial year of implementation for the continuous rating model, two assumptions were made. Because the CRM program did not exist in 2000, the prior year's yield ratio cannot be determined. Furthermore, the yield span base rate cannot be determined because these yield spans and their associated base rates are not determined in the initial year of the CRM. Therefore, the preliminary base premium rate, determined solely from step two of the CRM procedure, is used as the continuous rating base rate for this study. Although these assumptions may appear to be very restrictive, the base rates generated in the model were identical to 2001 quotes provided by the RMA and other private vendors.

When hedging with future and option contracts, a producer does not know the quantity that will be produced in the upcoming fall, but must decide on March 15th how many contracts to enter when hedging 33% of expected production. Thus, for modeling purposes, the APH yield was assumed to be the expected yield when hedging a certain percentage of production. With this assumption, a producer may be over- or under-hedged relative to actual production, and this disparity is reflected in revenue calculations. In a similar fashion, forward contract quantities are based on a percentage of APH yields. If grain is under-contracted, the remainder is sold on the cash market; if grain is over-contracted, then additional bushels are purchased at harvest prices to fulfill the contract.

Government payments contribute to net farm revenues. Loan deficiency payments (LDPs) were calculated with loan rates set at the 2002–2003 values: $2.03 per bushel for corn and $5.12 per bushel for soybeans. Countercyclical payments (CCPs) are also included using the target price and loan rate for the 2002–2003 time period. In order to simplify the analysis, base acres and payment yields were updated to the 1998–2001 average as allowed in the 2002 FSRIA, and CCP payments are made on September of the year following harvest of the crop. An interest cost of 7% was used to discount the CCP payments back to harvest.

Results

Using the previously described simulation process, revenue distributions are generated for the benchmark strategy and each of 73 risk management strategies. Because downside risk protection is of primary importance, strategies are first evaluated according to value-at-risk (VaR). Later analysis ranks strategies by mean net returns.

The top 10 strategies (those with the highest 5% VaR values) are shown in Figure 1, along with the benchmark strategy of cash sale at harvest with no insurance. The benchmark strategy (cash sale at harvest) is presented at the top of Figure 1, and has a 5% VaR of $187.58 per acre. This indicates there is a 5% chance that the benchmark strategy will yield $187.58 per acre or less at harvest.

The strategy listed immediately below the benchmark, purchase of Income Protection (IP) insurance at a 75% coverage level, is preferred to the benchmark strategy in terms of downside protection because of its higher 5% VaR ($207.47). The strategy with the highest 5% VaR level (located at the bottom of Figure 1) is Crop Revenue Coverage (CRC) at the 85% coverage level. This strategy's 5% VaR is $225.24 per acre. For those producers who are concerned about downside revenue risk, this strategy provides the greatest protection against downside risk, even after accounting for relatively high premiums.

In order to determine statistical significance, a 95% confidence interval can be constructed for the 5% VaR values of the 10 highest ranking strategies graphed in Figure 1 (Winston, 2000). The 5% VaR confidence intervals of these 10 strategies do not overlap with the 5% VaR confidence interval of the benchmark strategy, indicating the downside protection of each of these 10 risk management strategies is statistically higher than the benchmark.[14]

Several generalizations can be drawn from the strategies listed in Figure 1. Nine of the top 10 strategies have some form of price insurance in addition to yield

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[14] Although the confidence intervals of the benchmark strategy and the 10 selected strategies of Figure 1 do not overlap, some of the remaining strategies do have confidence intervals which overlap with the benchmark. As correctly noted by a reviewer, it is entirely possible that confidence intervals, based upon each random variable's variance, overlap another, and yet, when the covariance between the random variables is considered, they would be statistically different from one another. However, since we focus only on the top 10 strategies, where overlapping confidence intervals are not a problem, additional significance testing was not conducted.

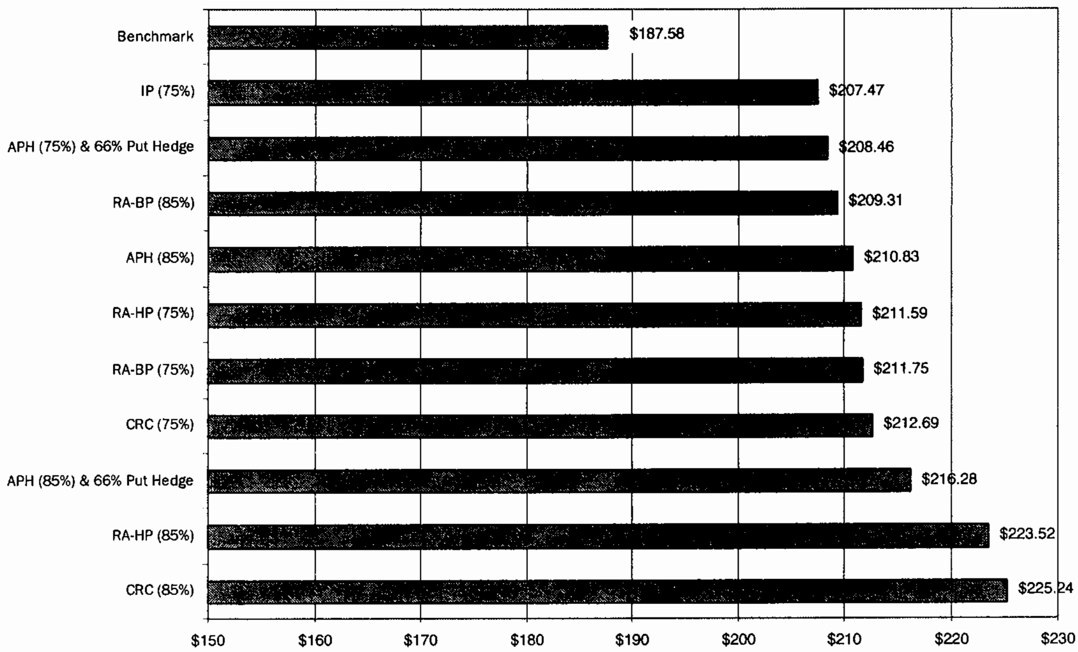

Figure 1. 5% VaR Levels for the 10 Highest Ranking Strategies and the Benchmark ($ per acre)

insurance. Revenue insurances (RA-BP), RA-HP, IP, and CRC) have indemnity triggers based on the difference between spring and harvest prices, as do two strategies which combine yield insurance with a put options hedge [i.e., APH (85%) & 66% Put Hedge (March 15th)]. The combination strategies in Figure 1 act as a synthetic revenue insurance—i.e., the producer obtains a return or an "indemnity" from the risk management tool when either yields are low or prices decline sufficiently from spring to harvest. In addition, the CRC and RA-HP strategies in Figure 1 adjust guarantee levels to reflect increases in the value of a growing crop if prices are higher at harvest. Likewise, a put option hedge in combination with APH will not preclude the producer from taking advantage of higher harvest prices. Six strategies in Figure 1—those involving CRC, RA-HP, and the APH/put option hedge combination—share the characteristic of increasing guarantee levels and higher potential indemnities. Adjustment of indemnities gives these six strategies an advantage in terms of downside risk protection.

Group risk insurance strategies do not appear in Figure 1. Rather, the strategies all trigger indemnities based on individual yield performance. The result is intuitive; individual insurances provide more downside risk protection because poor farm yields will trigger indemnity payments. This is not the case with group plans in which county losses trigger indemnity payments. It is possible an individual farm may have a loss even when the county does not; therefore, group risk insurances will tend to have lower 5% VaR values than individual coverage-based insurances such as APH and CRC.

Also absent from Figure 1 are stand-alone marketing strategies (e.g., hedging 66% of expected production with futures). Their 5% VaR values are not among the top 10.

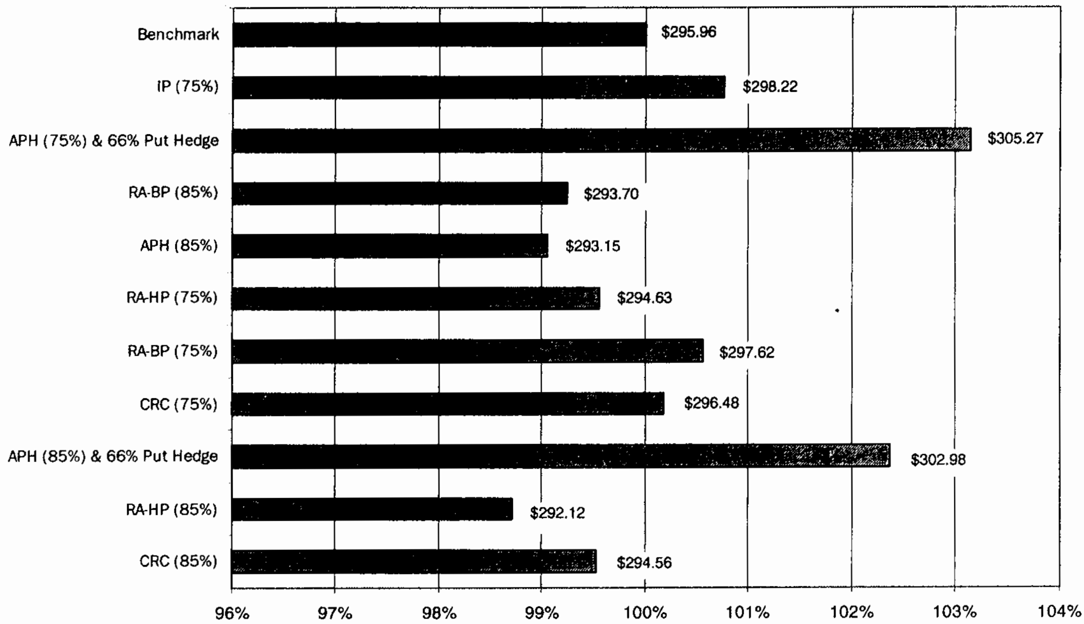

Figure 2. Mean Revenues of the Top 5% VaR Strategies as a Percentage of the Benchmark Strategy

The performance of stand-alone marketing strategies with respect to the 5% VaR levels suggests the model farm was more susceptible to yield risk than price risk.

A tradeoff between risk mitigation and mean revenues is expected. If a particular risk management strategy reduces the chance of loss, it may also preclude the opportunity to take advantage of exceptionally high returns. Furthermore, risk management strategies often have a direct cost in terms of a premium for insurance or premiums for marketing strategies (i.e., option hedges). Thus, some strategies that provide good downside protection may have relatively low mean revenues, but, as shown in Figure 2, this general belief is not confirmed for every strategy in the current study. Figure 2 presents the mean revenues for the strategies in Figure 1 as a percentage of the cash sale at harvest benchmark. The benchmark strategy, at the top of Figure 2, has a mean revenue of $295.96 per acre.

As shown in Figure 2, a limited risk/return tradeoff exists for the strategies with the highest 5% VaR levels. As an example, consider the CRC (85%) strategy located at the bottom of Figure 2. This strategy, which had the highest 5% VaR level, has a mean revenue level of $294.56 per acre, nearly equal to that of the benchmark strategy. Furthermore, none of the top 10 strategies from Figure 1 fall lower than 99% of the benchmark strategy's mean revenue, with the exception of the RA-HP (85%) alternative which is nearly 99% of the benchmark.

More importantly, half of the strategies in Figure 2 actually have mean revenues higher than the benchmark strategy. Foremost among these are the synthetic revenue insurances, APH with a put option hedge [specifically, the APH (75%) & 66% Put Hedge, and APH (85%) & 66% Put Hedge] with respective mean revenues of $305.27 and $302.98 per acre. APH insurance has relatively low premiums, and put option hedges will guarantee a minimum price and allow the decision maker to take advantage of higher prices. Perhaps this explains the high VaR values and slightly higher mean revenues of these strategies when compared to the benchmark.

The 10 strategies with the highest mean revenues are illustrated in Figure 3. Mean revenues are shown as a percentage of the cash sale at harvest benchmark with dark bars. The crosshatched bars represent the 5% VaR levels as a percentage of the benchmark's 5% VaR. Each of the top 10 strategies outperforms the benchmark in terms of mean revenues. The 100% futures hedge (March 15th), located at the bottom of Figure 3, has a mean return 5% higher than the benchmark strategy.

Several generalizations can be made regarding the strategies in Figure 3. First, all 10 of the strategies with the highest revenues contain at least one marketing component; indeed, half of the strategies are stand-alone marketing strategies. The only crop insurance alternative included among the strategies is GRP, which is a relatively inexpensive form of yield insurance. However, this yield insurance only appears in combination with marketing tools.

Second, in terms of mean revenues, a marketing strategy that establishes a price for a larger portion of the expected production is more advantageous than a similar strategy that establishes a price for a smaller portion of expected production. The highest mean returns involve pricing 100% of production, indicating the gains from pricing a larger portion of expected production outweigh the costs inherent in iterations which involve a yield shortfall or those iterations where a producer is forced to take a speculative position in the futures or options market.

Third, pricing earlier in the season, rather than later, appears beneficial. The March 15th mean revenues are consistently larger than June 1st mean revenues for a given quantity marketed. For example, the 100% futures hedge initiated on March 15th (located at the bottom of Figure 3) had a greater mean revenue than the 100% futures hedge initiated on June 1st (located in the middle of Figure 1). In part, pricing early takes advantage of early season high prices for corn and soybeans. Better pricing opportunities often existed on March 15th relative to June 1st in the crop years 1986–2001, which is why these strategies tend to perform well. The presence of consistent seasonal pricing opportunities may exist because of risk premiums bid into commodity futures markets (Miffre, 2002).

Fourth, futures hedges perform better than options hedges in terms of mean revenues. In part, this may be due to the relatively low direct costs that futures hedges have relative to the premiums for put options. The low direct costs must outweigh the higher opportunity cost associated with futures hedges when compared to options hedges.[15]

Fifth, an interesting dichotomy exists among the strategies with respect to downside risk. The strategies either perform poorly, or they outperform the benchmark. Strategies that outperform the benchmark include the combinations of GRP insurance and a marketing tool. In contrast, the stand-alone marketing strategies (i.e., the 100% Forward Contract strategy) have as little as 82% of the benchmark strategy's 5% VaR. Consequently, a tradeoff does exist between risk and return for marketing strategies, and to a lesser extent for the combinations of insurance and marketing strategies. This suggests yield risk is more of a contributor to downside revenue risk than price risk, especially in the presence of loan deficiency payments (LDPs).

[15] As mentioned previously, futures hedges preclude producers from taking advantage of price increases, but option hedges allow for this upside potential. Thus, use of a futures hedge entails an opportunity cost not present with options hedges.

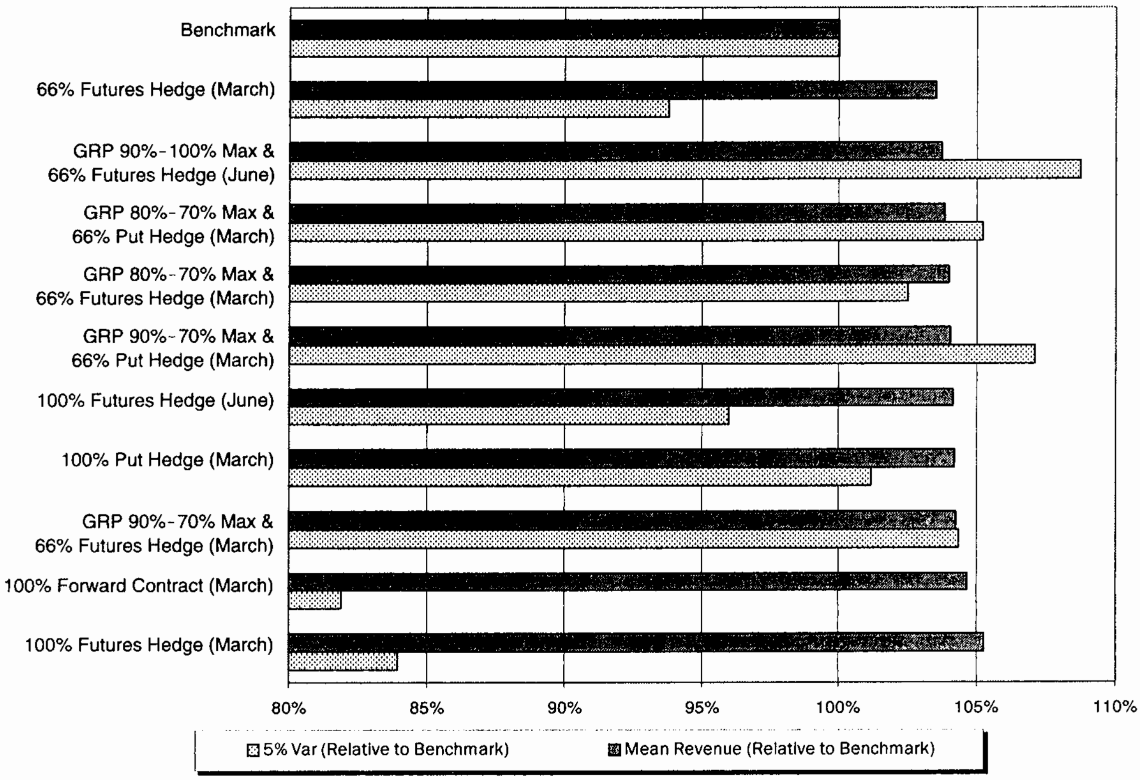

Figure 3. Mean Revenues of the 10 Highest Ranking Strategies with Respective 5% VaR Levels

The 5% VaR and mean revenue analysis is useful for producers who must balance risks and returns when choosing among risk management strategies. For example, stand-alone marketing strategies in Figure 3 had a high mean revenue when compared to the benchmark, but suffered from relatively low 5% VaR values. Crop insurance strategies in Figures 1 and 2 outperformed the benchmark in terms of 5% VaR, and were nearly equivalent to the benchmark's mean revenue. Combination strategies found in Figures 1, 2, and 3 often exceeded the benchmark in terms of 5% VaR and mean revenue.[16]

Concluding Remarks

Revenues were simulated for a corn and soybean model farm located in Carroll County, Indiana. Seventy-three risk management strategies, including pre-harvest marketing positions, crop insurance, revenue insurance, as well as combinations of pre-harvest marketing and crop insurance, were analyzed in terms of 5% VaR and mean revenues for crop years from 1986–2001.

A simulation model incorporating the recent increase in premium subsidy rates

[16] Using efficiency criteria adds understanding to producer choices, so a stochastic dominance analysis was performed using the generated revenue distributions. In general, as risk aversion increases, marketing strategies are coupled with yield insurance, and group insurance gives way to individual yield or revenue insurance. These rankings appear consistent with the participation rates of Corn Belt producers in crop insurance and their utilization of marketing tools (Patrick and Collins, 2000). Full details of the mean return, VaR, and stochastic dominance analysis are available from the authors upon request.

and government programs provides interesting results. Most notably, combination strategies involving a form of crop insurance along with a price marketing strategy tend to provide good downside protection in terms of 5% VaR, while allowing for higher mean returns when compared to the benchmark, a cash sale at harvest with no insurance.

Risk management alternatives that increase the revenue guarantee if prices increase from spring to harvest (CRC, RA-HP, APH-Put Option) were among the highest ranking strategies at the 5% VaR level. These strategies provided some of the best downside protection relative to the other risk management alternatives specified. Furthermore, strategies that provide the greatest 5% VaR levels have mean revenues nearly equivalent to the benchmark. In contrast to these revenue-protecting alternatives, strategies solely providing price protection offer some of the poorest relative downside protection as measured by 5% VaR. In this specific example, it appears downside risk protection can be achieved without sacrificing revenues, especially under the premium subsidy.

Marketing strategies that hedge price risk for a larger share of the expected harvest generated greater mean revenues than similar strategies that hedged a smaller share. Furthermore, stand-alone marketing strategies, particularly strategies involving pricing early in the crop year (March 15 vs. June 1), were among the top strategies in terms of mean revenues. This result is consistent with past research. Importantly, stand-alone marketing strategies provide the poorest downside protection.

In summary, strategies do exist that provide good downside risk reduction without sacrificing mean revenues. Specifically, those strategies involving a combination of crop insurance and a price marketing strategy can provide an effective mechanism for protecting downside risk, while maintaining the level of mean revenues. In contrast, strategies providing only price protection offer poorer downside protection with only modest improvements in mean revenues.

Numerical results are specific to Carroll County, Indiana, and care should be taken when attempting to generalize results to other areas. In particular, the natural hedge, or price/yield correlation, in Carroll County may be distinctly different in other areas, especially those outside the Corn Belt. Further, subsidized crop insurance premiums differ by county, so an insurance product sold in Carroll County may be relatively more/less expensive in other areas.

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Deciding When to Replace an Open Beef Cow

Gregory A. Ibendahl, John D. Anderson, and Leslie H. Anderson

Abstract

A cow that fails to conceive must either be kept for a year without revenue or replaced by a bred heifer. This choice is a unique case of comparing investments with different economic lives because the potential replacement asset is just a newer version of the old asset. In this study, a net present value model is developed that eliminates the problem of finding a common timeframe. Results indicate there are often times producers should keep the open cow. Whenever feed costs are low, the price differential between cull cows and replacement heifers is high, or the calf crop value is low, retaining open cows becomes more desirable.

Key words: bred heifer, net present value, open cow, perpetual annuity, replacement decision, unequal asset life

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Beef producers have traditionally been faced with the decision to either retain or replace a cow that fails to conceive during the breeding season (termed an "open cow").[1] If the producer retains the open cow, then the producer incurs all expenses related to upkeep of the cow for a year without the cow generating income. A small percentage of cows fail to conceive during the breeding season due to a permanent biological alteration in their ability to conceive. Thus, open cows are potentially less likely to conceive in the subsequent breeding season than similarly aged cows.

However, a far greater percentage of cows fail to conceive due to improper management[2] (e.g., inadequate nutrition resulting in reduced fertility). These open cows will enter the subsequent breeding season with an excellent opportunity to conceive early. Cows that conceive early are more productive because they wean older, and therefore heavier calves. Also, cows that conceive early in one breeding season are more likely to conceive early in subsequent seasons because they will have a longer post-partum recovery period before the next breeding season begins. Therefore, a majority of open cows have the potential to become productive cows.

[1] An open cow is one that has been found not to be pregnant. In spring-calving beef herds, pregnancy checking is typically done at or shortly after the previous year's calves are weaned (i.e., generally in October or November), by which time bred cows should be in the second trimester of pregnancy.

[2] Stevenson (2000) reports that the three most important factors influencing whether or not a cow is capable of rebreeding are body condition (influenced primarily by nutritional management), age, and days post-partum.

Producers who replace the open cow with a bred heifer do not invest annual feed and other maintenance costs without a calf being produced. They essentially replace a shorter life asset with a similar, longer life asset. There are more differences between the assets than just life, however. Cows do not reach their maximum productivity until four years of age. Consequently, it will be three years before a replacement heifer will wean as heavy a calf as a fully mature cow.[3] More importantly, until they reach maturity, replacement heifers run a considerably higher risk than mature cows of not rebreeding, especially if the heifers are not properly managed. This high probability of either failing to rebreed or conceiving late in the breeding season could dramatically affect the productivity of replacement females, and therefore the decision to either retain or replace.

The objective of this study is to determine under what circumstances an open beef cow should be replaced with a bred heifer. Replacement decisions are examined in a net present value framework which compares the costs and returns from keeping the open cow until her normal replacement age against the costs and returns from replacing the cow with a bred heifer. The model employed here solves a unique set of asset replacement decisions where the current asset has a temporary disturbance in normal cash flows and the potential replacement asset is a newer version of the original asset. However, the model can also solve more general cases of asset replacement decisions as well as evaluate two assets with unequal lives.

This model is applied to a Kentucky cow-calf operation to determine for what age of an open cow is replacement with a bred heifer the optimal decision. Sensitivity analysis is conducted to assess how differences in productivity between heifers and mature cows as well as price differences between mature cows and replacement heifers affect the optimal culling/replacement decision. Finally, the decision is analyzed in a stochastic environment where prices reflect the last 10 years of variability.

Previous Research

Cow-calf producers constantly evaluate how long to keep their animals. Schroeder and Featherstone (1990) considered optimal calf retention and marketing strategies for cow-calf producers. Other studies have specifically addressed the replacement of breeding stock. Larson, McLemore, and Stokes (2000) analyzed whether producers should purchase heifer replacements or raise their own replacements. Whittier (2000) considered this same issue. Investigations by Tronstad and Gum (1994), Azzam and Azzam (1991), and Frasier and Pfeiffer (1994) analyzed when to replace beef cows.

The dairy science literature also includes several studies examining cow replacement decisions. These dairy cow replacement decisions must consider milk value in addition to the calf value. Van Arendonk (1986, 1988), Van Arendonk and Dijkhuizen (1985), and DeLorenzo et al. (1992) all evaluated decisions about insemination and replacement of dairy cows.

Many of these earlier studies use dynamic programming to solve for the optimal cow replacement decision. Using a model developed by Van Arendonk and Dijkhuizen (1985), Van Arendonk (1988) employed dynamic programming to calculate management guides that tell a producer what to do with a cow in a given production and price situation.

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[3] This occurs because young cows have not yet reached their mature body weight. A portion of their energy thus goes to supporting their own growth rather than to fetal development or milk production. Brown, Brown, and Butts (1972) found that both Angus and Hereford cows continued to increase body weight until the age of six or seven years; however, the increase in weight beyond about 48 months was very small. Results from later investigations on this subject, including work on other breeds, have yielded very consistent results (e.g., Brown, Fitzhugh, and Cartwright, 1976; Jenkins et al., 1991).

His objective was to maximize the present value of cash flow of present and future replacement cows. Van Arendonk considered three alternatives in the model for the open cow: insemination, leave open, or replace immediately. In a 1986 analysis, Van Arendonk expanded upon the other two models by adding a variable for month of calving to account for seasonal variation in production and prices. DeLorenzo et al. (1992) also solved for optimal dairy cow replacement decisions using dynamic programming. Their study maximizes the net present value of a cow and replacements over a 20-year horizon, with state variables including class of parity, production level, calving month, lactation month, and days open.

More recently, dynamic programming has been applied by Tronstad and Gum (1994) in determining culling decision rules for open beef cows. They present a biannual calving model (i.e., within the same herd, some cows are bred to calve in the spring, some in the fall) that treats prices as stochastic rather than deterministic, addresses age-dependent fertility, and has different costs for spring versus fall calving. Pregnancy status, cow age, calf price, replacement price, and cull value are all state variables. Frasier and Pfeiffer (1994) use a dynamic framework that attempts to incorporate the effects of management practices on future productivity. Specifically, the cow's body condition, the winter feed level, and the length of calving season were incorporated into the model.

Based on results from previous studies, open cows are most often culled. Frasier and Pfeiffer (1994) developed policies that always culled open cows. Tronstad and Gum (1994) concluded open cows should be kept 26% of the time. However, their study allowed for biannual calving so that an open cow could be rebred in six months. Operations which only practiced spring calving would have to wait a year to rebreed, which further discourages keeping open cows. Azzam and Azzam (1991) showed that open cows should always be culled even when fall calving was considered.

Using dynamic programming presents some limitations, particularly concerning the usability of the model by a beef producer. Tronstad and Gum (1994) only consider a 15-year planning horizon that does not incorporate discounting future cash flows. However, the usability is addressed by developing Classification and Regression Trees (CART), which presents a flowchart illustrating how to analyze different values of the decision variables. Although Frasier and Pfeiffer (1994) use an infinite planning horizon with discounted cash flows, the results are limited should prices change. Producers would need to be familiar with dynamic programming to adopt this model. A more effective approach would be to use net present value analysis to evaluate keeping an open cow versus replacement with a bred heifer.

Perrin (1972) developed a framework for these types of problems. Perrin examines two different types of asset replacement decisions. The first considers when an asset should be replaced with a new version of itself. Decisions in this category include when to harvest a forest and when to replace a truck. The second decision considered by Perrin is when to replace an asset with a technologically improved asset. The open cow replacement decision roughly fits into this category. However, there are some differences, as the cow's revenue stream changes when she becomes open. Her marginal revenue goes down and then back up, making application of Perrin's criteria for replacement difficult.

The Mathematical Model

The model employed here is an extension of net present value (NPV) analysis of investments with different economic lives that are purchased on a recurring basis. The cow replacement problem fits into this category because an ongoing beef operation will use a whole series of cows over the life of the farm. Thus, comparing the NPV of keeping the open cow versus the NPV of a single replacement heifer is inaccurate. The replacement heifer has a longer life and will generate more years of cash flows when compared to the open cow. If the open cow is kept, she will eventually be replaced at the end of her useful life.

As shown by Barry et al. (2000), in order to properly evaluate these types of investments, they must be placed on a common time basis. The value of keeping the open cow and the value of a single replacement heifer are defined, respectively, in equations (1) and (2):

$$(1)\quad V(c) = \sum_{n=1}^{LC} \frac{P_n(c)}{(1+i)^n} + \frac{S_{LC}(c)}{(1+i)^{LC}},$$

$$(2)\quad V(h) = \sum_{n=1}^{LH} \frac{P_n(h)}{(1+i)^n} + \frac{S_{LH}(h)}{(1+i)^{LH}} - H_0(h),$$

where $V(c)$ and $V(h)$ are the respective values of the retained cow and a single replacement heifer, LH represents the expected lifespan of the heifer, and LC represents the remaining life of the cow. Therefore, LC is the difference between LH and the age of the open cow. $P_n(c)$ and $P_n(h)$ are the net values of the calf crop produced in each year n, and $S_{LC}(c)$ and $S_{LH}(h)$ are the salvage values if the cow or heifer is kept to the end of her expected useful life. The discount rate is denoted by i, and the cost of a new replacement heifer is $H_0(h)$.

Equations (3) and (4) represent the formulation for evaluating the problem when the beef farm is considered as an ongoing operation. The equations convert the problem into a perpetual annuity decision, thereby eliminating the difficulty of comparing assets with unequal lives. Multiple replacements over time will be purchased whether the open cow is kept or replaced immediately. Equations (3) and (4) use equations (1) and (2) as their foundation:

$$(3)\quad V_0\,(Replace\ Cow) = S_0(c) + \frac{1}{1-(1+i)^{-LH}} * [V(h)],$$

$$(4)\quad V_0\,(Retain\ Cow) = V(c) + \frac{1}{1-(1+i)^{-LH}} * [V(h)] * (1+i)^{-LC}.$$

Equation (3) sells the open cow, $S_0(c)$, and starts with a series of replacement heifers immediately. The value of each replacement heifer, $V(h)$, comes from equation (2). Equation (4) starts with retaining the open cow [equation (1)] and also adds a series of replacement heifers. However, in equation (4), the series of replacement heifers does not start until the lifespan of the open cow is reached.

Equations (3) and (4) become very similar once the series of replacement heifers starts. The only difference is that in equation (4) the replacement series starts later. Both equations use the term,

$$\frac{1}{1-(1+i)^{-LH}} * [V(h)].$$

This term is based on an equation in Perrin (1972) and represents the present value of a perpetual annuity received every LH years. Again, from equation (2), $V(h)$ represents the amount of each annuity payment received every LH years. Perrin originally used his equation to determine the optimal life of a replaceable asset. It can also be applied to find the present value of a perpetual series of replacement heifers, given that we already know the optimal life of the replacement heifers.

Because both equations (3) and (4) have similar terms and are examining calf returns, cow expenses, and cow and heifer prices, the effects of taxes and inflation should be minimal. In other words, what affects one equation will also affect the other as well. In both models, a calf is sold each year, except for equation (4) which has no calf crop in the initial year. Both equations will also sell a series of mother cows, although these sales will be in different years. For example, in equation (3), cows may be sold in years 1, 8, 15, 22, etc. (assuming a seven-year life for the cows), while in equation (4), cows may be sold in years 4, 11, 18, 29, etc. Thus, there could be some small inflation and tax effects because of timing differences. We have not specifically examined taxes and inflation in this model. The use of an NPV model implies producers maximize wealth.

There is likely to be uncertainty at several points in the model. Specifically, $P_n(c)$, $P_n(h)$, $S_{LC}(c)$, $S_{LH}(h)$, and $H_0(h)$ are expected values. The current salvage values and replacement costs (S and H) in the model are known quantities, but become less certain in the future. We assume current salvage and replacement costs are the best price estimates for future replacements. Most of the uncertainty in the model comes from the yearly revenue numbers, P_n. By assuming risk-neutral cattle producers and taking expectations, a single number can be used for the formula. The model still works for risk-averse producers by using a certainty equivalent approach to calculate P_n, or by adding a risk premium to the discount rate.

Because risk is an important part of any cull decision, this model allows for a certain degree of risk. The current salvage value and replacement costs are two of the more important variables, and they are known quantities. Uncertainty about future costs is minimized because these future values are discounted and thus become less important to the decision. Because both equations (3) and (4) sell a calf each year, uncertainty about prices should affect both decision equations approximately the same. As in the tax and inflation discussion, the main difference for cow price uncertainty comes from selling cows in different years. However, current prices are known, and future prices, although uncertain, will be reduced by the discount rate chosen to find a present value. The application section of the paper also examines the decision when bred heifer prices, calf prices, salvage cow values, and hay prices are all stochastic.

The Empirical Model

The empirical model includes all variables needed to calculate the elements of (3) and (4). These include annual variable costs per cow and calf value per head [used to calculate $P_n(c)$ and $P_n(h)$], age of the open cow, cost of a bred replacement heifer, current salvage value of the open cow, salvage value of the cow or replacement heifer at the end of its productive life, length of the typical reproductive life of a cow, and discount rate.

For this analysis, an 11-year life is used for the typical cow—i.e., a cow that is never open. The salvage value of an open cow is $400, while the salvage value of a cow at the end of her 11 years is $350. The peak calf value is $400, and a real discount rate of 7% is used. Variable costs range from $240 to $390 per year, while heifer replacement costs range from $750 to $875.

According to Kentucky Farm Business Management (KFBM, 2002) data, Kentucky cow-calf producers in 2000 had variable costs of $272 for the top one-third of producers, while the bottom one-third of producers had variable costs of $348. The variable costs and heifer replacement costs are the most likely to change from year to year, so the focus is on finding the combination of these two variables to illustrate those years in which it is best to retain an open cow. However, variations in calf values, cow salvage values, and discount rates are examined as well.

The value of the calf at the cow's productive peak is used as the basis of the calf value for reproductive years 4 through 11. Before a cow reaches her fourth reproductive year, she is reproductively less efficient and usually produces a smaller calf. Therefore, the calf crop value

Table 1. Production Data Used to Develop the Open Cow Replacement NPV Model

Description	**Calving Rates for Pregnant Cows by Age**								
Cow Age (years)	**2.5**	**3.5**	**4.5**	**5.5**	**6.5**	**7.5**	**8.5**	**9.5**	**10.5**
% Pregnant to no calf	2.17	2.78	3.23	3.53	3.68	3.68	3.52	3.22	2.76
% Pregnant to live calf	97.83	97.22	96.77	96.47	96.32	96.32	96.48	96.78	97.24
	Estimated Fertility of Open Cows with Calf by Age								
Cow Age (years)	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
% Calf at side to pregnant	81.95	80.80	79.33	77.52	75.39	72.94	70.15	67.04	63.59
% Calf at side to open	14.59	14.59	14.59	14.59	14.59	14.59	14.59	14.59	14.59
% Calf at side to cull (unsound)	1.40	1.86	2.65	3.77	5.21	6.98	9.08	11.51	14.26
% Calf at side to cow died	2.06	2.75	3.43	4.12	4.81	5.49	6.18	6.87	7.55
	Estimated Fertility of Open Cows with No Calf by Age								
Cow Age (years)	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
% Open to pregnant	70.99	69.26	67.03	64.41	61.52	58.49	55.44	52.49	49.75
% Open to open	25.09	24.09	23.08	22.08	21.08	20.08	19.07	18.07	17.07
% Open to cull (unsound)	3.32	5.58	8.21	11.09	14.10	17.13	20.04	22.72	25.05
% Open to cow died	0.60	1.07	1.68	2.42	3.29	4.30	5.44	6.71	8.12

Notes: Data in table are based on Tronstad et al. (1993). Unsound cows are culled because of reasons other than fertility.

is assumed to decline by 4% (of the peak calf value) per year for years three to one (Anderson, 2002). This means the replacement heifer, in her first productive year, will usually produce a calf with a value $48 less than that of a mature cow's calf [$400 * 4% * 3 years = $48]. The calf crop in reproductive years 11 onward is 4% less than the calf crop from a peak reproductive cow (Anderson, 2002). Because cows develop more fertility and soundness problems after 11 years of age, we assume the cows are sold at this age. The model assumes that the cost to maintain the cow is not affected by age. Revenues and costs from one heifer replacement to the next are assumed to be the same.

A fertility discount, based on the Tronstad et al. (1993) data reported in Table 1, is subtracted from the value of the calf crop. There is always a risk that a cow will not rebreed. This risk is higher for the open cow than it is for a cow of the same age with a calf. Data from Tronstad et al. (1993) provide probabilities for various outcomes (pregnant, open, culled, or dead) for open cows, both with and without calves, by age group. These probabilities are used to quantify the risk of failure to rebreed for cows of various ages and pregnancy status (Table 1). For example, a four-year-old cow currently with a calf has a 14.59% chance of being open in the following year, while a four-year-old cow currently open has a 24.09% chance of being open next year as well. The fertility discounts are multiplied by the calf value to obtain an expected cost of not having a calf. One deficiency of Table 1 is that the data do not reflect the fact that first-calf heifers may have more trouble rebreeding. Implications of this data limitation will be addressed using sensitivity analysis.

The empirical model was programmed in an Excel spreadsheet. The critical output from the model is an NPV of future cash flows from a bred replacement heifer and from a retained open cow. The appropriate management decision (retain the open cow or replace with a bred heifer) is indicated by the higher of these two NPVs.

Simulation analysis is used to test the robustness of a decision by making replacement heifer prices, cull cow prices, calf prices, and hay prices stochastic. Using the computer program Simetar®, a multivariate empirical (MVE) distribution of the prices is estimated from 10 years of data. Parameter estimation for the MVE distribution is estimated following the procedure outlined in Richardson (2002). First, the deterministic component and the error term for each random variable are calculated. Next, the sorted and unsorted fractional residuals are calculated for each variable. Probabilities are assigned to the sorted fractional residuals, and the correlation matrix is calculated from the unsorted residuals. The final step is to simulate the stochastic part of each variable. For all the prices, the simulated value is added back to either the mean or the expected price.

The existence of somewhat regular changes in cattle inventories has been widely recognized (Aadland, 2002). However, this length can vary significantly, as the most recent cattle cycle indicates. To address the cattle cycle potential, the model is also simulated as a vector autoregressive (VAR) model where the cow prices, calf prices, and replacement heifer prices are correlated.

Results

Table 2 presents the main results assessing when to keep an open cow versus replacing immediately. This table shows the difference between equation (3), *replace*, minus equation (4), *retain*. Thus, whenever the reported value is negative, farmers would be better off retaining the open cow. (For clarity, these negative values appear in boldfaced italics in Table 2.)

Obviously, results obtained from the model will be influenced by values selected for the variables listed earlier. Among the most critical of these variables are age of the open cow, variable costs per cow, and cost of replacement heifers. Sensitivity analysis can be employed to determine what will be the appropriate decision (retain or replace an open cow) under a variety of circumstances. As presented in Table 2, variable costs, age of open cow, and heifer replacement costs are all varied while holding the other variables constant. There is likely some correlation between heifer cost, cow salvage value, and calf value. However, the purpose of the table is to illustrate price situations where retaining an open cow might be optimal.

Results indicate that as the cost of replacement heifers increases relative to the salvage value of cows and the calf value, retaining cows becomes an increasingly viable option. This is also true as variable maintenance costs decrease and as the age of the open cow decreases. As a general principle, these results certainly have intuitive appeal; however, previous studies did not find the retention of open cows to be the optimal decision unless the cows could be rebred for a fall calving season.

Based on results from Table 2, with a bred replacement heifer cost of $850 and annual variable maintenance costs of $300/cow, retaining an open cow that is up to four years old is an appropriate decision. Thus, it appears that calculating NPV as a perpetual annuity, as developed here, can potentially lead to somewhat different conclusions from those derived through other methods of evaluating replacement decisions represented in the literature.

Consideration of the physiological component of the replacement decision provides at least circumstantial evidence in support of the result noted above. From data presented in Table 1, as noted earlier, replacement heifers are not as efficient as mature cows (i.e., their calves are lighter at weaning). Therefore, replacing a three- to five-year-old cow with a heifer entails replacing an animal just entering her peak productivity with one that will be going through her least productive phase. There is undoubtedly a tradeoff involved in replacing an open cow with a replacement heifer. Specifically, culling an open cow

Table 2. Difference in NPV from Replacement Heifer and Retained Open Cow (dollars) [V_0 *(Replace)* – V_0 *(Retain)*]

Variable Cost	Age of Open Cow (years) 3	4	5	6	7	8	Replacement Heifer Cost
$240	$10	$26	$57	$90	$125	$163	$750
$270	$27	$45	$77	$111	$148	$187	
$300	$45	$64	$97	$133	$171	$212	
$330	$63	$83	$117	$154	$194	$237	
$360	$80	$102	$137	$176	$217	$261	
$390	$98	$121	$158	$197	$240	$286	
$240	***($12)***	$7	$40	$75	$113	$154	$775
$270	$6	$26	$60	$96	$136	$178	
$300	$24	$45	$80	$118	$159	$230	
$330	$41	$64	$100	$140	$182	$227	
$360	$59	$83	$120	$161	$205	$252	
$390	$77	$102	$141	$183	$228	$277	
$240	***($33)***	***($12)***	$23	$60	$101	$144	$800
$270	***($15)***	$7	$43	$82	$124	$169	
$300	$2	$26	$63	$103	$147	$193	
$330	$20	$45	$83	$125	$170	$218	
$360	$59	$83	$120	$161	$205	$252	
$390	$56	$82	$124	$168	$216	$267	
$240	***($54)***	***($31)***	$6	$46	$89	$135	$825
$270	***($36)***	***($12)***	$26	$67	$112	$160	
$300	***($19)***	$7	$46	$89	$135	$184	
$330	***($1)***	$26	$66	$110	$158	$209	
$360	$17	$44	$87	$132	$181	$233	
$390	$34	$63	$107	$154	$204	$258	
$240	***($75)***	***($50)***	***($11)***	$31	$77	$126	$850
$270	***($58)***	***($31)***	$9	$53	$100	$150	
$300	***($40)***	***($13)***	$29	$74	$123	$175	
$330	***($22)***	$6	$49	$96	$146	$199	
$360	***($5)***	$25	$70	$117	$169	$224	
$390	$13	$44	$90	$139	$192	$249	
$240	***($97)***	***($69)***	***($28)***	$17	$65	$116	$875
$270	***($79)***	***($51)***	***($8)***	$38	$88	$141	
$300	***($61)***	***($32)***	$12	$60	$111	$165	
$330	***($44)***	***($13)***	$33	$81	$134	$190	
$360	***($26)***	$6	$53	$103	$157	$215	
$390	***($8)***	$25	$73	$124	$180	$239	

Notes: Negative values (appearing in boldfaced italics) denote situation in which open cow should be retained. Calf value at weaning is assumed to be $400; cull values of open cow and 11-year-old cow are $400 and $350, respectively; the discount rate is 7%. Results for 9- and 10-year-old cattle are not reported here.

eliminates maintenance costs tied to that cow, but will also reduce income until the open cow's replacement reaches full maturity. Results reported in Table 2 seem to appropriately reflect this tradeoff (i.e., age of cows which may be retained increases as production costs decrease).

While data used in this study do indicate lighter weaning weights for calves, they do not reflect any differences in fertility between heifers and mature cows. In fact, without special management, first-calf heifers (i.e., heifers that have just had their first calf) are unlikely to rebreed at a rate as high as mature cows. Heifers take longer to recover from the physical stress of calving (see footnote 2).

Survey data from the USDA's Animal and Plant Health Inspection Service (APHIS) indicate few producers actually practice the type of management necessary to keep first-calf heifer breeding percentages on par with those of mature cows (U.S. Department of Agriculture, 1994). For example, only about 13% of operations reported breeding replacement heifers earlier than the rest of the herd. (This practice results in earlier calving—giving heifers a longer post-partum recovery period prior to start of the next breeding season.) Additionally, less than one-third of operations reported feeding heifers separately from mature cows. (This strategy ensures the higher nutritional requirements of heifers are met, allowing them to recover from calving, maintain their own growth, and support the growth of their calf.)

Because relatively few operations are likely to realize the same level of fertility in first-calf heifers as in mature cows, additional sensitivity analysis on this parameter is in order. The Tronstad et al. (1993) data reported in Table 1 show that 14.59% of the cows in a beef herd will fail to rebreed, and this percentage is constant across age groups. To investigate the effect of first-calf heifer fertility on the results of the NPV model developed here, this percentage of open cows was examined at two additional levels (19.59% and 24.59%) for three-year-old cows. Table 3 presents results from the NPV model for the three different levels of first-calf heifer fertility (14.59% open, 19.59% open, and 24.59% open) at bred replacement heifer costs of $750 and $800. The upper panel of Table 3, with a 14.59% open rate, repeats portions of Table 2, and is included to show the original baseline.

As expected, with higher levels of open first-calf heifers, retaining open cows becomes the preferred option more often (i.e., for older cows and with higher production costs). This follows from the fact that as first-calf heifer fertility decreases, replacing mature cows with bred heifers involves increasing production (and therefore income) risk. This is an important result because it provides managers some basis for considering the replacement decision within the framework of overall herd management.

For example, a manager with low costs of production (e.g., a producer in the southeastern United States intensively managing improved forage varieties) who lacks the on-farm infrastructure to separate heifers from mature cows may find it advantageous to keep four- or possibly even five-year-old open cows. In contrast, a relatively high-cost producer who can manage heifers and cows separately would possibly never find it advantageous to keep an open cow.

A second sensitivity analysis was conducted to evaluate the impact of open cow fertility on model results. Specifically, changes in the probability that an open cow of any age would remain open through the subsequent breeding season ("% open to open" in Table 1) were examined. In this analysis, the "% open to open" values from Table 1 were adjusted to 90% and 110% of their reported value. Results are presented in Table 4. The center panel of Table 4 duplicates the scenario from Table 2 with a replacement heifer cost of $800.

Table 3. Effect of First-Calf Heifer Fertility on Difference in NPV from Replacement Heifer and Retained Open Cow (dollars)

Variable Cost	Age of Open Cow (years) 3	4	5	Age of Open Cow (years) 3	4	5
	— Replacement Heifer Cost = $750 —			— Replacement Heifer Cost = $800 —		
P(first-calf heifer open) = 0.1459:						
$240	$10	$26	$57	***($33)***	***($12)***	$23
$270	$27	$45	$77	***($15)***	$7	$43
$300	$45	$64	$97	$2	$26	$63
$330	$63	$83	$117	$20	$45	$83
$360	$80	$102	$137	$59	$83	$120
$390	$98	$121	$158	$56	$82	$124
P(first-calf heifer open) = 0.1959:						
$240	***($5)***	$13	$45	***($47)***	***($25)***	$11
$270	$13	$32	$65	***($30)***	***($6)***	$31
$300	$30	$51	$85	***($12)***	$13	$52
$330	$48	$70	$106	$6	$31	$72
$360	$66	$89	$126	$23	$50	$92
$390	$83	$108	$146	$41	$69	$112
P(first-calf heifer open) = 0.2459:						
$240	***($20)***	***($0)***	$33	***($62)***	***($38)***	***($0)***
$270	***($2)***	$19	$54	***($44)***	***($19)***	$20
$300	$16	$38	$74	***($27)***	***($1)***	$40
$330	$33	$57	$94	***($9)***	$18	$60
$360	$51	$76	$114	$9	$37	$80
$390	$69	$94	$134	$26	$56	$100

Notes: Negative values (appearing in boldfaced italics) denote situation in which open cow should be retained. Calf value at weaning is assumed to be $400; cull value of open cow is $400, while the cull value of a typical cow replaced at the end of year 11 is $350; the discount rate is 7%. The optimal decision for all ages above 5 is to cull the open cow.

Changes of the magnitude investigated here have a relatively minor impact on model results; however, it is clear that as open cow fertility increases (i.e., as the probability that an open cow will fail to rebreed in the following breeding season decreases), the value of the open cow relative to a bred heifer increases. Conversely, as open cow fertility decreases, the value of the open cow relative to a bred heifer decreases.

Three final sets of sensitivity analyses were run to evaluate the effects of discount rates, calf crop values, and cull cattle prices. These sensitivity analyses were compared to the scenario from Table 2 in which the replacement heifer cost is $800. Increasing the discount rate makes the decision of whether to replace or retain less important as the NPV differences become slightly smaller at each combination. For a range of discount rates from 4% to 10%, the retain decision was nearly identical. There was one additional retain decision at the 10% discount rate. For three-year-old open cows and variable costs of $240, the retain cow decision was $38 better at a 4% discount rate and $30 better at a 10% discount rate.

The next sensitivity analysis considers how different calf crop values affect the retain versus replace decision. Because the

Table 4. Effect of Open Cow Fertility on Difference in NPV from Replacement Heifer and Retained Open Cow (dollars)

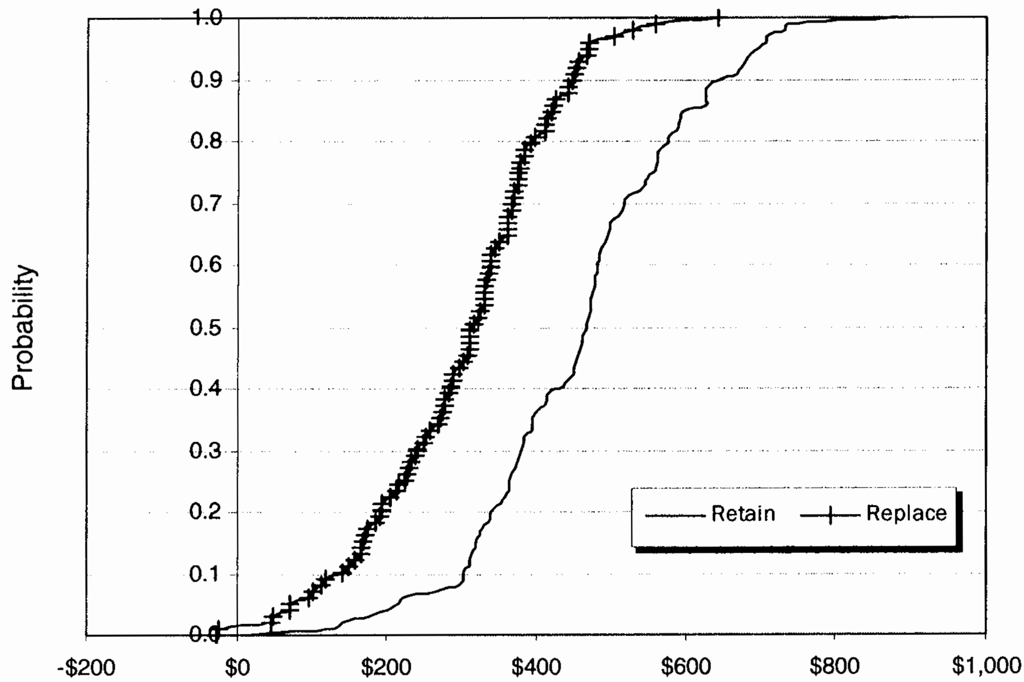
Variable	Age of Open Cow (years)					
Cost	3	4	5	6	7	8
10% Decrease in *P*(open to open):						
$240	***($42)***	***($21)***	$15	$52	$93	$137
$270	***($24)***	***($2)***	$35	$74	$116	$162
$300	***($6)***	$17	$55	$96	$139	$186
$330	$12	$36	$75	$117	$162	$211
$360	$29	$55	$95	$139	$185	$235
$390	$47	$74	$115	$160	$208	$260
Base *P*(open to open):						
$240	***($33)***	***($12)***	$23	$60	$101	$144
$270	***($15)***	$7	$43	$82	$124	$169
$300	$2	$26	$63	$103	$147	$193
$330	$20	$45	$83	$125	$170	$218
$360	$59	$83	$120	$161	$205	$252
$390	$56	$82	$124	$168	$216	$267
10% Increase in *P*(open to open):						
$240	***($24)***	***($3)***	$31	$68	$108	$151
$270	***($7)***	$16	$51	$90	$131	$176
$300	$11	$34	$71	$111	$154	$201
$330	$29	$53	$92	$133	$177	$225
$360	$46	$72	$112	$154	$200	$250
$390	$64	$91	$132	$176	$223	$274

Notes: Negative values (appearing in boldfaced italics) denote situation in which open cow should be retained. Calf value at weaning is assumed to be $400; replacement heifer cost is assumed to be $800; cull value of current open cow is $400, while the cull value of a typical cow replaced at the end of year 11 is $350; the discount rate is 7%.

replace decision produces a calf sooner, any situation where calves become relatively more valuable favors this replacement action. With a three-year-old open cow and calf values of $350, open cows are retained as long as variable costs are below $330. For the same open cow but calf values of $450, any variable cost above $250 results in the cow being replaced.

The final sensitivity analysis examines various cull cattle prices. In this analysis, both the salvage value of the current open cow and the salvage value of an 11-year old cow are adjusted in $50 increments. As expected, when cull cow values become less valuable relative to other values, retaining open cows becomes more likely. This result follows the discussion about retaining more open cows when the relative price of heifers increases. Thus, whenever the spread between open cow prices and replacement heifers increases, the NPV for retaining the open cow increases.

Figure 1 shows the CDF of the retain versus replace decision using simulation analysis without any autocorrelation. This simulation is based on an expected price of $1,000 for replacement heifers, $400 for peak calf value, $240 for feed, and $350 for the salvage value of a cow. The cow is open in her third productive year. As the figure demonstrates, making prices



Notes: Simulation is based on expected price of $1,000 for replacement heifers, $400 for peak calf value, $240 for feed, and $350 for the salvage value of a cow.

Figure 1. Examining the Retain versus Replace Decision in a Stochastic Environment: CDF of NPV Values

stochastic has little effect on the decision. The retain decision exhibits first-degree stochastic dominance, with the CDF always lying to the right of the CDF for the replace decision. The VAR simulation model produces a similar CDF with first-degree stochastic dominance. The single point estimate from the NPV model gives a $164 advantage to the retain decision. Because the two alternatives are basically examining a time shift of the same beef cow series, it is not surprising to find the deterministic and stochastic models provide the same answer.

Summary and Conclusions

This analysis solves a unique set of asset replacement decision problems where the potential replacement asset is a new version of the current asset but the current asset has developed a temporary problem that prevents it from being used for a time. This situation is similar to problems concerning when to replace an asset with a better asset, and problems associated with examining two new assets with different lives. However, the break in the current asset's revenue stream makes this problem unique.

In addition, the NPV model developed here can solve more than just this specialized case of an asset replacement decision. Because the assets are being evaluated as a perpetual annuity, the model can also be used to evaluate all assets with different lengths of lives as well as more general asset replacement decisions.

The NPV model developed in this analysis forms the basis of a beef cow replacement decision model in which assets with different lengths of life (i.e., mature open cows and bred replacement heifers) can be fairly compared. Results of the model indicate that, while replacement of open cows with bred heifers is generally advantageous, it may not always be so. Specifically, replacing young open cows (< 4 years old) is not necessarily the best decision. The replacement decision is sensitive to production costs and relative replacement heifer costs. For operations with high production costs, replacement of open cows of any age may, in fact, be the optimal decision unless replacement heifer cost is very high (i.e., > $850). In contrast, for low-cost producers, keeping young open cows may make good economic sense even at moderate replacement heifer prices (i.e., below $800).

Sensitivity analysis was used to demonstrate the impact of first-calf heifer and open cow fertility on the replacement decision. The issue of first-calf heifer fertility is particularly important since this variable can be influenced by management practices. Operations with the ability to intensively manage first-calf heifers to minimize calving and rebreeding problems will more often find it preferable to replace rather than retain young open cows. The variability of open cow fertility can also affect the keep or replace decision, but it may not be as important as first-calf heifer fertility since managers have less control over the fertility of open cows.

The key point this model clearly illustrates is that managers need to be aware of how their production costs and management practices influence their replacement decisions. Younger open cows should not automatically be culled, as previous research has suggested. Whenever feed costs are low, the price differential between cull cows and replacement heifers is high, or the calf crop value is low, retaining open cows becomes more desirable.

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The DuPont Profitability Analysis Model: An Application and Evaluation of an E-Learning Tool

Jon Melvin, Michael Boehlje, Craig Dobbins, and Allan Gray

Abstract

Successful farm business managers must understand the determinants of profitability and have an overall long-term or strategic management focus. The objective of this research was to explore the use of an e-learning tool to help producers understand the impacts of different production, pricing, cost control, and investment decisions on their farm's financial performance. This objective was accomplished by developing and testing a computer-based training and application tool to facilitate determination of the financial health of farm businesses using the DuPont profitability analysis model. The results of the two experiments indicate that the computer software was effective for teaching techniques of profitability analysis contained within the DuPont model.

Key words: computer-assisted analysis, DuPont profitability analysis, e-learning, return on assets (ROA), return on equity (ROE)

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It is generally perceived that financial management is important as a management function of any business, including farm businesses. Poor financial practices rank second only to economic conditions as a cause of business failure, according to Dun & Bradstreet's (1994) *Business Failure Record.* In a study examining causes of business failure in the apparel industry, Gaskill, Van Auken, and Manning (1993) found poor financial control is a main cause of business failure. Wichmann (1983) reported accounting capacity was an important factor in determining small business success or failure.

Lauzen (1985) characterizes the first five years of a business as being the critical time period. He argues that by analyzing financial statements and developing good managerial skills, an owner can increase the business' chances of success. Wood (1989) specifically cites the importance of financial education and training as a determinant of whether a business will succeed. Plumley and Hornbaker (1991) found that the economic environment encountered by the farm sector places much importance on finance in farm management.

Farm financial performance analysis has been synopsized by the Farm Financial Standards Council (1997) as the assessment of five critical dimensions: (a) solvency, (b) liquidity, (c) profitability, (d) financial efficiency, and (e) repayment capacity. The metrics or measures used in this analysis are commonly referred to as the "Sweet Sixteen." All of these metrics are important, but the focus of this discussion is on profitability as impacted by managerial decisions concerning pricing, cost control, technology and production practices, asset acquisition and use, and financing and capital structure.

Profitability Analysis

Profitability analysis and assessment of the fundamental drivers of profitability is a critical component of evaluating financial performance. Performance measures like the operating profit margin, asset turnover ratio, return on assets, and return on equity—and more importantly how they are impacted by marketing, operations, investment, and financing decisions—are extremely valuable to a farm manager.

The operating profit margin shows the amount each dollar of sales yields to net income. The asset turnover rate measures the revenues generated per dollar of assets and indicates how efficiently the business uses its assets. The return on assets is a measure that managers can use to determine if capital is generating an acceptable rate of return. Return on equity helps managers assess whether or not the debt of the farm business is working for or against them. Together, these measures help to show how well the farm business is performing financially. These four measures are core to the manager's analysis of business financial performance, and are succinctly summarized in the DuPont profitability analysis model.

The DuPont Model

The DuPont model is a common and useful tool for assessing and understanding the drivers of profitability (Barry et al., 2000, p. 121). The DuPont model is a ratio-based analysis allowing managers to observe the interactions among the important variables in the cost-volume-profit chain (Van Voorhis, 1981).

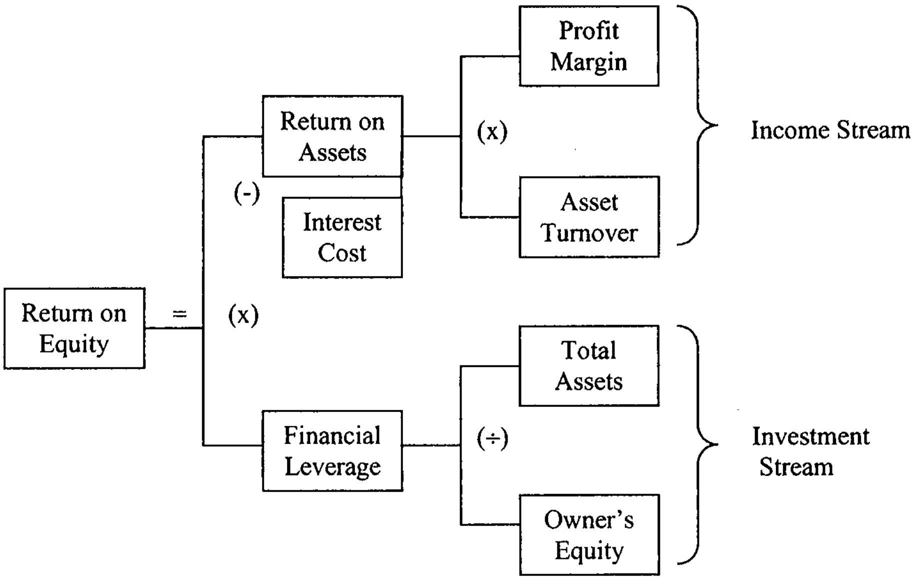
As characterized by Blumenthal (1998), the DuPont model is a useful framework for visualizing financial information and is a good tool for assisting managers in understanding how operating, financing, and investment decisions impact financial performance.

Firer (1999) explains the DuPont model as a financial analysis and planning tool intended to develop an understanding of the factors that affect the return on equity (ROE) of the firm using straightforward accounting relationships. He argues that the DuPont model allows for the assessment of the components of ROE and assists management in examining the possible influence of strategic initiatives on financial performance.

Ross, Westerfield, and Jordan (1999) further identify three factors that impact ROE as it is represented in the DuPont model: (a) operating efficiency (measured by operating profit margin and calculated as operating margin divided by gross revenue), (b) asset use efficiency (measured by asset turnover and calculated as gross revenue divided by assets), and (c) financial leverage (measured by the equity multiplier and calculated as assets divided by equity). In agreement with this description, Eisemann (1997) states that the ratios establishing ROE reflect three major performance characteristics: one income statement management feature (profit generated per sales dollar) and two balance sheet management features (sales generated per dollar of assets and the amount of solvency risk).

Application to Farm Businesses

The DuPont model allows producers to analyze the potential for improved financial performance by concentrating on variables having the most bearing on that performance. A graphical representation of the DuPont model is presented in Figure 1. A mathematical representation of the relationships reflected in Figure 1 is as follows:



Source: Adapted from Van Voorhis (1981).

Figure 1. DuPont Financial Analysis Model

(1) $$ROE = \left(\left(\frac{NI + I}{GR} \right) - \frac{I}{A} \right) * \frac{A}{E}$$

or

$$\left(ROA - \frac{I}{A} \right) * \frac{A}{E},$$

where *ROE* is return on equity, *NI* is net income, *I* is interest expense, *GR* is gross revenue, *A* is total assets, *E* is equity, and *ROA* is return on assets.

A standard measure of financial success for any business, farm, or other enterprise is the return on equity (ROE). Assuming a producer has an accrual adjusted income statement to obtain net income and a cost basis balance sheet to obtain owner equity, the ROE is an easy metric to calculate using the simple formula of net income divided by owner equity. However, viewing the ratio separately, rather than in combination with other metrics, does little to inform management on how to improve performance (Van Voorhis, 1981). If ROE is found to be less than return on assets (ROA) or has declined recently, the DuPont model suggests two basic approaches to improve performance. Analysis can be done to determine whether the ROE can be improved through the income stream or the investment stream, as shown in Figure 1.

Initially, most producers may be concerned more with the income stream than the investment stream, because the production decisions made in the farm business will usually have a more direct effect on the variables in the income stream. The income stream involves variables such as selling price, expenses, net sales, profit margin, and the use of assets. If the producer discovers a major weakness in the ROE, backtracking through the income stream and determining where changes can be made will easily identify a set of potential reasons for the weakness.

For example, if the producer discovers ROA is unsatisfactory, this weakness can be tracked back to asset turnover and net operating profit margin. The analysis can be further tracked to net sales and total cost if the operating profit margin is determined to be the main reason for the low ROA. Net sales could be improved by increasing the price received (better marketing) or by increasing the volume of product sold (increasing yields or productivity). A farmer will most likely consider these actions, but the DuPont model offers an opportunity to do comparative statics and determine what options will most benefit the producer.

The second approach to improving ROE, through the investment stream, culminates in the financial leverage multiplier (assets divided by equity). Most of the backtracking through the investment stream will follow total assets. From basic accounting, we know that total assets are equal to total liabilities plus owner equity. This simply means all assets are either claimed by creditors or owners—allowing the investment stream to be broken into two additional sections, total debt and owner equity.

It is important for a producer to understand what changes occur in ROE when liabilities, equity, and assets are restructured. For example, a producer might hypothesize that by decreasing the business' debt load, profitability will increase because the interest expense of the business will decrease. However, by analyzing the investment stream of the DuPont model, the producer will realize that if this reduced debt load requires an increase in owner equity to maintain the asset base of the business, the financial leverage multiplier will decline and the ROE may also decline. Again, by performing simple comparative statics, the producer will see the consequences of different financing decisions.

DuPont Model Software

To help farm producers better understand the impacts of different production, pricing, cost control, and investment decisions on financial performance, a computer-based financial analysis training and application tool was developed to facilitate analyzing the financial health of farm businesses. The software analysis tool was intended to introduce the DuPont profitability analysis in a user-friendly setting with audio help and instruction. The computer software was created using Microsoft Visual Basic 6.0,[1] and packaged as a stand-alone program. The computer software is segmented into two main sections: a tutorial and an analysis application.

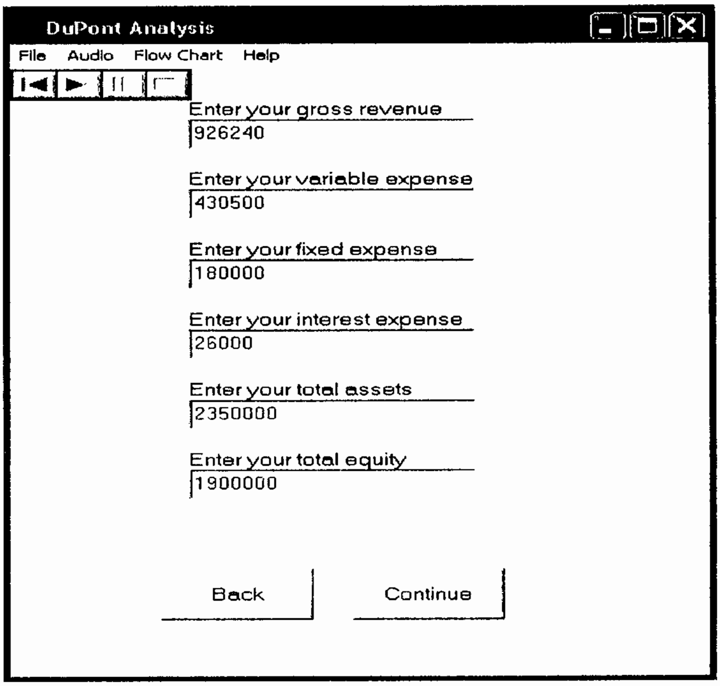
The tutorial was developed to familiarize the user with the DuPont financial analysis model as well as how to operate the software. The tutorial begins by explaining the general organization and concepts of the DuPont model. Once this is complete, the tutorial continues by describing the formulas used to perform the profitability analysis and provides a corresponding flow chart to better visualize the calculations. The tutorial finishes by illustrating how to complete the DuPont analysis with an example farm business.

The analysis application was developed to enable users to evaluate the profitability of their farm business. The analysis portion of the DuPont software allows the farm manager to look at areas for improvement and conduct preliminary long-run planning. The analysis section is divided into three levels. The Level I analysis only requires data on gross revenue, fixed expense, variable expense, interest expense, total assets, and total equity (Figure 2, Panel 2A) to perform the DuPont analysis, and is the most straightforward of the three levels of analysis. The results of the analysis are summarized as return on equity (ROE), return on assets (ROA), operating profit margin (OPM), and asset turnover ratio (ATR), as illustrated in

[1] Microsoft Visual Basic 6.0 is a registered trademark of Microsoft Corporation, 1987-2000.

Figure 2. Level I DuPont Analysis Screens

Panel 2A. Input Data



Panel 2B. Analysis Results

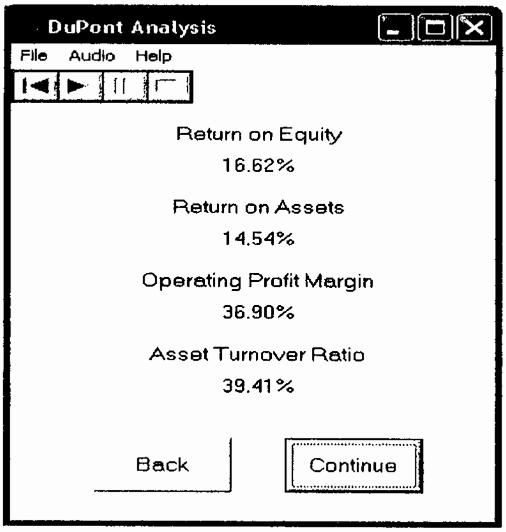
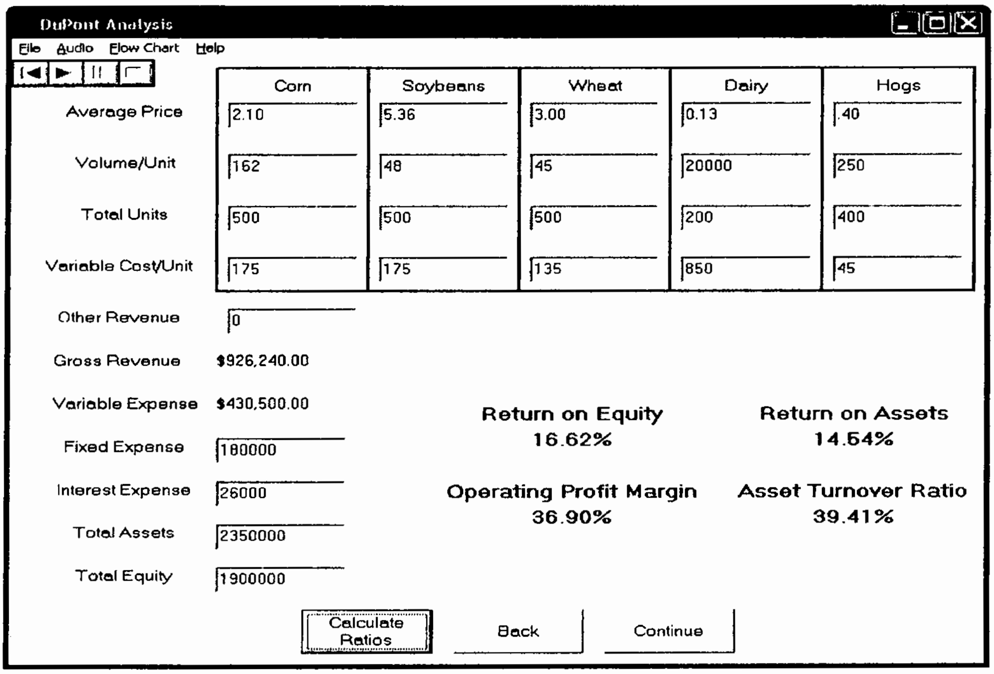


Figure 3. Level II DuPont Analysis Screens

Panel 3A. Input Data



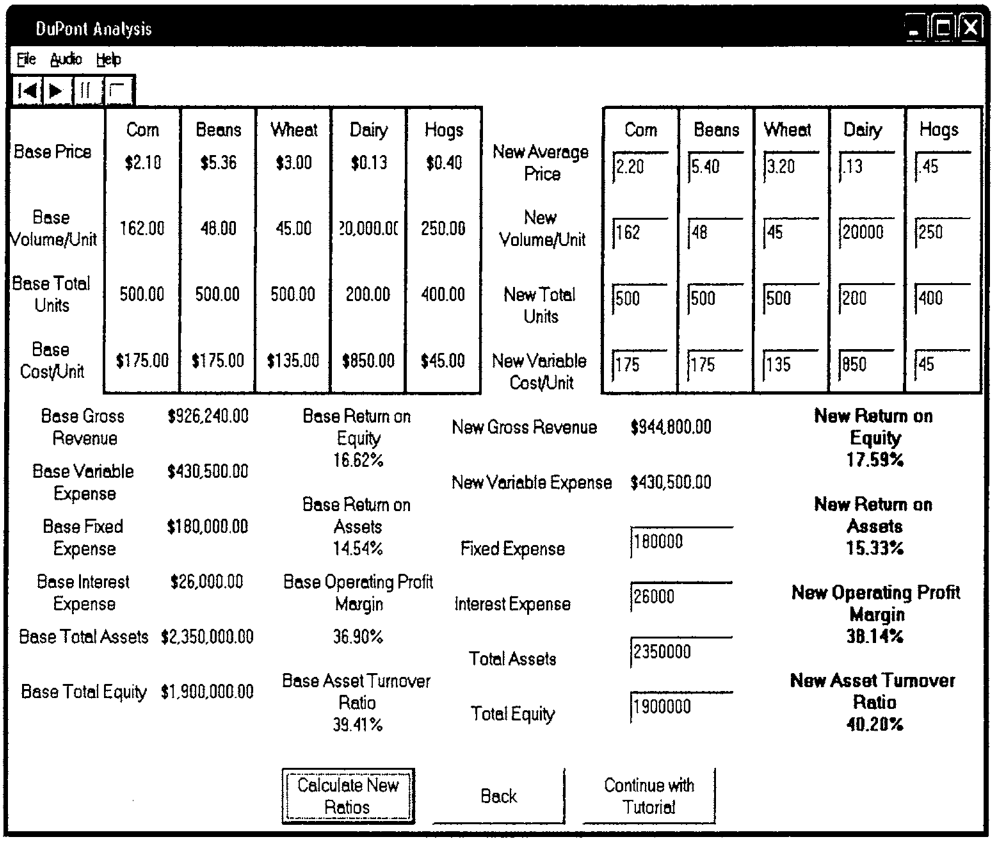
Panel 2B of Figure 2. The Level I analysis follows the typical structure of the DuPont analysis described by most finance textbooks and publications.

The Level II analysis was designed to help managers diagnose the effect of specific pricing, cost control, enterprise choice, and productivity-enhancing strategies. The Level II analysis requires more detailed information. For each enterprise or business unit, average price, volume per unit of production (acres, head, etc.), total units, and variable cost per unit must be entered (Figure 3, Panel 3A). Up to five enterprise classifications can be entered in the Level II analysis. The Level II analysis allows the manager to easily compare and alter assumptions about price, production levels, and costs (Figure 3, Panel 3B).

The Level III analysis allows for two long-run changes to be made to the farm business: an expansion analysis and a contraction analysis (Figure 4). Level III uses the base size, financial, and cost and return information entered for Level II to initiate the analysis. This means the Level III analysis can be conducted only after the Level II analysis has been completed. Additional information on the changes in enterprise size and the asset and financial structure of the business is inputted as shown in Panel 4A of Figure 4. The Level III analysis was intended to assist the farm producer in assessing the financial implications of strategic positioning decisions related to growth or downsizing the business, as well as different business ventures such as contract production or custom farming (Figure 4, Panel 4B).

Audio instruction is included throughout the tutorial and the analysis sections to provide guidance in the use of the computer program and assistance in interpretation of the results. The audio

Panel 3B. Analysis Results



instruction should be especially helpful to inexperienced users in the tutorial section as new ideas and program usage are explained. Text help messages are also included in the computer software. These messages provide a synopsis to clarify terms and commands used in the program and should be particularly helpful to users in the analysis section of the program. An additional feature of the program is an illustrative flow chart showing the general organization of the DuPont model. The flow chart provided in the program is a modification of the one appearing in Figure 1.

Software Test

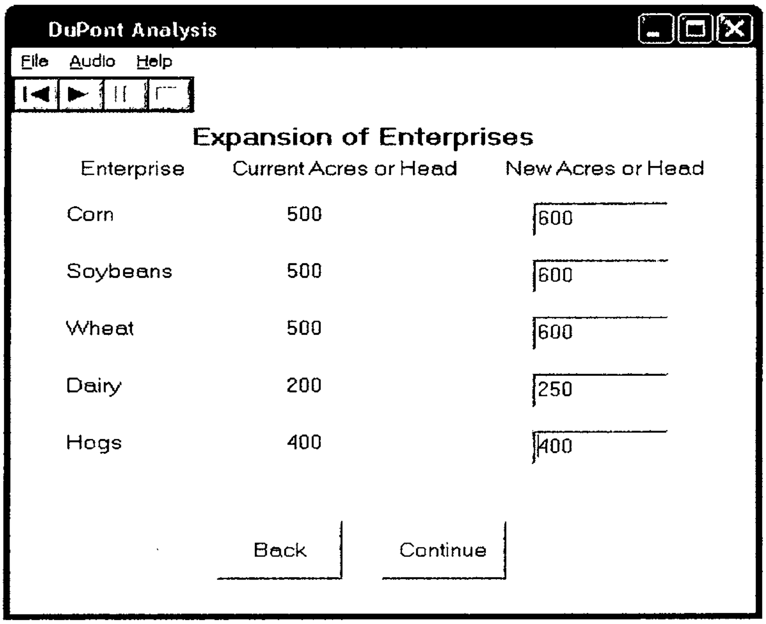
An experiment was conducted to test the differences in the participant's knowledge and understanding of profitability analysis prior to and after use of the computer-assisted educational program. Two sample groups were used: Purdue graduate students and farm producers. The two groups were tested separately; however, the same experiment was applied to both groups.

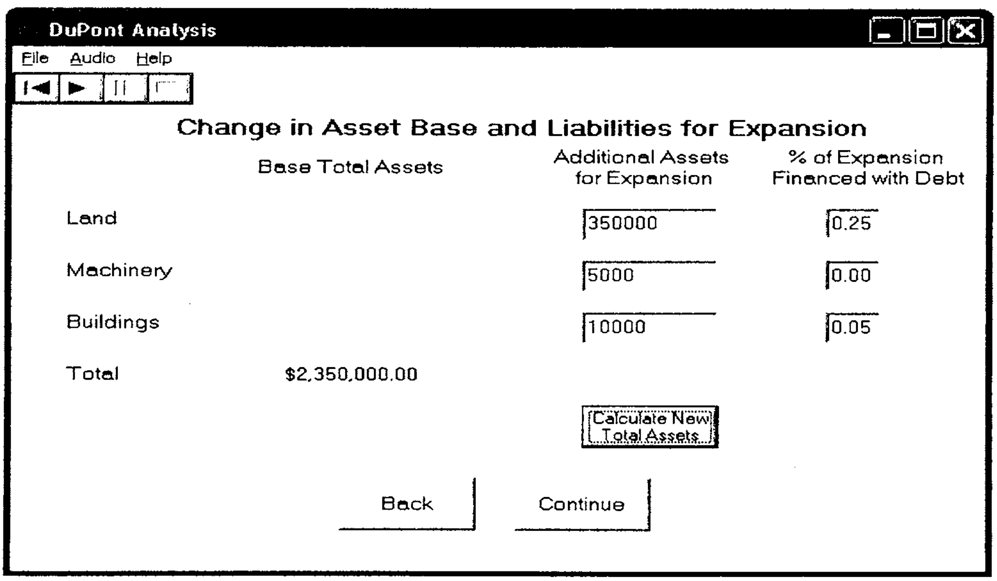
For the experiment, each participant was given initial instructions by the test administrator and an instructional sheet. The instructions for the experiment were as follows:

- Take Test #1.
- Go through the tutorial.
- Go through the analysis using the provided case study.
- Take Test #2.

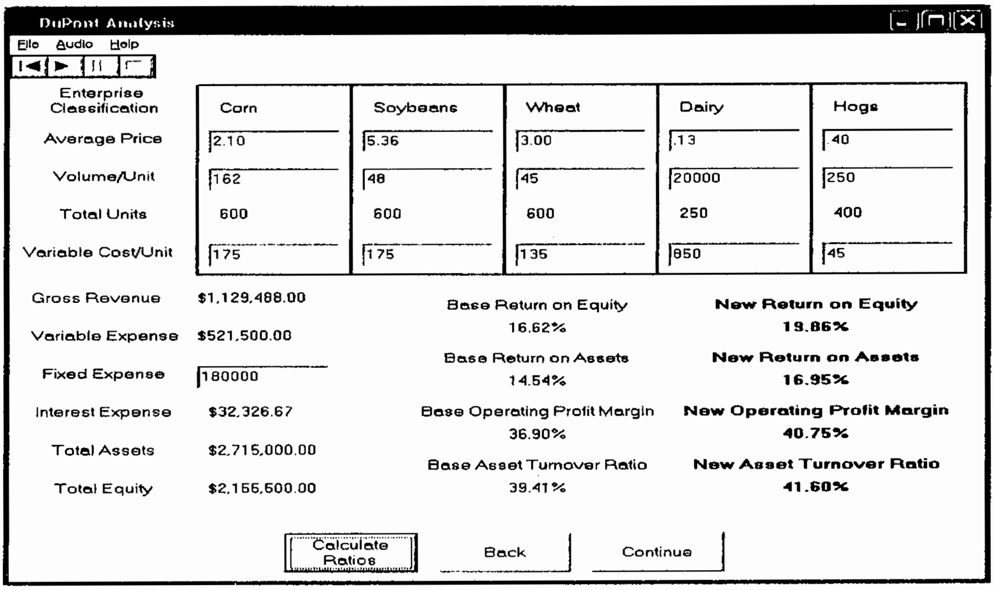
Figure 4. Level III DuPont Analysis Screens

Panel 4A. Input Data (two screens)





Panel 4B. Analysis Results



The approximate time to complete the experiment was about one hour.

Test #1 and Test #2 were identical and consisted of 10 multiple-choice questions based on ideas and principles of financial analysis that are components of the DuPont profitability analysis model. (See the Appendix for the 10 subject matter questions of the questionnaire.) The questions were categorized into three areas of learning: (a) calculation procedures of the DuPont model, (b) financial concepts contained in the DuPont model, and (c) application of financial concepts to managerial decisions.

Questions 1, 2, and 10 are calculation-based questions and were included to determine how well the participants learned the mechanical and operational details included in the DuPont model. Questions 3, 4, and 9 are conceptual-based questions and were included to evaluate the participants' ability to comprehend fundamental financial concepts that are embodied in any business. Questions 5, 6, 7, and 8 are application-based questions and were included to help determine how well the participants were able to combine calculations and concepts to solve real-life problems.

Results

Graduate Students

A random sample of 20 Purdue University agricultural economics graduate students was used for the first experimental group. None of the graduate student subjects were pre-selected, and their knowledge of financial concepts was unknown to the experiment administrator. Panel A of Table 1 reports the results from the graduate student group. Test #1 and Test #2 are the respective test scores for participants before and after the use of the computer program. Other information gathered included educational level, academic disciplinary subject matter area of emphasis in education, rating of knowledge of financial concepts, rating of computer skills, and previous participation in an experiment of this nature.

Table 1. Test Scores: Graduate Students and Farm Producers

PANEL A. Graduate Students (*n* = 20)

	Overall		Calculation		Application		Conceptual		Self-Assessment [a]	
Description	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Financial Concepts**	**Computer Proficiency**
Average	4.25	6.65	1.30	2.35	0.80	1.85	2.15	2.50	2.25	3.85
Std. Dev.	1.74	1.79	0.92	0.93	0.77	1.23	0.93	0.83	1.07	0.59
Minimum	0	3	0	0	0	0	0	0	1	3
Maximum	7	10	3	3	2	4	3	3	4	5
Median	4	6	1	3	1	2	2	3	2	4
Increases	17		15		14		8			

PANEL B. Farm Producers (*n* = 20)

	Overall		Calculation		Application		Conceptual		Self-Assessment [a]	
Description	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Test #1**	**Test #2**	**Financial Concepts**	**Computer Proficiency**
Average	3.68	5.21	1.50	2.20	0.45	1.00	1.80	1.95	2.37	3.11
Std. Dev.	1.95	2.02	0.89	0.83	0.60	1.08	1.06	0.83	1.12	1.05
Minimum	0	2	0	0	0	0	0	0	1	1
Maximum	8	9	3	3	2	3	3	3	4	5
Median	4	5	2	2	0	1	2	2	2	3
Increases	13		13		8		8			

[a] Self-assessment of financial concepts and computer proficiency is based on a scale of 1–5, with 1 = poor and 5 = excellent.

Self-assessments of financial concepts and computer skills were based on a scale of 1 to 5, with 1 = poor and 5 = excellent.

Of the 20 graduate students who participated in the experiment, there were fourteen M.S. and six Ph.D. students. Different academic disciplinary areas included: agribusiness, international development, agricultural marketing, and agricultural finance. None of the graduate student participants indicated they had ever participated in a study of this nature. The average self-assessment rating of knowledge of financial concepts before the experiment was 2.25 and the average self-assessment rating of computer proficiency was 3.85 (Table 1).

The results of the graduate student tests are summarized in Table 1 (Panel A). The averages are the average score of all the participants out of 10 points. Overall, the scores increased for the graduate students after using the software; 17 of the 20 graduate students increased their score from the first test to the second. The average score for the first test was 4.25, and the standard deviation was 1.74. The average score for the second test was 6.65, with a standard deviation of 1.79. The minimum score on Test #1 was 0, and the maximum score was 7. On Test #2, the minimum score was 3, and the maximum score was 10.

As seen from Table 1, the average test scores for the three areas of learning also increased from the pre-test to the post-test. The average score for the calculation-based questions on the pre-test was 1.3, and the average score for the post-test was 2.35 out of three questions. The average score for the application questions was 0.8 on the first test and 1.85 on the second test out of three questions. The final area of learning, conceptual, exhibited an average first test score of 2.15 and an average second test score of 2.5.

Overall, the calculation and application questions exhibited a larger number of test participants increasing their score from the pre-test to the post-test than the conceptual questions. For the calculation questions from the first test to the second, 15 students increased their scores; and 14 students increased their scores for the application questions. However, the initial scores for the conceptual-based questions averaged over a full point higher than the average score for the application-based questions, and was almost a full point higher than the average score for the calculation questions. The conceptual-based questions also had the highest post-test average (2.5) of the three areas of learning.

Farm Producers

A random sample of 20 farm producers was used for the second experimental group. None of the farm producer test subjects were pre-selected, and their knowledge of financial concepts was unknown to the experiment administrator. Participants for the farm producer group were recruited through ag extension educators and through leads provided by faculty and students in the Department of Agricultural Economics at Purdue University. Participants for the farm producer group came from Indiana, Tennessee, and North Dakota. Each participant was given initial instructions by the test administrator to follow the instructional sheet provided on the front of the test packet.

Panel B of Table 1 reports the test score results for the farm producer group. Different academic disciplinary areas for the farm producers included agribusiness, accounting, and ag science. None of the farm producer participants indicated they had ever participated in a study of this nature. The average self-assessment rating of financial concepts before the experiment was 2.37, and the average self-assessment rating of computer proficiency was 3.11 (Table 1).

Overall, the scores increased for the farm producers, with 13 of the 20 participants increasing their score from the first test to the second, and two producers exhibiting a lower score on the second test. The average score for the first test was 3.68, and the standard deviation was 1.95. The producers' average score for the second test was 5.21, and the standard deviation was 2.02. The minimum score on Test #1 was 0, and the maximum score was 8. On Test #2, the minimum score was 2, and the maximum score was 9.

As observed from Table 1, the average test scores for the three areas of learning also increased from the pre-test to the post-test. The average score for the calculation-based questions on the pre-test was 1.50, and the average score for the post-test was 2.20. The average score for the application questions was 0.45 on the first test and 1.00 on the second test. The final area of learning, conceptual, exhibited an average first test score of 1.80 and an average second test score of 1.95. The calculation questions had 13 producers increase their score from the first test to the second. For both the application and conceptual questions, eight participants increased their scores from the first test to the second.

Statistically Significant Differences

The graduate student and farm producer test results were examined to determine if the increases in test scores from Test #1 to Test #2 are statistically significant. To test for the differences in the paired data, a sign test was employed. The sign test for the differences is a nonparametric method for determining if two columns of observations are significantly different from one another (Siegel, 2003). The sign test requires that the data set is a random sample from the population of interest and is a two-tailed test. To determine whether or not the two samples are significantly different, the sign test uses a ranking system based on a modified sample of the data. The ranks for the sign test are presented in Table 2.

Table 2. Ranks for the Sign Test

Modified Sample Size, *m*	— 10% Test Level — Sign Test Is Significant if Number Is Either: Less than	or	More than	Modified Sample Size, *m*	— 10% Test Level — Sign Test Is Significant if Number Is Either: Less than	or	More than
6	0.5		5.5	14	3.7		10.3
7	0.9		6.1	15	4.1		10.9
8	1.3		6.7	16	4.5		11.5
9	1.7		7.3	17	4.9		12.1
10	2.1		7.9	18	5.3		12.7
11	2.5		8.5	19	5.7		13.3
12	2.9		9.1	20	6.1		13.9
13	3.3		9.7				

Source: Adapted from Siegel (2003).

The procedure for the sign test is as follows (Siegel, 2003):

1. Find the modified sample size, *m*, by calculating the sum of data values that change between the first and second columns.
2. Establish the limits for *m*.
3. Count the data values that went up and compare to the limit.
4. If this count falls outside the limits, then the two samples are significantly different. If the count falls within the limits, the two samples are not significantly different.

The graduate student group consisted of 20 participants. However, the number of data values that went either up or down is 18; thus the modified sample size is 18 (Table 3). It should be noted that it does not matter if a test score increased or decreased from the first test to the second when determining the modified sample size. Because absolute values are assigned, it only matters that the scores are different. The limits for testing at the 10% level at a modified sample size of 18 are 5.3 and 12.7, as shown in Table 2. The graduate student group had 17 participants with higher overall test scores on the second compared to the first test, which indicates there is a statistically significant difference between the test scores. Thus the computer program was statistically significantly helpful in improving the participants' understanding of profitability analysis.

Sign tests were also conducted on the respective categories of questions (calculation based, conceptual based, and application based) to determine if there are differences in these areas of learning. The results are summarized in Table 3 and show there is a statistically significant increase from Test #1 to Test #2 for the calculation-based and application-based questions, but not for the conceptual-based questions. However, it should be noted that for the conceptual-based questions, the number of participants who increased their scores is close to the upper limit of 8.5.

The farm producer tests were also examined to determine if the increases in test scores from Test #1 to Test #2 are significant. The farm producer group contained 20 participants. However, the number of data values that went either up or down is 15, and thus the modified sample size is 15. The limits for testing at the 10% level at a modified sample size of 15 are 4.1 and 10.9, as shown in Table 2. The farm producer group had 13 participants with higher overall test scores on the second compared to the first test,

Table 3. Statistical Test of Differences in Test Scores: Graduate Students and Farm Producers

PANEL A. Graduate Students (n = 20)

Description	All Questions	Calculation Questions	Application Questions	Conceptual Questions
Modified sample size	18	18	16	11
10% limits [a]	5.3, 12.7	5.3, 12.7	4.5, 11.5	2.5, 8.5
Number increased	17	15	14	8
Statistical significance	Significant	Significant	Significant	Not Significant

PANEL B. Farm Producers (n = 20)

Description	All Questions	Calculation Questions	Application Questions	Conceptual Questions
Modified sample size	15	15	10	12
10% limits [a]	4.1, 10.9	4.1, 10.9	2.1, 7.9	2.9, 9.1
Number increased	13	13	8	8
Statistical significance	Significant	Significant	Significant	Not Significant

[a] These numbers are the upper and lower bounds, respectively, from Table 2 for the appropriate modified sample size.

indicating there is a statistically significant difference between the scores on the two tests for this group. As with the student group, these findings suggest the program was successful in improving the participants' understanding of profitability analysis.

Sign tests were also conducted on the respective categories of questions (calculation based, conceptual based, and application based) for the farm producers. The results, as summarized in Table 3, reveal there is again a statistically significant increase from Test #1 to Test #2 for the calculation-based and application-based questions, but not for the conceptual-based questions. But again it should be noted that for the conceptual-based questions, the number of participants who increased their scores is close to the upper limit of 9.1.

Conclusions

The modern farm business manager must function in the critically important role of general manager, understand the determinants of profitability, and have an overall long-term and strategic management focus. The objective of this research was to help producers understand the impacts of the different production, pricing, cost control, and investment decisions on their farm's financial performance. This objective was accomplished by developing a computer-based financial analysis training and application tool to facilitate determination of the financial health of farm businesses. The tool was based on the DuPont financial analysis model for assessing determinants of profitability and financial performance. The computer software is structured into two main sections: a tutorial and an analysis application. The tutorial was developed to familiarize users with the DuPont model as well as how to operate the software.

The computer-based educational tool was tested in two pre-test/post-test experiments—one with 20 graduate students and one with 20 farm producers. The financial test used for the experiments consisted of 10 multiple-choice questions divided into three areas of learning: application, calculation, and conceptual. The results of the two experiments indicate that the computer software was effective for teaching techniques of profitability analysis contained within the DuPont profitability analysis model.

Analysis of the graduate student group and the farm producer group shows the improvement associated with the overall test scores is statistically significant. Based on analysis of the categories of questions, both the graduate student and producer groups had a statistically significant improvement in test scores for the calculation- and application-based questions, but significant improvements were not found in test scores for conceptual-based questions.

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Appendix: Financial Analysis Questionnaire

Answer the following multiple-choice questions by circling the correct answer.

1. Which of the following financial data items are used in the DuPont profitability analysis model?
   (a) total assets
   (b) variable expense
   (c) interest expense
   (d) all of the above
   (e) (a) and (b) only

2. In the DuPont profitability analysis model, return on assets (ROA) can be derived directly from which of the following ratio(s)?
   (a) operating profit margin
   (b) return on equity
   (c) asset turnover ratio
   (d) all of the above
   (e) (a) and (c) only

3. Which of the following measures the return the owner of a business receives on his/her invested money?
   (a) return on equity
   (b) return on assets
   (c) operating profit margin
   (d) asset turnover ratio
   (e) none of the above

4. Which of the following measures the revenues generated per dollar invested in assets?
   (a) return on equity
   (b) return on assets
   (c) operating profit margin
   (d) asset turnover ratio
   (e) none of the above

5. Which of the following managerial strategies affect return on assets (ROA)?
   (a) decrease operating costs
   (b) increase commodity prices
   (c) lower interest costs
   (d) all of the above
   (e) (a) and (b) only

6. Which of the following managerial strategies affect return on equity (ROE)?
   (a) increase crop productivity
   (b) increase livestock efficiency
   (c) increase liabilities
   (d) all of the above
   (e) (a) and (b) only

7. Of the following managerial strategies, which will affect the asset turnover ratio?
   (a) increase commodity prices
   (b) decrease operating costs
   (c) lower interest on debt
   (d) all of the above
   (e) (a) and (b) only

8. Which of the following managerial strategies will affect the operating profit margin?
   (a) increase commodity prices
   (b) decrease operating costs
   (c) lower interest on debt
   (d) all of the above
   (e) (a) and (b) only

9. In order for borrowing to enhance the return of equity, the cost of interest per dollar of assets must be:
   (a) more than ROA
   (b) less than ROA
   (c) more than the operating profit margin
   (d) more than the asset turnover ratio
   (e) none of the above

10. What expense item is included in the calculation of ROE that is not included in the calculation of ROA?
    (a) variable expense
    (b) interest expense
    (c) fixed expense
    (d) depreciation expense
    (e) seed expense

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