RISK MANAGEMENT AND FINANCE IN AGRICULTURE

by

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(Under the Direction of Barry J. Barnett)

ABSTRACT

This dissertation consists of three studies in risk management and finance applied in agriculture. The studies address several important issues ranging from the provision and innovation of agricultural insurance to the credit risk migration in agricultural lending.

The first study proposes a temperature-humidity index insurance product and examines whether this product can effectively protect against the risk of reduced milk production caused by heat stress. Results suggest that even when premiums are loaded and the insurance purchaser is faced with both geographical and temporal basis risk, a temperature-humidity index insurance product would provide risk management benefits to a representative south-central Georgia dairy producer.

The second study compares the risk reduction performance between GRP and MPCI for cotton and soybean in Georgia and South Carolina under three premium rating schemes. Results suggest that even in agricultural heterogeneous production regions, GRP is still viable if adverse selection and moral hazard inherent in MPCI create a large positive wedge.

The third study introduces two variants of Markov chain models to analyze farm credit risk migration as alternatives to the traditional discrete time model cohort method. Results indicate that Markov chain models provide more accurate and reliable migration probability estimates by capturing indirect and transient changes in farm credit risk ratings that are omitted under the cohort method. Metric comparisons between the cohort migration matrix and each of the variant of Markov chain models are found to be much more substantial in magnitude in farm credit risk transition compared to the comparison results obtained for corporate bond ratings migration.

INDEX WORDS: Key word: index-based insurance, crop insurance, THI, GRP, risk aversion, mean-variance, expected utility, certainty equivalent, value-at-risk, credit risk migration, cohort method, Markov chain, transition probability

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DEDICATION

This dissertation is dedicated to three most important people in my life. To my mother, Houlan Wang, for her unselfish and endless love and for being the wonderful model in my life by which I strive to pattern my life. To my father, Yanjun Deng, for his guidance, encouragement and confidence in me all the time. You brought me to this world, being my initial teachers, and you are always my light in my life. I am deeply indebted. Finally, to my dear husband, Yingzhuo Yu, for his unwavering love and generous support throughout this endeavor and throughout our lives. You are my soul-mate. Wherever I go, I know for sure that you are always beside.

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CHAPTER 1

INTRODUCTION

1.1 Background

Agricultural production has always been a risky endeavor. Farmers constantly have to deal with unfavorable weather conditions, variability in prices of inputs and outputs, livestock disease outbreaks, etc. These risks will in turn affect their ability of loan payment. Thus, lending institutions are less willing to provide loans to farmers, since the probability of default is very high. For a long time U.S. policy makers have been concerned with helping farmers to manage agricultural production risk through insurance institutions. Reduction in agricultural production risk not only benefits farmers but also, in turn, lending institutions. Meanwhile, lending institutions have been studying and developing financial models to accurately estimate the credit risk from farm borrowers.

U.S. government involvement in the provision of crop insurance goes back to the 1930s. Title V of the Agricultural Adjustment Act of 1938 established the Federal Crop Insurance Corporation (FCIC) to provide crop farmers with Multiple Peril Crop Insurance (MPCI) policies that protect against individual farm yield losses. The first policies were written for wheat production in 1939. The program's actuarial performance later, however, proved disappointing. The program was actually terminated in 1943 and then resurrected in 1945 (Kramer).

The major reforms in Federal Crop Insurance started from the Federal Crop Insurance Act of 1980 which provided for nationwide expansion of a comprehensive crop insurance plan. The Act authorized the FCIC to extend the insurance to all commercial crops in all agricultural counties and permitted the federal government to subsidize farmer premium payments. The Federal Agricultural Improvement and Reform Act of 1994 modified the Federal Crop Insurance Program by authorizing a premium - free new Catastrophic (CAT) coverage level available to farmers. The Act also created the Noninsured Assistance Program (NAP), a permanent disaster payment program for crops not covered by crop insurance.[1] The Federal Agricultural Improvement and Reform (FAIR) Act of 1996 required the Secretary of Agriculture to establish an independent office, which is now the Risk Management Agency (RMA), for supervision of the FCIC. The FAIR Act implemented farm program contract payments that do not increase as agricultural prices fall, shifting farm policy toward a greater emphasis on risk management and, in particular, on crop insurance. This shift has resulted in the introduction of new types of insurance policies; especially those that provide both yield and price protection (Harwood and Novak). The Agricultural Risk Protection (ARPA) Act of 2000 essentially maintains the same structure of subsidies that was largely put in place during the last century. It increased crop insurance premium subsidies substantially and changed them on coverage levels above 65 percent from a per-acre dollar amount to a percent of premium. Different percent subsidies are applied to different coverage levels, with subsidy percentages decreasing with the increase in coverage levels (Babcock, Hart and Hayes).

Credit risk migration analysis helps track an individual's historical risk rating from one category to another within a given period of time. Credit risk migration, per se, has received a great deal of academic attention especially in corporate finance. Numerous studies have examined how credit ratings assigned to bonds and other publicly traded securities by rating agencies such as Moody's and Standard & Poor's transition over time. Compared to the

[1] Source: http://www.usda.gov/news/releases/1999/02/crop

traditional measurement of historic loan default rate, the credit risk estimates obtained from the migration approach provide richer, broader information on the risk stability and quality of a lender's loan portfolio, especially when based on more extensive historical data (Katchova and Barry).

Deriving transition probabilities is a natural use of the output of an institutional risk rating system. These systems are widely used by lending institutions, and in the future will form the basis for credit risk measurement in determining the regulatory requirements for economic capital held by many banks and other types of financial institutions (Basel Committee on Banking Supervision). However, similar to estimating the traditional default rates, the migration approach utilizes extensive historical data. Such data histories are seldom available. Actually one major reason that credit risk migration analysis is relatively unexplored in agricultural lending is mostly due to the limitation arising from the proprietary nature of the data. The small portfolios and thus sample size for many lenders, and the tendency for the lenders to change their rating system and approaches over time hinder the analysis of credit risk migration in agricultural lending (Gloy, LaDue, and Gunderson).

In addition, agricultural lending has several unique characteristics compared to other types of lending in corporate finance. Agriculture has a lengthy production cycle, which often leads to less frequent, seasonal payments of loans (Barry). Agriculture is also capital intensive with 87% of the total assets consisting of farm real estate and machinery.[2] In addition, financial performance of farms can be highly correlated, especially for farms in the same geographic and climatic region. Because financial institutions, especially agricultural lenders, usually do not hold random portfolios of loans, geographic and industry correlations lead to higher correlations in default and losses (Bliss).

[2] Source: USDA statistics for 2002.

1.2 Problem Statement

Since the mid-1980s, MPCI yield guarantees have been based on the actual production history (APH) yield for the insured unit.[3] In recent years, various APH-based revenue insurance products have also been offered through the FCIP.[4] For 2004, APH-based insurance products (MPCI and the various APH-based revenue insurance products) accounted for over 90% of FCIP premiums. Several studies have described how APH-based insurance products are subject to misclassification (adverse selection) and moral hazard problems (Quiggin, Karaginannis, and Stanton; Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). In addition, APH-based insurance products have high transaction costs related to establishing and verifying APH yields and conducting on-farm loss adjustment.

Missclassification and moral hazard problem create a "wedge" between the premium cost and the expected indemnity for insureds (Wang, Hanson, and Black). Missclassification can cause either positive or negative wedges. In some cases, insureds will be misclassified to their detriment so that they face a premium cost that exceeds the expected indemnity (positive wedge). In other cases, insureds may be misclassified to their benefit (negative wedge). Moral hazard problems always create positive wedges. Federal premium subsidies increase participation in the FCIP by masking the impact of positive wedges (Wang, Hanson, and Black). However, some potential insureds face positive wedges that more than offset the federal premium subsidy. Thus, despite significant federal premium subsidies, APH-based insurance products can still have a negative expected value for many potential insureds (Skees 2001).

Skees said "Government-subsidized agricultural insurance is costly, complex, and leads to potentially significant inefficiencies. If efficiency is a performance goal, there are no

[3] The APH yield is a rolling 4-10 year average of realized yields on the insured unit.
[4] APH-based revenue insurance products are generally offered only for crops with exchange-traded futures contracts. Indemnities are triggered by the product of farm-level yield losses and a price index based on futures market prices.

successful experiences with government supported farm-level crop insurance in the world." (Skees 2000).

Premium subsidies, a prominent feature of the U.S. crop insurance program since the early 1980s, have increased recently, lowering the cost of crop yield and revenue insurance coverage to producers. ARPA 2000 set APH-based crop insurance products subsidy percentages that depend on the coverage level as follows: 59 percent subsidy for coverage levels of 65 and 70 percent; 55 percent subsidy for coverage levels of 75 percent; 48 percent for 80 percent coverage; and 38 percent for 85 percent coverage. This setup has two implications. First, the move of premium subsidy from per-acre base to a constant subsidy rate for a given coverage will make the subsidy per-acre vary, and likely increase, thus increasing the incentives for participation especially at higher coverage levels. Second, the decline in percentage of the premium subsidy is generally less than the increase in the dollar amount of insurance premium. Thus per-acre subsidies in dollars so increase as coverage levels increase. The total effect of the new premium subsidy setup encourages farmer to purchase higher coverage levels (Babcock, Hart and Hayes).

While increase in premium subsidy rates reduce producers' costs and increase participation, it also greatly increases the government expenditure. As producers have moved to higher coverage levels and to products with higher premiums, subsidies have increased both as a total dollar amount and a proportion of total premium.

At the proportional level, between crop years 1995 and 1998, premium subsidies rates were constant and accounted for 50 to 57 percent of total premium. At the total dollar amount level, in 1995, the first year after enactment of the crop insurance reform that introduced CAT coverage (premium entirely subsidized), premium subsidy expenditures were about $890 million. In 1996, as the increased buy-up participation and increased crop prices lifted total premium, the annual premium subsidy amount rose to $980 million even though CAT participation declined. In 1997, premium subsidies decreased to about $900 million as crop prices fell and as CAT participation continued to decline while buy-up participation held constant. In 1998, total premium subsidies increased with a rise in buy-up insured acres (Agricultural Outlook).

Regarding credit risk migration analysis, although there are numerous studies in corporate finance, they usually employ a straightforward discrete time (cohort) approach in developing migration matrices, which has even become an "industry standard" approach used even by the large corporate rating agencies (Lando and Skodeberg; Schuermann and Jafry). Cohort method is straightforward and easy to apply. However, this approach ignores any rating change activity within sub-periods of a given time frame and focuses only on migrations observed at the two time endpoints (i.e. the beginning and the end of a time period). The omission of "transient" class migrations in-between the endpoints might reduce the reliability of the cohort approach in consistently producing accurate and efficient estimates of migration rates.

There have been relatively few studies of agricultural loan credit risk migration, although anticipating changes in credit risk is crucial to a lender's financial performance. Lenders incur substantial costs monitoring credit risk. The loan servicing costs associated with high risk borrowers have been estimated at nearly 100 basis points (Gloy, Gunderson, and LaDue). If changes in a borrower's credit risk are identified early, the lender can protect his/her interest, address the situation with the borrower's management, and probably avoid the costs incurred by the default. Anticipating credit risk changes also allows the lender to direct scarce monitoring resources to the loans that are the most likely to transit to a higher credit risk category.

1.3 Rationale

High subsidized crop insurance products transfer the cost from agricultural producers to taxpayers, an expensive drain on public purse. Moreover, subsidized insurance can lead to distorted production incentives due to asymmetric information via moral hazard and adverse selection.

In the late 20 century, more and more prudent researchers notice the problems associated with the high subsidized farm-level yield insurance products. They diligently probe and propose innovative agricultural insurance designs to correct the problems. Among the innovations being widely discussed are area yield and weather index insurance products, which belong to the family of index insurance products.

These innovations can ameliorate the asymmetric information problems because the underlying indexes are transparent, objective, and reliable based on long time series of historical data. Any individual subjective action can hardly affect the trigger level for indemnity payment since the indemnity payment depends on an index related to the risk being hedged rather than the risk itself.

Area yield insurance is essentially a put option on an *index*, the expected area yield. For the current implemented area yield insurance in U.S., the Group Risk Plan (GRP) and area revenue insurance, Group Risk Income Protection (GRIP), the area is defined by county boundaries. Indemnities are triggered only when the county yields or revenues are below a preset critical yield or threshold.

Weather index insurance is designed to insure specific event which causes the result, say "crop deficit" rather than the result itself. Obviously this implies that crop yield loss does not need to be proven in order to receive indemnity from an insured specific event (Turvey).

Applications of weather derivatives[5] originated in the energy sector. In late '90s firms explored the possibility of hedging against weather-related variability though weather derivatives. The impetus for developing weather markets was stimulated by the deregulation of the US energy sector, when local monopolies had to start competing on broader markets and find measures to stabilize fluctuating revenues. Since early 1997, market participants in the electricity and natural gas sectors have used temperature-based derivatives to offset their exposure to extreme temperatures. Tailored over-the-counter contracts are based on a specified temperature index such as cumulative heating degree days (HDD) or cumulative cooling degree days (CDD) for a given location over a given period of time. In September 1999, the Chicago Mercantile Exchange began trading standardized monthly cumulative HDD and CDD futures and options contracts. Contracts were originally traded for Atlanta, Chicago, Cincinnati, Dallas, Des Moines, Las Vegas, New York, Philadelphia, Portland, and Tucson[6].

Applications of weather derivatives in the energy sector are logically extended to agricultural sectors since weather events are still a major source of economic risk for agricultural production. In order to develop weather derivatives for agriculture, just as weather derivatives for energy sectors, the weather variables need to be measurable, adequate, objective, transparent, reliable and easily assessable with relatively low less cost. In addition, the existence of a complex relationship between the agricultural product and the weather factor must be carefully explored (Vedenov and Barnett). This normally does not happen in energy sectors. For instance, the relationship between temperature and demand for heating is simple and straightforward: the lower the HDD the lower the demand for energy. In agricultural production the relationship is

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[5] Weather index insurance and weather derivative are conceptually equivalent. However, they are sold though different conduits. Weather derivative is sold through financial exchanges and weather index insurance is sold though insurance channels.

[6] Source: http://www.financewise.com/public/edit/energy/weather99/wthr99-exchangep.htm. retrieved in March 2005.

more complicated since differences in products, crop growth and development stages, and soil texture among others have different responses to the same weather factor. In addition, the more skilled and advanced cultivating techniques and the greater entrepreneurial influence on yields make the proportion of production variability generated by the specific weather elements smaller. Generally speaking, the development of weather derivatives in agricultural production is not restricted by the availability of the data since most developed and developing countries have extensive and reliable weather records. The crucial issue for the application of weather derivatives in agriculture lies in the actual presence of a clear and reliable relationship between the weather factor and the agricultural production variable. The designed weather derivatives need to explain a large proportion of the variation in production; otherwise they lose their attractiveness as a hedging device. Hence, appropriate identification of the relationship between the weather variables and production is vital (Stoppa and Hess).

Regarding credit risk migration analysis, several studies in corporate finance have adopted a duration "Markov chain" approach based on survival analysis to address the deficiency of the cohort method (Lando and Skodeberg; Israel, Rosenthal, and Wei). The Markov chain approach has been used to capture intra-year risk-rating changes to calculate annualized migration rates, which are then averaged across time periods to construct an overall (summary) migration matrix. Formal ratings and re-ratings generally occur annually even though true changes in risk occur more frequently. The intra-year bond migration rates help to fill this information gap.

In farm finance where farmers do not maintain records of intra-year changes in financial conditions, the Markov chain approach could be applied to the treatment of annualized migration rates in constructing the migration matrix for each time period. This modification is relevant considering that actual credit risk transition assessment practices by farm lenders usually lean toward averaging of multi-year financial ratios and measures (Novak and LaDue). For instance, one such method acknowledged by lenders is the 3x1 method which measures the transition from a credit rating based on the average financial performance during the first 3 years to the risk rating given to the borrower on the 4th year (Barry, Escalante, and Ellinger).

The practical relevance of introducing the alternative Markov chain models for farm credit risk migration analysis is established through the following arguments. First, while annual data are generally used in the re-rating process, a lender's monitoring of a borrower's performance can reveal likely changes in farmers' risk positions during the year, i.e. marking risk to changes in growing and/or market conditions, especially for higher risk borrowers. Thus, subjective transitions may occur much more frequently, and the Markov process helps in quantifying such movements. Second, our study's results will show that multi-year averaging of annualized financial data and the discrete-time (cohort) framework used in developing the summary migration matrix will result in the significant understatement of transition probability rates. Thirdly, such probability estimates would, in turn, produce understated, if not misleading, estimates of overall portfolio default probability rates, which is one of several loan portfolio quality indicators that lenders could generate from the migration framework (Katchova and Barry). Finally, our statistical test results indicate that distinctions between cohort and Markov chain matrices are even more pronounced when applied to farm finance conditions than when applied in corporate bond analysis.

1.4 Objectives

This dissertation is composed of three related studies in risk management and finance in agriculture. The primary objective is to seek ways to reduce production risk or credit risk for the relevant parties, being producers or lending agencies. The specific objectives are, however, more pertinent to each separate studies. The three studies are (1) Using Weather-Based Index Insurance to Protect against Dairy Production Losses Caused by Heat Stress; (2) Testing the Viability of Area Yield Insurance for Cotton and Soybeans in the Southeast; and (3) Markov Chain Models for Farm Credit Risk Migration.

The first study proposes a temperature-humidity index (THI) insurance product and examines whether this product can effectively protect against the risk of reduced milk production caused by heat stress. Specifically, it: (1) develops a THI insurance product to protect against milk production risk faced by dairy producers in south-central Georgia; (2) prices the THI insurance product; and (3) assesses the risk reduction impacts of the THI insurance product for a representative Georgia dairy farm.

The second study compares farm-level risk reduction from MPCI with that from an area yield insurance product like GRP for selected South Carolina cotton and soybean production regions and Georgia cotton production regions. Specifically, it: (1) constructs the restricted optimal and optimal GRP and MPCI with three coverage levels under three different premium rating schemes; (2) assesses the viability of GRP relative to MPCI under the expected utility framework.

The third study proposes Markov chain models for farm credit risk migration using farm-level financial data from the Illinois Farm Business and Farm Management System. Specifically, it: (1) tests the validity of Markov chain assumption for the farm credit migration data set; (2) estimates the credit migration rates and portfolio default probabilities under cohort and markov chain models using the 2x1 measurement method the farm lenders' 3x1 method ; and (3) assesses the reliability of estimates under Markov chain models.

1.5 Organization

The dissertation consists of five chapters. Chapter 1 reviewed the history of the Federal Crop Insurance Program and the associated problems inherent in the current APH-based insurance products. It also provided some background on farm credit risk migration. The rationale of the study and objectives were also presented. Chapter 2 offers a general overview of the literature on current federal insurance products including APH-based insurance and index insurance products, and credit risk migration on farm lending. Chapter 3 focuses on the theory of economic decision-making under conditions of uncertainty. It reviews different risk measurements and decision making criteria. Chapter 4, 5, and 6, are dedicated for the specific analysis on each separate study. Each of the three chapters is independently presented as an integrated essay. Chapter 7 finally summarizes the results and offers some concluding remarks.

CHAPTER 2

LITERATURE REVIEW

2.1 Review on Current Major Implemented Crop Insurance Products

The Federal Crop Insurance Program came into existence in 1938. The first insurance policy was written for wheat in 1939. Since then the Federal Crop Insurance Program has experienced a great change, termination due to disappointing performance, and passage of new authorizing legislation. The Federal Crop Insurance Act of 1980 initiated significant changes in the scope, delivery and purpose of the Federal Crop Insurance Program. Later, the Federal Agricultural Improvement and Reform Act of 1994 and 1996, and Agricultural Risk Protection Act of 2000 strengthened the safety net for agricultural producers by providing more affordable risk management tools and products.

Currently the U.S. crop insurance products can be defined by two determinants: (1) What is insured – yield, price, or revenue; (2) What is the insured yield based on – APH-based or index-based? The summary of different major insurance products is presented in Table 2.1.

<u>APH-Based Insurance Products</u>

APH-based or farm-level insurance products provide risk protection against shortfalls in production or revenue occurring at the insured farm due to various weather or market causes.

Multiple Peril Crop Insurance (MPCI) is based on the Actual Production History (APH) which is reported by the insured. It is a farm-level yield insurance product. It insures producers against yield losses due to natural causes such as drought, excessive moisture, hail, wind, frost, insects, and disease. The farmer decides the target yield he/she wishes to insure from 50 to 75 percent (in some areas 85 percent of the APH). The farmer also can select the percent of the predicted price he/she wants to insure between 55 and 100 percent of the crop price established annually by RMA. The farmer is paid an indemnity based on the shortfall of the realized yield relative to the target yield. Indemnities are calculated by multiplying this shortfall by the insured percentage of the established price selected when crop insurance was purchased (RMA online).

Catastrophic Coverage (CAT) pays 55 percent of the established price of the commodity on crop losses in excess of 50 percent. The premium on CAT coverage is paid by the Federal Government; however, producers must pay a $100 administrative fee for each crop insured in each county. Limited-resource farmers may have this fee waived. CAT coverage is not available on all types of policies (Knight and Coble; RMA online). If farmers buy higher levels of coverage, the federal government will subsidize a portion of the premium. While MPCI covers most crops in the U.S., it is not available for some specific crops in specific regions. For those crops, the Noninsured Crop Disaster Assistance Program (NAP), managed by USDA's Farm Service Agency, provides financial assistance to producers of noninsurable crops when low yields, loss of inventory, or prevented planting occurs due to natural disasters (RMA online). Producers must enroll acreage prior to planting and area average yield must be reduced by at least 35% before any payments are made to individuals (Knight and Coble).

Income Protection (IP) was developed by the Federal Crop Insurance Corporation (FCIC), under the USDA, as a pilot program in 1996. IP protects producers against reductions in gross income when either price or yield declines from early-season expectations. The target revenue or revenue guarantee of IP is equal to APH yield times a base price times a coverage level. Base prices are calculated using futures contracts[7] in early season before harvest (RMA online; Edward and Hofstrand).

Crop Revenue Coverage (CRC) was developed by American Agrisurance, Inc. and was approved by FCIC as a pilot program in 1996. The revenue guarantee of CRC equals the APH yield, times the higher of the base price or harvest price, times the coverage level. Harvest prices are calculated using futures contracts after harvest to reflect market conditions during harvest[8] (RMA online; Edward and Hofstrand).

Revenue Assurance (RA) was developed by the Iowa Farm Bureau and approved by the FCIC as a pilot program in 1997. RA policies have two distinct options: Revenue Assurance-Base Price (RA-BP) and Revenue Assurance-Harvest Price (RA-HP). RA-BP contracts are written in a manner similar to IP, in which the level of the revenue guarantee is determined solely by the February futures prices, and does not increase even if the futures price rises by harvest. The difference between IP and RA-BP is that IP only allows enterprise units while RA-BP allows basic, optional, enterprise, and whole farm units. The producer may elect to purchase RA insurance with the harvest price (HP) option (RA-HP), under which the revenue guarantee does increase if the harvest price is higher than the February price, just as it does under CRC. The differences are: (1) CRC can be used to insure basic, optional, and enterprise units while RA-HP has these units along with a whole farm unit. (2) Under CRC, there are price increase

[7] For example, Chicago Board of Trade futures contracts are used for CRC contracts for corn and soybeans. For corn, the base price equals the average of settlement prices of the December corn contract during the month of February. For soybeans, the base price equals the average of settlement prices of November soybean contract during the month of February. Base prices are released in early March prior to the deadline for purchasing crop insurance.

[8] For example, for corn, the settlement prices for the December contract from CBOT are averaged during October. For soybeans, the settlement prices for the November contract are averaged during October.

limits when updating the revenue guarantee[9]. RA-HP does not have limits (RMA online; Edward and Hofstrand).

Index-Based Insurance Products

Group Risk Plan (GRP) is a type of index insurance product. It uses a county index, county yield, as the base for determining a loss. When the county yield for the insured crop, as determined by the National Agricultural Statistics Service (NASS)[10], falls below the trigger level chosen by the insured farmer, an indemnity is paid. GRP coverage is available for many primary crops in major production areas thought the United States (Skees, Black, and Barnett). Coverage levels are available from 70 percent up to 90 percent of the expected county yield with 5 percent increment (RMA online). GRP protection involves less paperwork and costs less than the farm-level coverage described above. However, since payments are based on the county yield loss not the individual farmer's loss, individual crop losses may not be covered if the county yield does not suffer a similar level of loss. This raises the problem of basis risk.

Gross Risk Income Protection (GRIP), like GRP, is another index insurance plan. It makes indemnity payments only when the average county revenue for the insured crop falls below the revenue chosen by the farmer. The coverage for the county yield can be selected between 70 percent and 90 percent with 5 percent increment. The amount of payment the farmer receives depends on the level of protection selected when the farm is enrolled. The value of protection can be as high as 90 percent of the RMA maximum protection level and as low as 60 percent. For GRIP the maximum protection level is the average futures prices for the five business days prior to March 1, multiplied by the expected county yield (RMA online; Edward and Hofstrand).

[9] For instance, the limits are $1.50 for corn and $3.00 for soybean.
[10] NASS releases county yields in March of the year following harvest.

2.2 Comparison between APH-Based Insurance and Index-Based Insurance

MPCI, IP, CRC, and RA are APH-based insurance products since the yield guarantee is based on farm-level yield (APH); GRP and GRIP are index-based insurance products since the yield guarantee is based on an index, county-level yield.

Since APH-based insurance products, such as MPCI, provide crop producers with protection against many natural causes risk, what is the incentive and where is the market for purchasing index-based insurance products?

Index-based insurance products have several advantages relative to APH-based insurance products. The major advantage is that index-based insurance products are not susceptible to the common insurance problems of moral hazard and averse selection due to asymmetric information.

Moral hazard occurs when, because they have purchased insurance, policyholders change their behavior in such a way that the frequency and/or severity of a loss are increased. Policyholders intend to forego good management after purchasing farm-level yield insurance since losses will be covered by the insurance. Since moral hazard increases the frequency and/or severity of loss for the policyholder, the insurer's exposure to risk is increased. In the short run, the indemnity payment will be higher than anticipated when premium rates were established. Over time, the insurer will respond by increasing premium rates for all policyholders. This does not correct the moral hazard but exacerbates the problem. Those who are not engaged in moral hazard may choose to quit purchasing insurance rather than pay the higher premium rate. As premiums are ratcheted up over time, those engaged in moral hazard are more and more disproportionately represented in the pool of insurance purchasers. In the extreme case, only those who intend to engage in moral hazard will purchase insurance at a very high premium rate (Barnett 2004).

Adverse selection occurs when the insurer can not accurately classify potential policyholders according to their risk exposure. As a result of the risk exposure heterogeneity, potential policyholders who have been misclassified to lower risk exposure, but actually belong to higher risk exposure, are more likely to purchase insurance; while potential policyholders who have been misclassified to higher risk exposure, but actually belong to lower risk exposure, are less likely to purchase insurance. Barnett (2004) names the former "misclassified to their benefit" and the latter "misclassified to their detriment". Since the pool of insurance purchasers is disproportionately composed of those who are misclassified to their benefit, indemnities are higher than anticipated when premium rates were established. Over time, the insurer will respond by increasing premium rates for all policyholders. This again does not correct the problem but makes it worse. Each successive increase in premium rate will result in the insurance pool more and more disproportionately composed of those misclassified to their benefit. In the extreme case, only those who are misclassified to their benefit will purchase insurance at a very high premium rate (Barnett 2004).

A number of studies have identified moral hazard and/or adverse selection problems in the APH-based insurance products offered by FCIP. (Skees and Reed; Quiggin, Karaginannis, and Stanton; Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). These problems have led to higher premium rates, though often masked by federal premium subsidy, and inequities in program benefits (Skees 2001; Glauber and Collins).

Index-based insurance products, however, are not susceptible to moral hazard and adverse selection. On the one hand, the indemnity payments are based on an index over which the policyholders have no control, so the moral hazard problem is solved since the policyholders are not able to change their behavior to affect the frequency and/or severity of the loss. On the other hand, the policyholders have no better information about the index than the insurer. Their risk exposures to the index are more homogeneous and easily classified, so the adverse selection problem is solved.

In addition, index-based insurance products take advantage of objective and long data series. In practice, it is extremely difficult to verify the accuracy of the farm-level yield data which are reported by the potential policyholders. Even if they are accurately reported, it is hard to estimate the true expected yield based only on limited (often four to ten years) historical yield data. Barnett et al. demonstrated the potential for error in MPCI estimates of expected yield based on a representative corn farm. Index-based insurance products, however, are typically easily accessible, transparent, and verifiable. For example, the estimate of expected county yield used in GRP is based on at least 45 years of publicly accessible NASS county yield data. Using long series of data greatly reduces the potential of overestimating or underestimating the true expected value. Less volatility of the county yields also ensures the result of more accurate estimate of the true expected value than farm-level yield. Other benefits of index insurance products include no need for farm-level loss adjustment and lower transaction costs (Barnett 2004).

While index-based insurance products have many advantages over the APH-based insurance products, they also have one extremely important limitation named as basis risk.

Basis Risk in futures market reflects the difference between the prices in the futures market and the spot market. For index-based insurance products, basis reflects the difference between the realized index and the farm-level yield. Because farm-level yields are not perfectly correlated with the insured index, purchasers of index-based insurance are exposed to some degree of basis risk. For instance, it is possible for the purchaser of an area yield insurance policy to experience production losses on his/her farm and yet not receive an indemnity because there has been no shortfall in the area average yield. Similarly, it is possible for a policyholder to receive an indemnity on an area yield insurance policy when no farm-level losses have occurred. Basis risk on area yield insurance policies is generally lower (higher) the more homogeneous (heterogeneous) the production area (Barnett et al.). Variability in elevation, soil type, drainage, and other relevant factors will cause farm-level yields to be less correlated with the area average yield (Chaffin and Black). Thus the advantage of using index insurance products could be dwarfed by high basis risk.

2.3 Literature Reviews on Index-Based Insurance Products

In 1920, Chakravati proposed an area yield insurance program for India. Independently, Halcrow, in 1949, suggested an area yield insurance design for the United States. These proposals were largely ignored until 1990 when Barnaby and Skees presented arguments for area yield insurance and described how such a program might operate. In 1991, Miranda formalized these earlier ideas into a theoretical framework for evaluating the effectiveness and equity of area yield crop insurance. Specifically, Miranda showed that if $\tilde{y}_i$ is projected orthogonally onto $\tilde{y}$ then

$$\tilde{y}_i - \mu_i = \beta_i(\tilde{y} - \mu) + \tilde{\varepsilon}_i$$

(2.1)

where $\tilde{y}_i$ is the realization of the stochastic yield on farm *i* with $E(\tilde{y}_i) = \mu_i$, $\tilde{y}$ is the realization of the stochastic county yield with $\mu = E(\tilde{y})$. This implies that

$$\beta_i = \frac{\mathrm{cov}(\tilde{y}_i, \tilde{y})}{\mathrm{var}(\tilde{y})} \tag{2.2}$$

which is consistent with the notion of β in the capital asset pricing model (CAPM).

In his empirical analysis, Miranda compared farm-level yield insurance (such as MPCI) with area yield insurance for 102 soybean farms in western Kentucky.[11] As with all analyses published to date, Miranda's analysis was constructed such that both the farm-level yield insurance and area yield insurance contracts were actuarially fair in sample. This allows one to evaluate the relative performance of the contracts by considering only reductions in the variability of net yield.

Miranda defined a "full coverage" area yield insurance contract as having *coverage* set at 88.5% and *scale* set at 100%. An "optimal coverage" contract was defined as having *coverage* set at 95% and *scale* optimized to minimize the variance of net yield. On average, the purchase of "optimal coverage" area yield insurance reduced the variance of net yield more than the purchase of farm-level yield insurance. However, the "full coverage" area yield insurance contract did not reduce the variance of net yield as much as the farm-level yield insurance contract.

Smith, Chouinard, and Baquet compared farm-level yield insurance to three different area yield insurance contracts for a sample of 123 dryland wheat farms in Chouteau County, Montana. The first area yield insurance contract had *coverage* restricted between 70% and 90%, and *scale* between 90% and 150% as in GRP. The second contract, which they called "almost ideal," had *scale* restricted to 100% while *coverage* was optimized to minimize the variance of net yield. The third area yield insurance contract, which they called "ideal," optimized both *coverage* and

[11] With the exception of Barnett et al., all of the articles reviewed here compared MPCI with the standard area-yield insurance contract (without a disappearing deductible) described in Miranda (1991) rather than with the actual GRP contract.

scale to minimize the variance of net yield. They found that even the contract with restricted *coverage* and *scale* reduced net yield variability more than a farm-level yield insurance contract with 75% *coverage*. The "almost ideal" contract reduced net yield variability almost as much as a farm-level yield insurance contract with 90% *coverage*. The "ideal" area yield insurance contract reduced net yield variability only slightly more than the "almost ideal" contract but at significantly higher premium cost.

Barnett et al. analyzed the viability of area-yield insurance for 66,686 corn farms in 10 states (Indiana, Illinois, Iowa, Kansas, Kentucky, Michigan, Minnesota, Nebraska, Ohio, and Texas) and 3,152 sugar beet farms in North Dakota and Minnesota. They compared the performance of farm-level yield insurance at 65%, 75%, and 85% *coverage* with three different area yield insurance contracts. The first area yield insurance contract had *coverage* set at 90% and *scale* at 100%. The second contract had *coverage* restricted between 70% and 90%, and *scale* between 90% and 150% as in GRP. The third contract had *coverage* restricted between 70% and 130% while *scale* was restricted only to be nonnegative. For the second and third area yield insurance contracts, optimal values for *coverage* and *scale* were calculated across all farms in the state. These optimal values were then applied to all farms in the state. In reality, each individual farmer would presumably attempt to optimize *coverage* and *scale* for his/her farm. However, given the relatively short time-series of available farm-level yield data, Barnett et al. decided that farm-level in sample optimizations of *coverage* and *scale* would be unrealistically favorable to area yield insurance. They argue that optimizing these choice variables at the state level provides a more conservative estimate of the risk reduction generated by area yield insurance.

For corn Barnett et al. found that their first contract (*coverage* set at 90% and *scale* at 100%) provided more risk reduction than farm-level yield insurance with 65% *coverage* for all states except Nebraska, Texas, and Michigan. Their second contract (*coverage* restricted between 70% and 90%, and *scale* between 90% and 150%) provided more risk reduction than farm-level yield insurance with 65% *coverage* for all states except Nebraska and Michigan and more risk reduction than farm-level yield insurance with 75% *coverage* in Illinois, Indiana, Iowa, Kentucky, Minnesota, and Ohio. Their third contract (*coverage* restricted between 70% and 130% and *scale* restricted only to be nonnegative) provided more risk reduction than farm-level yield insurance with 65% *coverage* for all states except Michigan, more risk reduction than farm-level yield insurance with 75% *coverage* in all states except Texas and Michigan, and more risk reduction than farm-level yield insurance with 85% *coverage* in Illinois, Iowa, Kentucky, and Ohio.

The analysis of area yield insurance for sugar beets was segregated by processors rather than by state. For farmers who produced for the Southern Minn cooperative in southwestern Minnesota, all three area yield insurance contracts provided more risk reduction than farm-level yield insurance with 75% *coverage*. The third contract provided more risk reduction than farm-level yield insurance with 85% *coverage*. For farmers who produced for American Crystal in the mid- and northern Red River Valley, all three area yield insurance contracts generated more risk reduction than farm-level yield insurance with 65% *coverage*. Only the third contract generated more risk reduction than farm-level yield insurance with 75% *coverage*. None of the contracts generated as much risk reduction as farm-level yield insurance with 85% *coverage*. For farmers who produced for the Min-Dak cooperative in the southern Red River Valley, none of the area yield insurance contracts generated as much risk reduction as farm-level yield insurance with

65% *coverage*. Barnett et al. attribute differences in the performance of area yield insurance across geographic regions to differences in the extent of heterogeneity of soil productivity, drainage, and other production factors.

In the turn of the new millennium there are increasing interests and discussions about applying weather index insurance products to protect against weather-related agricultural production losses. A number of studies have investigated the potential agricultural applications of weather index insurance.

Martin, Barnett and Coble found that precipitation index insurance could provide effective protection against cotton yield and quality losses due to excess late-season precipitation in the delta region of Mississippi. Turvey examined the economics and pricing of weather index insurance in Ontario and suggested that temperature- and precipitation-based insurance contracts could be used to insure against yield losses for some crops. Vedenov and Barnett investigated the feasibility of using weather index insurance to protect against shortfalls in corn and soybean yields in Iowa and Illinois and cotton yields in Mississippi and Georgia. Their findings were mixed causing them to caution against "blanket assessments" of the feasibility of weather index insurance in agricultural applications. Cao examined the feasibility of weather insurance for corn in Georgia and she found that the ability of weather insurance to reduce yield loss risk for farmers in Georgia is limited.

There are also some pilot programs using weather index insurance to provide risk protection in agricultural production. AGROASEMEX, the state agricultural reinsurance company in Mexico has used weather index contracts to transfer part of its weather-related crop insurance risk into international capital markets. AGRICORP, the state agricultural insurance corporation in Canada offered Forage Pilot Program in Ontario in 2002 to protect the forage loss due to drought. Under the Forage Pilot Program, indemnities were triggered once the rainfall measured from May through August is less than 80% of the long-term average for the area. The pilot program turned out to be very successful in promoting the participation rates and matured to a normal insurance product in 2003/2004.

The World Bank in recent years has been leading studies and pilot programs, in collaboration with the International Food Research Institute, several universities and private consulting firms, to explore the feasibility and applicability of weather index insurance in developing countries. Current participating counties include Ethiopia, Morocco, Nicaragua, Tunisia, Argentina, and Mongolia. There are various reasons why most weather index insurance pilot programs are initiated and tested in developing counties. First, agricultural production in developing countries is highly, if not completely, tied with the weather-related conditions. It is more vulnerable to bad weather. Moreover, most developing countries are not climatic and/or geographically diversified. Thus weather-related yield losses are usually systemic. Second, in developing countries, weather data is of high quality and easier to obtain than area yield data. It may be less expensive to set up a weather system to measure weather events than set up a procedure to estimate the area yield. Third, developing counties have limited fiscal resources. In many developed countries, the U.S. for example, agricultural production is highly subsidized. The opportunity cost of transferring those limited fiscal resources to agricultural production may be significantly greater in developing countries. Finally, developing countries have far less access to the global risk-sharing markets and lack enforcement and the institutional regulatory environment to attract outside capital inflow.

Most current weather index insurance pilot programs in developing counties are promising. For example, Skees et al. tracked the rainfall-yield relationship by assigning specific weights to different growth phase, taking into account that different growth stages need different water. They found that a rainfall index insurance scheme could be feasible in Morocco.

2.4 Literature Review on Farm Credit Risk Migration

Credit migration analysis is still a relatively unexplored concept in agricultural lending. One of the major causes that limit its exploration is due to the lack of proper extensive historical data. However, a number of farm lenders, such as the Farm Credit System institutions, are compiling the data needed to use migration as a tool for analyzing their loan portfolios although their data histories tend to be shorter at less than five years in length and the updating of the borrower's financial data can be sporadic.

Barry, Escalante, and Ellinger estimated credit ratings from a farm record-keeping association – Illinois Farm Business and Farm Management system – which provided longitudinal farm-level financial data. They also introduced the measurement of transition probability matrices and financial stress rates for farm businesses using several time horizons and credit risk classification variables. Their study demonstrated the practical relevance of the migration framework in the assessment of credit portfolio qualities and its potential appeal to farm lenders.

Sherrick, Barry, and Ellinger used credit value-at-risk (VaR) techniques to calculate empirical estimates of the cost of insuring against credit risk in pools of agricultural mortgage loans. Katchova and Barry have demonstrated the application of the CreditMetrics migration model in estimating farm lenders' economic capital requirements to protect them against unexpected losses and provisions for allowances to cover expected losses under the New Basel Capital Accord. Another study applied ordered logit techniques to a panel farm-level dataset to identify significant determinants of farm credit migration probabilities among demographic, financial performance and macroeconomic variables (Escalante, *et al.*). Phillips and Katchova also tested for the presence of rating drift by conditioning farm transition rates on business cycles and previous migration trends.

Table 2.1: Crop Insurance Products in U.S.

What is insured		What is the yield based on: APH-based (farm-level yield)	What is the yield based on: Index-based (county-level yield)
Yield Insurance		MPCI	GRP
Revenue Insurance	no guarantee increase	IP, RA-BP	GRIP
	guarantee increase	CRC, RA-HP	

CHAPTER 3

DECISION MAKING UNDER UNCERTAINTY

This chapter reviews several decision making criteria that have been and are continuously being widely employed in risk management.

3.1. Value-at-Risk

Value at risk is a dollar measure of the minimum loss that would be expected in a portfolio with a given probability within a period of time (Chance). The basic idea behind value-at-risk is to determine the probability distribution of the underlying source of risk and to isolate the worst given percentage of outcomes. Figure 3.1 illustrates the principle behind VaR where the distribution of the hypothetical portfolio change in value is continuous and follows a standard normal distribution. 5% VaR is 1.65 standard deviations from the expected change in portfolio value, which, in this example, is 0. Table 3.1 provides a simple illustration with a discrete classification of the change in the value of a hypothetical portfolio, assuming initial portfolio is worth of $10,000,000[12]. In that example, VaR at 5% is $ 3,000,000. It would be interpreted as follows: There is a 5 percent probability that over the given time period, the portfolio will lose at least $3 million or the final portfolio will worth at most $7 million.

[12] The example is from Chance, 2004. The original example does not have the initial value and the second column. We insert them to express VaR either in terms of minimum loss or maximum revenue .

3.2 Expected value criterion

This might be the oldest, simplest and most naïve criterion but it has been widely used in the area of life insurance. By this criterion, one evaluates the value of a risky wealth, say a lottery $\tilde{x}$, simply by calculating its expected value, i.e.

$$V(\tilde{x}) = E(\tilde{x})$$

(3.1)

where $V(\tilde{x})$ denotes the value of $\tilde{x}$ and $E(\tilde{x})$ is the usual expected value, which by definition is

$$E(\tilde{x}) = \sum_{i=1}^{n} p(x_i)x_i \qquad \text{for discrete case} \qquad (3.2a)$$

$$E(\tilde{x}) = \int_a^b xf(x)dx \qquad \text{for continuous case} \qquad (3.2b)$$

where p_i is the mass probability function of $\tilde{x}$ if the risk is discrete and $f(x)$ is the probability density function of $\tilde{x}$ if the risk is continuous.

Suppose that one has an initial wealth of w_0 and final wealth $\tilde{w}_f$ after taking the lottery $\tilde{x}$, then his/her value of final wealth $\tilde{w}_f$ by the expected value criterion is simply

$$V(\tilde{w}_f) = V(w_0 + \tilde{x}) = E(w_0 + \tilde{x}) = w_0 + E(\tilde{x}) \qquad (3.3)$$

To illustrate a case where the expected value criterion is adequate, consider an individual who faces a risk of disaster described as follows[13]:

$\tilde{x}$	$p(\tilde{x})$
0	0.9

[13] This example is from Eeckhoudt and Gollier 1995.

-1000	0.1

Then $E(\tilde{x}) = -100$ and $Var(\tilde{x}) = \sigma^2(\tilde{x}) = 300^2$

Of course, $\sigma(\tilde{x})$ is far from negligible. Suppose now that there are 10,000 people that face the same risk independently in the area where this individual resides. If these 10,000 people form an insurance company with the idea of reimbursing the losers from the contributions of everyone, each member must make a contribution of

$$\tilde{c} = \left(\frac{1}{10{,}000}\right)(\tilde{x}_1 + \tilde{x}_2 + \ldots + \tilde{x}_{10{,}000})$$

Employing the well known findings from mathematical statistics, $E(\tilde{c}) = -100$ and $Var(\tilde{c}) = \sigma^2(\tilde{c}) = 3^2$.

The risk of disaster is very small relative to its expected value and it would be zero for all practical purposes if the number of individuals approaches to infinity. In this case, where there is a large portfolio of independent risks, each risk can be evaluated, without risk, by its expected value.

This criterion is completely reasonable for evaluating lotteries that are part of a large portfolio of identical and independent risks. For a single lottery or lotteries with dependent risks, this criterion is not a very good indicator of value and can be misleading.

For example, consider an individual who uses the expected value criterion to make a decision between two lotteries A and B, each associated with two different outcomes as following:

Lotteries	$\tilde{x}$	$p(\tilde{x})$	$E(\tilde{x})$
A	0 10,000	0 1	10,000
B	-4,000	0.3	11,400

	18,000	0.7	

Based on the expected value criterion, a decision maker will always choose lottery B. However in reality, offered a choice between A and B, many individuals would naturally prefer A without worrying about any possible losses.

3.3 Mean-Variance Criterion

The expected value criterion successfully captures the “return” of the lottery but, unfortunately, is completely unable to judge its risk, thus leading to the consideration of other criteria such as mean-variance.

The mean-variance criterion was promoted by Markowitz. Since then it has been widely used as a tool for portfolio optimization in financial sectors. This criterion recognizes the role of expected value in evaluating a lottery but supplements it by considering the risk (variance) of the lottery.

$$V(\tilde{w}_f) = f[E(\tilde{w}_f), \quad \sigma^2(\tilde{w}_f)] \tag{3.4}$$

The form of function f provides some important information about the preferences of the decision-maker.

Skipping some lengthy derivation and proof, for a risk averse decision-maker, $\frac{\partial f}{\partial E} > 0$ and $\frac{\partial f}{\partial \sigma^2} < 0$, a special case of function f is

$$V(\tilde{w}_f) = E(\tilde{w}_f) - k\sigma^2(\tilde{w}_f)] \tag{3.5}$$

where k is a constant which measure the degree of risk aversion. The larger k is the higher is the degree of risk aversion.

To illustrate a case with mean-variance criterion, consider an individual who uses this criterion to make a decision between two lotteries A and B, each associated with two outcomes described below:[14]

$k = 0.1$	$\tilde{w}_f$	$p(\tilde{w}_f)$	$E(\tilde{w}_f)$	$\sigma^2(\tilde{w}_f)$	$V(\tilde{w}_f)$	Conclusion
A	-6 10	0.5 0.5	2	64	-4.4	A is preferred to B
B	-10 20	0.5 0.5	5	225	-17.5	

Under the mean-variance criterion, both return captured by the expected value and risk captured by the variance are considered. Note A is preferred to B by mean-variance criterion but B is preferred to A by expected value criterion.

The mean-variance criterion, as well as the expected value criterion, takes into account *all* possible outcomes and their respective probabilities. They are attractive mainly due to their great simplicity and very intuitive nature. In reality, the mean-variance criterion is mainly used when one can assume that the risky wealth is normally distributed. However, is it true that a decision-maker is only concerned about the first moment (mean) and the second moment (variance) of a lottery/portfolio? Do higher moments matter? What if the return of the lottery/portfolio is not normally distributed?[15] An expected utility criterion is more flexible with different assumptions about the functional form of utility relative to the risky wealth as long as the utility is an increasing monotonic transformation of wealth.

[14] This example is from Eeckhoudt and Gollier 1995.
[15] Barnett (1993) gave an example of irrational choice between two lotteries using mean-variance when the returns associated with the two lotteries are not normally distributed.

3.4 Expected Utility

The expected utility theory was initiated by Bernoulli in 1738 and put into axiomatic form by Von Neumann and Morgenstern in 1944. Since then expected utility theory has become the dominant paradigm for modeling decision-making under risk and uncertainty. The theory itself is rich if not all-inclusive and it deserves its own book. In this section, its implications are highlighted and two specific expected utility models, which are used in the first two studies in Chapter 4 and 5, are reviewed.

The expected utility replaces the objective values of $\tilde{w}_f$ by the subjective measurement $U(\tilde{w}_f)$, an increasing monotonic transformation function of wealth $\tilde{w}_f$, but keeps the values of the original corresponding probability. The evaluation of the final wealth $\tilde{w}_f$ by its expected utility following the definition of expected value is

$$V(\tilde{w}_f) = \sum_{i=1}^{n} (w_0 + x_i) p_i \qquad \text{for discrete case} \tag{3.6}$$

$$V(\tilde{w}_f) = \int_a^b U(w_0 + x) f(x) dx \qquad \text{for continuous case} \tag{3.7}$$

Here it is easily seen that V is a linear function of the probabilities p_i but not of the value of the final wealth represented by $w_0 + \tilde{x}$. Once this evaluation criterion is adopted, it is natural to ask the question: how much certainty wealth (without the lottery) would yield a decision-maker with utility function U the same level of satisfaction as taking the lottery. If denoting this *certainty equivalent* by w^* then its mathematical definition, by using continuous case, is:

$$U(w^*) = \int_a^b U(w_0 + x) f(x) dx \tag{3.8}$$

Taking the advantage of the fact that U, being monotonic, has an inverse function, we can solve for w^* and express is as:

$$w^* = U^{-1}\left(\int_a^b U(w_0 + x) f(x) dx\right) \tag{3.9}$$

A relevant concept of *certainty equivalent* is *risk premium*, which is defined as:

$$\pi = E(\tilde{w}_f) - w* \quad \text{or} \tag{3.10a}$$

$$w* = E(\tilde{w}_f) - \pi \tag{3.10b}$$

Risk premium π is used to determine the risk attitude of the decision maker. $\pi > 0$ implies the decision-maker is risk averse and the higher it is the more risk averse is the decision-maker. $\pi = 0$ implies the decision-maker is risk neutral and $\pi < 0$ implies risk loving. When $\pi > 0$, it measures how much a decision-maker would be willing to sacrifice from his/her expected final wealth to achieve certainty equivalent, eliminating the uncertainty, to arrive at the expected utility level. So (3.8) can be rewritten as:

$$U(E(\tilde{w}_f) - \pi) = \int_a^b U(w_0 + x) f(x) dx$$

(3.11)

Figure 3.1 displays a generic utility function, which is concave implying the decision maker is risk averse. w^* is certainty equivalent and $E(\tilde{w}_f)$ is the expected final wealth. The difference between the two, π, is the risk premium. Note according to Jensen's inequality, $U(w^*) = E(U(\tilde{w}_f) < U(E(\tilde{w}_f))$.

For illustration purpose, suppose a decision-maker uses a Cramer's utility function, $U = (w_f)^{\frac{1}{2}}$, and an initial wealth of 5 along with a lottery defined by:

$\tilde{x}$	$\tilde{w}_f$	$p(\tilde{x})$
-4	1	0.2
+4	9	0.8

Then the expected utility is 2.6. Its certainty equivalent is 6.76, and the expected final wealth is 7.4, so the risk premium is 0.64.[16] This example illustrates that for the decision-maker, he/she prefers to sacrifice \$0.64 or 8.65% from his/her expected final wealth of \$7.4, to achieve the expected utility level at 2.6 without uncertainty.

Other than risk premium, absolute risk aversion and relative risk aversion are two widely used measures for the degree of risk aversion. Arrow and Pratt have been able to show in two famous articles that the risk premium is tied with absolute risk aversion or relative risk aversion depending on if the risk is additive or multiplicative. Absolute risk aversion A_a and relative risk aversion A_r are defined as:

$$A_a = -\frac{U''(\tilde{w}_f)}{U'(\tilde{w}_f)} \qquad \text{and} \qquad A_r = -\frac{U''(\tilde{w}_f)}{U'(\tilde{w}_f)} \times \tilde{w}_f \text{ [17]} \tag{3.12}$$

Depending on the assumptions about the curvature of the absolute risk aversion over wealth, there are decreasing absolute risk aversion (DARA) if $\frac{\partial A_a}{\partial \tilde{w}_f} < 0$, constant absolute risk aversion (CARA) if $\frac{\partial A_a}{\partial \tilde{w}_f} = 0$, and increasing absolute risk aversion (IARA) if $\frac{\partial A_a}{\partial \tilde{w}_f} > 0$.

[16] The expected utility is $E(U(\tilde{w}_f)) = (0.2)(1)^{\frac{1}{2}} + (0.8)(9)^{\frac{1}{2}} = 2.6$, its certainty equivalent satisfies $(w^*)^{\frac{1}{2}} = 2.6 \Rightarrow w^* = 6.76$. The expected final wealth is $E(\tilde{w}_f) = (0.2)(1) + (0.8)(9) = 7.4$. So the risk premium is $\pi = E(\tilde{w}_f) - w^* = 0.64$

[17] It is proved that by approximation $\pi \cong \frac{1}{2}\sigma^2_{\tilde{w}_f} A_a$ if the risk is additive and $\pi' \cong \frac{1}{2}\sigma^2_{\tilde{w}_f} A_r$ if the risk is multiplicative. (Eeckhoudt and Gollier)

Correspondingly, there are decreasing relative risk aversion (RARA), constant relative risk aversion (CARA) and increasing relative risk aversion (IARA)) if $\frac{\partial A_r}{\partial \tilde{w}_f} < (=)\ (>)\ 0$.

The negative exponential function has a constant absolute risk aversion coefficient. Mathematically it is defined as:

$$U(w_f) = -\exp(-\beta w_f) \text{ or } U(w_f) = 1 - \exp(-\beta w_f) \tag{3.13}$$

The absolute risk aversion coefficient, $A_a = \beta$,[18] is a constant. Constant absolute risk aversion utility functions imply the absolute risk aversion coefficient and the risk premium of any given additive risk are constant function of wealth. In other words the additive change in an individual's wealth will not affect his/her absolute attitude to risk.

The constant relative risk aversion coefficient utility function is mathematically defined as:

$$U(w_f) = \begin{cases} \dfrac{{w_f}^{1-r}}{1-r} & r \neq 1 \\ \ln(w_f) & r = 1 \end{cases}$$

(3.14)

The relative risk aversion coefficient, $A_r = r$,[19] is a constant. Constant relative risk aversion utility functions imply the relative risk aversion coefficient and the risk premium in fraction of the wealth of any given multiplicative risk are constant function of wealth. In other

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[18] since $U'(w_f) = \beta \exp(-\beta w_f)$ and $U''(w_f) = -\beta^2 \exp(-\beta w_f)$, $A_a = -\frac{U''(w_f)}{U'(w_f)} = \beta$

[19] since $U'(w_f) = \frac{1-r}{1-r} w_f^{-r}$ and $U''(w_f) = \frac{1-r}{1-r}(-r) w_f^{-r-1}$, $A_a = -w_f \frac{U''(w_f)}{U'(w_f)} = r$ for $r \neq 1$

$U'(w_f) = \frac{1}{w_f}$ and $U''(w_f) = -\frac{1}{w_f^2}$, $A_a = -w_f \frac{U''(w_f)}{U'(w_f)} = 1 = r$

words the multiplicative change in an individual’s wealth will not affect his/her relative attitude to risk.

Table 3.1: Probability Distribution of Changes in Portfolio Value

Loss in Portfolio Value	Final Portfolio Value	Probability	Cumulative Probability
-$3,000,000 and lower	$7,000,000 and lower	.05	.05
-$2,000,000 to -$2,999,999	$7,000,000 to $7,999,999	.10	.15
-$1,000,000 to -$1,999,999	$8,000,000 to $8,999,999	.15	.30
$0 to -$999,999	$9,000,000 to -$9,999,999	.20	.50
$0 to $999,999	$10,000,000 to $10,999,999	.20	.70
$1,000,000 to $1,999,999	$11,000,000 to $11,999,999	.15	.85
$2,000,000 to $2,999,999	$12,000,000 to $12,999,999	.10	.95
$3,000,000 and higher	$13,000,000 and higher	.05	1.00

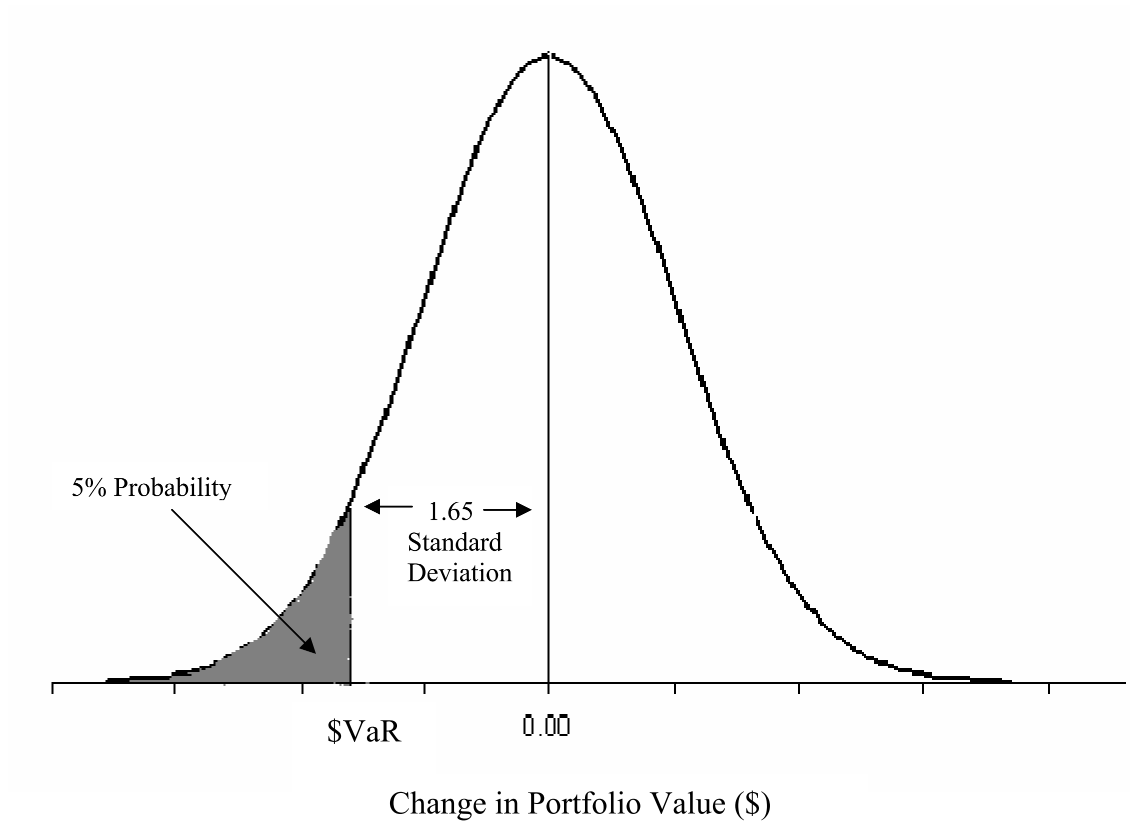

Figure 3.1: Value-at-Risk for Normality Distributed Change in Portfolio

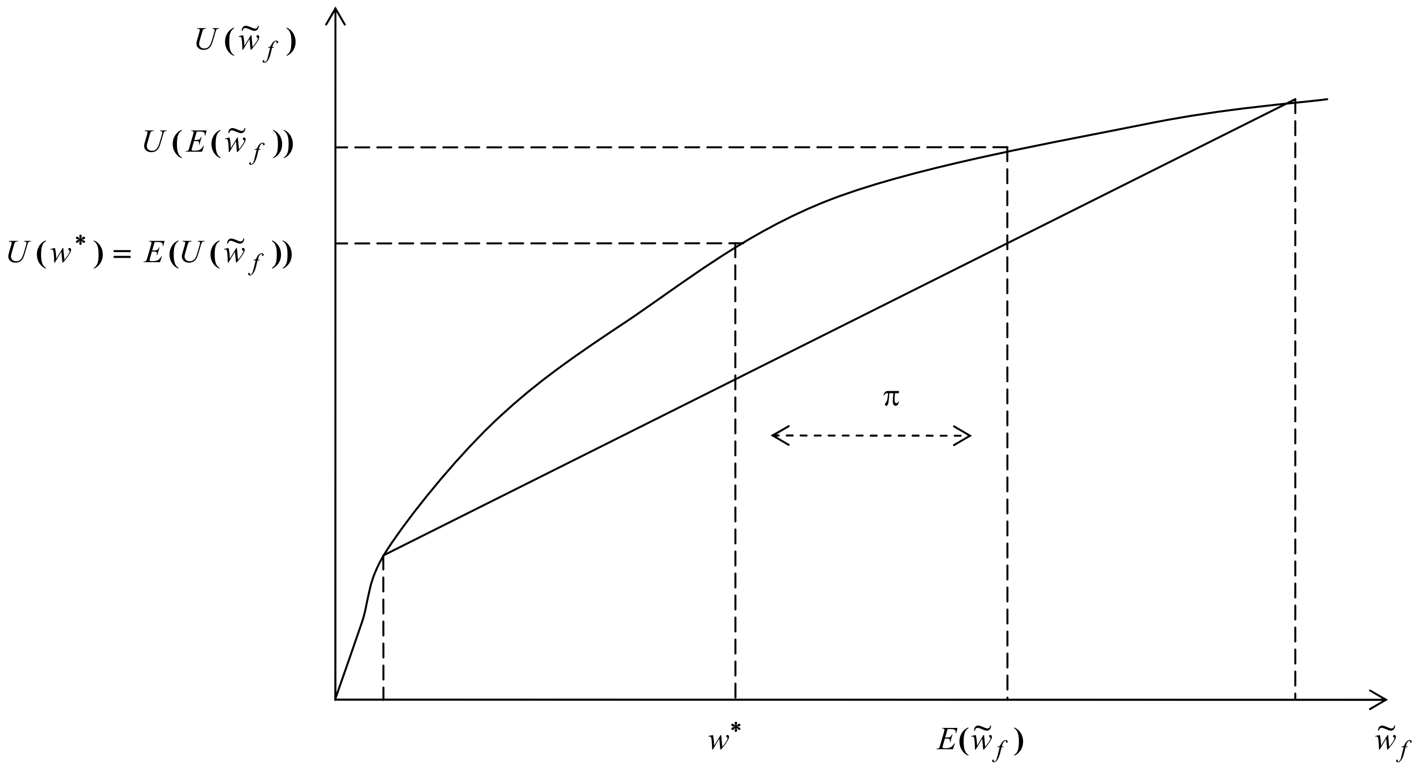

Figure 3.2: Generic Concave Expected Utility

CHAPTER 4

USING WEATHER-BASED INDEX INSURANCE TO PROTECT AGAINST DAIRY PRODUCTION LOSSES CAUSED BY HEAT STRESS

In recent years weather-based financial derivatives have received increased attention. For economic agents exposed to weather-related financial losses, weather derivatives provide a mechanism for sharing those risks with a broader pool of investors. Energy companies began to use temperature-based weather derivatives in early 1997 to hedge their financial risk associated with extreme temperatures. An example is Heating Oil Partners use of temperature-based derivatives to manage unpredictable revenue losses due to abnormally warm winters causing reduced demand for oil (Forrest). Thus far, natural gas, oil, and electric companies have been the largest users of weather derivatives. However, agricultural applications of such products are increasingly being discussed since many agricultural production enterprises are highly sensitive to extreme weather conditions (Chen, Roberts, and Thraen; Mahul; Martin, Barnett, and Coble, 2001; Miranda and Vedenov; Skees et al.; Turvey; Varangis, Skees, and Barnett; and Vedenov and Barnett).

In the U.S., government-subsidized insurance products are the primary risk management tools used by agricultural producers. The Federal Crop Insurance Program facilitates the offer of insurance products that protect crop producers against yield and revenue risks from various sources including weather-related risks. However, the program has struggled with problems such as moral hazard and adverse selection (Skees and Reed; Quiggin, Karaginannis, and Stanton;

Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). While the Federal Crop Insurance Program has also pilot-tested products that protect against livestock price risk, there are currently no federally-facilitated products that protect against livestock production risks. Livestock producers, however, are also exposed to a variety of risk factors including weather-related risks. For example, extreme heat or cold can cause death losses or, for confinement operations, large expenditures for cooling or heating (Martin, Barnett, and Coble 2000).

This article proposes a temperature-humidity index (THI) insurance product and examines whether this product can effectively protect against the risk of reduced milk production caused by heat stress.[20] Specifically, the article: (1) develops a THI insurance product to protect against milk production risk faced by dairy producers in south-central Georgia; (2) prices the THI insurance product; and, (3) assesses the risk reduction impacts of the THI insurance product for a representative Georgia dairy farm.

An overview of weather index insurance is presented in the next section, followed by a discussion of the relationship between the THI and dairy production. The subsequent section describes the design of the proposed index insurance product. Empirical analysis section describes the data utilized in the study, the decision criterion used to optimize key insurance choice variables, the impacts of geographical and temporal basis risk on THI insurance risk reduction, and a description of alternative risk reduction measures. The final section presents the empirical results.

[20] While the instrument proposed is conceptually analogous to a weather derivative, we use the term "weather insurance" because it would likely be sold through traditional insurance channels rather than exchange markets.

4.1 Weather Index Insurance

Weather-based index insurance contracts pay an indemnity conditional on the realization of an *index* that is defined as either a single weather variable or a mathematical function of multiple weather variables. The index is measured at a weather station over a specified period of time.[21] Unlike conventional insurance products, the indemnity on weather index insurance is not directly tied to realized farm-level production. In this sense, weather index insurance is similar to the area-based Group Risk Plan (GRP) and Group Risk Income Protection (GRIP) index insurance products offered under the Federal Crop Insurance Program.

Using daily weather data available from the National Climate Data Center (NCDC) one can construct objective and transparent weather insurance indices that cannot be manipulated by insurance purchasers. These data are available for many weather stations across the U.S. that are associated with the National Oceanic and Atmospheric Administration (NOAA). Since indemnities are based strictly on the realized values of specified weather variables measured at a given weather station, there is no need for purchaser-specific loss adjustment. This greatly reduces transaction costs relative to conventional insurance products. Further, since the data used to construct the weather index are widely available, there are no information asymmetry problems such as adverse selection and moral hazard.

On the other hand, since payoffs of weather index insurance contracts are not directly tied to production shortfalls, agricultural purchasers of weather insurance would be exposed to some degree of basis risk. The basis risk in this context reflects the fact that the producer may not receive an indemnity even if he/she suffers a production loss, or, alternatively, may receive an indemnity even though no loss has occurred.

[21] More complicated weather indices can be constructed as weighted averages across multiple weather stations.

A number of empirical studies have investigated potential agricultural applications of weather index insurance. Skees et al. found that a rainfall index insurance scheme could be feasible in Morocco and Argentina. AGROASEMEX, the state agricultural reinsurance company in Mexico has used weather index contracts to transfer part of its weather-related crop insurance risk into international capital markets. Martin, Barnett and Coble (2001) found that precipitation index insurance could provide effective protection against cotton yield and quality losses due to excess late-season precipitation in the delta region of Mississippi. Turvey examined the economics and pricing of weather index insurance in Ontario and suggested that temperature- and precipitation-based insurance contracts could be used to insure against yield losses for some crops. Vedenov and Barnett investigated the feasibility of using weather index insurance to protect against shortfalls in corn and soybean yields in Iowa and Illinois and cotton yields in Mississippi and Georgia. Their findings were mixed causing them to caution against "blanket assessments" of the feasibility of weather index insurance in agricultural applications.

4.2 Temperature-Humidity Index and Dairy Production

Dairy cows that are exposed to high ambient temperature and high humidity usually respond with reduced milk production. West, Mullinix, and Bernard found that when temperature and humidity increased, cows consumed less feed and produced less milk. Also, at a given high temperature, cows exposed to low humidity performed better than those exposed to high humidity.

The THI is a commonly used measure of heat stress that incorporates the effects of both temperature and relative humidity. It is calculated as

$$THI = TD - \left(0.55 - \left(0.55 \times RH\right)\right) \times \left(TD - 58\right) \tag{4.1}$$

where *THI* is the daily mean temperature-humidity index, *TD* is the mean dry bulb temperature in degrees Fahrenheit, and *RH* is the daily mean relative humidity in decimals (NOAA 1976). Johnson et al. suggest that milk production will be reduced whenever THI exceeds a value of 72. Though many studies have examined the effect of heat stress on same day milk production, other studies suggest that the more significant impact might occur a few days after dairy cows are exposed to extreme heat stress (Linvill and Pardue; West, Mullinix and Bernard).

We are aware of only one study that considers the application of weather index insurance to managing livestock production risk. Chen, Roberts, and Thraen examined the use of THI insurance contracts to hedge milk production losses for hypothetical dairy farms in Ohio, Illinois, New York, and Wisconsin. The relationship between daily THI and same day milk production loss was based on a model proposed by St-Pierre, Cobanov, and Schnitkey. Daily THI data were then used to simulate several years of daily milk production losses using this deterministic model. Thus, simulated milk production losses were identical for days with the same daily average THI. Each hypothetical dairy farm was assumed to purchase a THI insurance product for the entire period during which milk production was assume to be affected by heat stress. The risk reduction generated by the insurance contract was assessed using a mean-variance utility measure. Also, for each hypothetical dairy farm, the impact of geographical basis risk was assessed by comparing the risk reduction generated from THI insurance contracts based on different weather stations.

This study expands and improves on the work of Chen, Roberts, and Thraen as described below. The analysis is extended to dairy production in the southeastern U.S. – a region characterized by high summer temperatures and humidity. Based on recent research findings, this study examines the relationship between the daily THI and lagged milk production. Because of the limited availability of daily milk production data, this study fits a milk production function similar to that used by Chen, Roberts, and Thraen. However daily milk production is simulated by incorporating the random errors from the estimated milk production function to bootstrap around the predicted milk production based on the daily THI. Thus, days with the same daily average THI will not necessarily have the same simulated milk production. Failure to incorporate these idiosyncratic elements of milk production risk will cause the correlation between simulated farm-level milk production and the THI to be overstated. To test for robustness of results across alternative measures of risk reduction, this study presents results based on three different measures. In addition, this study analyzes the impacts of both geographical and temporal basis risks by considering THI insurance contracts based on different weather stations and by allowing separate contracts to be purchased for different subperiods during the entire period for which milk production is affected by heat stress.

4.3 Index Insurance Design

Milk production risk can be orthogonally decomposed into systematic risk related to heat stress and idiosyncratic risk caused by other factors uncorrelated with heat stress. Then

$$\tilde{y} = \mu + \beta \tilde{z} + \tilde{\varepsilon} \tag{4.2}$$

where $\tilde{y}$ denotes the summation $\tilde{y} = \sum_{t=1}^{T} \tilde{y}_t$ of daily random realizations of total milk production (measured in pounds) per cow over a period of T days, $\mu_{\tilde{y}} = E(\tilde{y})$, and

$$\tilde{z} = \sum_{t=1}^{T} \max\left(i_t^f - Threshold, 0\right) \tag{4.3}$$

where i_t^f is the random realization on day t of THI measured at the farm. Realizations of i_t^f greater than *Threshold* are expected to cause reduced milk production. The coefficient β, which measures the sensitivity of milk production to the systematic risk of heat stress, is expected to be negative, where

$$\beta = \frac{\mathrm{cov}(\tilde{y},\tilde{z})}{\mathrm{var}(\tilde{z})} = \frac{\sigma_{\tilde{y},\tilde{z}}}{\sigma_{\tilde{z}}^{2}} = \rho_{\tilde{y},\tilde{z}}\frac{\sigma_{\tilde{y}}}{\sigma_{\tilde{z}}}. \tag{4.4}$$

In principle, a THI insurance product could be created based on the farm-specific index $\tilde{z}$. However, the transaction costs of such an insurance product would be rather high since it would require that a weather station be located at each farm. Thus, for practical applications, the index insurance product would be based on THI measured at the closest weather station.

The proposed insurance product would function much like a call option on the THI. In particular, define a standard contract that pays an indemnity conditional on the realization of the THI according to the following schedule:

$$\tilde{n}_t(i_t \mid i_{strike}, \lambda) = \begin{cases} 0 & if \quad i_t < i_{strike}, \\ i_t - i_{strike} & if \quad i_{strike} \le i_t < \lambda, \\ \lambda - i_{strike} & if \quad i_t \ge \lambda \end{cases} \tag{4.5}$$

where $\tilde{n}_t$ is the indemnity for day *t*, i_t is the THI realization on day *t* measured not at the farm as in (4.3) but rather at the weather station referenced in the insurance contract, i_{strike} is the strike, and λ is a choice variable that defines the upper bound of the layer of i_t over which indemnities are paid. The contract triggers an indemnity whenever i_t exceeds i_{strike}. For the standard contract, the daily maximum indemnity $(\lambda - i_{strike})$ is paid whenever i_t exceeds λ. Thus, the standard contract can be uniquely identified by fixing the two parameters i_{strike} and λ.[22] The total indemnity paid on the index insurance contract over a period of *T* days is

[22] A standard contract is presented here for ease of exposition. Later a choice variable is introduced that allows the purchaser to scale the insurance liability up or down to meet individual needs.

$$\tilde{n}(i_{strike}, \lambda) = \sum_{t=1}^{T} \tilde{n}_t\left(i_t \mid i_{strike}, \lambda\right). \tag{4.6}$$

Similar index insurance contract designs are presented in Martin, Barnett, and Coble (2001) and Vedenov and Barnett. As shown, the indemnity is denominated in increments of THI. The indemnity can be converted into pounds of milk production as $|\beta| \times \tilde{n}$ or into monetary units as $p \times |\beta| \times \tilde{n}$, where p is a given price per pound of milk.

The premium on the standard THI contract is a function of i_{strike}, λ, and the probability distribution of i_t. The distribution can be estimated based on historical THI data either by fitting a standard parametric distribution or by using a nonparametric approach such as kernel smoothing. For this study, kernel smoothing is used to derive a continuous probability density function $h(i)$ of i_t. Formally, for index realizations i_t; $t = 1,\ldots,J$ and $J = T \times$ years of available THI data, the kernel density function of the index is calculated as

$$h(i) = \frac{1}{J\Delta} \sum_{t=1}^{J} K\left(\frac{i - i_t}{\Delta}\right)^{23} \tag{4.7}$$

where $K(\cdot)$ is a kernel function, and Δ is a degree of smoothness or bandwidth (Härdle). The expected payoff and hence the actuarially fair premium for the contract can be determined by

$$\begin{aligned}\mu_{\tilde{n}}(i_{strike}, \lambda) &= \sum_t \mu_{\tilde{n}_t} = \sum_t \int \tilde{n}_t(i_t \mid i_{strike}, \lambda) h(i) di \\ &= \sum_t \int_{i_{strike}}^{i_t} (i_t - i_{strike})\, h(i) di + \sum_t \int_{\lambda}^{i_t} (\lambda - i_{strike}) h(i) di.\end{aligned} \tag{4.8a}$$

If one further assumes that a proportional premium load γ ($\gamma \geq 0$) is applied to the actuarially fair premium to cover transaction costs, return on investment, and reserve-building, then the loaded premium is

[23] Since the distribution of THI is stationary, the kernel density functions *h(i)* for each period were estimated using all available years of daily THI data from 1949 to 2000.

$$\pi(i_{strike}, \lambda, \gamma) = (1+\gamma)\mu_{\tilde{n}}(i_{strike}, \lambda)\,. \qquad (4.8b)$$

4.4 Empirical Analysis

Data

Historical data on daily average temperature and daily average relative humidity were collected at four locations: Tifton, Georgia; Macon, Georgia; Atlanta, Georgia; and Tallahassee, Florida. The temperature and humidity data for Tifton were collected from automated weather stations operated by the College of Agricultural and Environmental Sciences at the University of Georgia. The temperature and humidity data for Macon, Atlanta, and Tallahassee were collected from the NCDC. These data were available for the period 1992-2002 for Tifton and 1949-2000 for Macon, Atlanta, and Tallahassee. The daily temperature and relative humidity data were used to calculate daily THI according to (4.1).

Data on daily average milk production per cow were obtained from the University of Georgia's Coastal Plain Experiment Station located at Tifton, Georgia. The data were from a study on the effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows (West, Mullinix and Bernard). The study was conducted for 85 days between April 28 and July 21, 1993. The 22 Holstein cows that completed the experiment were housed and fed under the same conditions and had no fans or misters for cooling. Feeding and management methods were kept consistent both across animals and across testing days so that variation in daily milk production would be affected primarily by ambient environmental conditions (West et al.). The study found a two-day lag between heat stress events and the largest subsequent reductions in daily average milk production. We conducted a cluster analysis of the data generated by this study and determined that milk production could be categorized into 2 time periods with May 31 as a distinct separation date. Therefore, the 36 days prior to and including May 31 were designated as the "cool" period. The 49 days after May 31 were designated as the "hot" period.

For this analysis a relationship between the daily THI and two-day lagged daily milk production was fit using the Tifton daily milk production data and the corresponding daily THI at Tifton. The quadratic regression results were

$$\tilde{y}_{t+2} = -157.0971 + 7.0358\, THI_t - 0.0530\, THI_t^2 - 5.3704\, D + \varepsilon \tag{4.9}$$

where THI_t is the THI measured on day *t*, $\tilde{y}_{t+2}$ is the daily average milk production in pounds per cow measured two days subsequent to day *t*, and *D* is a binary variable that takes a value of 0 during the cool period and 1 during the hot period.[24] The R^2 for the regression is 0.8777. All coefficients are significant at a 5% level of significance. A Shapiro-Wilk test failed to reject the null hypothesis that ε was normally distributed. The distribution of ε was estimated to have a mean of zero and a standard deviation of 3.10.

Using the relationship between the THI and milk production estimated in (4.9) it is possible to simulate daily milk production for a representative dairy farm in the region. To utilize a longer time series of available THI data, it was assumed that the representative dairy farm was located in Macon (approximately 100 miles north of Tifton). For the representative Macon dairy farm, 52 years of daily milk production were simulated based on the available 52 years of daily Macon THI data. Bootstrapping was used to reintroduce the idiosyncratic risk ε into the simulated 4,420 estimates (85 days × 52 years) of daily milk production. Figure 4.1 displays the simulated relationship between $\tilde{y}_{t+2}$ and THI_t at Macon.

[24] Since the available milk production data are for the period April 28 through July 21, the THI data used in the analysis are for the period April 26 through July 19.

Decision Criteria

Dairy farmers manage investment portfolios that include, but are not necessarily limited to, the assets that constitute the dairy operation. A dairy farmer who adds a weather index insurance product with a loaded premium to his/her investment portfolio expects, as a result, to have lower expected returns on the portfolio but also less risk (measured by the variance of returns on the portfolio).

Suppose a representative dairy producer's investment portfolio consists only of dairy production assets and THI insurance contracts. Further suppose that this producer values investment returns according to the mean-variance criterion:

$$V = E(R) - \frac{1}{2} k \times \mathbf{var}(R) \tag{4.10}$$

where R is returns and k is assumed to be positive, implying that the individual is risk averse (Eeckhoudt and Gollier). If the portfolio does not include a THI insurance contract, returns are calculated as

$$R = p\widetilde{y} \tag{4.11a}$$

where p is the market price of milk.

Consider a choice variable $\phi > 0$ that can be used to scale the liability of the THI insurance contract relative to the liability of the standard contract. This variable is conceptually analogous to the scale variable in GRP (Skees, Black, and Barnett). Contracts specified with ϕ less than (greater than) one have less (more) liability than the standard contract. Thus, if the portfolio includes a THI insurance contract, returns are calculated as

$$R^{net} = p\widetilde{y} + p\phi \mid \beta \mid \left[\widetilde{n}\left(i_t \mid i_{strike}, \lambda\right) - \pi\left(i_{strike}, \lambda, \gamma\right)\right] \tag{4.11b}$$

where $\widetilde{n}$ and π are defined in (4.6) and (4.8b).

For given i_{strike}, λ, and γ, the producer's objective is to choose the value of ϕ that maximizes $\Delta V = V\left(R^{net}\right) - V\left(R\right)$. The optimal ϕ is calculated (see derivation in the Appendix A) as

$$\phi^* = \rho_{\tilde{z},\tilde{n}} \frac{\sigma_{\tilde{z}}}{\sigma_{\tilde{n}}} - \frac{\gamma \mu_{\tilde{n}}}{|\beta| k \sigma_{\tilde{n}}^2}. \tag{4.12}$$

Notice that if the premium load $\gamma = 0$, then $\phi^* = \rho_{\tilde{z},\tilde{n}} \frac{\sigma_{\tilde{z}}}{\sigma_{\tilde{n}}}$ which is analogous to an optimal hedge ratio for futures contracts. If the THI insurance is not actuarially fair (i.e., $\gamma > 0$), then ϕ^* is lower than if $\gamma = 0$.

The risk reduction analysis was performed under the assumption that the THI insurance contracts are bought by a representative dairy farmer located at Macon. The farmer can purchase THI insurance based on weather stations at Macon, Atlanta, or Tallahassee. It is further assumed that the market price of milk is \$15 per hundredweight.

Basis Risk

Basis risk occurs because the indemnities on a THI insurance contract are not perfectly correlated with the actual losses experienced by milk producers. Purchasers of a THI insurance contract would be exposed to at least two types of basis risk. Geographic basis risk occurs because the temperature and humidity data used to construct the index are measured at a location other than the farm. Temporal basis risk may occur because the probability distribution of daily THI is not stationary across days in the insurance period and/or because heat stress has different effects on milk production during different time periods.

To help assess the impact of geographic basis risk, an initial scenario is constructed where the representative Macon dairy farmer is assumed to purchase THI insurance based on the

Macon weather station. Since the Macon THI data were used to simulate milk production for the representative Macon dairy farmer, this scenario has, by construction, no geographical basis risk. From a practical standpoint, this is obviously an unrealistic scenario. However, it is instructive since it establishes a baseline that can be used to assess the impact of geographic basis risk on the efficacy of THI insurance.

It is assumed that the farmer can also purchase THI insurance based on measurements taken at the Atlanta and Tallahassee weather stations. Purchasing THI insurance based on these two locations exposes the representative farmer to some degree of geographic basis risk. Table 4.1 reports descriptive statistics for THI at each of the three locations. The correlations between Macon and Atlanta are consistently higher than those between Macon and Tallahassee. This is as expected since Atlanta is only about 80 miles north of Macon while Tallahassee is approximately 200 miles south of Macon. This implies that for a representative dairy farm in Macon, THI insurance based on Tallahassee would be expected to have higher geographic basis risk than THI insurance based on Atlanta.

In addition to geographical basis risk, there are at least two possible sources of temporal basis risk. First, due to seasonality, the probability distribution for daily THI may not be stationary across days in the insurance period. For example, based on the 52 years of available weather data, the mean THI values for the 85-day study period are 71.50, 73.74, and 75.06 for Atlanta, Macon, and Tallahassee, respectively. However, when measured separately the mean THI values at the same locations are 67.37, 69.67, and 71.36, respectively, for the cool period and 74.73, 76.54, and 77.78, respectively, for the hot period. Thus, a potential insurance purchaser would likely prefer to choose different strikes for different time periods.

Second, heat stress may have different effects on milk production during different time periods. Following a heat stress event, milk production is more likely to return to normal levels during the cool period than during the hot period (West, Mullinix, and Bernard). This suggests that the sensitivity of milk production to heat stress may vary across different time periods.

A tradeoff exists between temporal basis risk and transaction costs. At one extreme, temporal basis risk could be largely eliminated by using separate insurance contracts for each day. However, the transaction costs would likely be unacceptably high. On the other hand, if only a single THI insurance contract were available for the entire 85-day period under consideration, temporal basis risk would be higher, though transaction costs would be lower. For this analysis, we first consider a single THI insurance contract for the entire 85-day period and then two separate THI insurance contracts – one each for the cool period and hot period.

<u>Risk Reduction Measures</u>

Three different measures were used to assess the robustness of the risk reduction performance of the THI insurance contract: mean-variance (MV), certainty-equivalent revenues (CER), and value-at-risk (VaR). MV is a widely-used measure of relative risk and return in many finance applications. It assumes that decision-makers value investment results based only on the first two moments of the distribution of returns. For a specified utility function, CER is the level of return that if received with certainty would be equal to the expected utility of the risky investment. While it allows for consideration of higher moments of the return distribution, CER also requires one to make assumptions about the decision-maker's utility function over returns. VaR measures the minimum return (or maximum loss) that would be expected from an investment with a given probability. It is typically used when one believes that investors are concerned primarily about downside risk (Hogan and Warren; Markowitz).

The mean-variance criterion is presented in (4.10). Expectations and variances of R and R^{net} were calculated by numerical integration of corresponding kernel density functions. These calculations were done separately for each of the three contracts; the single contract that covers the entire 85 day period, the cool period contract, and the hot period contract.[5]

Certainty-equivalent revenues were calculated by using a negative exponential utility function:

$$U = 1 - \exp(-A_\alpha R) \tag{4.13}$$

where the absolute risk aversion coefficient A_a was calibrated so as to correspond to a prespecified risk premium θ (Babcock, Choi, and Feinermean; Schnitkey, Sherrick, and Irwin; Vedenov and Barnett). More specifically, for a given level of risk premium θ, the parameter A_a was selected so that the expected utility of the revenue without THI is equal to the utility of the certain revenue $(1-\theta)\times E(R)$, i.e.,

$$\mathrm{E}U(R) = \mathrm{E}_R(1-\exp(-A_a R)) = 1 - \exp(-A_a \times (1-\theta)\times E(R)) = U((1-\theta)\times E(R)). \tag{4.14}$$

Once A_a was determined, the certainty-equivalent revenues (CER) without and with the THI contract were calculated as

$$U(CER_{without}) = \mathrm{E}_R U(R)\text{, and} \tag{4.15a}$$

$$U(CER_{with}) = E_R U(R^{net})\,. \tag{4.15b}$$

For a given distribution of revenues R, the value-at-risk at an $\alpha\%$ level is defined as a level of revenue VaR_α such that $\mathbf{Pr}(R < \mathrm{VaR}_\alpha) = \alpha$ and can be calculated by using the cumulative distribution function (CDF) of R (Manfredo and Leuthold). For this analysis, the series of revenues without and with the THI contract in (11a) and (11b), respectively, are used to generate the corresponding empirical CDFs by integrating their empirical density function obtained by the kernel smoothing procedure. VaR is then calculated for both distributions at 2.5%, 5%, and 10% levels for both single and separate contracts.

4.5 Results

For given combinations of i_{strike} and MV parameter *k*, the optimal scale variable ϕ^* was calculated by fixing λ = 95 and load factor γ = 10%. Table 4.2 presents the optimized combinations of i^*_{strike} and ϕ^* for each weather station. These are the combinations that yield the largest reduction in the mean-variance measure ΔV for a specific level of *k*. The maximum daily indemnity that can be received on the THI insurance contract in (4.5) is $p\,\phi\,|\,\beta\,|\left(\lambda - i_{strike}\right)$. Thus, the liability for the *T* days covered by the THI insurance contract is $T\,p\,\phi\,|\,\beta\,|\left(\lambda - i_{strike}\right)$. Liabilities and premiums measured in dollars per cow are also presented in table 4.2. From these data the premium rates can be calculated as premium divided by liability. For the single contract at the strikes indicated, the premium rates are 13.3%, 9.5%, and 13.6% for Macon, Atlanta, and Tallahassee, respectively. The average premium rates for the separate contracts at the strikes indicated are 9.2%, 8.7%, and 9.0% for Macon, Atlanta, and Tallahassee, respectively.[25]

Optimized combinations of i^*_{strike} and ϕ^* were calculated for both a single contract for the entire time period and separate contracts for the cool and hot periods. For the separate contracts the optimal i^*_{strike} was higher in the hot season than in the cool season. This suggests the need for separate contracts to reduce the impact of temporal basis risk. Also, for a specific *k* and a given weather station, each optimized combination of i^*_{strike} and ϕ^* for the separate contracts consistently generated lower premium rates than for the single contract.

[25] For the separate contracts the average premium rates are calculated as the sum of the premiums for the two contracts divided by the sum of the liabilities for the two contracts.

The optimal i^{*}_{strike} are lowest at Atlanta and highest at Tallahassee. This finding is consistent with the relative levels of THI at these locations. The values of ϕ^{*} for Macon are consistently higher than those for the two other locations. This reflects the fact that there is no geographical basis risk with the THI insurance contract based on Macon while geographical basis risk does exist with contracts based on the other two locations. Further, as shown in (4.12) ϕ^{*} increases with higher levels of k.

Tables 4.3 - 4.5 present risk reduction from purchasing THI insurance as measured by MV, CER, and VaR, respectively. The CER and VaR measures in Tables 4.4 and 4.5 are calculated using i^{*}_{strike} and ϕ^{*} from table 4.2 for $k = 0.2$. Each of the tables presents results under three scenarios: no purchase of THI insurance; purchase of a single THI insurance contract over the entire period; and purchase of separate THI insurance contracts for the cool and hot periods. For both the single and separate contract scenarios, the simple difference change relative to the no insurance scenario is presented for both the MV and CER measures.[26] Positive (negative) changes imply that the representative dairy producer is better (worse) off as a result of purchasing THI insurance.

In general, the findings are robust across the three measures of producer well-being. Regardless of the measure used, the representative risk-averse dairy producer is generally made better off by purchasing THI insurance even though the premium included a 10% proportional load. The only exception is for the single THI contract based on Tallahassee. In this case, both the MV measure when $k = 0.1$ and the $VaR_{0.10}$ measure indicate that the insurance purchase would make the representative dairy producer slightly worse off. As discussed below, this

[26] Simple difference changes in VaR are affected by the curvature of the revenue distribution and thus, are not meaningful measures of risk reduction.

reflects the fact that the contract based on Tallahassee has more geographic basis risk than contracts based on the other locations. Given this basis risk and the assumed risk preference, the risk reduction generated by the index insurance is not sufficient to offset the effect of the 10% premium load.

The impact of geographical basis risk can be seen by comparing results from a Macon THI insurance contract (which has no geographical basis risk) to those from Atlanta and Tallahassee. If the representative dairy producer purchases an index insurance product, he/she is always better off purchasing the insurance based on Macon. Geographical basis risk reduces, but does not eliminate, the benefits of the index insurance product. In general, the representative dairy producer is better off with index insurance purchased on Atlanta rather than Tallahassee. This reflects the fact that Macon is geographically closer to Atlanta than to Tallahassee and thus, the THI in Macon is more highly correlated with the THI in Atlanta than the THI in Tallahassee. Exceptions to this general finding occur with both the single and separate contracts for the $VaR_{0.05}$ measure and the single contract for the $VaR_{0.025}$ measure.

The results also demonstrate the importance of temporal basis risk. With the exceptions of $VaR_{0.05}$ and $VaR_{0.025}$ for Tallahassee and $VaR_{0.05}$ for Atlanta, the risk reduction measures suggest that the representative dairy producer is better off using separate contracts rather than a single contract. The exceptions demonstrate an interesting characteristic of the VaR measure relative to the other measures. While the other measures are based on the entire revenue distribution, the VaR measure is based only on the lower tail. Table 4.2 shows that the optimal strike for the single contract is always lower than the optimal strike for the hot period. This implies that during the hot period the optimized single contract will trigger payments more frequently than the optimized hot period contract. Revenue occurrences in the lower tail of the revenue distribution are associated with extreme heat stress events that are much more likely to occur during the hot period. Since the optimized strike on the single contract "overprotects" during the hot season, the VaR for the extreme lower tail of the distribution can be higher for the single contract than for the separate contracts.[27] This outcome is less likely to occur for higher levels of α (e.g., $\alpha = 0.10$ in table 4.4).

[27] It is interesting to note that this occurs most noticeably for the contract with the highest geographical basis risk (Tallahassee). All other things equal, the higher the basis risk (either geographical or temporal) the more likely that i^*_{strike} (for a risk-averse decision-maker) will overprotect. Setting i_{strike} so that the contract triggers more often increases the likelihood that the contract will, in fact, trigger when a farm-level loss event occurs. Thus, setting i_{strike} more "in the money" compensates, to some extent, for basis risk.

Table 4.1:THI Descriptive Statistics

Weather Station Location	Entire Period (April 26-July 19)			Cool period (April 26-May 31)			Hot period (June 1-July 19)		
	THI Mean	THI variance	Correlation with Macon THI	THI mean	THI variance	Correlation with Macon THI	THI mean	THI variance	Correlation with Macon THI
Macon	73.74	30.51	1	69.67	26.45	1	76.54	12.40	1
Atlanta	71.50	32.28	0.9363	67.37	27.53	0.9142	74.73	14.07	0.8670
Tallahassee	75.06	23.87	0.8764	71.36	21.37	0.7376	77.78	8.06	0.6688

Table 4.2: Optimized Parameters of the THI Insurance Contracts

Weather Station Location	Single Contract i^*_{strike}	ϕ^*	Liability ($/cow)	Premium ($/cow)	Separate Contracts $i^*_{strike\,(cool)}$	$i^*_{strike\,(hot)}$	ϕ^*_{cool}	ϕ^*_{hot}	Liability ($/cow)	Premium ($/cow)
					$k = 0.1$					
Macon	73	1.03	$50.56	$6.78	73	75	1.23	1.20	$56.47	$5.19
Atlanta	72	0.67	$34.38	$3.28	70	73	0.71	0.73	$37.51	$3.26
Tallahassee	74	0.67	$31.39	$4.29	74	76	0.88	0.83	$37.99	$3.40
					$k = 0.2$					
Macon	73	1.07	$52.52	$7.00	73	75	1.27	1.23	$58.19	$5.33
Atlanta	72	0.69	$35.41	$3.37	70	73	0.74	0.75	$38.81	$3.37
Tallahassee	74	0.71	$33.27	$4.53	74	76	0.93	0.87	$39.78	$3.56
					$k = 0.3$					
Macon	73	1.08	$53.01	$7.07	73	75	1.28	1.24	$58.77	$5.38
Atlanta	72	0.69	$35.41	$3.41	70	73	0.75	0.76	$39.24	$3.40
Tallahassee	74	0.72	$33.74	$4.61	74	76	0.94	0.89	$40.38	$3.62

Notes:

1. $\beta =$ -0.175 for the entire 85-day period; $\beta =$ -0.178 for the cool period; and $\beta =$ -0.177 for the hot period.

2. In the historical data, the highest daily relative humidity was 100% and the highest daily temperature was 95 degrees Fahrenheit. Thus, λ was set equal to 95.

3. $Liability = T\ p\ \phi\,|\,\beta\,|\left(\lambda - i^*_{strike}\right)$ where T is the number of days in the insurance period. For the separate contracts the total liability is the sum of the liabilities for each contract.

Table 4.3: Mean-Variance (MV)

Location	MV Without THI Contract ($/cow)	Single Contract: MV With THI Contract ($/cow)	Single Contract: Change ($/cow)	Separate Contracts: MV With THI Contract ($/cow)	Separate Contracts: Change ($/cow)
			k = 0.1		
Macon	$868.14	$870.36	$2.21	$871.40	$3.26
Atlanta	$868.14	$869.59	$1.45	$870.51	$2.36
Tallahassee	$868.14	$868.06	($0.08)	$868.54	$0.39
			k = 0.2		
Macon	$860.78	$869.23	$8.45	$870.40	$9.62
Atlanta	$860.78	$865.63	$4.85	$866.39	$5.61
Tallahassee	$860.78	$863.12	$2.34	$863.52	$2.74
			k = 0.3		
Macon	$853.42	$868.18	$14.75	$869.44	$16.02
Atlanta	$853.42	$861.70	$8.27	$862.31	$8.88
Tallahassee	$853.42	$858.26	$4.84	$858.55	$5.13

Note: Higher (lower) value of MV corresponds to lower (higher) risk exposure. The higher the value of *k*, the more risk averse the insurance purchaser.

Table 4.4: Certainty Equivalent Revenues (CER)

Location	CER without THI Contract ($/cow)	Single Contract: CER with THI Contract ($/cow)	Single Contract: Change ($/cow)	Separate Contracts: CER with THI Contract ($/cow)	Separate Contracts: Change ($/cow)
		Risk Premium = 2%			
Macon	$870.22	$872.77	$2.56	$875.32	$5.11
Atlanta	$870.22	$872.49	$2.28	$872.75	$2.54
Tallahassee	$870.22	$871.93	$1.71	$872.10	$1.89
		Risk Premium = 5%			
Macon	$866.42	$873.86	$7.44	$874.76	$8.34
Atlanta	$866.42	$872.07	$5.65	$873.41	$6.99
Tallahassee	$866.42	$868.36	$1.94	$871.02	$4.60
		Risk Premium = 10%			
Macon	$864.28	$873.45	$9.17	$874.26	$9.98
Atlanta	$864.28	$870.53	$6.25	$873.36	$9.08
Tallahassee	$864.28	$867.15	$2.87	$869.37	$5.09

Note: Higher (lower) value of CER corresponds to lower (high) risk exposure. The higher the risk premium, the more risk averse the insurance purchaser.

Table 4.5: Value-at-Risk (VaR)

Location	VaR Without THI Contract ($/cow)	Single THI Contract VaR ($/cow)	Separate THI Contracts VaR ($/cow)
		$VaR_{0.025}$	
Macon	$850.27	$862.96	$864.30
Atlanta	$850.27	$856.15	$858.37
Tallahassee	$850.27	$856.67	$855.02
		$VaR_{0.05}$	
Macon	$854.41	$864.50	$865.74
Atlanta	$854.41	$858.92	$858.39
Tallahassee	$854.41	$860.36	$859.11
		$VaR_{0.10}$	
Macon	$861.98	$865.63	$866.68
Atlanta	$861.98	$864.66	$865.65
Tallahassee	$861.98	$861.75	$863.03

Note: Higher (lower) value of VaR corresponds to lower (higher) risk exposure.

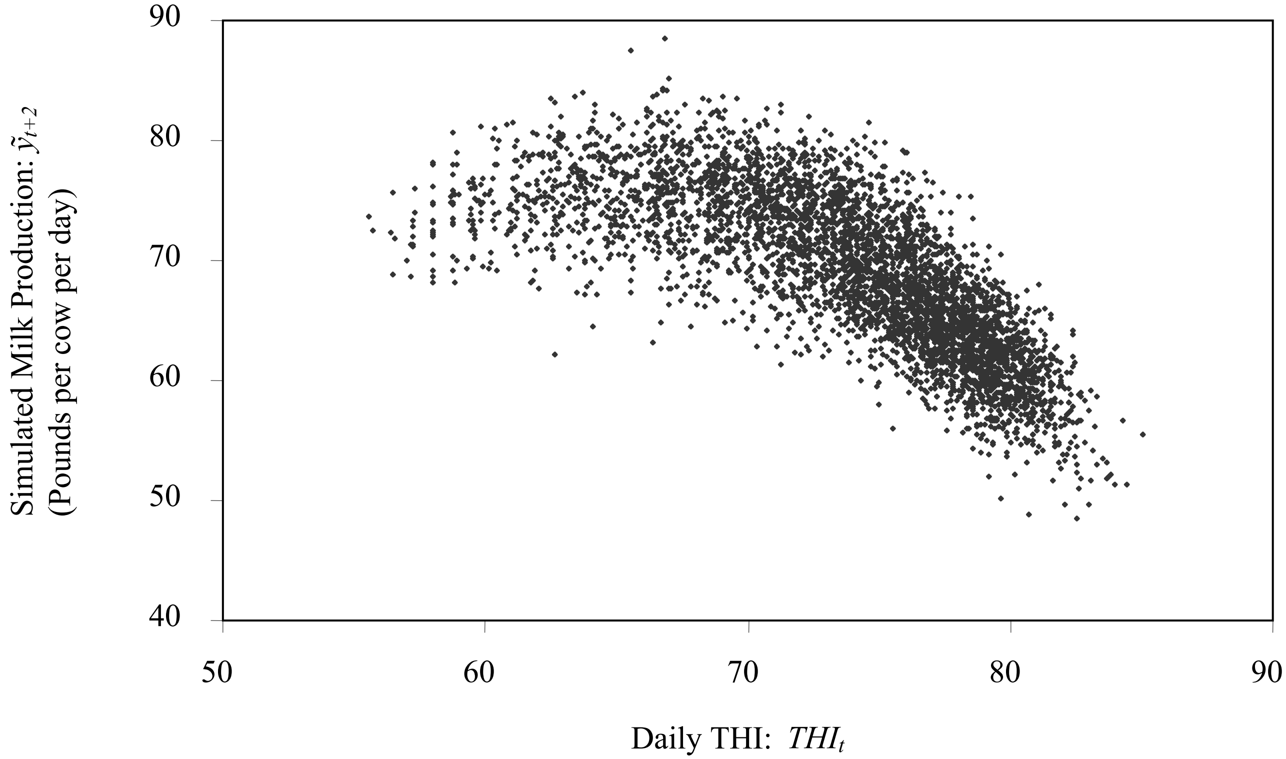

Figure 4.1: Simulated Daily Milk Production and Daily THI at Macon.

CHAPTER 5

TESTING THE VIABILITY OF AREA YIELD INSURANCE FOR COTTON AND SOYBEANS IN THE SOUTHEAST

From its inception in 1938 the U.S. Federal Crop Insurance Program (FCIP) has provided Multiple Peril Crop Insurance (MPCI) policies that protect against individual farm yield losses. Since the mid-1980s, MPCI yield guarantees have been based on the actual production history (APH) yield for the insured unit. The APH yield is a rolling 4-10 year average of realized yields on the insured unit.

In recent years, various APH-based revenue insurance products have also been offered through the FCIP.[28] For 2004, APH-based insurance products (MPCI and the various APH-based revenue insurance products) accounted for over 90% of FCIP premiums. Several studies have described how APH-based insurance products are subject to misclassification (adverse selection) and moral hazard problems (Quiggin, Karaginannis, and Stanton; Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). In addition, APH-based insurance products have high transaction costs related to establishing and verifying APH yields and conducting on-farm loss adjustment.

Missclassification and moral hazard problems create a “wedge” between the premium cost and the expected indemnity for insureds (Wang, Hanson, and Black). Missclassification can cause either positive or negative wedges. In some cases, insureds will be misclassified to their detriment so that they face a premium cost that exceeds the expected indemnity (positive wedge).

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[28]APH-based revenue insurance products are generally offered only for crops with exchange-traded futures contracts. Indemnities are triggered by the product of farm-level yield losses and a price index based on futures market prices.

In other cases, insureds may be misclassified to their benefit (negative wedge). Moral hazard problems always create positive wedges. Federal premium subsidies increase participation in the FCIP by masking the impact of positive wedges (Wang, Hanson, and Black). However, some potential insureds face positive wedges that more than offset the federal premium subsidy. Thus, despite significant federal premium subsidies, APH-based insurance products can still have a negative expected value for many potential insureds (Skees 2001).

Area yield insurance is an alternative insurance product that is not susceptible to many of the problems that plague APH-based insurance products. Area yield insurance is essentially a put option on the average yield for a production region. Indemnities are triggered by shortfalls in the area average yield rather than farm-level yields. For this reason, area yield insurance requires no risk classification. If the area is sufficiently large, area yield insurance is also not susceptible to moral hazard problems since the actions of an individual farmer will have no noticeable impact on the area average yield. Area yield insurance also has relatively low transaction costs since there is no need to establish and verify APH yields for each insured unit nor is there any need to conduct on-farm loss adjustment.

Because farm-level yields are not perfectly correlated with the area average yield, purchasers of area yield insurance are exposed to some degree of basis risk. It is possible for the purchaser of an area yield insurance policy to experience production losses on his/her farm and yet not receive an indemnity because there has been no shortfall in the area average yield. Similarly, it is possible for a policyholder to receive an indemnity on an area yield insurance policy when no farm-level losses have occurred. Basis risk on area yield insurance is generally lower (higher) the more homogeneous (heterogeneous) the production area (Miranda).

Variability in elevation, soil type, drainage, and other relevant factors will cause farm-level yields to be less correlated with the area average yield (Chaffin and Black).

Since 1993 an area yield insurance product called the Group Risk Plan (GRP) has been offered through the FCIP for selected crops and regions. In recent years, an area-based revenue insurance product called the Group Revenue Insurance Policy (GRIP) has also been offered for selected crops (all of which have exchange-traded futures contracts) and regions. Both GRP and GRIP areas are defined based on county political boundaries. GRP policies (and the yield component of GRIP policies) settle based on National Agricultural Statistics Service (NASS) estimates of county average yields.

This article compares farm-level risk reduction from MPCI with that from an area yield insurance product like GRP for selected South Carolina cotton and soybean production regions and Georgia cotton production regions. MPCI premium rates are relatively high in this region. While this reflects the inherent production risk, anecdotal evidence suggests that MPCI premium rates also reflect significant positive wedges caused by adverse selection and moral hazard problems.

Soybean GRP is currently available for 19 counties in South Carolina however no policies have been sold since 1999. GRP is not currently available for cotton production in either South Carolina or Georgia. Area-yield insurance purchasers in the Southeast would likely be exposed to relatively high levels of basis risk since the region is characterized by significant geographic variability in production factors such as soil quality, drainage, and production practices (e.g., irrigated versus dryland production). Despite this, if MPCI premium rates contain positive wedges that are sufficiently large, area-yield insurance may be a viable alternative for many producers in the region.

Previous studies have compared the risk reduction performance of MPCI and GRP under the assumption that both products are actuarially fair in sample (Miranda; Smith, Chouinard, and Baquet; Barnett et al.). The results from such studies are biased in favor of MPCI since, for most farmers, actual MPCI premium rates contain much larger positive wedges than GRP premium rates (Barnett et al.). The analysis presented here extends previous work by relaxing the assumption that premium rates are actuarially fair.

The article is organized as follows. The next section compares MPCI and GRP insurance policies by briefly describing how indemnities and actuarially fair premium rates are calculated for each. The subsequent section focuses on data and procedures used in the empirical comparison of farm-level risk reduction from MPCI and GRP insurance policies. This is followed by a discussion of empirical results.

5.1 Comparing MPCI and GRP Insurance Contracts

For simplicity, suppose that insurance indemnities and premiums are paid in units of production per acre. The MPCI indemnity is then calculated as

$$\tilde{n}_{MPCI}\left(\tilde{y}_i \mid coverage\right) = \max\left(y_{ic} - \tilde{y}_i, 0\right) \tag{5.1}$$

where $\tilde{n}_{MPCI}$ is the indemnity per acre, $\tilde{y}_i$ is the realization of the stochastic yield on farm *i* with $E\left(\tilde{y}_i\right) = \mu_i$, and $y_{ic} = \mu_i \times coverage$. For MPCI, $50\% \leq coverage \leq 85\%$ in 5% increments and μ_i is the APH yield described earlier.

The actuarially fair premium π^f_{MPCI} is the expectation of (5.1)

$$\pi^f_{MPCI} = E\left(\tilde{n}_{MPCI}\left(\tilde{y}_i \mid coverage\right)\right) = E\left(\max\left(y_{ic} - \tilde{y}_i, 0\right)\right). \tag{5.2}$$

The liability (the maximum possible indemnity) is y_{ic} so the actuarially fair premium rate ρ^{f}_{MPCI} is

$$\rho^{f}_{MPCI} = \frac{E(\max(y_{ic} - \tilde{y}_i, 0))}{y_{ic}} \tag{5.3}$$

The GRP indemnity is calculated as

$$\tilde{n}_{GRP}(\tilde{y} \mid coverage,\ scale) = \max\left(\frac{(y_c - \tilde{y})}{y_c}, 0\right) \times yfcast \times scale \tag{5.4}$$

where $\tilde{n}_{GRP}$ is the indemnity per acre, $\tilde{y}$ is the realization of the stochastic county yield, *yfcast* is the forecast of the county yield per acre, the critical yield $y_c = yfcast \times coverage$, and *scale* is a choice variable selected by the insured. Currently, for GRP, 70% ≤ *coverage* ≤ 90% in 5% increments and 90% $\leq scale \leq$ 150%.[29] The GRP indemnity contains a disappearing deductible. In the extreme, if $\tilde{y}$ is zero, the indemnity will be 100% of the liability $(yfcast \times scale)$ regardless of the insureds choice of *coverage* (Skees, Black, and Barnett).

The actuarially fair premium is

$$\pi^{f}_{GRP} = E(\tilde{n}_{GRP}(\tilde{y} \mid coverage,\ scale)) = E\left(\max\left(\frac{(y_c - \tilde{y})}{y_c}, 0\right) \times yfcast \times scale\right) \tag{5.5}$$

and the actuarially fair premium rate ρ^{f}_{GRP} is

$$\rho^{f}_{GRP} = \frac{E\left(\max\left(\frac{(y_c - \tilde{y})}{y_c}, 0\right) \times yfcast \times scale\right)}{yfcast \times scale} = E\left(\max\left(\frac{(y_c - \tilde{y})}{y_c}, 0\right)\right) \tag{5.6}$$

For farm *i* and insurance scenario *j*, the yield net of insurance premiums and indemnities is

[29] As indicated in Barnett et al., terms are used somewhat inconsistently in the area yield insurance literature. For example, the term "*coverage*" is sometimes used to mean what is here called "*scale*." Throughout this article, we use the terminology found in Skees, Black, and Barnett which is consistent with that used for the actual GRP product.

$$\tilde{y}_{ij}^{net} = \tilde{y}_i - \pi_{ij} + \tilde{n}_{ij} \tag{5.7}$$

where j is either MPCI, GRP, or no insurance purchasing. In the case of no insurance purchasing $\tilde{y}_{ij}^{net} = \tilde{y}_i$.

Empirical Analysis

Data

Farm-level cotton and soybean yield data were obtained from the USDA's Risk Management Agency (RMA). These data are the 4 to 10 year yield histories used to establish APH yields for MPCI purchasers. The data are aggregated to the level of an enterprise unit meaning that for a given crop/year combination, the data include all of the acreage and production assigned to a given taxpayer identification number within the county. The data are for the 10-year period 1991-2000. To be included in the analysis, each farm had to have yield data for at least the last 6 consecutive years of the period (i.e., 1995-2000). The APH yield is calculated as the simple average of the annual yields.

Historical county-level yield data were collected from NASS. These data were available for cotton production in Georgia for the period 1971-2000 and for cotton and soybean production in South Carolina for the period 1972-2000. To be included in the analysis the county had to have at least 20 available farm observations that meet the conditions indicated above.[30]

For Georgia cotton, 26 counties located in four crop reporting districts (CRDs) were included in the analysis. These counties, shown in figure 1, accounted for 57% of Georgia cotton production in 2001. As indicated in table 1, the lowest yields in 2001 occurred in CRD 60 where cotton is produced primarily under dryland conditions. The highest yields occurred in

[30] Counties with more than 6 total years of missing county yield data or more than 3 consecutive years of missing county yield data were excluded from the analysis. Any missing county yields were replaced by the average yield for the crop reporting district (CRD) of which the county is a part. All missing county yield data occur prior to 1991. Thus, the substitution of CRD yields for missing county yields may affect actual unsubsidized and subsidized GRP premium rates but does not affect GRP indemnities during the 1991-2000 period analyzed.

CRD 70 which has significant irrigation. CRDs 50 and 80, located in the south central part of the state, have both dryland and irrigated production. For South Carolina, six counties located in two CRDs were included in the cotton analysis and seven counties located in the same two CRDs were included in the soybean analysis (see figures 2 and 3). Both cotton and soybean yields were similar across the two CRDs in 2001.

Scatter plots showed no time trend in the county-level soybean yield data, so the county yield forecast *yfcast* can be calculated simply as the in-sample average yield. On the other hand, cotton county yield data in both states display a significant time trend. To account for the temporal component, a simple detrending procedure was implemented by fitting a log-linear trend model

(6) $$\log(\tilde{y}_t) = \alpha_0 + \alpha_1(t - T_0)$$

where t is the year and T_0 is 1971 for Georgia cotton and 1972 for South Carolina cotton. Detrended yields were then calculated as:

(7) $$y_t^{det} = \frac{\tilde{y}_t}{\hat{y}_t}\hat{y}_{2000}$$

where $\hat{y}_t$ is the predicted value for year t from (6).

Premium Rating

Three different MPCI and GRP premium rates are considered in this analysis: 1) in-sample actuarially fair premium rates; 2) actual unsubsidized premium rates; and, 3) actual subsidized premium rates.

For an MPCI contract, the actuarially fair premium π_{MPCI}^f is the expectation of (1)

(8) $$\pi_{MPCI}^f = E(\tilde{n}_{MPCI}(\tilde{y}_i \mid coverage)) = E(\max(y_{ic} - \tilde{y}_i, 0)).$$

Since the liability (i.e., the maximum possible indemnity) is y_{ic}, the actuarially fair premium rate ρ^{f}_{MPCI} is

$$\text{(9)} \qquad \rho^{f}_{MPCI} = \frac{E\left(\max\left(y_{ic} - \tilde{y}_{i}, 0\right)\right)}{y_{ic}}.$$

Similarly, for a GRP contract, the actuarially fair premium is the expectation of (2)

$$\text{(10)} \qquad \pi^{f}_{GRP} = E\left(\tilde{n}_{GRP}\left(\tilde{y} \mid coverage,\ scale\right)\right) = E\left(\max\left(\frac{\left(y_{c} - \tilde{y}\right)}{y_{c}}, 0\right) \times yfcast \times scale\right)$$

and the actuarially fair premium rate ρ^{f}_{GRP} is

$$\text{(11)} \qquad \rho^{f}_{GRP} = \frac{E\left(\max\left(\frac{\left(y_{c} - \tilde{y}\right)}{y_{c}}, 0\right) \times yfcast \times scale\right)}{yfcast \times scale} = E\left(\max\left(\frac{\left(y_{c} - \tilde{y}\right)}{y_{c}}, 0\right)\right).$$

For each MPCI contract, actuarially fair premium rates were calculated according to (9) as the in-sample average loss costs (indemnities divided by liability) for each farm over the 6-10 year period for which farm-level yields are available. The actual unsubsidized and subsidized premium rates for MPCI were obtained from 2001 RMA FCI-35 coverage and rate tables available on the RMA website (U.S. Department of Agriculture). Unsubsidized GRP premium rates were calculated using the available NASS data and procedures similar to those used for the actual GRP program as described by Skees, Black, and Barnett.[31] For the counties were GRP is currently available, actual GRP premium rates can be obtained. However, to maintain consistency, generated GRP premium rates were used for all counties included in the analysis. For those South Carolina counties where soybean GRP is currently available, the GRP premium

[31] Relative to actual GRP premium rating procedures the primary differences in the procedures used to generate GRP premium rates for this analysis are: 1) no geographic smoothing of premium rates was imposed; and, 2) coverage level rate relativities were based on a distribution estimated using kernel smoothing procedures rather than the combination of empirical and parametric procedures described by Skees, Black, and Barnett.

rates from our procedure were similar to the actual GRP premium rates. Subsidized MPCI and GRP premium rates were calculated by applying the actual subsidy percentages at each coverage level (shown in table 2) to the calculated unsubsidized premium rates.

To generate unsubsidized GRP premium rates at various coverage levels, it is necessary to estimate the probability density function of trend-adjusted county-level yields for each crop/county. Several studies have described procedures for estimating crop yield distributions (Just and Weninger; Sherrick et al.). Some have used parametric distributions with known attributes, such as the beta distribution or the log-normal distribution (Nelson and Preckel; Tirupattur, Hauser, and Chaherli). Others use non-parametric approaches (Ker and Goodwin). For this analysis, county-level yield distributions were estimated non-parametrically using a kernel-smoothing approach. Formally, for realizations y_t, $t = 1, ..., T$, of county yield, the kernel density function of the county-level yield was calculated as:

$$h(y) = \frac{1}{T\Delta} \sum_{t=1}^{T} K\left(\frac{y - y_t}{\Delta} \right) \tag{12}$$

where $K(\cdot)$ is a kernel function and Δ is a degree of smoothness or bandwidth (Härdle). The expected indemnity, which is the long-run estimate of the breakeven premium, can then be determined by

$$\pi(coverage, scale) = \int \tilde{n}(y \mid coverage, scale) h(y) dy \, . \tag{13a}$$

Following actual GRP rating procedures, a proportional reserve load is applied to the breakeven premium to generate the unsubsidized premium

$$\pi(coverage, scale) = \frac{1}{0.9} \times \int \tilde{n}(y \mid coverage, scale) h(y) dy \, . \tag{13b}$$

The subsidized premium can then be determined as

$$(13c) \quad \pi(coverage, scale) = (1 - subsidy\ \%)\left[\frac{1}{0.9} \times \int \tilde{n}(y \mid coverage, scale) h(y) dy\right].$$

Finally, for all three cases, premium rates are calculated as premiums divided by the liability $(yfcast \times scale)$.

Decision Criterion

Previous studies have, by construction, used GRP and MPCI premiums that are actuarially fair in-sample. Thus, each insurance product could be compared against other products and against a no insurance scenario by simply considering the resulting variance of net yield (net of insurance premiums and indemnities). Given that wedges exist for MPCI policies and federal premium subsidies exist for all FCIP policies, an assumption of actuarial fairness is not very realistic. However, when the assumption of actuarial fairness is relaxed, the variance of net yield is no longer sufficient for evaluating the relative performance of the insurance products. Therefore, we asume that farmers value revenues according to the mean-variance criterion

$$(14) \qquad V = E(R) - \frac{1}{2} k \times \mathrm{var}(R)$$

where R is revenue and k is assumed to be positive, implying that the individual is risk averse (Eeckhoudt and Gollier). For this analysis, revenue is calculated as

$$(15) \qquad R_{ij} = p\tilde{y}_{ij}^{net}$$

where R_{ij} is revenue for farm i and insurance scenario j, $\tilde{y}_{ij}^{net}$ is as defined in (3), and p is a constant price per unit for each commodity.[32]

For MPCI, *coverage* was fixed at 65%, 75%, and 85%. GRP *coverage* and *scale* were optimized at either the state or CRD level. When only a short time-series of farm-level yields are

[32] The price for cotton is the 2001 New York Board of Trade November average price on the December contract. The price for soybeans is the 2001 Chicago Board of Trade October average price on the November contract.

available, farm-level optimization of GRP *coverage* and *scale* data is problematic. Thus, consistent with Barnett et al., this study employs the more conservative approach of optimizing these parameters at a state or CRD level and then applying the optimized values to every farm in the state or CRD. If the production region is very heterogeneous (i.e., basis risk is high) GRP should perform better when *coverage* and *scale* are optimized at the CRD level rather than at the state level.

The optimal values of GRP *coverage* and *scale* are those that maximize the acreage-weighted sum φ of differences between the mean-variance valuation of GRP revenues relative to the valuation of revenues with no insurance at the farm level. Specifically

$$
\begin{aligned}
\varphi_{coverage,\,scale} &= \max_{coverage,\,scale} \frac{\sum_i \Delta V_i^{GRP} \times a_i}{\sum_i a_i} = \max_{coverage,\,scale} \frac{\sum_i \left(V_i^{GRP} - V_i^{without}\right) \times a_i}{\sum_i a_i} \\
&= \max_{coverage,\,scale} \frac{\sum_i \left\{ \left(\left[E(\tilde{n}) - \pi\right] - \frac{1}{2} k \left[2\operatorname{cov}(\tilde{y},\tilde{n}) + \operatorname{var}(\tilde{n})\right] \right) \times a_i \right\}}{\sum_i a_i}
\end{aligned} \tag{16}
$$

where V is as defined in (14) and a_i are weights that reflect planted acreage of the crop on farm i in 2000. The optimal *scale* and *coverage* were found simultaneously using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Greene; Miranda and Fackler).

Optimal GRP *coverage* and *scale* were first calculated within current policy constraints; i.e., 70% ≤ *coverage* ≤ 90% and 90% ≤ *scale* ≤ 150%. These constraints were then relaxed so that the optimal *coverage* and *scale* were allowed to take any non-negative values.[33]

Certainty-Equivalent Revenues

[33] If the optimal *coverage* is higher than 90%, the subsidized premium is calculated using the subsidy percentage for 90% *coverage*.

The relative performance of MPCI and GRP insurance contracts was evaluated based on certainty-equivalent revenues (CER) from the constant relative risk aversion utility function

$$(17)\qquad \begin{aligned} U &= \frac{R^{1-\gamma}}{1-\gamma} \quad \text{when } \gamma \neq 1, \text{and} \\ U &= \log(R) \quad \text{when } \gamma = 1 \end{aligned}$$

where R is as defined in (15) and γ is the measure of relative risk aversion.

For this analysis γ was calibrated to correspond to a prespecified risk premium θ (Babcock, Choi, and Feinermean; Schnitkey, Sherrick, and Irwin; Vedenov and Barnett). More specifically, for a given level of risk premium θ, the parameter γ was computed numerically so that the expected utility of the revenue without the insurance contract was equal to the utility of certain revenue $(1-\theta)\times E(R)$, i.e.,

$$(18)\qquad EU(R) = E_R\left(\frac{R^{1-\gamma}}{1-\gamma}\right) = \frac{[(1-\theta)\times E(R)]^{1-\gamma}}{1-\gamma} = U((1-\theta)\times E(R))$$

where $E(R)$ is the expected revenue without insurance. Once the parameter γ has been determined, the CERs without and with the insurance contracts can be calculated as

$$(19a)\qquad U(CER_{without}) = \mathrm{E}_R U(R)\text{; and}$$

$$(19b)\qquad U(CER_{with}) = \mathrm{E}_R U(R^{net})\text{ .}$$

For this analysis, CERs were calculated for each farm i and then averaged over the area using the 2000 farm-level planted acreage a_i as weights.

Results

Table 3 presents optimal GRP *coverage* and *scale* for a given region (state or CRD) when the premium rates are calculated under the three premium rating schemes (actuarially fair in-sample, actual unsubsidized, and actual subsidized), respectively . The third and fourth columns present optimal *coverage* and *scale* levels when these choice variables are restricted as in the existing GRP policy. In every case, the restricted optimal *coverage* is at the upper limit of 90%. In half the regions considered for each rating scheme, the restricted optimal *scale* for cotton is at the upper limit of 150%. In two of the regions considered, the restricted optimal *scale* for soybeans is at the lower limit of 90%.

Since GRP is not exposed to moral hazard problems, there is no conceptual rationale for imposing constraints on the choice of *coverage* and *scale*. In fact, Barnett et al. point out that the current politically-imposed restrictions on GRP *coverage* and *scale* are analogous to restricting choices of strike and hedge ratio for those who use futures and options contracts to hedge price risk. Skees, Black, and Barnett attribute the current restrictions on these GRP choice variables to the fact that RMA decision-makers have backgrounds in farm-level crop insurance and are thus uncomfortable with allowing high levels of *coverage* and *scale*. It may be that upper bounds on these choice variables are also intended to limit federal premium subsidies for GRP.

Unrestricted optimal *coverage* and *scale* levels are presented in the fifth and sixth columns of table 3. When *coverage* and *scale* are unrestricted, the optimal *coverage* is always significantly higher than in the restricted case while the optimal *scale* is generally lower. This finding suggests that under current GRP restrictions, policy-holders would use higher levels of *scale* to partially compensate for the upper bound on *coverage*. The upper bound on *coverage* means that the restricted GRP policy will not trigger an indemnity as often as policyholders would wish. Increasing *scale* allows policyholders to compensate for this to some degree by increasing the indemnity that is paid whenever the restricted GRP policy does trigger a payment.

Table 4 presents the average premium rates[34] for 75% MPCI and for the restricted and unrestricted optimal GRP coverage levels reported in table 3. Because of the very high coverage levels, the premium rates for unrestricted optimal GRP are prohibitively high. For this reason, the subsequent comparison of MPCI and GRP performance focuses only on the restricted optimal GRP policy.

Table 4 demonstrates the limitations of performance comparisons conducted with premium rates that are actuarially fair in-sample. On average, across all the crops and regions studied, the actual unsubsidized premium rate for the restricted optimal GRP is 57% higher than the in-sample actuarially fair premium rate. The impact of positive wedges in actual MPCI premium rates is shown by the fact that the actual unsubsidized premium rate for 75% MPCI is on average 286% higher than the in-sample actuarially fair premium rate.

Table 5 shows the performance of GRP and MPCI, measured by CERs, when premium rates are actuarially fair in-sample. The table shows CERs without insurance and then the change in the CER with restricted optimal GRP and MPCI at 65%, 75%, and 85% *coverage*. Positive (negative) changes imply that producers are better (worse) off as a result of purchasing the specific insurance contract. The higher (lower) the *coverage* on the MPCI contract, the higher (lower) the change in CERs.

Except for one GRP case when the risk premium is only 5%, producers are always better off by purchasing an insurance product (either MPCI or GRP). The CERs without insurance purchasing decrease (increase) as the risk premium increases (decreases). The higher (lower) the risk premium the higher (lower) the change in CERs from insurance purchasing. In most cases, even the MPCI policy with 65% *coverage* performs better than the restricted optimal GRP. The

[34] Premium rates were calculated at county base and the average premium rates at CRD- or state-level, comprising of the corresponding counties, were then presented in table 4.

only exceptions are for Georgia cotton in CRD 70 when the risk premium is 10% and 15% and Georgia cotton in CRD 60 when the risk premium is 15%.

Table 6 demonstrates the importance of extending the analysis beyond in-sample actuarially fair premium rates to consider actual premium rates. The results presented here are based on actual unsubsidized premium rates. The changes in CERs are now frequently negative (particularly for lower risk premiums), indicating that producers are made worse off by purchasing insurance at actual unsubsidized premium rates. More importantly, though the restricted optimal GRP contract often generates a negative change in CERs, its performance relative to MPCI is much better than when premium rates were calculated to be actuarially fair in-sample. In most cases, the restricted optimal GRP policy performs better than MPCI at any level of *coverage* (MPCI at 65% *coverage* always performs better than MPCI at higher levels of *coverage*). This would seem to confirm that previous work, based on premium rates that were actuarially fair in-sample, likely generated results that were biased in favor of MPCI. Note that for South Carolina soybeans, 85% *coverage* is not available for MPCI.

Table 7 presents results based on actual subsidized premium rates. At the 5% risk premium, restricted optimal GRP performs better than MPCI at any level of *coverage* (again, 65% MPCI *coverage* performs better than MPCI at higher levels of *coverage*) with the exception of cotton in Georgia CRD 50. At the 10% risk premium MPCI at 65% *coverage* performs better than restricted optimal GRP for cotton in Georgia CRD 50, cotton in South Carolina CRD 30, and all South Carolina soybean production regions. At the 15% risk premium MPCI at 65% *coverage* also performs better than restricted optimal GRP when GRP *coverage* and *scale* are optimized at the state level. These findings suggest that when the comparison is based on actual subsidized premium rates, GRP is a viable alternative to MPCI in many cotton producing regions of Georgia and South Carolina. The results for South Carolina soybeans are somewhat less compelling and depend on assumptions about the magnitude of risk aversion.

Table 5.1: Crops and Counties Selected for Analysis

Crop	State/District	Counties Selected	Number of Farmers Included	Average Acreage Per County (2001)	Average Yield/Acre (2001)
Cotton	GA/D50	Bleckley, Dodge, Laurens, Pulaski	146	19100.00	631 lbs
Cotton	GA/D60	Bullock, Burke, Candler, Emanuel, Jefferson, Jenkins, Screven	275	27985.71	616 lbs
Cotton	GA/D70	Early, Mitchell, Thomas	160	43666.67	868 lbs
Cotton	GA/D80	Ben Hill, Brooks, Coffee, Colquitt, Cook, Crisp, Dooly, Irwin, Tift, Turner, Wilcox, Worth	861	37700.00	708 lbs
Cotton	SC/D30	Darlington, Dillon, Marlboro	101	30000.00	700 lbs
Cotton	SC/D50	Calhoun, Lee, Orangeburg	110	27766.67	662 lbs
Soybean	SC/D30	Darlington, Dillon, Florence, Horry	145	42950.00	20.5 bu
Soybean	SC/D50	Clarendon, Lee, Sumter	123	28366.67	21.0 bu

Table 5.2: MPCI and GRP Premium Subsidy Percentages by Coverage Level

	Premium Subsidy Percentages	
Coverage	MPCI	GRP
50%	67%	NA
55%	64%	NA
60%	64%	NA
65%	59%	NA
70%	59%	64%
75%	55%	64%
80%	48%	59%
85%	38%	59%
90%	NA	55%

Table 5.3: Restricted and Unrestricted Optimal Coverage and Scale levels of GRP Contracts under Three Premium Rating Schemes

Crop	State/CRD	Restricted Optimal GRP		Optimal GRP	
		Coverage (70% - 90%)	*Scale* (90% - 150%)	*Coverage*	*Scale*
In Sample Actuarially Fair Premium Rates					
Cotton	GA/50	90.00%	150.00%	172.76%	139.80%
Cotton	GA/60	90.00%	150.00%	120.70%	179.37%
Cotton	GA/70	90.00%	117.97%	144.52%	113.74%
Cotton	GA/80	90.00%	139.34%	161.15%	135.89%
Cotton	GA/All	90.00%	150.00%	140.96%	135.95%
Cotton	SC/30	90.00%	106.24%	141.12%	100.85%
Cotton	SC/50	90.00%	150.00%	144.35%	134.31%
Cotton	SC/All	90.00%	127.32%	138.97%	119.85%
Soybean	SC/30	90.00%	90.00%	142.50%	65.40%
Soybean	SC/50	90.00%	98.36%	140.55%	90.54%
Soybean	SC/All	90.00%	90.00%	139.93%	90.68%
Actual Unsubsidized Premium Rates					
Cotton	GA/50	90.00%	150.00%	154.66%	125.58%
Cotton	GA/60	90.00%	150.00%	127.06%	176.06%
Cotton	GA/70	90.00%	119.96%	124.91%	112.09%
Cotton	GA/80	90.00%	129.74%	141.44%	113.45%
Cotton	GA/All	90.00%	150.00%	131.88%	134.75%
Cotton	SC/30	90.00%	90.00%	140.89%	90.83%
Cotton	SC/50	90.00%	150.00%	137.91%	128.17%
Cotton	SC/All	90.00%	115.20%	138.33%	113.29%
Soybean	SC/30	90.00%	90.00%	143.57%	60.11%
Soybean	SC/50	90.00%	107.72%	137.74%	87.31%
Soybean	SC/All	90.00%	90.00%	145.39%	71.68%
Actual Subsidized Premium Rates					
Cotton	GA/50	90.00%	150.00%	184.68%	145.94%
Cotton	GA/60	90.00%	150.00%	164.72%	187.33%
Cotton	GA/70	90.00%	129.46%	166.78%	162.35%
Cotton	GA/80	90.00%	146.98%	173.57%	183.56%
Cotton	GA/All	90.00%	150.00%	162.78%	185.18%
Cotton	SC/30	90.00%	105.00%	166.57%	134.66%
Cotton	SC/50	90.00%	150.00%	155.58%	167.81%
Cotton	SC/All	90.00%	129.36%	162.38%	153.31%
Soybean	SC/30	90.00%	90.00%	167.50%	70.00%
Soybean	SC/50	90.00%	107.72%	147.87%	85.87%
Soybean	SC/All	90.00%	90.00%	145.39%	71.68%

Table 5.4: Premium Rates for Insurance Contracts under Three Premium Rating Schemes

Crop	State/CRD	In Sample Actuarially Fair Premium Rates			Actual Unsubsidized Premium Rates			Actual Subsidized Premium Rates		
		Restricted Optimal GRP	Optimal GRP	MPCI 75%	Restricted Optimal GRP	Optimal GRP	MPCI 75%	Restricted Optimal GRP	Optimal GRP	MPCI 75%
Cotton	GA/50	7.94%	42.17%	10.75%	9.90%	40.31%	29.65%	4.46%	23.22%	13.34%
Cotton	GA/60	9.45%	23.95%	14.56%	10.93%	27.44%	21.44%	4.92%	19.85%	9.65%
Cotton	GA/70	7.86%	39.09%	4.69%	7.35%	25.63%	18.93%	3.06%	20.81%	8.52%
Cotton	GA/80	5.65%	40.38%	6.22%	8.03%	33.84%	20.91%	3.06%	21.41%	9.41%
Cotton	GA/All	6.85%	32.91%	8.10%	8.64%	29.32%	21.68%	3.89%	19.60%	9.75%
Cotton	SC/30	3.88%	25.92%	4.68%	9.35%	32.80%	17.34%	4.21%	19.85%	7.80%
Cotton	SC/50	6.08%	30.97%	5.50%	8.01%	32.00%	22.38%	2.52%	18.09%	10.07%
Cotton	SC/All	5.03%	26.81%	5.11%	8.65%	31.91%	19.96%	3.89%	19.23%	8.98%
Soybean	SC/30	1.74%	26.54%	5.43%	4.49%	33.66%	32.89%	2.02%	20.13%	14.80%
Soybean	SC/50	2.58%	27.42%	6.04%	3.53%	30.43%	29.85%	1.59%	16.18%	13.43%
Soybean	SC/All	2.13%	26.07%	5.71%	4.05%	34.65%	31.49%	1.82%	15.59%	14.17%

Table 5.5: Certainty Equivalent Revenues with Actuarially Fair Premium Rates

Crop/District	State/CRD	CERs	Change in CERs with Insurance			
		Without Contract	Restricted Optimal GRP	MPCI 65%	MPCI 75%	MPCI 85%
		Risk Premium 5%				
Cotton	GA/50	$215.60	$1.62	$2.54	$3.47	$5.07
Cotton	GA/60	$211.60	$4.75	$6.33	$7.43	$8.54
Cotton	GA/70	$255.60	$1.43	$1.96	$3.36	$5.39
Cotton	GA/80	$232.22	$1.09	$2.94	$4.33	$6.13
Cotton	GA/All	$229.23	$2.07	$3.55	$4.84	$6.49
Cotton	SC/30	$241.95	-$2.01	$0.87	$3.24	$5.78
Cotton	SC/50	$220.82	$2.26	$2.46	$3.69	$5.18
Cotton	SC/All	$233.19	$1.78	$2.71	$4.32	$6.30
Soybean	SC/30	$103.16	$0.02	$1.26	$1.88	$2.72
Soybean	SC/50	$115.62	$0.54	$2.06	$2.69	$3.62
Soybean	SC/All	$109.33	$0.28	$1.66	$2.28	$3.17
		Risk Premium 10%				
Cotton	GA/50	$204.25	$3.11	$6.21	$8.18	$11.46
Cotton	GA/60	$195.74	$12.40	$15.83	$18.21	$20.49
Cotton	GA/70	$242.63	$3.44	$2.60	$8.12	$12.38
Cotton	GA/80	$219.03	$3.53	$7.30	$10.44	$14.19
Cotton	GA/All	$215.60	$5.35	$8.84	$11.72	$15.16
Cotton	SC/30	$227.23	$2.69	$7.35	$11.56	$16.41
Cotton	SC/50	$209.37	$4.96	$6.16	$8.81	$11.85
Cotton	SC/All	$219.83	$3.56	$6.85	$10.42	$14.52
Soybean	SC/30	$97.33	$0.14	$3.15	$4.53	$6.28
Soybean	SC/50	$108.17	$1.50	$5.22	$6.64	$8.64
Soybean	SC/All	$102.70	$0.80	$4.17	$5.58	$7.45
		Risk Premium 15%				
Cotton	GA/50	$192.67	$10.92	$11.04	$14.08	$18.85
Cotton	GA/60	$177.04	$39.31	$28.54	$32.24	$35.67
Cotton	GA/70	$230.91	$8.35	$8.19	$13.18	$19.34
Cotton	GA/80	$206.27	$6.40	$12.18	$17.04	$22.54
Cotton	GA/All	$201.73	$12.00	$15.28	$19.75	$24.80
Cotton	SC/30	$212.94	$3.54	$12.29	$18.83	$25.98
Cotton	SC/50	$197.89	$7.65	$10.65	$14.79	$19.29
Cotton	SC/All	$206.70	$5.13	$11.61	$17.16	$23.21
Soybean	SC/30	$91.62	$0.29	$5.41	$7.53	$10.13
Soybean	SC/50	$100.77	$2.42	$8.88	$11.07	$14.03
Soybean	SC/All	$96.15	$1.33	$7.13	$9.29	$12.06

Table 5.6: Certainty Equivalent Revenues with Actual Unsubsidized Premium Rates

Crop/District	State/CRD	CERs	Change in CERs with Insurance			
		Without Contract	Restricted Optimal GRP	MPCI 65%	MPCI 75%	MPCI 85%
		Risk Premium 5%				
Cotton	GA/50	$215.60	-$10.72	-$9.83	-$20.19	-$40.78
Cotton	GA/60	$211.60	-$2.79	$4.58	-$2.99	-$21.25
Cotton	GA/70	$255.60	$4.63	-$14.07	-$24.92	-$45.96
Cotton	GA/80	$232.22	-$6.74	-$10.94	-$21.39	-$42.59
Cotton	GA/All	$229.23	-$5.20	-$7.73	-$17.57	-$38.04
Cotton	SC/30	$241.95	-$13.38	-$11.66	-$20.26	-$37.65
Cotton	SC/50	$220.82	-$7.65	-$14.22	-$25.57	-$48.52
Cotton	SC/All	$233.19	-$11.39	-$12.73	-$22.46	-$42.16
Soybean	SC/30	$103.16	-$3.37	-$9.70	-$18.10	NA
Soybean	SC/50	$115.62	-$7.66	-$6.98	-$15.01	NA
Soybean	SC/All	$109.33	-$6.72	-$8.35	-$16.57	NA
		Risk Premium 10%				
Cotton	GA/50	$204.25	-$7.91	-$6.58	-$16.13	-$37.11
Cotton	GA/60	$195.74	$4.27	$13.97	$7.52	-$9.83
Cotton	GA/70	$242.63	$7.04	-$11.69	-$20.89	-$39.55
Cotton	GA/80	$219.03	-$5.47	-$7.12	-$16.00	-$35.50
Cotton	GA/All	$215.60	-$2.74	-$2.88	-$11.31	-$25.07
Cotton	SC/30	$227.23	-$11.08	-$7.84	-$14.26	-$29.28
Cotton	SC/50	$209.37	-$3.69	-$11.10	-$21.23	-$42.89
Cotton	SC/All	$219.83	-$9.07	-$9.19	-$17.15	-$34.92
Soybean	SC/30	$97.33	-$7.36	-$8.26	-$14.42	NA
Soybean	SC/50	$108.17	-$0.68	-$4.15	-$11.56	NA
Soybean	SC/All	$102.70	-$2.70	-$6.22	-$13.00	NA
		Risk Premium 15%				
Cotton	GA/50	$192.67	-$5.89	-$2.00	-$10.62	-$28.47
Cotton	GA/60	$177.04	$21.36	$26.64	$21.37	$5.13
Cotton	GA/70	$230.91	$11.33	-$8.72	-$16.17	-$33.32
Cotton	GA/80	$206.27	$3.43	-$2.55	-$9.80	-$26.64
Cotton	GA/All	$201.73	$3.73	$3.32	-$3.62	-$12.82
Cotton	SC/30	$212.94	-$11.07	-$3.32	-$7.49	-$20.30
Cotton	SC/50	$197.89	$0.05	-$7.01	-$15.74	-$36.07
Cotton	SC/All	$206.70	-$8.26	-$4.85	-$10.91	-$26.84
Soybean	SC/30	$91.62	-$4.53	-$6.26	-$13.09	NA
Soybean	SC/50	$100.77	-$5.57	-$0.68	-$7.42	NA
Soybean	SC/All	$96.15	-$1.83	-$3.50	-$10.28	NA

Table 5.7: Certainty Equivalent Revenues with Actual Subsidized Premium Rates

Crop/District	State/CRD	CERs	Change in CERs with Insurance			
		Without Contract	Restricted Optimal GRP	MPCI 65%	MPCI 75%	MPCI 85%
			Risk Premium 5%			
Cotton	GA/50	$215.60	$12.86	$25.12	$21.92	$6.09
Cotton	GA/60	$211.60	$19.05	$15.09	$14.31	$0.38
Cotton	GA/70	$255.60	$19.05	-$2.53	-$5.93	-$22.32
Cotton	GA/80	$232.22	$9.17	$0.88	-$1.93	-$18.33
Cotton	GA/All	$229.23	$7.65	$3.76	$1.35	-$14.44
Cotton	SC/30	$241.95	$0.38	-$0.77	-$2.39	-$15.43
Cotton	SC/50	$220.82	$10.34	-$1.68	-$4.89	-$22.70
Cotton	SC/All	$233.19	$3.86	-$1.15	-$3.43	-$18.44
Soybean	SC/30	$103.16	-$0.86	-$1.52	-$4.61	NA
Soybean	SC/50	$115.62	$1.03	$0.89	-$2.03	NA
Soybean	SC/All	$109.33	$0.02	-$0.33	-$3.33	NA
			Risk Premium 10%			
Cotton	GA/50	$204.25	$14.89	$31.70	$29.39	$14.43
Cotton	GA/60	$195.74	$27.05	$24.78	$25.19	$12.18
Cotton	GA/70	$242.63	$21.93	$0.27	-$1.40	-$15.80
Cotton	GA/80	$219.03	$11.64	$5.14	$4.00	-$10.71
Cotton	GA/All	$215.60	$10.97	$9.01	$8.11	-$6.14
Cotton	SC/30	$227.23	$1.44	$3.53	$4.19	-$6.56
Cotton	SC/50	$209.37	$13.45	$1.88	$0.01	-$16.52
Cotton	SC/All	$219.83	$5.64	$2.85	$2.46	-$10.69
Soybean	SC/30	$97.33	-$0.35	$0.25	-$2.15	NA
Soybean	SC/50	$108.17	$1.96	$4.00	$1.79	NA
Soybean	SC/All	$102.70	$0.42	$2.11	-$0.20	NA
			Risk Premium 15%			
Cotton	GA/50	$192.67	$22.82	$39.46	$37.81	$23.61
Cotton	GA/60	$177.04	$38.58	$37.69	$39.35	$27.29
Cotton	GA/70	$230.91	$25.04	$3.48	$3.58	-$9.03
Cotton	GA/80	$206.27	$13.68	$9.99	$10.53	-$2.59
Cotton	GA/All	$201.73	$16.92	$15.49	$16.12	$3.31
Cotton	SC/30	$212.94	$2.15	$7.82	$11.06	$1.91
Cotton	SC/50	$197.89	$16.57	$6.29	$5.87	-$9.37
Cotton	SC/All	$206.70	$7.24	$7.52	$9.07	-$2.28
Soybean	SC/30	$91.62	-$0.13	$2.47	$0.76	NA
Soybean	SC/50	$100.77	$2.86	$7.66	$6.16	NA
Soybean	SC/All	$96.15	$0.81	$5.04	$3.44	NA

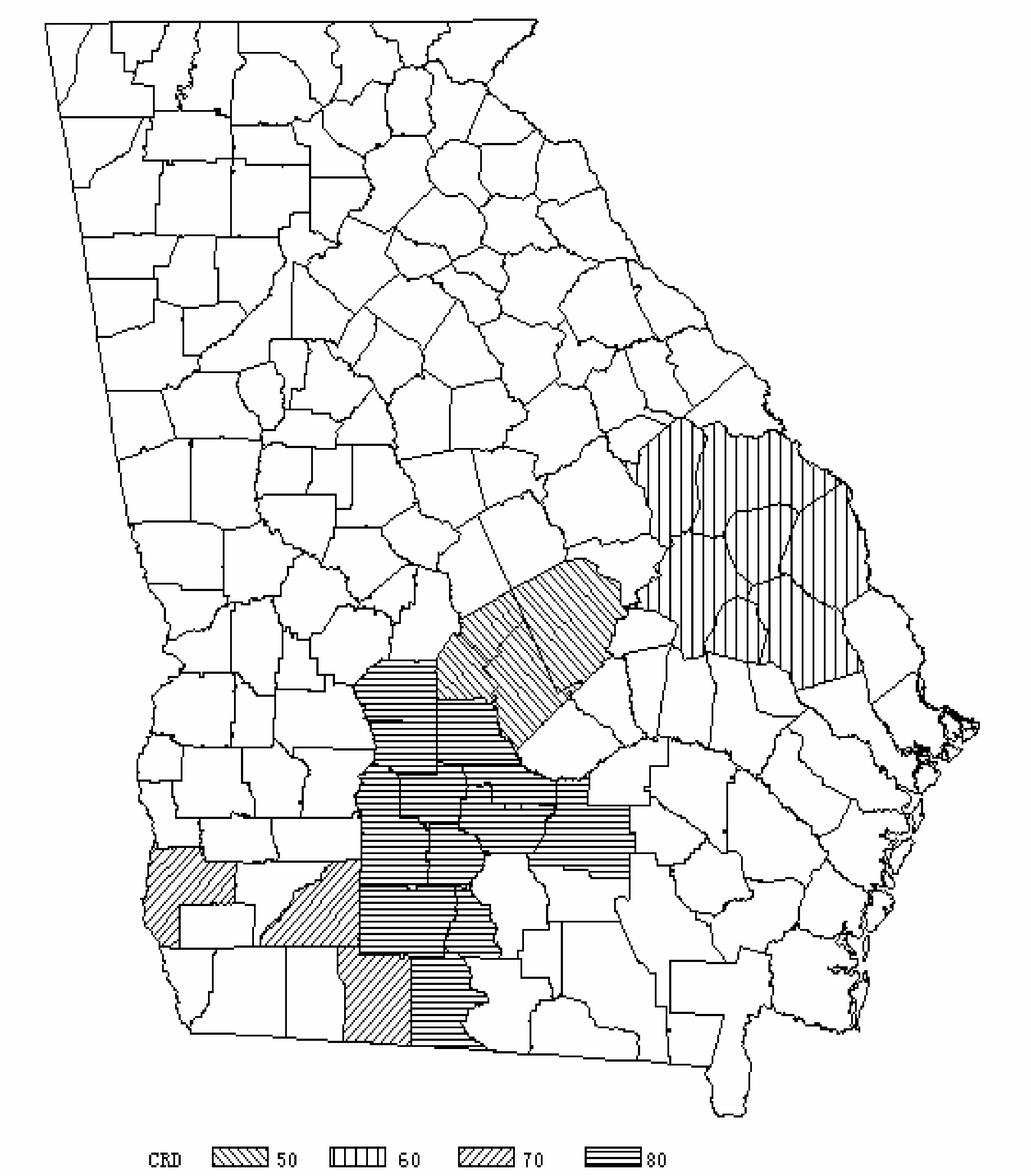

Figure 5.1: Georgia Counties Producing Cotton Included in the Study

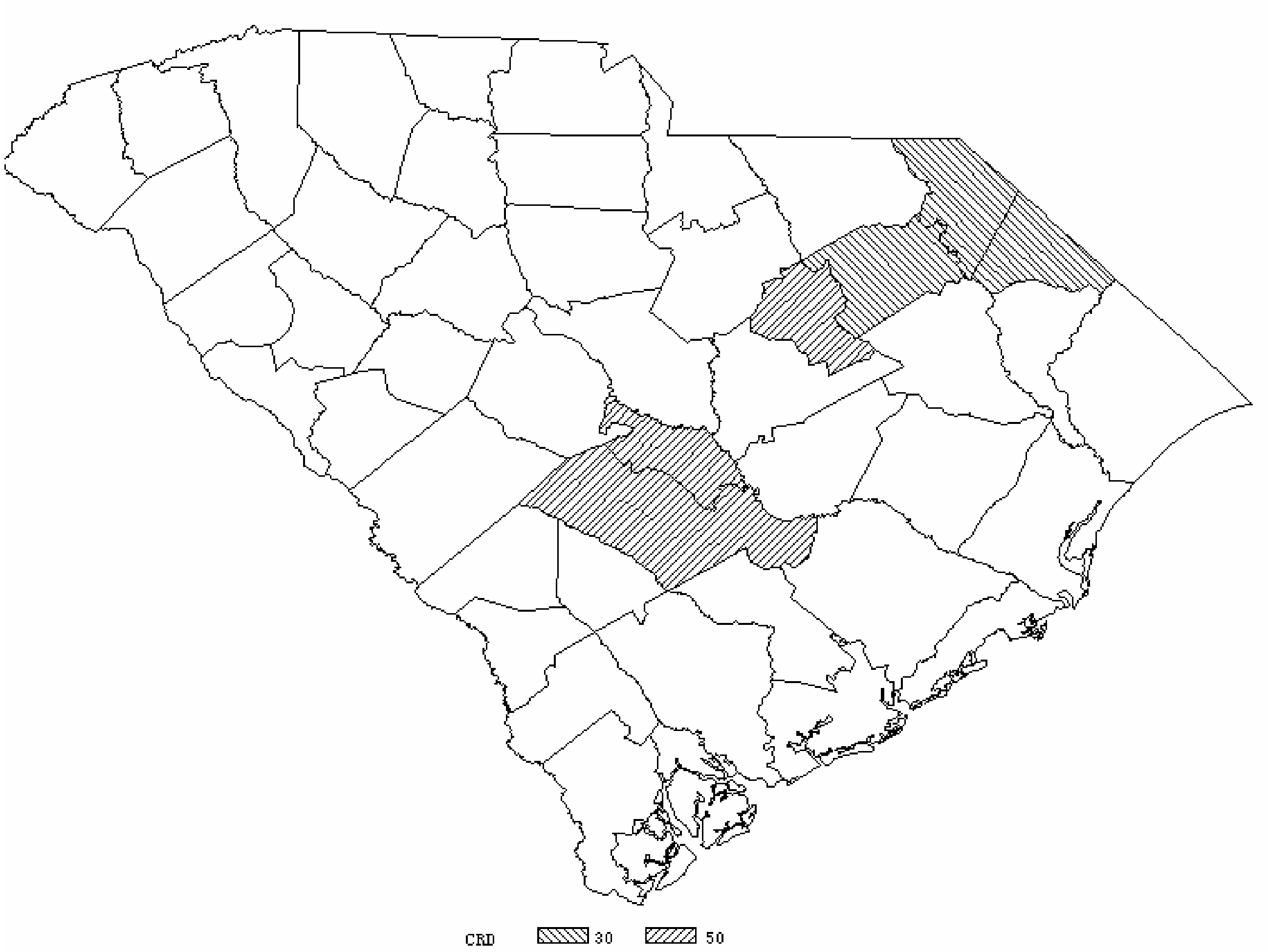

Figure 5.2: South Carolina Cotton Producing Counties Included in the Study

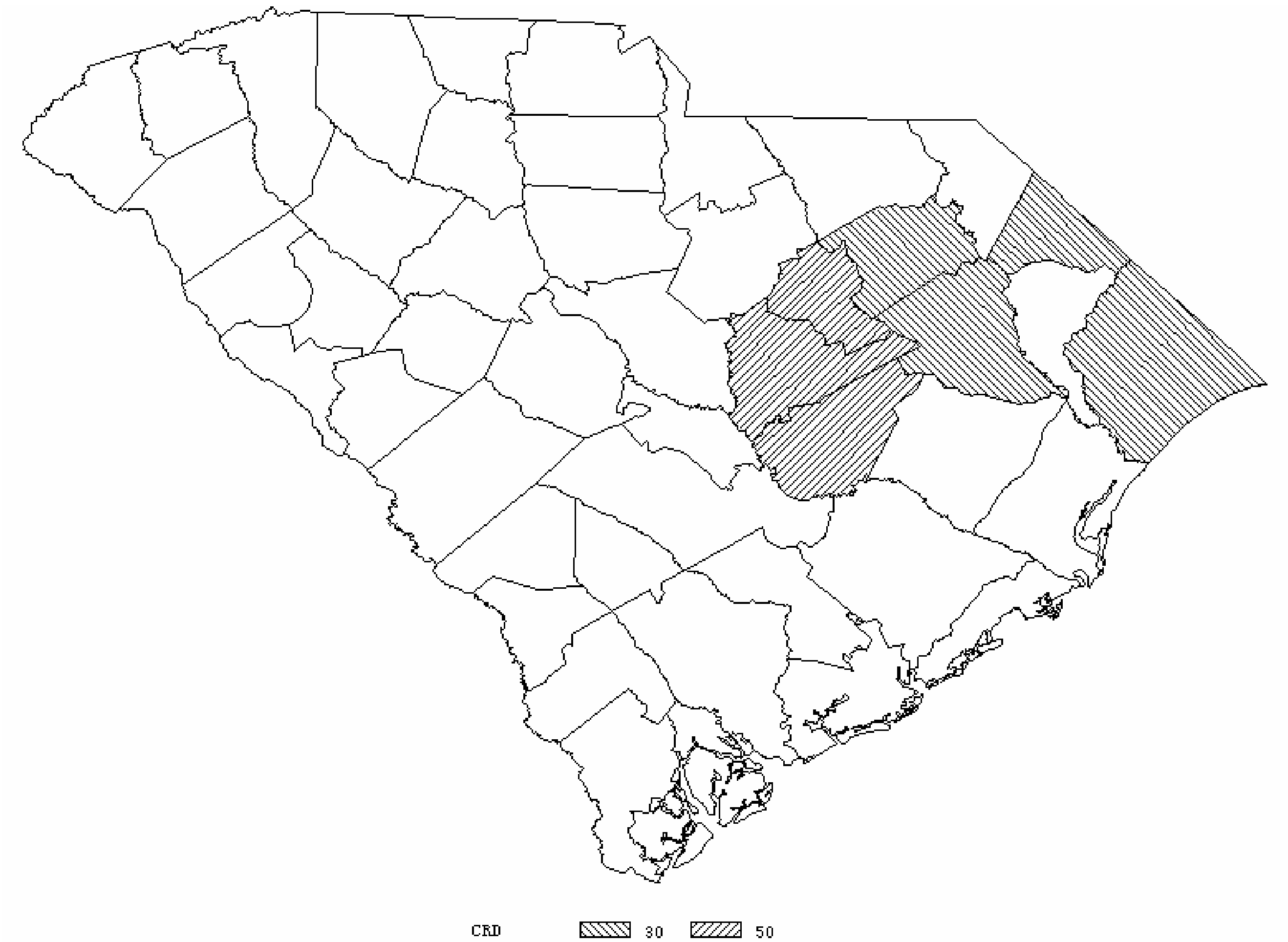

Figure 5.3: South Carolina Soybean Producing Counties Included in the Study

CHAPTER 6

MARKOV CHAIN MODELS FOR FARM CREDIT RISK MIGRATION

In corporate finance, migration analysis has been employed extensively as an important analytical decision aid for investors, lenders and asset managers. Major rating companies such as Moody's and Standard and Poor's have routinely measured and reported rating migration rates for bonds and other publicly traded securities. Transition or migration analysis is based on the extrapolation into the future of historic rates of movement (i.e. transition probabilities) among risk rating classes. The decision tool, a summary migration matrix, is a compilation of longitudinal (time–series) averages of transition rates from matrices for subsets of shorter time periods. The time period matrices are, in turn, are constructed from a panel transitions data set. Analysts and investors use such matrices to determine likelihoods of intertemporal changes in the quality of bond and security issues that are factored into portfolio risk management decisions.

Migration analysis is essential to the credit risk component of economic capital management employed by the top tier of financial institutions and recently adopted by the new Basel Accord as the vanguard method of determining regulatory capital (Altman and Saunders). Commercial lenders use transition rating matrices to develop probability estimates of financial stress/loan default rates and other indicators of their loan portfolio quality. Migration rates for commercial loans, agricultural loans and other types of loans, however, are more difficult to compile due to shorter data histories, less updated term loan underwriting histories, and use of relatively newer risk rating systems (Barry, Escalante, and Ellinger). Nonetheless, credit rating transition rates offer richer, broader information on risk stability and loan portfolio quality than historic loan default rates derived using traditional measurement methods (Katchova and Barry).

Numerous studies on credit risk migration in corporate finance and limited number of studies in agricultural lending employed a straightforward discrete time (cohort) approach in developing migration matrices, which has even become an "industry standard" approach used even by the large corporate rating agencies (Lando and Skodeberg; Schuermann and Jafry). Notably, the cohort approach ignores any rating change activity within sub-periods of a given time frame and focuses only on migrations observed at the two time endpoints (i.e. the beginning and the end of a time period). The omission of "transient" class migrations in-between the endpoints reduces the reliability of the cohort approach in consistently producing accurate and efficient estimates of migration rates.

In recent years, a duration "Markov chain" approach based on survival analysis is emerging in corporate finance to address the deficiency of the cohort method (Lando and Skodeberg; Israel, Rosenthal, and Wei). Our study applies the same Markov chain model variants they used (time homogenous and non-homogenous Markov chain models) to the estimation of farm credit risk migration rates using farm-level financial data from the Illinois Farm Business Farm Management (FBFM) system. The farm data will be tested initially for conformity with the Markov property of independence, which is a precondition for the adoption of such models. These tests will include eigenvalue/eigenvector analyses and a semi-parametric multiplicative hazard model to test the existence of rating drift that violates the Markov chain assumption.

In this analysis, we start with a 2 x 1 migration framework to lay out the theoretical strengths and arguments of the proposed alternative Markov chain models.[35] The lenders' 3x1 migration framework is later used to verify the merits of the alternative methods.

The rest of the paper proceeds as follows: The next sections provide a description of this study's farm financial dataset and demonstrate the estimation of an aggregate cohort migration matrix using the 2x1 measurement method. The subsequent section tests for validity of the Markov chain process assumption as applied to this study's farm credit risk migration data set. The next sections present the estimation of the Markov chain matrices, develop portfolio default probability estimates under the cohort and Markov chain models, use the farm lenders' 3x1 method to validate earlier findings.

6.1 Farm Credit Risk Ratings Data

In the absence of lender data, this study utilizes farm-level financial data as a proxy for actual loan performance.[36] These financial data come from a database of certified usable annual farm financial and family living records compiled under the Illinois FBFM system for the period 1985 to 2001. While the FBFM system has an annual membership of about 7,000 farms, stringent procedures enforced for the certification of the soundness and acceptability of both sets of financial and family living records usually reduce the database to about 500 to 1,500 farms in each year. For purposes of this analysis, we initially considered selecting only those farm observations that have consistently been certified by the FBFM throughout the 17-year period.

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[35] The testing and application of the Markov chain process will require at least three consecutive annual data for each farm. In each 3-year period, the 2x1 method is the simplest migration measurement approach that is consistent with the farm lenders' practice of analyzing risk migration from multi-year averages to a one-year transition horizon (such as the 4th year in the 3x1 method).

[36] Use of farm record data as proxy for lender data could yield higher rates of transition across risk classes due to the omission of the influence of lenders' discretionary judgment that could stabilize movements among risk classes as well as their use of risk mitigation techniques in developing loan packages, and the inclusion of non-borrowing farms that might not meet lenders' credit risk assessment standards, and the (Barry, Escalante, and Ellinger).

However, this approach significantly reduced the sample size. Hence, this study instead utilizes unbalanced annual datasets where sample composition was allowed to vary over time periods to include farms that were not present in most other time period data sets. Other studies have used this approach to ensure a sample size that is large enough to produce statistically reliable results. (Bangia, *et al.*; Barry, Escalante, and Ellinger)

The credit risk classification variable used in this analysis is a farm's risk rating determined through a uniform rating model for term loans reported by Splett, *et al.* This model was developed for the Sixth Farm Credit District lenders in the early 1990s using a joint experience and statistical approach. Five financial ratios recommended by the Farm Financial Standards Council representing a farm's solvency, repayment capacity, profitability, liquidity, and financial efficiency are used in this model. The measurement procedures, pre-determined weights assigned to each component of the rating model, and the intervals used to classify the scores into 5 credit classes (where class 1 is the most favorable, lowest risk rating class and class 5 is the highest risk rating, default class)[37] as specified in Splett, *et al.* will be used in this analysis (See also Barry, Escalante, and Ellinger; Escalante, *et al.)*.

6.2 Developing the Cohort Migration Matrix

The cohort method, which calculates migration rates under a discrete-time framework is currently the standard approach used by most industry rating companies. It has been employed in several earlier migration studies in corporate and farm finance literature. Under this method, migration rates are calculated over a specific time horizon Δt by considering the change from Ni farm observations that belong to rating category i at the start of the time horizon to N_{ij} farms that

[37] Class 5 farms include both those in "default" or other cases of high credit risk. Since the sample composition is allowed to vary in this study from each 3-year grouping to another, defaulting farms in a particular period most likely have not remained in the database when the successive groups of observations are determined. These cases are analogous to those that belong to the "withdrawn" rating class used by S&P and Moody's.

migrate to rating category *j* at the end of the time horizon. The probability estimate, $P_{ij}^{\Delta t}$, which corresponds to the probability of migrating from category *i* to *j* over Δt is

$$\hat{P}_{ij}^{\Delta t} = \frac{N_{ij}}{N_i} \qquad (6.1)$$

In any given period, the migration possibilities for each farm are either upward migration to a more favorable risk rating category, downward migration to a higher risk category, or retention in their current rating class.

Several potential measurement approaches represent different amounts and time sequences of data employed in the measurement process (Barry, Escalante, and Ellinger). Empirical works on corporate bond migration usually employ the year-to-year transition approach (movement from a year t to a year t + 1 classification). This study will initially use the 2x1 measurement approach (movement from credit class based on the average of years t_1 and t_2 to risk rating in t_3) to introduce and develop the proposed alternative migration frameworks. This measurement approach is the simplest version of the farm lenders' multi-year averaging approach in tracking migration to a one-year horizon. Later, we will adopt the 3x1 measurement approach actually used by farm lenders that measures the transition from a credit score rating based on the average of the first three years to the risk rating given to the borrower on the 4th year (Barry, Escalante, and Ellinger), to validate the strengths and relevance of our proposed models.

Given the sample farms in this analysis, the 2x1 approach resulted into fifteen migration matrices, constructed from data on three consecutive years, over the 17-year sample period. A data set for each 3-year period consists of farms that were consistently in the FBFM record system during those 3 consecutive years. This procedure produced a total of 8,751 farm observations for all 15 three-year groupings (details of the breakdown will be presented later in Table 6.6). The transition rates are calculated based on the farms' risk classifications using the average financial data for 1st two years (t_1 and t_2) and the risk classifications at t_3. The averages of the transition rates calculated for each of the fifteen 3-year groupings are then summarized into an overall unconditional transition matrix reported in Table 6.2 where the diagonals correspond to the retention rates and the matrix elements above (below) the diagonal represent downward (upward) migration. This summary transition matrix, thus, represents credit risk migration tendencies over the entire sample period from which loan portfolio quality indications can be deduced.

6.3 Time Measurement Issues and the Markov Chain Process

Time horizon measurement is an important consideration in migration analysis. Normally fewer rating changes are omitted when using shorter time horizons. However, shorter duration could also result in lower rating volatility enhanced by the interplay of business cycle effects. Moreover, shorter duration is subject to "noise" which would eventually be cancelled out in the long term (Bangia, *et al.*). More longitudinal, detailed data histories in corporate finance allow for migration studies to analyze time horizons that are shorter than one year.

Farm finance studies on migration, however, have to contend with limited data histories that are more aggregated since farmers do not maintain records of intra-year changes in financial conditions. Moreover, farm lenders usually resort to averaging of multi-year financial ratios and measures (Novak and LaDue), such as the 3 x1 method earlier described.

In this study we adopt a duration "Markov chain" approach based on survival analysis that has been used in corporate finance studies to factor in intra-year changes in risk ratings in constructing year-to-year transition matrices (Lando and Skodeberg; Israel, Rosenthal, and Wei).

In our analysis the Markov chain process will be applied to the treatment of annualized migration rates in determining migration matrices for each time period that altogether determine a farm loan portfolio's summary migration matrix. This approach is expected to produce more reliable, accurate transition probability estimates than those obtained by farm lenders using multi-year averaging of annualized financial data under the cohort method.

A Markov process is a sequence of random variables $\{X_t \mid t = 0, 1, 2, ...\}$ with common space S whose distribution satisfies

$$\mathbf{Pr}\{X_{t+1} \in A \mid X_t, X_{t-1}, X_{t-2, ...}\} = \mathbf{Pr}\{X_{t+1} \in A \mid X_t\} \quad A \subset S. \tag{6.2}$$

In this process movement from one state to another is dependent (only) on what happened in the previous n states. The number of previous states (n) affecting the choice in the current state determines the order (n) of the process (Voskoglou). In this analysis we consider the first-order process where the current state is influenced solely by the previous state. Using equation 6.2, the distribution of X_{t+1} conditional on the history of the process through time t is completely determined by X_t and is independent of the realization of the process prior to time t. A Markov chain is a process with a finite state-space $S = \{1, 2, 3,\ldots ,n\}$ and is completely characterized by its transition probabilities

$$P_{ij} = \mathbf{Pr}\{X_{t+1} = j \mid X_t = i\} \quad i, j \in S \tag{6.3}$$

Most corporate finance studies that adopt the Markov chain process in transition probability modeling have assumed their data sets' compliance with the first-order Markov process without performing the necessary validating tests (Jarrow, Lando, and Turnbull; Lando and Skodeberg; Schuermann and Jafry). Phillips and Katchova tested for the Markov chain property of a sample of Illinois FBFM farms for the same 17-year period used in this study. Using an overall singular value metric test to determine significant differences between unconditional and conditioned matrices (which will be discussed in detail later), their results indicate the violation of the Markov property of independence and established significant trend reversal tendencies, a reverse form of path dependence. In this study, we validate the presence of Markovian behavior in the Illinois farm dataset using two test methods: eigenvalue/vector analysis and semi-parametric multiplicative hazard tests.

Analysis of Eigenvalues and Eigenvectors

The analysis of eigenvalues and eigenvectors[38] has been a widely used approach to test the Markovian property of a matrix (Bangia, *et al.*). The information of any transitional matrix could be divided into its eigenvalues and eigenvectors, written as

$$\boldsymbol{P} = \boldsymbol{U}_{\boldsymbol{n}\times\boldsymbol{n}} \boldsymbol{\Lambda}_{\boldsymbol{n}\times\boldsymbol{n}} \boldsymbol{U}^{T}_{n\times n}, \tag{6.4}$$

where $\boldsymbol{P}$ is the transitional matrix; $\boldsymbol{\Lambda}$ is a diagonal matrix where each element on the diagonal represents one eigenvalue of $\boldsymbol{P}$; $\boldsymbol{T}$ is the time horizon; and $\boldsymbol{U}$ is a matrix with columns $\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_n$ representing $\boldsymbol{P}$'s eigenvectors that correspond to each element of $\boldsymbol{\Lambda}$. Moreover, any transition matrix can be taken to k^{th} power by increasing its eigenvalues to its k^{th} power while leaving its eigenvectors unchanged. This will modify the above $\boldsymbol{P}$ expression into

$$\boldsymbol{P}^{k} = \boldsymbol{U}_{\boldsymbol{n}\times\boldsymbol{n}} \boldsymbol{\Lambda}^{k}_{n\times n} \boldsymbol{U}^{T}_{n\times n}. \tag{6.5}$$

Under this approach, two conditions have to be satisfied to confirm that the transition matrices follow the Markov chain process. In this study, we test these conditions following the analytical framework used by Bangia, et al.. The first condition requires that eigenvalues ($\boldsymbol{e_i}$) should "decay exponentially" with increasing time horizons. This can be shown graphically by ranking

[38] Eigenvalues are a special set of scalars (also known as characteristic roots) associated with a linear system of equations such as a matrix equation. Each eigenvalue is paired with a corresponding eigenvector. Any square matrix has at least one nonzero vector v such that $Mv = \lambda v$. In this case, v is said to be an eigenvector of the matrix with an eigenvalue λ.

the eigenvalues of the transition matrices in the order of their magnitude. A linear relationship between log(e_i) and time horizon T in these plots would provide evidence of Markovian behavior.

The second condition requires an identical set of eigenvectors for all transition horizons. This can be verified graphically by separately plotting for each transition horizon the eigenvector element values against the different rating categories considered in the empirical transition matrices. The existence of the Markovian property in the dataset is verified if identical plots are obtained for the different time horizons. Bangia, *et al.* applied this criterion by analyzing the plots of the 2nd eigenvector of matrices for different transition horizons.[39]

Figure 6.1 presents a plot of the 2nd to 5th eigenvalues of the empirical matrices with transition horizons varying from 1 to 4 years. The calculated eigenvalues show a strong log-linear relationship over the increasing transition horizons, thus providing evidence that farm credit migration rates tend to follow the Markov chain process. This finding is corroborated by the results of the eigenvector analysis presented in Figure 6.2. The plots provide the trends 2nd eigenvector values for the transition matrices across rating categories using different time horizons. The similarity of the 2nd eigenvector plots again fails to reject the Markov chain process assumption. Notably, our results are consistent with the findings of Bangia, et al.

<u>Semi-parametric multiplicative hazard model</u>

A second test of the Markovian property uses a quantifiable measure to confirm the trends in the earlier eigenvalue and eigenvector graphs. The semi-parametric multiplicative hazard (SPMH) approach can detect the incidence of Markovian behavior in every possible

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[39] The choice of the 2nd eigenvector is justified as follows: All transition matrices have at least one eigenvalue of *unity*, which is of the highest magnitude and stems from the nature of transition matrices where the sum of the row elements equal to one. The remaining eigenvalues have magnitudes smaller than *unity*. The *unity* eigenvalue implies that the transition matrix will decay to steady state eventually and the 2nd largest eigenvalue provides an indicator of the speed of such decay (Jafry and Schuermann).

direction of a rating migration instead of calculating an overall statistic for matrix comparisons (such as the singular value metric test employed by Phillips and Katchova).

The SPMH framework used in this study is based on the testing procedures used by Lando and Skodeberg in their bond migration analysis. The key assumption is that the each rating migration can be influenced by a previous migration direction (upward, downward, or retention). The statistical formulation of the SPMH model used here is defined as follows:

$$\lambda_{hj}(t) = Y_h(t)\alpha_{hj}(t, Z(t)), \tag{6.6}$$

where $\alpha_{hj}(t, Z(t))$ has the multiplicative form

$$\alpha_{hj}(t, Z(t)) = \alpha_{hj0}(t)\exp(\beta_{hj} Z(t)). \tag{6.7}$$

In the above expressions, $\lambda_{hj}(t)$ denotes the migration probability from category *h* to *j* during time *t;* $Y_h(t)$ denotes an indicator process which takes on a value of 1 when the process is in category *h* and 0 otherwise; $\alpha_{hj0}(t)$ is the time-varying baseline hazard that is obtained when $Z(t)$ is 0; and the covariate $Z(t)$ is designed to track the last rating change which takes on a value of 1 when such change is the transition process being evaluated (i.e. one of the three possible changes: upward/downward/retention) and a value of 0 if otherwise. For example, if the focus of the analysis is only on observations that experienced a previous upgrade in their credit risk classification, then

$$Z(t) = \begin{cases} 1, & \text{last migration is upward} \\ 0, & \text{otherwise} \end{cases} \tag{6.8}$$

The parameter of interest here is the regression coefficient β_{hj} for each migration possibility. If the coefficient estimates β_{hj} are not significantly different from zero, the Markovian chain assumption will not be rejected. Positive, significant β_{hj} estimates will support path dependence or momentum (reversal) tendencies that are contrary to the Markov chain process assumption.

In this analysis we use the same 3-year groupings used earlier in developing the cohort matrix. However, instead of the 2x1 method, the SPMH framework requires the measurement of two year-to-year (1x1) transitions: movement from t_1 to t_2 and from t_2 to t_3. The direction of the risk rating changes from t_1 to t_2 of every 3-year period is used to classify each farm under three categories of previous transitional direction: upgrades, retention, and downgrades. Matrices are then developed for each of these three categories for every 3-year period using risk rating changes during the period t_2 to t_3. These matrices are called conditioned matrices since they are conditional upon previous migration trends. Thus, given 15 three-year periods developed in this dataset and 3 previous migration categories, we produce a total of 45 conditioned matrices. The transition probabilities in these matrices correspond to the variable $\lambda_{hj}(t)$ in equation 6.6.

Ordinary least squares (OLS) regression techniques are applied to the various runs of equation 6.6 (using logarithmic transformations of both sides of the equation) as applied to each rating class in t_2 and its migration possibilities in t_3.[40] For example, farms that experienced a rating downgrade during the period t_1 to t_2 and were in class 2 at the end of t_2 would have 3 "neighboring" migration possibilities at t_3: an upgrade to class 1 (trend reversal), retention in class 2, or a downgrade to class 3 (a case of sustained momentum or path dependence).

40 . Lando and Skodeberg performed the SPMH tests only on probable momentum situations. Specifically, they limited their analysis only on succeeding downgrade situations for previous downgrades and consequent upgrades for previous upgrades. This approach, however, excludes other possibilities of trend reversals and the absence of both reversal and momentum tendencies. In our analysis we consider more migration possibilities, although we limited our analysis only to migration to neighboring risk rating classes since most migration activities during the short duration period (year-to-year) are concentrated among these classes anyway. Regression runs for migration activities beyond neighboring classes will utilize much fewer usable observations that will produce results that are not statistically reliable.

Table 6.3 reports the OLS coefficient estimates obtained with their corresponding standard errors and p values. The results are classified according to the previous migration trend categories and include all "neighboring" migration possibilities given each farm's risk classification at the end of t_2.

The regression results for all possible migration directions/possibilities associated with each rating class in t_2 are actually interdependent. Either an insignificant or a significant negative coefficient for any migration possibility during the period t_2 to t_3 would suggest that a probable significant consequential trend (trend reversal or path dependence) will occur in another migration possibility for that rating class at t_2. The key is to identify this possibility through a significant positive coefficient result. If no such result is obtained for all migration directions associated with a particular rating class at t_2, then no evidence of path dependence is established. To illustrate, based on the results in Table 6.3, for farms that experienced previous downgrading from t_1 to t_2 and ended up in class 2 at t_2, significant negative coefficient results were obtained for retention (in class 2) and downgrade (to class 3) possibilities. The remaining direction, an upgrade to class 1, however, produced a positive coefficient result. These results indicate that class 2 farms in t_2 that were previously downgraded provide evidence of significant trend reversal. The same result has been obtained for class 3 farms in the previous downgrade category. In the pervious rating upgrade category, similar results of significant trend reversal were obtained for farms that were rated as classes 1 and 4 at t_2.

In both previous class downgrade and upgrade categories, only two out four t_2 rating classes produced significant trend reversal results. Farms in rating classes 4 and 5 in the previous class downgrade category and classes 2 and 3 in the previous class upgrade category did not produce significant positive coefficient results for any t_2-t_3 migration possibility. Thus, no overwhelming evidence among the previous upgrade and downgrade categories supports the rejection of the Markov chain assumption.

The previous retention cases provide further evidence supporting the non-rejection of the Markov chain assumption. The results for 4 out of 5 t_2 rating classes (1 to 4) indicate no significant consequential or sustained retention trends. Only class 5 farms showed a tendency toward significant upgrading tendencies during the last 2 years of every three-year period.

6.4 Developing the Markov Chain Models

The "cohort" transition matrix presented in Table 6.2 was derived using the conventional, "industry standard" matrix generation method. This approach, however, does not depict accurately actual migration trends due to the omission of certain important information. First, the cohort method is primarily concerned with comparing rating categories at both ends of the time horizon (averaged t_1-t_2 versus t_3 in the 2x1 method in the 2x1 method). Any rating class change occurring in-between the endpoints (for instance, transition changes between t_1 and t_2 in the 2x1 method) is ignored. Secondly, the cohort model only considers direct migration between classes. For instance, if direct migrations are recorded only from risk rating class 1 to 2 and from class 2 to 3 but none in the direction of class 1 to 3, the cohort method will yield a zero migration rate for the latter case.

On the other hand, the Markov chain models capture such indirect transition from class 1 to 3 through the successive downgrades recorded in the above direct migration examples. In this case, the Markov chain approach calculates a non-zero maximum-likelihood estimator for the transition rate for class 1 to 3. The estimated probability would most likely be a very small, but definitely a non-zero, value. The following sections discuss the two variants of the Markov chain migration approach.

The Time Homogeneous Markov Chain Model

A distinct feature of the time homogeneous approach is its non-emphasis of period or time-specific identification. Under this model, only the length of the time interval matters. This feature suggests, for instance, that 2x1 transition rates recorded from 1992 to 1994 will carry the same weight as those calculated for the period 1993 to 1995. This strong assumption on time homogeneity will be revisited and relaxed in the other Markov chain model in the next section.

Following Lando and Skodeberg, we define $\boldsymbol{P}(t)$ as a $K \times K$ transition matrix of Markov chain processes for a given time horizon (where K represents the number of rating category states) whose ij^{th} element is the probability of migrating from state i to state j in a time period of t. The generator matrix $\boldsymbol{\Lambda}$ is a $K \times K$ matrix for which

$$\mathbf{P}(t) = \exp(\boldsymbol{\Lambda} t) \cong \sum_{k=0}^{\infty} \frac{\boldsymbol{\Lambda}^k t^k}{k!} \qquad t \geq 0 \tag{6.9}$$

where the exponential function is a matrix exponential, which would be approximated by the infinite summation defined by the most right-hand side expression.

The entries of the generator $\boldsymbol{\Lambda}$ satisfy

$$\begin{aligned} \lambda_{ij} &\geq 0 \quad \text{for } i \neq j \\ \lambda_{ii} &= -\sum_{i \neq j} \lambda_{ij} \end{aligned} \tag{6.10}$$

The second equation merely guarantees that the sum of the rows of the matrix is equal to one.

The problem of estimating the transition matrix is then transformed to estimating the generator matrix $\boldsymbol{\Lambda}$. We are left with obtaining the estimates of the entries of $\boldsymbol{\Lambda}$. The maximum likelihood estimator of λ_{ij} is given by

$$\hat{\lambda}_{ij} = \frac{N_{ij}(T)}{\int_0^T Y_i(s)\,ds} \tag{6.11}$$

where $N_{ij}(T)$ is the total number of transitions over the period T from credit category *i* to *j* and $Y_i(s)$ is the number of observations assigned credit category *i* at time *s*. The numerator counts the number of observed transitions from *i* to *j*. The denominator, the integral of $Y_i(s)$, effectively collects all observations assigned with category *i* over the period T. Thus, within the duration of time T, any period spent in a particular rating class will be picked up through the denominator. To illustrate, suppose a farm spent only a portion of the time period T in transit from class 1 to 2 before eventually landing in class 3 at the end of T. The portion of time spent in class 2 will be factored into the estimation of the transition rates for classes 1 to 3. In the cohort method this "transient" migration information is ignored. These indirect transition activities are captured in this model for which positive, though possibly very small, transition rates are estimated.

Table 6.4 presents the summary matrix for the time homogeneous approach generated as the average of 15 three-year matrices utilizing the same three-year groupings used for the 2 x 1 cohort matrices averaged to produce the matrix reported in Table 6.2. However, in lieu of the discrete time formula in equation 6.1, the average transition rates in Table 6.4 are calculated using the maximum likelihood estimator defined in equation 6.11 where T=3.

The Time Non-Homogeneous Markov Chain Model

The time homogeneity assumption of the previous model is relaxed in this version of the Markov chain transition matrix. Again following Lando and Skodeberg, we define $\mathbf{P}(s,t)$ as the transition probability matrix from time *s* to *t*. The ij^{th} element of this matrix corresponds to the transition probability from rating class *i* in time *s* to rating class *j* in time *t*. Given a sample of *m* transitions over the period from *s* to *t*, the maximum likelihood estimator of $\boldsymbol{P}(s,t)$ could be derived using the following nonparametric product-limit estimator (Klein and Moeschberger)

$$\hat{\boldsymbol{P}}(s,t) = \prod_{k=1}^{m} (\boldsymbol{I} + \Delta \hat{\boldsymbol{A}}(T_k)) \tag{6.12}$$

where T_k is a jump in the time interval from s to t. The matrix component of the above equation is constructed as follows:

$$\Delta \mathbf{A}(T_k) = \begin{bmatrix} -\frac{\Delta N_{1\bullet}(T_k)}{Y_1(T_k)} & \frac{\Delta N_{12}(T_k)}{Y_1(T_k)} & \frac{\Delta N_{13}(T_k)}{Y_1(T_k)} & \cdots & \frac{\Delta N_{1p}(T_k)}{Y_1(T_k)} \\ \frac{\Delta N_{21}(T_k)}{Y_2(T_k)} & -\frac{\Delta N_{2\bullet}(T_k)}{Y_2(T_k)} & \frac{\Delta N_{23}(T_k)}{Y_2(T_k)} & \cdots & \frac{\Delta N_{2p}(T_k)}{Y_2(T_k)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \frac{\Delta N_{p1}(T_k)}{Y_p(T_k)} & \frac{\Delta N_{p2}(T_k)}{Y_p(T_k)} & \frac{\Delta N_{p3}(T_k)}{Y_p(T_k)} & \cdots & -\frac{\Delta N_{p\bullet}(T_k)}{Y_p(T_k)} \end{bmatrix} \tag{6.13}$$

where the numerator of each off-diagonal entry, $\Delta N_{ij}(T_k)$, denotes the number of specific transitions moving away from rating class i to some other class (like j) at time T_k. The numerator of the diagonal entry, $\Delta N_{i\bullet}(T_k)$, counts the total number of transitions away from i at time T_k while the denominator, $Y_i(T_k)$, is the number of farms at rating class i right before time T_k.

In other words, the diagonal entries of the matrix count, at any time T_k, the fraction of farms in class i migrating away from that rating class, regardless of which class they migrated to. The off-diagonal entries count the fraction of rating class i farms that migrate away to another specific rating class at time T_k. Note that the sum of the rows of the matrix $\boldsymbol{I} + \Delta \hat{\boldsymbol{A}}(T_k)$ in equation 6.12 is equal to one. Moreover, when there is only one transition case between time s and t (i.e. $m = 1$), the resulting product-limit estimator (equation 6.12) collapses the non-homogenous transition matrix into a cohort (discrete-time) matrix. In essence, the time non-homogeneous transition matrix is a more time microscopic (detail-oriented) version of the cohort migration matrix method applied to extremely shorter time intervals.

Table 6.4 presents the summary matrix of average transition rates developed from 15 three-year matrices using the same three-year groupings of the cohort matrix in Table 6.2 and generated using the $\Delta\hat{\boldsymbol{A}}(T_k)$ matrix estimator defined in equation 6.12.

Comparing Cohort and Markov Chain Transition Matrices

In order to determine significant differences among the three matrices presented in Tables 6.2 and 6.4, we apply singular value decomposition (SVD) analysis, a metric test based on singular values (Jafry and Schureman). Appendix B presents details of the derivation of the SVD statistic, $\overline{S(\tilde{\mathbf{P}})}$, calculated for the cohort (Table 6.2) and the Markov chain (Table 6.4) matrices. These values will be labeled as $\overline{S(\tilde{\mathbf{P}}^d)}$, $\overline{S(\tilde{\mathbf{P}}^h)}$, and $\overline{S(\tilde{\mathbf{P}}^{nh})}$ with the superscripts *d, h*, and *nh* denoting discrete-time, time homogenous, and time non-homogenous methods, respectively. The pair-wise differences between the $\overline{S(\tilde{\mathbf{P}})}$s are calculated as

$$m_{svd}^{d-h}(\tilde{\mathbf{P}}^d, \tilde{\mathbf{P}}^h) = \overline{S(\tilde{\mathbf{P}}^d)} - \overline{S(\tilde{\mathbf{P}}^h)}$$

$$\text{(14)}\quad m_{svd}^{d-nh}(\tilde{\mathbf{P}}^d, \tilde{\mathbf{P}}^{nh}) = \overline{S(\tilde{\mathbf{P}}^d)} - \overline{S(\tilde{\mathbf{P}}^{nh})}$$

$$m_{svd}^{h-nh}(\tilde{\mathbf{P}}^h, \tilde{\mathbf{P}}^{nh}) = \overline{S(\tilde{\mathbf{P}}^h)} - \overline{S(\tilde{\mathbf{P}}^{nh})}$$

In order to determine significant differences between any pair of matrices under comparison based on the resulting distance metrics, m_{svd}, we use 1000 bootstrapping samples (random draws with replacement) of 15 observations from the original three-year groupings to calculate 1000 singular values $m_{svd}^{(k)}$ where k=1, … 1000. This will give us a bootstrap distribution of singular value based distances from which we can calculate the confidence interval for the singular value metric. Significant differences between any pair of matrices will be determined by checking whether zero is within the estimated $1-\alpha$ confidence interval.

6.5 Results

The results of pair-wise differences between the $\overline{S(\widetilde{\mathbf{P}})}$s calculated for the summary matrices reported in Tables 6.2 and 6.4 indicate the greater relevance of Markov chain models to farm credit risk migration analysis. Using the formulas defined in equation 6.14, the mean difference (m_{svd}) between the cohort and time homogenous matrices is 0.1924; the mean difference between the cohort and the time non-homogeneous matrices is 0.1956; and the smallest mean difference is obtained at 0.0031 between the two Markov chain matrices.

The resulting 95% confidence intervals for each of these differences are (0.1776, 0.2072) for the cohort and time homogeneous matrices, (0.1700, 0.2211) for the cohort and time non-homogeneous matrices, and (-0.0207, 0.0270) for the two Markov chain matrices. Only the last confidence interval includes zero in its range, thereby indicating that while the cohort matrix is significantly different from the two Markov chain matrices, the time homogeneous and non-homogeneous matrices are not really significantly different from zero at the 0.05 confidence level.

Our results are consistent with the findings obtained by Schuermann and Jafry for the three methods using S&P bond ratings data for the period 1981-2001. The compelling result is that the mean difference values they obtained (difference (m_{svd}) values of 0.012, 0.014 and 0.002 for comparisons between cohort and time homogenous matrices, cohort and time non-homogenous matrices, and time homogenous vs. non-homogenous matrices, respectively) are much lower than the values we reported here. The disparity of mean difference values obtained for corporate bond ratings and for farm credit risk ratings suggests that farm finance conditions create a greater necessity for making important distinctions between discrete and Markov time models of migration. Examining the three types of matrices reported in Tables 6.2 and 6.4, the

Markov chain matrices produced higher average retention rates of 60.02% and 59.71% for the time homogenous and non-homogenous methods, respectively. The average retention rate for the cohort matrix is only 42.72%. In contrast, corporate bond retention rates range from 70% to 75% for matrices derived under the same three methods (Lando and Skodeberg).

The more practical and crucial evidence presented here, however, is the capture of "transient" migration events using the Markov chain approaches. In the cohort matrix in Table 6.2, for example, the average transition probability rates for migrating from class 5 to 1 and vice versa are 0.25% and 0.11%, respectively. When indirect transitions were captured in the other two models, the transition estimates were higher. The time homogenous approach produced a rate of 3.11% for class 5 to 1 migrations and 0.75% for the reverse migration. The equivalent rates under the time non-homogenous approach were 2.56% and 0.50%, respectively. Elsewhere in the alternative Markov chain matrices, upgrading, retention, and downgrading rates were much higher than their counterparts in the cohort matrix. In a later section, we will recall these matrices to calculate default probability estimates, which is an important portfolio quality indicator that can be obtained from the migration analytical framework.

6.6 Replication Using the Farm Lenders' 3 x 1 Method

We validate the relevance of the alternative Markov chain matrices relative to the conventional cohort method by shifting from a 2 x 1 migration measurement approach to the farm lenders' 3 x 1 method. This study's 17-year sample period is re-grouped into subset time periods of 4 consecutive years producing a total of 14 four-year groups, involving an aggregate size of 6,131 farm observations. Under the cohort method, migration rates are recalculated as the transition from the credit class associated with the average of each farm's farm financial measures from t_1 to t_3 to the farm's credit classification in t_4. Migration rates under the Markov chain time homogenous approach were calculated using the maximum likelihood estimator defined in equation 6.11 where T=4 given the 3x1 method used. The time non-homogeneous migration matrices were estimated using the $\Delta\hat{\boldsymbol{A}}(T_k)$ matrix estimator defined in equation 6.12. The summary matrices for these three methods are presented in Table 6.5.

As in the previous analysis, we calculate the pair-wise differences between the SVD statistics $\overline{S(\tilde{\mathbf{P}})}$s calculated for the three matrices. Our results indicate that the mean difference (m_{svd}) between the cohort and time homogenous matrices is 0.1863; the mean difference between the cohort and the time non-homogeneous matrices is 0.1925; and the two Markov chain matrices have a mean difference of 0.0062.[41] Again these results remain well above the mean difference values obtained by Schuermann and Jafry using corporate bond ratings migration. Moreover, the same trends in retention rates and cell-to-cell comparisons between the cohort and Markov chain migration matrices noted when the 2x1 method was used for the cohort matrix are also evident in the results for the 3x1 method. The following section wraps up the argument in favor of the alternative Markov chain models through the estimation of loan default probabilities.

<u>Loan Stress/Default Probabilities</u>

Table 6.6 presents a breakdown of the loan stress/default probability estimates for the 2 x 1 and 3 x 1 measurement methods under the cohort and Markov chain models.[42] These estimates represent the overall frequencies of migrating to (or remaining in) Class 5. They are calculated

[41] The resulting 95% confidence intervals for each of these differences are (0.1677, 0.2048) for the cohort and time homogeneous matrices, (0.1700, 0.2150) for the cohort and time non-homogeneous matrices, and (-0.0149, 0.0273) for the two Markov chain matrices. As in the previous analysis, only the last confidence interval includes zero in its range.

[42] The time homogeneous and non-homogeneous methods produced the same loan default probability estimates since both methods track the same number of farms that migrate either directly or indirectly to Class 5.

as the weighted averages of the frequencies for Class 5 ratings using annual proportion of farm numbers as weights (Barry, Escalante, and Ellinger; Katchova and Barry).

The results in Table 6.6 show that probability estimates obtained under the Markov chain model are always above the levels produced by the cohort model for both the 2x1 and 3x1 methods.[43] Results for the 2x1 method indicate that the "cohort" overall estimate of 5.10% is understated by 0.43% compared to 5.53% estimated using the Markov chain approach. The discrepancy is larger in the 3 x1 migration method where the Markov chain model produced an overall estimate of 7.47%, which is more than 1% higher than the "cohort" estimate of 6.37%. For purposes of loan portfolio assessment and financial planning for lenders, more conservative estimates of loan stress/default probability might be preferred to adopt more cautious, prudent lending plans and policies that should provide sufficient cushion against unexpected losses. This stance has greater relevance in a more volatile, uncertain credit environment, much like the challenging lending conditions confronted by all farm lenders.

[43] The differences in un-weighted default probability estimates (class 5 transitions divided by total farm number in each time period) are even much larger (ranging from 1 to 3 percentage points) than when weighted estimates were compared.

Table 6.1: Credit Scoring Classification Intervals (Source: Splett, et al.)

VARIABLES (Measures)/Classes	*Interval Ranges*	*Weights*
LIQUIDITY (Current Ratio)		
1	>2.00	
2	1.60-2.00	
3	1.25-1.60	
4	1.00-1.25	
5	<1.00	______x0.10=______
SOLVENCY (Equity-Asset Ratio)		
1	>0.80	
2	0.70-0.80	
3	0.60-0.70	
4	0.50-0.60	
5	<0.50	______x0.10=______
PROFITABILITY (Farm Return on Equity)		
1	>0.10	
2	0.06-0.10	
3	0.04-0.06	
4	0.01-0.04	
5	<0.01	______x0.10=______
REPAYMENT CAPACITY (Capital Debt-Repayment Margin Ratio)		
1	>0.75	
2	0.50-0.75	
3	0.25-0.50	
4	0.05-0.25	
5	<0.05	______x0.10=______
FINANCIAL EFFICIENCY (Net Farm Income from Operations Ratio)		
1	>0.40	
2	0.30-0.40	
3	0.20-0.30	
4	0.10-0.20	
5	<0.10	______x0.10=______
	=Total Score (Numeric)	______________

Credit Score Classes

Class1	1.00-1.80
Class2	1.81-2.70
Class3	2.71-3.60
Class4	3.61-4.50
Class5	4.51-5.00

Table 6.2: Summary 2 x 1 Transition Matrix under the Cohort Method, 1985-2001

Period 1	Period 2 Farm Credit Risk Classes (Percent)				
Farm Credit Risk Classes	1	2	3	4	5
1	75.14	16.47	6.53	1.75	0.11
2	24.68	43.52	19.69	10.14	1.97
3	12.23	27.39	39.70	14.46	6.21
4	3.57	24.49	35.16	27.43	9.36
5	0.25	9.21	37.78	24.98	27.79

Table 6.3: Results of Semi-Parametric Multiplicative Hazard Tests

Rating Class at the end of time period t_2	Rating Class at end of time period t_3	Coefficient Estimate	Standard Error	P value	Evidence of Path Dependence (PD) or Trend Reversal (TR)
A. Conditional on a Previous Class Rating Downgrade (for the period t_1 to t_2)					
2	1	0.64182	0.21937	0.0054	Trend Reversal
	2	-0.28655	0.07214	0.0003	
	3	-0.57744	0.14822	0.0003	
3	2	0.48543	0.14165	0.0014	Trend Reversal
	3	-0.46897	0.06500	<0.0001	
	4	-0.50018	0.17272	0.0060	
4	3	0.09780	0.12003	0.4200	No PD/TR
	4	-0.30214	0.15349	0.0561	
	5	-0.86189	0.22402	0.0006	
5	4	0.01806	0.14935	0.9049	No PD/TR
	5	-0.52561	0.20272	0.0157	
B. Conditional on a Previous Class Rating Upgrade (for the period t_1 to t_2)					
1	1	-0.39923	0.06170	<0.0001	Trend Reversal
	2	0.35208	0.15826	0.0340	
2	1	-0.92026	0.19554	<0.0001	No PD/TR
	2	-0.14832	0.08106	0.0741	
	3	0.05729	0.16633	0.7322	
3	2	-0.53309	0.14408	0.0006	No PD/TR
	3	0.00854	0.09000	0.9296	
	4	0.20711	0.18678	0.2740	
4	3	-0.16916	0.12003	0.1757	Trend Reversal
	4	0.12119	0.18692	0.5206	
	5	0.80925	0.27882	0.0068	
C. Conditional on a Previous Class Rating Retention (for the period t_1 to t_2)					
1	1	0.03544	0.09622	0.7153	No consequential trend
	2	-0.48819	0.14527	0.0022	
2	1	-0.23210	0.23719	0.3332	No consequential trend
	2	0.04826	0.08377	0.5675	
	3	-0.26131	0.16172	0.1134	
3	2	-0.22721	0.15603	0.1526	No consequential trend
	3	0.13407	0.09389	0.1603	
	4	-0.23162	0.18608	0.2203	
4	3	-0.05535	0.12071	0.6490	No consequential trend
	4	0.14587	0.16493	0.3819	
	5	-0.08845	0.28397	0.7575	
5	4	0.53268	0.13686	0.0008	Significant upgrading trend
	5	0.31145	0.25929	0.2409	

Table 6.4: Summary 3x1 Transition Matrices under the Markov Chain Models, 1985-2001

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes (Percent)				
	1	2	3	4	5
A. Time Homogeneous Markov Chain Model					
1	76.22	13.50	7.45	2.08	0.75
2	17.10	58.05	15.83	6.64	2.38
3	8.88	15.53	61.01	9.92	4.66
4	6.05	14.59	20.91	52.23	6.23
5	3.11	8.96	22.59	12.74	52.60
B. Time Non-Homogeneous Markov Chain Model					
1	77.89	12.90	6.79	1.92	0.50
2	16.26	59.45	15.66	6.39	2.24
3	7.72	16.20	61.04	9.83	5.20
4	5.27	13.32	22.89	51.15	7.37
5	2.56	9.85	25.99	12.59	49.02

Table 6.5: Summary 3x1 Transition Matrices under the Cohort and Markov Chain Models, 1985-2001

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes (Percent)				
	1	2	3	4	5
A. Cohort (Discrete-Time) Model					
1	76.74	15.41	6.52	1.23	0.10
2	28.99	40.23	21.05	8.08	1.66
3	8.78	28.43	38.82	14.94	9.02
4	3.21	18.93	38.83	24.24	14.79
5	0.29	7.84	30.00	28.80	33.07
B. Time Homogeneous Markov Chain Model					
1	74.27	14.10	8.45	2.45	0.73
2	16.81	57.42	17.48	6.78	1.51
3	9.79	14.94	60.10	10.43	4.75
4	6.72	12.80	21.46	53.42	5.61
5	3.77	9.80	23.06	11.48	51.88
C. Time Non-Homogeneous Markov Chain Model					
1	78.03	12.88	6.72	1.89	0.49
2	16.17	59.43	15.71	6.54	2.15
3	7.42	16.35	61.33	9.87	5.03
4	5.19	13.03	23.46	50.94	7.39
5	2.54	10.16	26.61	12.53	48.15

Table 6.6: Loan Stress/Default Probability Estimates under Cohort and Markov Chain Models, 1985-2001.

Time Period[a]	No. of Farms, 2 x 1 Method	No. of Farms, 3 x 1 Method	2 x 1 Method (percent)		3 x 1 Method (percent)	
			Cohort	Markov	Cohort	Markov
1	201	174	0.03	0.05	0.21	0.23
2	310	229	0.30	0.31	0.06	0.08
3	345	311	0.11	0.16	0.10	0.11
4	486	404	0.13	0.15	0.96	1.00
5	586	480	0.97	1.05	0.11	0.18
6	656	530	0.17	0.22	0.16	0.28
7	745	570	0.30	0.32	0.47	0.52
8	800	456	0.43	0.47	0.52	0.83
9	566	423	0.16	0.23	0.36	0.70
10	516	406	0.16	0.24	0.49	0.63
11	609	474	0.24	0.24	1.02	0.62
12	675	565	0.35	0.31	0.45	0.49
13	768	610	0.38	0.47	0.41	0.57
14	756	539	0.48	0.53	1.05	1.25
15	732		0.86	0.80		
Total	8,751		5.10	5.53	6.37	7.47

Notes: [a] The time periods were labeled in generic terms to apply to the two measurement methods. The 2 x 1 method uses three-year groupings, hence, time period 1 corresponds to 1985-1987, time period 2 is 1986-1988, and so forth. On the other hand, the 3x1 method uses four-year groupings, hence, time period 1 is for 1985-1988, time period 2 is for 1986-1989, and so forth.

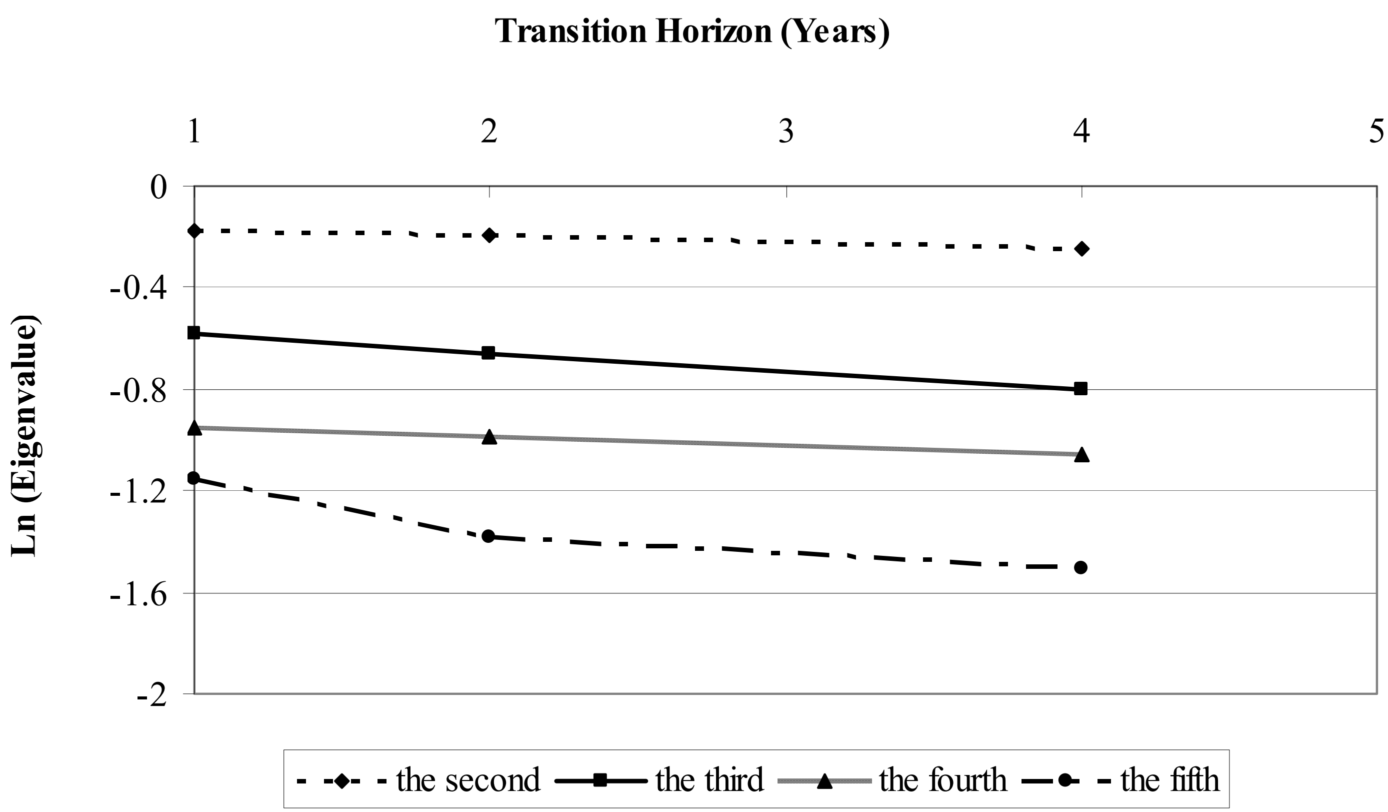

Figure 6.1: Decay of Eigenvalues with Different Transition Horizons

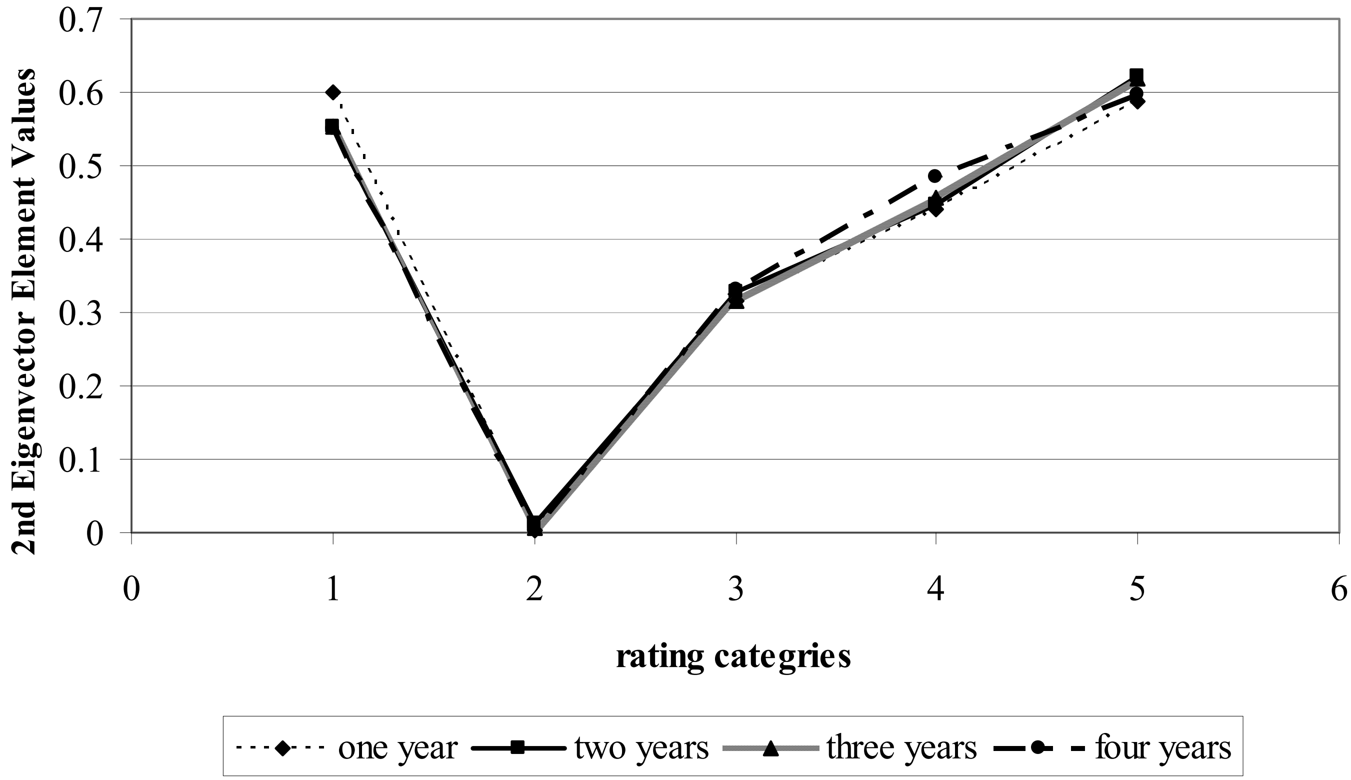

Figure 6.2: 2nd Eigenvector Element Values of Matrices for Different Transition Horizons

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 Summary and Conclusion

This dissertation is comprised of three studies on risk management and finance in agriculture. Though specific focuses are different in each study, the primary objective is to find out ways to reduce relevant risks, being production or credit risk, for the relevant parties. General results indicate that index-based insurance products are potentially effective to reduce agricultural production risk for agricultural producers in Southeast U.S.. Markov chain models are proven to provide better estimation of credit risk migration using the Illinois FBFM database.

The first study focuses on a proposed THI insurance product to protect against shortfalls in milk production due to heat stress. THI has been identified, in dairy science, as a composite index that negatively affects dairy cows' milk production when dairy are exposed to high ambient temperature and humidity. High THI above 72 is found significantly reduce the dairy physical performance and milk production. It, however, has not been studied as a potential insurance tool to hedge against the milk production loss due to heat stress. One crucial issue of using weather-based insurance requires the existence of clear relationship and high correlation between the weather phenomenon and the realized yield loss. Otherwise basis risk will be so high that loose its competitiveness with traditional insurance products. Considering the intrinsic relationship between THI and dairy milk production, we expect that THI will work effectively as an index-based insurance product to insure against milk loss due to the heat stress.

This study constructed the THI insurance products at three locations in Atlanta GA, Macon GA, and Tallahassee, FL, where three hypothetical insurance companies are located. A representative farm in Macon is assumed being able to purchase THI insurance products from any of the three insurance companies which construct the contracts based on the local THI measurements. Due to the lack of lengthy milk production data history, a bootstrapping procedure is used to simulate the longer series of milk production data conditional on THI and, at the same time, account for the idiosyncratic effects in milk production. This overcomes the problems of a simple deterministic model to simulate milk production that overstates the correlation between farm-level milk production and the THI. Thus, the approach used here provides a more realistic analysis of the impacts of THI insurance purchasing.

In addition, this study applies recent findings from the dairy science literature that suggest that the largest impact on milk production occurs approximately two days after a heat stress event. This makes THI capture more portions of milk production losses due to heat stress and ensures THI a better risk hedging device.

This study explicitly analyzes the impacts of both geographical and temporal basis risk. Geographical basis risk has been widely recognized and studied in most index-based insurance literatures. Temporal basis risk, however, has not caught enough attention. Results in this study indicate that temporal basis risk does exist and can not be ignored. Its effects can be reduced by using separate cool period and hot period THI insurance contracts rather than a blanket single contract.

The insured may have different objectives and therefore use different risk evaluation criteria. This study uses Mean-variance, expected utility certainty equivalence, and value-at-risk to assess the robustness of the effectiveness of THI. Finding indicates the general robustness across different measures of producer well-being.

The second study emphasizes the feasibility of another index-based insurance product, area yield insurance product GRP, in the Southeast U.S. It particularly compares the risk reduction performance of GRP and MPCI for cotton and soybeans in South Carolina and Georgia. The regions considered is characterized by heterogeneity in production factors such as soil quality and drainage and thus, in principal, should not be as well suited to GRP as more homogeneous production regions such as the corn belt. However, the region is also characterized by relatively high MPCI premium rates due, in part, to positive wedges caused by moral hazard and adverse selection problems.

The findings suggest that when the comparison is based on the actual subsidized premium rates that farmers would expect to pay for these insurance products (rather than hypothetical actuarially fair premium rates), GRP is often very competitive with MPCI. A limitation of this analysis is that it cannot account for losses due to prevented planting, replanting, or poor quality. These losses are covered to some extent by MPCI but are not covered by GRP.

In order to compare the risk reduction performance of GRP and MPCI under more realistic conditions and treat both fairly, this study presented results based on three premium rating schemes: 1) actuarially fair in sample premium rates (as in previous studies); 2) actual unsubsidized premium rates; and, 3) actual subsidized premium rates. Comparing results across these three premium rating schemes provides insight into the magnitude of bias that exists in studies where premium rates are constructed to be actuarially fair in sample. The bias favorably improves the risk reduction performance of MPCI.

Since premium rates are not breakeven, the relative performance of MPCI and GRP cannot be evaluated by simply comparing reductions in the variance of net yield. Thus, this study extends previous efforts by evaluating the relative performance of MPCI and GRP using certainty equivalent revenues under an expected utility framework.

With actual subsidized premium rates, GRP performs better than MPCI for some crops and regions. This indicates although GRP basis risk may be relatively high in the southeastern U.S. due to heterogeneous agricultural production conditions, the significant positive wedge in MPCI premium rates make GRP a viable alternative for farmers in the region.

The third study presents arguments establishing the relevance of Markov chain models in the estimation of credit risk transition probability matrices for farm businesses. The pre-condition of a Markov chain process was validated through an analysis of the eigenvalue/eigenvector of the farm credit risk transition matrix and the semi-parametric multiplicative hazard tests. Our results do not provide strong evidence to reject the Markov property of independence assumption.

This study's empirical evidence supports the application of Markov chain models to farm finance in lieu of cohort models that incorporate the farm lenders' multi-year averaging tendencies in credit risk analysis. More substantial mean differences in singular value decomposition (SVD) are produced between farm credit risk migration matrices developed under the cohort and Markov chain models than when similar comparisons are made in corporate finance literature using bond ratings migration. This suggests that the derivation of farm credit risk migration rates under the "cohort" model could result in more costly omission of important indirect, transient changes in farm credit risk ratings. The understatement of transition probability estimates would, in turn, produce lower, if not misleading, indicators of farm loan portfolio quality such as portfolio default probability estimates. For instance, we have shown tendencies to produce lower estimates of loan portfolio default probability under the cohort model than when the Markov chain method is used.

Given the highly volatile and largely uncertain farm operating environment where abrupt changes in weather, market, or macroeconomic conditions could influence ad hoc modifications of business plans and decisions, lenders would certainly need more accurate, if not conservative, indicators of loan portfolio quality that need to be factored into their own financial plans and lending policies. This study has shown that Markov chain models of migration could provide a more accurate, reliable representation of farm credit risk migration activities than the conventionally used cohort model, which could produce omission of important risk transition information that could be much more costly in farm finance as they are in corporate finance.

7.2 Recommendation for further Research

Results from any study can not be extended to other studies blankly. Cautions need to be taken to make general conclusions. Though our current results favor the application of index-based insurance products to insure against agricultural production risks and the application of Markov chain models to estimate the credit risk migration, they are not conclusive.

Basis risk is always the primary concern in index-based insurance and it cannot be eliminated. The trade-off between basis risk and contract transparency must be considered. Weather-based insurance in agricultural production further requires better knowledge of agronomy into the weather-yield relationship to achieve satisfactory performance of weather insurance. Thus any study on index-based insurance, especially weather-based insurance, needs to be done on a commodity – and location – specific basis.

As for credit risk migration analysis in agricultural lending, our results are based on the farm record keeping association data. Though there is advantage of using these external farm financial data, it is not clear how closely the estimated credit ratings to the internal credit ratings assigned by agricultural lenders. The credit risk evaluation process, the factors considered in credit evaluation, and the loan officers' involvement in the process all make it unlikely that the internal credit risk ratings will exhibit the same variability as those estimated from the external farm financial data. Further studies can use internal data, if available, to replicate the current study to estimate the credit risk migration under cohort and Markov chain models to verify our results.

In addition, further study are warranted to determine if migration probabilities differ significantly across business cycles, types of agricultural production and geographical locations of farm business and agricultural borrowers. In order to do that, longer series of data history and national or regional data set encompassing multiple states would be required.

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APPENDICES

Appendix A: Derivation of optimal choice variable ϕ

To derive ϕ^*, substitute R^{net} from (4.11b) into (4.10)

$$\text{(A.1)}\qquad \begin{aligned} V^{net} &= E(R^{net}) - \frac{1}{2}k \times \mathrm{var}(R^{net}) \\ &= pE\left(\tilde{y} + \phi \mid \beta \mid \tilde{n} - \phi \mid \beta \mid (1+\gamma)\mu_{\tilde{n}}\right) - \frac{1}{2}pk \times \mathrm{var}\left(\tilde{y} + \phi \mid \beta \mid \tilde{n} - \phi \mid \beta \mid (1+\gamma)\mu_{\tilde{n}}\right). \end{aligned}$$

The purchase of THI insurance increases the mean-variance measure relative to the no insurance case by the amount

$$\text{(A.2)}\qquad \begin{aligned} \underset{\phi}{\Delta V} &= \max_{\phi} V^{net} - \underset{\phi=0}{V} \\ &= -p\gamma\phi \mid \beta \mid \mu_{\tilde{n}} - \frac{1}{2}pk\left[\phi^2 \mid \beta \mid^2 \ \mathrm{var}(\tilde{n}) + 2\phi \mid \beta \mid \mathrm{cov}(\tilde{y}, \tilde{n})\right] \ . \end{aligned}$$

By construction the systematic heat stress component of milk production risk $\tilde{z}$ and the idiosyncratic component of milk production risk $\tilde{\varepsilon}$ are independent. This implies that $\tilde{\varepsilon}$ and $\tilde{n}$ are also uncorrelated. Thus, $\mathbf{cov}(\tilde{y}, \tilde{n}) = \mathbf{cov}(\beta\tilde{z} + \varepsilon, \tilde{n}) = \mathbf{cov}(\beta\tilde{z}, \tilde{n}) + \mathbf{cov}(\varepsilon, \tilde{n}) = \beta\,\mathbf{cov}(\tilde{z}, \tilde{n})$ and (A.2) can be rewritten as

$$\text{(A.3)}\qquad \underset{\phi}{\Delta V} = -p\gamma\phi \mid \beta \mid \mu_{\tilde{n}} - \frac{1}{2}pk\left[\phi^2 \mid \beta \mid^2 \ \mathrm{var}(\tilde{n}) - 2\phi \mid \beta \mid^2 \ \mathrm{cov}(\tilde{z}, \tilde{n})\right].$$

The first order condition of (A.3) with respect to ϕ is

$$\text{(A.4)}\qquad \frac{\partial \Delta V}{\partial \phi} = -p\gamma \mid \beta \mid \mu_{\tilde{n}} - pk\phi \mid \beta \mid^2 \ \sigma^2_{\tilde{n}} + pk \mid \beta \mid^2 \ \sigma_{\tilde{z},\tilde{n}} = 0 \, .$$

Solving for the optimal ϕ yields $\phi^* = \rho_{\tilde{z},\tilde{n}} \dfrac{\sigma_{\tilde{z}}}{\sigma_{\tilde{n}}} - \dfrac{\gamma\mu_{\tilde{n}}}{\mid \beta \mid k\sigma^2_{\tilde{n}}}$.

Appendix B: Derivation of the Singular Value Decomposition Statistic

The diagonals of any migration matrix represent retention rates or the probability that no cross-state migration has occurred while off-diagonal elements capture the probabilities of migrating to other classes during a specific period of time. An *identity* matrix (denoted as **I**) could be treated as a specific migration matrix where only retention cases are observed and cross-state migrations are not realized. Since the migration framework is concerned about activity or dynamics, we then derive the *dynamic* part of migration called *mobility matrix* (denoted as $\tilde{\mathbf{P}}$) by subtracting the *identity* matrix from the original matrix (denoted as $\mathbf{P}$). That is

$$\tilde{\mathbf{P}} = \mathbf{P} - \mathbf{I} \tag{6.14}$$

Then following Schuermann and Jafry, we calculate the singular values (denoted as $S(\tilde{\mathbf{P}})$) of $\tilde{\mathbf{P}}$

$$S(\tilde{\mathbf{P}}) = \sqrt{eig(\tilde{\mathbf{P}}`\tilde{\mathbf{P}})} \tag{6.15}$$

where $eig(\bullet)$ is the eigenvalue of the corresponding matrix. Then the average of the singular values of the mobility matrix $\tilde{\mathbf{P}}$ is donated as $\overline{S(\tilde{\mathbf{P}})}$.