EVALUATING FARM POLICY CHANGES ACROSS COMMODITIES:

A STOCHASTIC SIMULATION APPROACH

A Thesis

by

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ABSTRACT

Since the 1930's, agricultural policy has played a major role in stabilizing the United States agricultural economy. Agricultural policy is a minor player in terms of overall federal budgetary impact, but the programs remain significant for US producers. Understanding how changes to farm safety net programs would affect government expenditures would be beneficial in maintaining and refining agricultural support programs into the future.

The objective of the project was to create a model that uses stochastic simulation to estimate expenditures or score agricultural policy changes, for 9 major agricultural commodities. The study used many of the factors that the federal government uses to accomplish the same goal including calculating payments based on a national scale. This was intentional because estimates for this project were expected to approximate the scores achieved by the Congressional Budget Office. As part of the analysis, a State based model was created as an alternative approach to scoring the main agricultural support programs. This alternative was compared to the original approach to determine differences between the two in terms of effectiveness and detail provided when estimating future program payments.

This research provided models that score the programs as they are currently, but allows for modifications to be made on various parameters. This has provided – and will continue to provide – the ability to evaluate effects of proposed program changes on projected program payments.

The results of the study indicate the national model scored projected program payments more accurately than the state model structure. However, after both models were adjusted to

limit the difference in the PLC projected payments and CBO, the state model preformed more closely to CBO.

The models are a useful tool for current analysis of ARC and PLC program expectations. Even more valuable though, is the potential to analyze future proposals to these programs. With that in mind, the national model is far more seamless to adjust program parameters, and the state model enables the regional effects of program changes to be seen.

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Contributors

This work was supervised by a thesis committee consisting of Dr. Joe L. Outlaw and Dr. Henry L. Bryant of the Department of Agricultural Economics and Dr. Monty Dozier of the Department of Soil and Crop Sciences.

The risk applied to the CBO means for price and yield projections was provided via the Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri. The draws used were from the 2019 FAPRI Baseline from January 2019.

Other data used was all from publically available sources, including the National Agriculture Statistics Service (NASS).

The data correlation induction portion of Chapter 3 was highly directed by Dr. Bryant. The covariance matrix in particular that was used in Chapter 3 was calculated by Dr. Bryant. All other work conducted for the thesis was completed by the student independently.

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NOMENCLATURE PAGE

Acronym	Definition
ARC	Agricultural Risk Coverage
PLC	Price Loss Coverage
CBO	Congressional Budget Office
RAF	Risk Adjustment Factor
FAPRI	Food and Agricultural Policy Research Institute
MYA	Marketing Year Average

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CHAPTER I

INTRODUCTION

Since the 1930's, agricultural policy has played a major role in stabilizing the United States agricultural economy. Legislators involved in the writing of the last farm bill that doesn't expire, the Agricultural Act of 1949 (1949 farm bill) recognized the importance of addressing the dynamic needs of the agricultural sector regularly. As a result, subsequent agricultural acts, or 'farm bills' as they are commonly referred to, have each been written to expire roughly every five years since the 1970s. This expiration creates a sense of urgency for future Congresses to act to pass farm bills or face reverting back to the provisions of the act of the 1940's. This provision is uncommon amongst other non-agricultural legislation. Regularly passing farm bills has enabled legislators to attempt to tailor changes in farm support programs to reflect producers' needs depending on the current state of the farm economy.

An important component of the farm bill deliberation process is the scoring of the legislation. Scoring is a term that refers to development of cost estimates for the proposed changes relative to Baseline or status quo estimates. Prior to 1974, many of the functions performed now by the Congressional Budget Office (CBO) were undertaken by analysts within the administration (Page 2005). However, in an effort to remove partisan issues that often arose over cost estimates, Congress passed the Congressional Budget and Impoundment Control Act of 1974 that requires CBO to work with Congressional budget committees. CBO provides cost estimates or "scores" of all legislation that has potential to change government spending. The goal of scoring is to make congress aware of the amount of funding going toward each individual part of major legislation, along with providing an overall cost of the entire bill. Scoring is used in agricultural policy as each farm bill is being developed to ensure the new farm bill does not spend more than the budget for the bill. The farm bill includes about 12 titles, depending on the bill, encompassing everything from commodity support programs, to Supplemental Nutrition Assistance Program (SNAP), to conservation programs, to federal crop insurance.

Agricultural producers and their commodity organizations are routinely asked to provide policy suggestions prior to the development of each farm bill. Groups often have several suggestions for potential policy changes, however, without knowing the cost of their policy proposals they have no idea what would be financially feasible. If they ask for a change that is too expensive it may be dismissed once CBO scores the changes. They may not get an opportunity to ask for additional changes beyond this point, and thus lose their chance to reform agricultural policy. Therefore, it is important to develop a scoring tool that can be used to assist producers, their associations and other interest groups in developing policy proposals that fit within budget guidelines.

Objectives

The primary objective of this thesis is to create a model that uses stochastic simulation to score changes in the two major agricultural support mechanisms, agricultural risk coverage (ARC) and price loss coverage (PLC), for 9 major agricultural commodities. The model will use many of the parameters and prices from the Congressional Budget Office (CBO) baseline in order to best approximate the CBO score of the same policy proposals. An alternative methodology will be developed and evaluated to determine which method provides the most similar payment projections to the CBO baseline.

The first approach scores the cost of programs based on nationally averaged parameters which is the approach CBO uses. The alternative methodology that will be used is to evaluate predicted program costs for each major state, and then aggregating them to form national expenditures estimates. This aggregation of data will be explained further in Chapter III. The state based model will provide more specific yield variability than the national model. Both approaches will be compared to the 2019 CBO Baseline to see which is the most effective.

Justification

Changes to farm safety net programs are regularly proposed by agricultural interest groups. A model that mimics CBO Baseline scoring for ARC and PLC creates ample opportunities to analyze potential changes. This research develops a model that scores the programs as they are currently but allows for modifications to be made on various parameters. This gives the user the ability to evaluate the effect of potential program changes on government expenditures. The user-friendly design of the model makes it suitable for a wide range of users and is, therefore, available for more what-if analyses.

Budgetary pressure frequently dictates which aspects of the agricultural policy framework will be retained, modified, or cut. Policy influencers have an advantage when proposal ideas are presented with facts and well-researched potential outcomes, specifically related to budget effects. The ability to estimate the cost of commodity program changes helps validate a policy proposal.

CHAPTER II

REVIEW OF LITERATURE

U.S. Agriculture relies heavily on the stability provided by the safety net programs provided by government programs. These programs are required to be reauthorized and potentially updated roughly every five years with the passage of a new farm bill. During this legislative process, it is required that the programs be scored by the CBO to create a baseline estimate of the cost of the programs assuming no changes to current program provisions. The score created by CBO is essential because the expected cost of a program can set the tone for how it is viewed by congress, as well as, the public during the legislative process.

Scoring History

In his work on policy analysis, Manski discusses what he refers to as inappropriate certitude (Manski, 2011). The desire for certainty and the peace of mind created by a forecast with simplicity that reflects a confident determination. The author argues, that the presentation of information in policy analysis should not be reflected in this way. In policy analysis, there are numerous variables that cannot be predicted with 100 percent certainty. The directly relatable point in Manski's work is that CBO reports scores that imply certitude in spite of the uncertainty of the assumptions made in order to create a 10 year forecast. Acknowledging the challenge of choosing the correct system of presenting risk, the author proposes that one process would be to present a low and high score based on various possible future circumstances and present both figures so that the user of the analysis has a clearer picture of the potential costs of the program being viewed. Although this methodology is not the most sophisticated, Manski raises many valid concerns.

In an extensive explanation of CBO scoring, Page reveals the introduction of the scoring process to congress in the Congressional Budget act of 1974. He describes that by definition a legislative score must be presented as a point estimate, and explains how this is necessary to make the scoring baselines more clear and concise.

In their work on the 1996 farm bill, Jagger and Hull explain the benefits of introducing a one-sided bet probability scoring model. According to the article, the research was relevant after the 1996 farm bill because the probability scoring model was used significantly for the first time in the farm bill process. In brief, the probability scoring concept aims to capture change in outlays due to shifts or changes from current circumstances, such as prices and yields. They introduce this methodology in contrast to the normal point-estimate procedure that has been commonly used in the CBO scoring process. This presentation is simple to understand by someone with limited knowledge of the program or industry, but does not reflect the amount of uncertainty around the point estimates. A brief example is as follows: if we expect that policy will drive wheat production down slightly in the coming years, then we can expect that wheat price will slightly increase. Thus, the policy forecast could take into account the new expected price when predicting program outlays for that year. The authors suggest the use of the one-sided bet as a forecasting system that does not change the cost of a given program in the baseline scenario. However, the one-sided bet does account for a possible change in the policy parameters which could change total outlays. In practice, the one-sided bet was only taken into account when the analysis led to an increase in program costs. An example the authors noted of a one-sided bet that was analyzed during the 1996 farm bill reconciliation is: increasing a commodity loan rate to just below baseline market prices. In this particular case study, the authors determine probability scoring was appropriate and effective in their analysis. This influence further validates the current project, but differs in that the current project will create 500 payment estimations that may be used to create an entire distribution of expected payments above and below the baseline.

Stochastic Forecasting in Agricultural Policy Analysis

Richardson, Klose, and Gray provide a detailed description of the usefulness of simulation in their work on multivariate empirical (MVE) probability distributions. Similarly, this thesis will utilize simulation, but will differ in that the forecasts will be taken from the Food and Policy Research Institute (FAPRI) at the University of Missouri as opposed to being created on a MVE distribution. The authors also explain the use of simulation of at least 500 iterations over whatever probability distribution is chosen. This scoring model will use simulation to establish expected means, and the probability density functions (PDF) for each projected payment for ARC and PLC. As is the case in the Richardson and Klose paper, simulation strengthens the findings.

Richardson, Outlaw, and Raulston analyzed the potential payments for ARC county (ARC-CO) and PLC from 2016 – 2021 for the United States. Their work explained the way the programs functioned based on the provisions of the 2014 farm bill. They discuss how the abrupt decline in commodity prices is what caused ARC-CO to be a favorable choice for corn and soybean farmers specifically. This analysis is applicable to the current research because movements like the one from 2011-2016 that caused high ARC-CO payments, could be a possible explanation of why the program pays well again in this analysis, or not. Beyond a brief historical explanation of the programs, the goal of their project was to arrive at payment projections from ARC-CO and PLC for the years 2016-2021. The details of this article outline how payments can be forecasted on a county level for the major covered commodities and then aggregated. The uncertainty of the future is accounted for by simulating probabilistic forecasts of the ARC-CO and PLC payments for each year 500 times. Their results show that the original thoughts that high ARC-CO payments on a national scale, were due to the high grain prices of the past, but will not be sustained without continued price decline holds true with the ARC-CO projection of $45.9/acre for 2016 versus $8.62/acre for 2021. The methodology used aggregate to the national level in their study is similar to what will be required to create a stochastic scoring model that shows total program outlays for both of these programs. The difference is that Richardson, Outlaw and Raulston based the payments off of county level information, and this project will use both national and state level models that are aggregated. The formulas to calculate payments are very similar between the PLC and ARC-CO of the 2014 farm bill, and the PLC and ARC of the 2018 farm bill because the programs only changed marginally.

The Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri provides analysis and projections on agricultural markets and policies (FAPRI, 2019). This study utilizes the baseline projections from the FAPRI 2019 Baseline Outlook for mean price, and yield projections. The FAPRI means are based on a range of projected market outcomes that account for uncertainty in each price and yield figure. The range is spread over 500 possible outcomes for each respective price and yield over the 10-year projection and based on a unique probability distribution. Due to the partnership between FAPRI and the Agricultural and Food Policy Center (AFPC) at Texas A&M University, this study is able to use the specific 500 price and yield draws from each year, explained above, to calculate expected payments. The risk associated with each crop's price and yield will then be used to create a distribution around the CBO mean prices and yields from the January 2019 CBO Baseline. This application of risk based on FAPRI's price and yield distributions is necessary because the CBO baseline does not report how their model assigns risk on their projections.

The results of this study will be compared to the January 2019 CBO Baseline. A one sample t-test will be conducted for each of the ARC and PLC payment projections to achieve the comparison. In this common statistical test, the population mean is the CBO Baseline projection and the sample mean is the payment projected by this study. The t-statistic will be used to get p-values by comparing them against tabulated values that indicate the likelihood of the population mean hitting that respective sample mean given the degrees of freedom (Whitney, 2002). The 2 tailed p-values will establish whether the sample means are statistically different at a 90% confidence interval. Meaning that any p-values < 0.10 are statistically significant, and result in a rejection of the null hypothesis. The methods used will be further explained in chapter 3.

Current Commodity Programs

All of the calculations for the ARC and PLC programs will be done based on the provisions of the Farm Security and Rural Investment Act of 2018 (2018 farm bill) text. It should be noted, however, that some discrepancies may exist between the current interpretation of the 2018 farm bill text, and the final regulations for the bill which are not yet public information. Specific changes to the programs in the 2018 farm bill that will effect ARC and PLC will be included in the model. One of the major assumptions used in scoring is that the baseline is developed assuming the programs being scored will retain their current provisions for the next 10 years. Therefore, CBO baselines are for 10 years into the future even though farm bills generally only last 5 years.

The ARC calculations for the state based model present a unique challenge with regard to the projected yields. The FAPRI yields that will be used to calculate the ARC variations in the national model are a national average yield. However, FAPRI does not project an average state yield. The use of this information will be further explained in Chapter III, but it is important to note here that a method of Correlation Induction will be used in the state based model to assign a state yield to each iteration that has the appropriate relationship respective to the iteration's national price and national yield. Evidence that the correlation induction process can be a viable one was found in research by Avramidis and Wilson, as well as Tew and Wilson. In this study, the induction of future state yields aligns most clearly with Tew's statement that this methodology may be used when seeking the prediction of future responses in a real system. Although the steps taken to achieve induced correlation in this study, as depicted in Chapter III, are slightly different than those laid out in the articles above, the foundation and intent are very similar.

CHAPTER III

METHODOLOGY

This thesis will develop estimates of future Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) program payments that make up the crop support portion of the commodity title, or Title I of the most recent farm bill. The estimates will then be compared to the CBO Baseline to determine the accuracy of the models. Both programs were created in the 2014 farm bill, and were amended slightly in the 2018 farm bill. These programs are dependent on commodity specific annual information such as crop yields among other variables. They are both briefly described below as they are administered.

Agriculture Risk Coverage (ARC)

ARC is a revenue based support program that develops a benchmark revenue using the previous 5-year Olympic average of market prices and county yields and provides a payment when the annual revenue (market price * county yield) is below the benchmark for that year. The specific variables and equations are below:

Variables:

BMY: Benchmark Yield is the 5-year Olympic average yield. The average of the previous 5 years of county yields after dropping the maximum and minimum.

BMP: Benchmark Price is the 5-year Olympic average price. The average of the previous 5 years of market prices after dropping the maximum and minimum.

BMR: Benchmark Revenue is the product of BMY and BMP and is unique for each county

Payment Factor: 0.85 based on current legislation

ARC Payment Rate: Per acre payment for Base Acres enrolled in the ARC Program. The ARC Payment Rate is limited to the 10% of the BMR. Payment is only made when this figure is positive.

Enrollment Proportion: Percentage of base acres in that particular crop enrolling in ARC. This number is reported in the CBO baseline.

Total ARC Payment: ARC Payments made nationally for that particular crop.

$$BMY_{2018} = \text{Olympic Average County Yield } 2013 - 2017$$

$$BMP_{2018} = \text{Olympic Average National MYA Prices } 2013 - 2017$$

$$BMR_{2018} = BMP_{2018} * BMP_{2018}$$

$$Revenue\ Gaurentee = BMR_{2018} * 0.86$$

$$Actual\ Revenue = Actual\ Yield_{2018} * Actual\ MYA\ Price_{2018}$$

$$ARC\ Payment\ Rate = (Actual\ Revenue - Revenue\ Guarentee)$$

$$Total\ ARC\ Payment = ARC\ Payment\ Rate * Base\ Acres * 0.85 * Enrolled\ Proportion$$

<u>Price Loss Coverage (PLC)</u>

PLC provides price protection by providing a payment if the market price drops below the commodity specific reference price. The quantity of the payment is dependent on producer payment yields for each farm as opposed to the ARC payment being based on county average yields.

PY = Payment Yield; designated yield per base acre established based on historical production. Unique based on information from each FSA farm number.

MYA = Marketing Year Average national price as determined by NASS

RP = Reference Price; established price for each covered commodity that determines price support level.

Payment Factor: 0.85 based on current legislation

PLC Payment Rate: Only paid if MYA price falls below the reference price.

Enrollment Proportion: Percentage of base acres in that particular crop enrolling in ARC. This Number is reported from the CBO baseline.

Total PLC Payment: PLC payments made nationally for that particular crop

$$PLC\ Payment\ Rate_{2018} = (RP_{2018} - MYA\ Price_{2018}) * PY$$

$$Total\ PLC\ Payment_{2018} = Base\ Acres * PLC\ Payment\ Rate 2018 * 0.85 * Enrollment\ Proportion$$

These programs are based on county (ARC) or individual (PLC) information. However, this study will estimate payments in an aggregated fashion based on state and national parameters. In order to score the programs into the future, projections of this information must be used within the model. When CBO publishes a scoring report their results are presented deterministically as point estimates. Evaluation of risk is accounted for in CBO’s forecasted scores, but their methodology is not made public. This project will use current support program parameters based on the formulas above and risk to create a scoring model designed to mimic that of the CBO. The intention being to provide an estimate that would be as close as possible to CBO's value. This scoring model will analyze major current agricultural support programs by producing national outlays for 9 major commodities: corn, wheat, soybeans, cotton, peanuts, sorghum, long grain rice, medium and short grain rice, and temperate japonica rice from 2018 - 2028. The model will emulate the methodology the CBO uses when possible, understanding that the distributions on price and yield projections are not known. The shapes and scales of these distributions are the only portion of CBO's model that cannot be duplicated.

Recent Program Description

For the calculation of Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) payments for each crop, the model incorporates provisions of the 2018 farm bill with only minor changes from the 2014 programs as described by Richardson, Outlaw, and Raulston. Additional minor changes made in the 2018 farm bill are as follows. First, scaling reference prices enable the reference prices used in the PLC and ARC programs to be raised up to 15% when 85% of the Olympic Average of the MYA price over the last 5 years is greater than the established reference price for that commodity. The formula for this change is written below:

$$Effective\ Reference\ Price_{2019} = 0.85 * (Olympic\ Average\ MYA\ price\ 2014 - 2018)$$

Second, there are new loan rates for many of the major covered commodities. These loan rates are fixed over the life of the bill as opposed to the reference prices. Likely the most significant change between the 2014 and 2018 farm bills with regard to the ARC and PLC programs was the re-incorporation of upland cotton as a covered commodity under the commodity title as seed cotton (H.R. 2). The seed cotton program structure was developed and passed into law in February 2018 through the Bipartisan Budget Act of 2018. The legislation describes seed cotton as the weighted average of cottonseed and cotton lint on a per pound basis. The MYA price of seed cotton is the MYA price of cottonseed and the MYA price of upland cotton lint weighted by each of their national production respectively.

$$Seed\ Cotton\ MYA\ Price_{2019} = (U.S.Lint\ Prod. * U.S.Lint\ MYA\ Price + U.S.Cottonseed\ Prod. * U.S.Cottonseed\ MYA\ Price)/(U.S.Lint\ Prod. + U.S.Cottonseed\ Prod.)$$

In the formula, cotton lint and cottonseed are both to be measured in pounds. This study calculated expected payments on upland cotton as a crop based on this recently established program.

Nationally Based Scoring Model

Commodity payments are, in practice, paid to tens of thousands of individuals each with their own specific program parameters. However, the CBO estimates of expected national payments for ARC and PLC each year are based on one equation for ARC and one equation for PLC using aggregated information for the nation. The same methodology will be used for the national scale model in this study. Aggregation of payment yield data in the case of PLC, and actual yield data in the case of ARC are intended to achieve the following motives: make the model concise enough to be run in Microsoft Excel, have the ability to analyze payments for 9 major crops at once, and mimic the methodology used by CBO.

Utilizing Risk in Projections

Historical national prices and yields used in the model will be obtained from the National Agricultural Statistic Service (NASS) for 2011 - 2017. For the years 2018 – 2028, the current research will use the Food and Agriculture Policy Research Institute (FAPRI) projections of 500 random draws for prices and yields. FAPRI projections are frequently used in conjunction with USDA forecasts as an alternative estimate for Congress (U.S. Baseline Outlook). The FAPRI projections are established as 500 random draws around the mean for each price and yield value in each year. The values are developed according to the variability of each commodity applied via their large structural model. Each of their 500 iterations of price and yield are associated with a given run of their model, so matched pairs of a price draw and a US yield draw automatically reflect their joint distribution as modelled by FAPRI.

The nationally aggregated payment projections will also be adapted to the CBO means reported in the 2019 CBO Baseline because the objective is to create projections that mimic CBO. However, since the CBO reports a single point estimate for the future prices and yields for each commodity, the risk associated with the 500 random draws from FAPRI will be assumed as the risk around the CBO mean estimates. The model will then provide the ability to determine the scores based on the FAPRI or CBO mean projections considering risk. The results for this study will all be in terms of the CBO means in accordance with the project objectives. Ideally the model would use the exact draws that CBO uses to assign risk to their projections, but that information is not available, so using FAPRI risk is the next best available alternative.

Limitations

This national scale payment method will provide a national payment estimate, but national models have no ability to reflect the differences in regional yields or regional program history factors. For example, for a given realized price and yield, the US ARC model may be close to having a payment trigged, but not quite. However, in such a situation a non-trivial number of producers are likely to be receiving payments.

State Based Scoring Model

This study will also evaluate the outlays for ARC and PLC using state level aggregation in order to address the objective of determining an alternative method to predict program outlays. This effort should overcome at least some portion of the aggregation issues described above. This assumption is sound because regional yield variability will be taken into account. A state-based analysis should also prove to be invaluable in further research because lawmakers will be able to understand how a policy change would directly affect their respective state.

States Included

A major limitation to this study is the size of the models because the more disaggregated the model, the larger the model becomes. Therefore, for the state level analysis, only the major producing states for each commodity will have specific program payment projections, and the remaining states will have their base acres summed creating an "other states" payment. The "other states" differ for each crop. For corn and soybeans, the top eight states in corn and soybean base acres respectively are included, followed by Texas, and then "other states." Texas is intentionally included individually because the project is being done in Texas, even though it is not actually the ninth highest in corn or soybean base acres. Peanut and rice base acres are both only found in a handful of states because of the unique growing conditions they require. The table below shows the states that are included and those that make up the "others states" for each crop.

Figure 3.1: States Included in the State-Based Model

	Corn	Soybeans	Wheat	Cotton	Peanuts	Sorghum	Long Grain Rice	Med and Short Grain Rice
1	IOWA	ILLINOIS	KANSAS	CALIFORNIA	GEORGIA	KANSAS	ARKANSAS	ARKANSAS
2	ILLINOIS	IOWA	NORTH DAKOTA	MISSISSIPPI	TEXAS	TEXAS	LOUISIANA	LOUISIANA
3	NEBRASKA	MINNESOTA	MONTANA	GEORGIA	ALABAMA	NEBRASKA	TEXAS	TEXAS
4	MINNESOTA	NORTH DAKOTA	OKLAHOMA	CALIFORNIA	NORTH CAROLINA	MISSOURI	MISSISSIPPI	MISSOURI
5	INDIANA	SOUTH DAKOTA	TEXAS	ARKANSAS	FLORIDA	OKLAHOMA	MISSOURI	MISSISSIPPI
6	SOUTH DAKOTA	INDIANA	COLORADO	LOUISIANA	OKLAHOMA	NEW MEXICO	CALIFORNIA	* CALIFORNIA
7	KANSAS	MISSOURI	WASHINGTON	NORTH CAROLINA	SOUTH CAROLINA	COLORADO		
8	WISCONSIN	OHIO	SOUTH DAKOTA	TENNESSEE	VIRGINIA	ARKANSAS		
9	TEXAS	TEXAS	NEBRASKA	ALABAMA	OTHER STATES	SOUTH DAKOTA		
10	OTHER STATES	OTHER STATES	OTHER STATES	OTHER STATES		OTHER STATES		
11	OHIO	NEBRASKA	MINNESOTA	OKLAHOMA	NEW MEXICO	LOUISIANA	FLORIDA	* Temperate Japonica
12	MISSOURI	KANSAS	IDAHO	ARIZONA	MISSISSIPPI	MISSISSIPPI	OKLAHOMA	
13	NORTH DAKOTA	ARKANSAS	MISSOURI	MISSOURI	ARKANSAS	ILLINOIS	TENNESSEE	
14	MICHIGAN	MICHIGAN	OREGON	SOUTH CAROLINA	TENNESSEE	GEORGIA	ILLINOIS	
15	KENTUCKY	NORTH CAROLINA	ILLINOIS	FLORIDA	LOUISIANA	TENNESSEE	KENTUCKY	
16	COLORADO	MISSISSIPPI	ARKANSAS	NEW MEXICO	ARIZONA	ALABAMA	SOUTH CAROLINA	
17	NEW YORK	KENTUCKY	OHIO	VIRGINIA	CALIFORNIA	NORTH CAROLINA	ALABAMA	
18	NORTH CAROLINA	WISCONSIN	CALIFORNIA	KANSAS	MISSOURI	KENTUCKY		
19	PENNSYLVANIA	TENNESSEE	MICHIGAN	MARYLAND	COLORADO	SOUTH CAROLINA		
20	TENNESSEE	LOUISIANA	NORTH CAROLINA	KENTUCKY	NEBRASKA	CALIFORNIA		
21	VIRGINIA	MARYLAND	NEW MEXICO	NEBRASKA		ARIZONA		
22	MARYLAND	VIRGINIA	INDIANA			FLORIDA		
23	CALIFORNIA	SOUTH CAROLINA	KENTUCKY			VIRGINIA		
24	SOUTH CAROLINA	PENNSYLVANIA	GEORGIA			MARYLAND		
25	GEORGIA	OKLAHOMA	TENNESSEE			INDIANA		
26	MISSISSIPPI	ALABAMA	WYOMING			IOWA		
27	LOUISIANA	DELAWARE	MISSISSIPPI			PENNSYLVANIA		
28	OKLAHOMA	GEORGIA	SOUTH CAROLINA			NORTH DAKOTA		
29	ALABAMA	NEW YORK	UTAH			DELAWARE		
30	IDAHO	NEW JERSEY	VIRGINIA			UTAH		
31	ARKANSAS	WEST VIRGINIA	ALABAMA			NEW JERSEY		
32	WASHINGTON	FLORIDA	LOUISIANA			MONTANA		
33	DELAWARE	COLORADO	MARYLAND			OHIO		
34	NEW MEXICO	MONTANA	WISCONSIN			IDAHO		
35	WYOMING	MAINE	ARIZONA			WISCONSIN		
36	FLORIDA	VERMONT	PENNSYLVANIA			OREGON		
37	MONTANA	WASHINGTON	NEW YORK			WEST VIRGINIA		
38	NEW JERSEY	OREGON	IOWA			MICHIGAN		
39	VERMONT	MASSACHUSETTS	DELAWARE			MINNESOTA		
40	WEST VIRGINIA	NEW MEXICO	NEVADA			WYOMING		
41	OREGON	CALIFORNIA	FLORIDA			NEVADA		
42	UTAH	ARIZONA	NEW JERSEY			NEW YORK		
43	ARIZONA	UTAH	WEST VIRGINIA			WASHINGTON		
44	MAINE	WYOMING	MAINE			VERMONT		
45	CONNECTICUT	IDAHO	VERMONT			CONNECTICUT		
46	MASSACHUSETTS	CONNECTICUT	ALASKA			NEW HAMPSHIRE		
47	NEW HAMPSHIRE	NEW HAMPSHIRE	CONNECTICUT			MASSACHUSETTS		
48	NEVADA		MASSACHUSETTS			RHODE ISLAND		
49	RHODE ISLAND					MAINE		
50								

Program Assumptions

Given that PLC payment yields are not publicly available by state, the PLC payment yields for each county will be weighted depending on their respective base acres for that commodity, to create state-level payment yields. For the "other states" category for each commodity, the PLC yields will be will be weighted on each state's weighted average payment yield, and their respective total base acres. The payment yields, the FAPRI 500 MYA price draws for 2018 –

2027, and the base acreages for each state, are all that is needed to generate the state level PLC payments.

The amount of base acres of each commodity in each county was last reported by FSA for the 2014 crop year. The base acres listed in this report do not match the amount of base used by CBO in the baseline. This can be explained by the fact the 100% of existing base acres are not enrolled in farm programs each year. This study will simply take the percentage of base acres of each crop in each state and apply that to the amount of total base acres reported for that crop in the CBO Baseline. For example, if Texas had 9% of the wheat base in the 2014 crop year according to FSA, then that 9% will be multiplied by the total wheat base in the CBO baseline to obtain an estimate of Texas wheat base.

In order to calculate a state based ARC payment, the MYA price will also use the FAPRI 500 draws for MYA price from 2018 – 2028. FAPRI, however, does not provide state-level average yield predictions. Thus, the yields that are yet to be realized (2019 – 2027) will be simulated for each state that is to be included in accordance to the table above. The historic yields used for the “other states” will be simulated by taking a weighted average of the historical production from the states. The ‘weight’ of each state will then be applied to the historical planted acre yields to create an entry that encompasses all of the states that cannot be modeled individually. Note that payment projections will be calculated for the “other states” just as they will be for the states that are included individually.

Correlation Induction for Yield Projections

The methods below explain the calculation of 500 unique state yields for 2019 - 2027 based on each state’s historical yield, the correlations among them, and their correlations with the national historic price and national historic yield deviates. The historic yields and prices will be obtained from NASS. For each year, stochastic draws are needed for J state yield deviates. These must be correlated with the US average yield and change in the natural logarithm of the market price, which are pre-drawn (i.e., they are from FAPRI). A general approach to inducing correlation among some pre-drawn random variables and some newly simulated variables is described below.

A covariance matrix from the historic yield deviates and historic log changes in price for each state will be calculated. The optimal level of shrinkage to use was found based on Ledoit's methods (Ledoit, 2003). The resulting covariance matrix is then decomposed based on the Cholesky Decomposition method.

Suppose K is the total number of variables in the system, J is the total number of variables to be drawn, K – J is the total number of pre-drawn variables, N is the total number of observations, while also noting that J ≥ K / 2. Also suppose **C** represents the Scaled, Correlated Variables, **L** represents the Cholesky Decomposition of the covariance matrix described in the previous paragraph (Lower Triangular), and that **Z** represents the Standard Normal Variables.

$$(1)\quad \boldsymbol{C} \;=\; \boldsymbol{L}\,\boldsymbol{Z}$$

Then, scaled correlated variables are calculated from independent standard normal variables using the following relationship. We can write (1) in terms of partitioned matrices as follows.

$$\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{Z_1} \\ \boldsymbol{Z_2} \end{bmatrix} \quad with\ dimension\ (K\ x\ N) \qquad \begin{array}{c} \boldsymbol{Z_1}\ \ is\ \ J\ x\ N \\ \boldsymbol{Z_2}\ \ is\ \ (K-J)\ x\ N \end{array}$$

$$\boldsymbol{C} = \begin{bmatrix} \boldsymbol{C_1} \\ \boldsymbol{C_2} \end{bmatrix} \quad with\ dimension\ (K\ x\ N) \quad \begin{matrix} \boldsymbol{C_1} = J\ x\ N \\ \boldsymbol{C_2} = (K-J)\ x\ N \end{matrix}$$

$$\boldsymbol{L} = \begin{bmatrix} \boldsymbol{L_{11}} & \boldsymbol{L_{12}} \\ \boldsymbol{L_{21}} & \boldsymbol{L_{22}} \end{bmatrix}$$

Note: $\mathbf{L_{12}} = 0$

The partitions of L have the following dimensions:

$\mathbf{L_{11}}$ J x J

$\mathbf{L_{12}}$ J x (K – J)

$\mathbf{L_{21}}$ (K – J) x J

$\mathbf{L_{22}}$ (K – J) x (K – J)

Then, the correlation induction process is as follows.

$$(2):\ \boldsymbol{Z_1} = \boldsymbol{L_{11}^{-1}}\,\boldsymbol{C_1}$$

Draw $\mathbf{Z_2}$

$$(3):\ \boldsymbol{C_2} = \boldsymbol{L_{21}}\,\boldsymbol{Z_1} + \boldsymbol{L_{22}}\,\boldsymbol{Z_2}$$

Once the Cholesky decomposition **L** is found, the “top” of the system is used to solve for $\mathbf{Z_1}$, given the pre-drawn realizations contained in $\mathbf{C_1}$ (2). Then, after drawing independent standard normal draws ($\mathbf{Z_2}$), the values for the non-pre-drawn variables ($\mathbf{C_2}$) are calculated using equation (3).

The correlations found for each state using this correlation induction methodology will be applied to create 500 unique state yield draws for each state for each projected year. The matrix operations, along with the generation of standard normal variables (Z) that are drawn in the formulas above will be calculated in an add-in to Microsoft Excel called Simetar (Richardson, et al.).

CHAPTER IV

RESULTS

Results from both the national and state-based models are discussed in this chapter. The national model is discussed first, providing a comprehensive look at the likelihood, and amount of an ARC or PLC Payments for each crop in each year. In addition, the scores from this study will be compared to those provided by the 2019 CBO Baseline.

National Model Results

The results are first shown based on average expected payments per year by crop and compared with the expected payments reported by CBO in the 2019 CBO Baseline report. The results for the crops are listed below and are organized based on fiscal year (FY) as opposed to crop year. This distinction is important because, in practice the 2016 - 2017 MYA price is based on the crop that is harvested in the fall of 2016. However, because of the schedules of ARC and PLC payments, those made from the parameters above are to be reported on FY2018. It is also important to note that the data from FY 18 and FY 19 is already established, and therefore has no uncertainty in the model. Table 4.1 is simply the January 2019 CBO baseline score for ARC and PLC for those same commodities. Table 4.2 includes the mean payments for each commodity in the national model, and Table 4.3 shows the difference in the scores from the national model and the CBO baseline. The basic formula for the differences calculated for the national and state models is below.

$$Difference = (Model\ Projection) - (2019\ CBO\ Payment\ Projection)$$

Table 4.1: 2019 CBO Baseline Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn												
PLC	265	270	169	2110	1706	1900	1859	1920	2053	2172	2608	2353
ARC	2917	1226	581	114	94	126	138	153	173	191	214	189
Subtotal	3182	1496	750	2224	1799	2026	1997	2073	2227	2363	2822	2542
Soybeans												
PLC	10	11	14	547	328	282	261	225	155	178	149	151
ARC	606	672	420	236	120	111	96	80	54	70	67	79
Subtotal	616	683	434	783	448	392	357	305	208	248	216	229
Wheat												
PLC	1369	718	372	728	702	702	705	689	721	689	683	711
ARC	511	423	209	65	67	73	53	59	55	61	65	72
Subtotal	1880	1140	581	793	769	775	758	748	776	751	747	784
Seed Cotton												
PLC	---	---	213	573	514	446	392	337	308	281	261	250
ARC	---	---	44	15	19	19	16	14	16	15	14	15
Subtotal	---	---	257	589	533	465	408	351	324	296	275	265
Peanuts												
PLC	607	414	417	388	412	412	406	406	415	425	432	446
ARC	1	0	0	0	0	0	0	0	0	0	0	0
Subtotal	608	414	417	388	412	413	406	406	415	426	433	447
Sorghum												
PLC	383	246	179	232	157	147	146	148	146	148	148	149
ARC	24	23	24	19	14	11	9	9	8	9	9	9
Subtotal	407	269	203	251	171	158	156	157	154	157	156	158
Rice												
PLC	1032	515	776	764	746	724	704	691	674	664	650	642
ARC	22	7	10	3	3	2	3	2	2	3	3	3
Subtotal	1054	522	786	767	749	727	706	693	677	666	653	645
Totals												
PLC	3666	2174	2140	5341	4564	4613	4473	4416	4472	4557	4931	4702
ARC	4081	2351	1287	452	317	342	315	318	309	348	371	367
Subtotal	7747	4524	3427	5794	4881	4955	4788	4733	4781	4906	5302	5068

Note: CBO reports all rice together. All figures are in terms of $1,000,000's.

Table 4.2: National Model Mean Projections - Unadjusted												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn												
PLC	209	210	64	1896	1963	2482	2341	2366	2575	2880	3204	3057
ARC	3906	0	0	47	48	84	79	101	146	173	196	191
Subtotal	4116	210	64	1943	2011	2566	2420	2467	2721	3052	3400	3248
Soybeans												
PLC	0	0	2	727	548	515	530	447	397	436	468	462
ARC	0	0	0	210	122	112	97	73	80	102	125	126
Subtotal	0	0	2	937	670	627	627	521	477	538	593	589
Wheat												
PLC	1378	667	344	936	1022	1074	1051	1009	1017	1039	1033	1057
ARC	735	593	0	9	20	21	31	37	40	48	45	46
Subtotal	2113	1260	344	946	1042	1095	1082	1046	1057	1088	1077	1103
Seed Cotton												
PLC	---	---	207	883	849	778	733	657	579	594	560	546
ARC	---	---	56	32	49	46	37	28	29	31	28	29
Subtotal	---	---	263	915	898	823	770	685	608	626	588	576
Peanuts												
PLC	597	348	439	433	424	417	417	413	415	419	432	442
ARC	2	0	0	0	0	0	0	0	0	0	0	0
Subtotal	599	348	439	433	424	417	418	413	416	420	433	442
Sorghum												
PLC	338	213	193	279	213	218	208	210	212	212	217	216
ARC	11	9	26	21	15	14	11	11	12	13	13	14
Subtotal	350	222	220	300	228	231	220	222	224	225	230	230
Rice												
PLC - LG Rice	947	539	687	697	680	621	581	543	530	523	521	519
PLC - MGSG Rice	35	21	18	24	23	24	24	25	23	23	22	21
PLC - TJ Rice	84	0	0	75	52	77	87	97	88	86	73	67
ARC - LG Rice	4	2	2	2	2	2	1	1	1	1	1	1
ARC - MGSG Rice	0	0	0	0	0	0	0	0	0	0	0	0
ARC - TJ Rice	1	0	0	0	0	0	0	0	0	0	0	0
Subtotal	1071	563	707	798	756	723	693	666	643	634	617	608
Totals												
PLC	3589	1998	1954	5948	5773	6205	5972	5767	5837	6213	6530	6387
ARC	4660	625	103	420	331	378	368	374	421	478	502	496
Total	8248	2623	2056	6368	6104	6583	6340	6140	6258	6690	7032	6882

Note: Fiscal year 2018 corresponds with crop year 2016. Seed Cotton was not covered until FY 20.

Table 4.3: National Model Differences - Unadjusted												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn												
PLC	-56	-60	-106	-214	257	582	483	445	522	707	596	705
ARC	990	-1226	-581	-67	-45	-42	-59	-52	-27	-18	-18	2
Subtotal	934	-1286	-686	-281	212	539	423	394	494	689	578	706
Soybeans												
PLC	-10	-11	-12	180	220	233	269	222	242	258	319	311
ARC	-606	-672	-420	-26	2	2	1	-7	26	33	58	48
Subtotal	-616	-683	-432	154	221	235	270	216	269	291	377	359
Wheat												
PLC	9	-51	-27	208	320	372	346	320	296	350	350	345
ARC	223	170	-209	-55	-47	-53	-22	-22	-15	-13	-20	-26
Subtotal	233	119	-236	153	273	320	323	298	281	337	330	320
Seed Cotton												
PLC	---	---	-7	310	335	332	340	320	271	314	299	296
ARC	---	---	12	16	30	27	22	14	14	16	14	14
Subtotal	---	---	6	326	365	359	362	334	285	330	313	311
Peanuts												
PLC	-10	-66	22	45	12	5	11	6	0	-6	0	-4
ARC	2	0	0	0	0	0	0	0	0	0	0	0
Subtotal	-8	-66	22	45	12	5	11	6	0	-6	0	-4
Sorghum												
PLC	-45	-33	14	46	57	71	62	63	67	64	69	67
ARC	-13	-13	3	2	1	3	2	2	4	4	4	5
Subtotal	-57	-46	17	49	58	74	64	65	70	68	73	72
Rice												
PLC	34	45	-72	32	8	-3	-12	-26	-33	-32	-35	-36
ARC	-17	-5	-8	-1	-1	0	-1	-1	-1	-1	-1	-1
Subtotal	16	41	-79	31	8	-4	-13	-27	-34	-33	-36	-37
Totals												
PLC	-78	-176	-180	297	874	1260	1158	1030	1094	1341	1300	1389
ARC	578	-1746	-1214	-147	-90	-91	-79	-79	-12	5	23	28
Subtotal	501	-1922	-1395	150	784	1169	1079	952	1081	1347	1323	1416

Note: Difference = (Natl. model) - (CBO Baseline). All scores are in terms of $1,000,000's.

The purpose of this project was to match the score from the model as close to the 2019 CBO Baseline as possible. To address this, the amount of risk applied to the CBO means, based on the draws from FAPRI, were multiplied by a Risk Adjustment Factor (RAF). This will reduce the differences between projected PLC payments for the national model and the CBO Baseline. The RAFs were applied directly to the percent deviate of each FAPRI draw of projected prices. The adjusted percent deviates were then applied to the CBO mean prices to create 500 unique draws for each projected year (2018 – 2027).

The fact that the ARC program depends on both price and yield variability, causes the scores for ARC to be more difficult to mimic. Meaning, the aggregated ARC scores are far less likely to match than the PLC scores. Assuming that CBO is using all of their own parameters for total base acres, average MYA price, payment yield, and ARC/PLC enrollment percentage, the only factors effecting PLC payments that can be different between the CBO Baseline and this model are the shape, and scale of the distribution of MYA prices.

In Table 4.3, corn has a positive difference on PLC in FY 21, or the national model has a larger payment projection than CBO. Thus, an RAF < 1 was applied to the percent deviates in that fiscal year in order to shrink this difference until the model scores the average national PLC payment within roughly $1 million of the CBO estimate for PLC in FY 22. This process is the best way to produce scores as close as possible to the CBO baseline without having access to their exact distribution of MYA projected prices. As seen below, each year from FY 20 – FY 29 was adjusted for each crop because they have differing price distributions, thus, they require a different RAF. As a reminder FY 18 and FY 19 were not scaled because their respective prices and yields are already established.

Table 4.4: National Model Risk Adjustment Factors

	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
Corn	8.25	1.1	0.901	0.7953	0.813	0.836	0.819	0.7585	0.796	0.7559
Soybeans	3	0.675	0.645	0.635	0.5875	0.65	0.62	0.61	0.555	0.5775
Wheat	7	0.55	0.45	0.415	0.43	0.445	0.512	0.433	0.43	0.453
Seed Cotton	1.8	0.1	0.1	0.1	0.1	0.08	0.26	0.305	0.36	0.395
Peanuts	5.75	0.5	0.87	0.945	0.885	0.945	1	1.08	1	1.07
Sorghum	4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Rice	1	2.2	1.3	2.2	2.28	2.63	2.335	2.27	2.02	1.72

The tables that are referred to as “adjusted” are labeled in that way to indicate that their respective RAF has been applied. Below in Figure 4.1 is the probability density function (PDF) of fiscal year 2021 corn prices depicting the price distributions, unadjusted and adjusted.

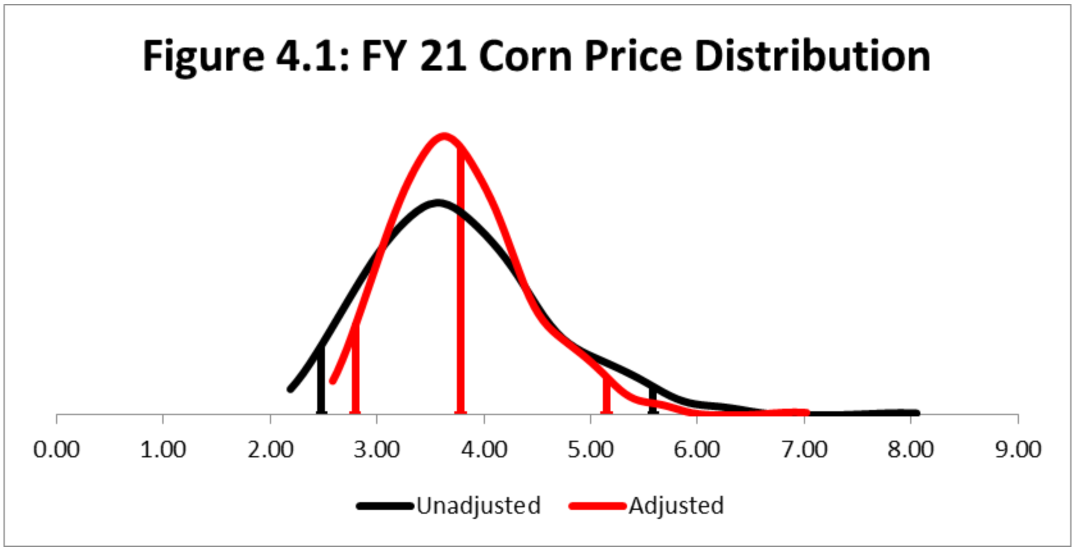


Table 4.5 on the following page shows the difference in the RAF based projections from the national model, and the CBO baseline.

Table 4.5: National Model Differences - Adjusted												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn												
PLC	-56	-60	1	-6	0	-1	1	0	-1	-1	0	0
ARC	990	-1226	-135	-46	-58	-76	-86	-84	-82	-95	-91	-80
Subtotal	934	-1286	-134	-52	-58	-77	-85	-84	-83	-96	-92	-80
Soybeans												
PLC	-10	-11	-1	0	0	1	0	0	0	0	-1	0
ARC	-606	-672	-266	-106	-73	-71	-80	-65	-44	-57	-52	-60
Subtotal	-616	-683	-267	-106	-73	-70	-80	-64	-44	-56	-53	-61
Wheat												
PLC	9	-51	0	-1	-1	1	1	-1	0	0	0	-1
ARC	223	170	-208	-64	-66	-73	-52	-55	-47	-57	-62	-66
Subtotal	233	119	-208	-65	-67	-72	-52	-56	-47	-58	-62	-66
Seed Cotton												
PLC	---	---	0	281	215	163	113	50	0	0	0	1
ARC	---	---	12	-7	10	5	-9	-11	-11	-12	-11	-11
Subtotal	---	---	12	274	224	168	104	38	-11	-12	-11	-10
Peanuts												
PLC	-10	-66	0	24	1	1	1	1	0	0	0	0
ARC	2	0	0	0	0	0	0	0	0	0	0	0
Subtotal	-8	-66	0	24	1	1	1	1	0	0	0	0
Sorghum												
PLC	-45	-33	15	21	10	15	11	10	13	9	14	13
ARC	-13	-13	6	2	-2	-2	-2	-3	-2	-2	-2	-2
Subtotal	-57	-46	21	23	8	13	8	7	11	7	12	12
Rice												
PLC	34	45	-72	0	0	0	0	0	0	0	0	0
ARC	-17	-5	-8	-1	-1	0	-1	0	0	-1	-1	-1
Subtotal	16	41	-79	-2	0	0	-1	0	0	-1	0	0
Totals												
PLC	-78	-176	-57	37	11	17	13	10	13	8	12	13
ARC	578	-1746	-610	-215	-200	-222	-221	-208	-175	-211	-208	-208
Subtotal	501	-1922	-667	-177	-189	-205	-208	-197	-163	-203	-195	-196
Note: Difference = (Natl. model) - (CBO Baseline). CBO reports all rice together. All figures are in terms of $1,000,000's.												

After the RAFs were introduced, the national level model results for PLC were much closer to the CBO Baseline, as shown above. Note that only the projections (FY 20 – FY 29) shifted because the FY 18 and FY 19 are both established years that do not contain any risk. There were differences in projected PLC scores in Table 4.5 for cotton, peanuts, sorghum, and rice that did not squeeze closer to zero as their respective RAF was adjusted. Barring some specific adjustment by CBO to these particular projections that is not reported, the reason the scores will not all match is due to the shape of their respective price distributions. The scale of the distribution is what was adjusted with the RAF's but the shape cannot be addressed because it is not public information. Therefore, nothing else can be done to make the scores match more closely without having the exact price distributions that CBO used in their model.

As introduced in Chapter II, p-values from the t-statistics based on the hypothesis that the projected mean from the model equals the CBO baseline mean, are reported to show how well the national model mimicked the CBO baseline. A 90% confidence interval was used to establish which projections differ enough from CBO to reject the hypothesis. Table 4.6 will shade the instances where the p-value is greater than 0.10. The shaded values are not significantly different than the CBO Baseline projection. The shading helps to see that the RAF's caused the model projections to no longer be significantly different than the CBO Baseline projections.

Table 4.6 : National Model P-Values from One Sample T-test										
	FY 20	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn										
PLC P-Value - Unadj.	0.00	0.06	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PLC P-Value - Adj.	0.89	0.96	1.00	0.99	1.00	1.00	0.99	0.99	1.00	1.00
ARC P-Value - Unadj.		0.00	0.00	0.00	0.00	0.00	0.03	0.19	0.21	0.92
ARC P-Value - Adj.	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Soybeans										
PLC P-Value - Unadj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PLC P-Value - Adj.	0.43	0.99	0.99	0.98	0.99	0.98	0.99	0.98	0.94	0.99
ARC P-Value - Unadj.		0.05	0.89	0.89	0.90	0.44	0.01	0.00	0.00	0.00
ARC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wheat										
PLC P-Value - Unadj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PLC P-Value - Adj.	0.97	0.96	0.98	0.97	0.99	0.97	1.00	0.99	0.99	0.98
ARC P-Value - Unadj.		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Seed Cotton										
PLC P-Value - Unadj.	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PLC P-Value - Adj.	0.96	0.00	0.00	0.00	0.00	0.00	0.97	0.98	0.99	0.93
ARC P-Value - Unadj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Peanuts										
PLC P-Value - Unadj.	0.00	0.00	0.30	0.68	0.35	0.60	0.97	0.63	1.00	0.73
PLC P-Value - Adj.	0.98	0.00	0.90	0.94	0.93	0.95	0.97	0.97	1.00	0.98
ARC P-Value - Unadj.		0.00	0.00	0.00	0.00	0.00	0.63	0.56	0.08	0.02
ARC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.07	0.08	0.00
Sorghum										
PLC P-Value - Unadj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PLC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARC P-Value - Unadj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARC P-Value - Adj.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Note: FY 20 is empty where no ARC payment occurred in any iteration for that crop.										

State Model Results

As opposed to the previous model, the state model establishes a score for each of the most prominent states and an all other for each crop (Table 4.7), and then these scores are summed by crop. This enables the state based scoring method to be compared to the CBO Baseline. Note the state model is less aggregated, allowing the scores to encompass more state-level information. In the PLC calculation, the payment per acre is based on a state level PLC payment yield, as opposed to using one for the entire country as the national model does. As discussed in detail in Chapter III, ARC includes yield variability based on each states' historical planted acre yield. An example of the top 3 unadjusted state scores for corn are shown in Table 4.7, but the entire collection of each crop score in each state can be found in the appendix.

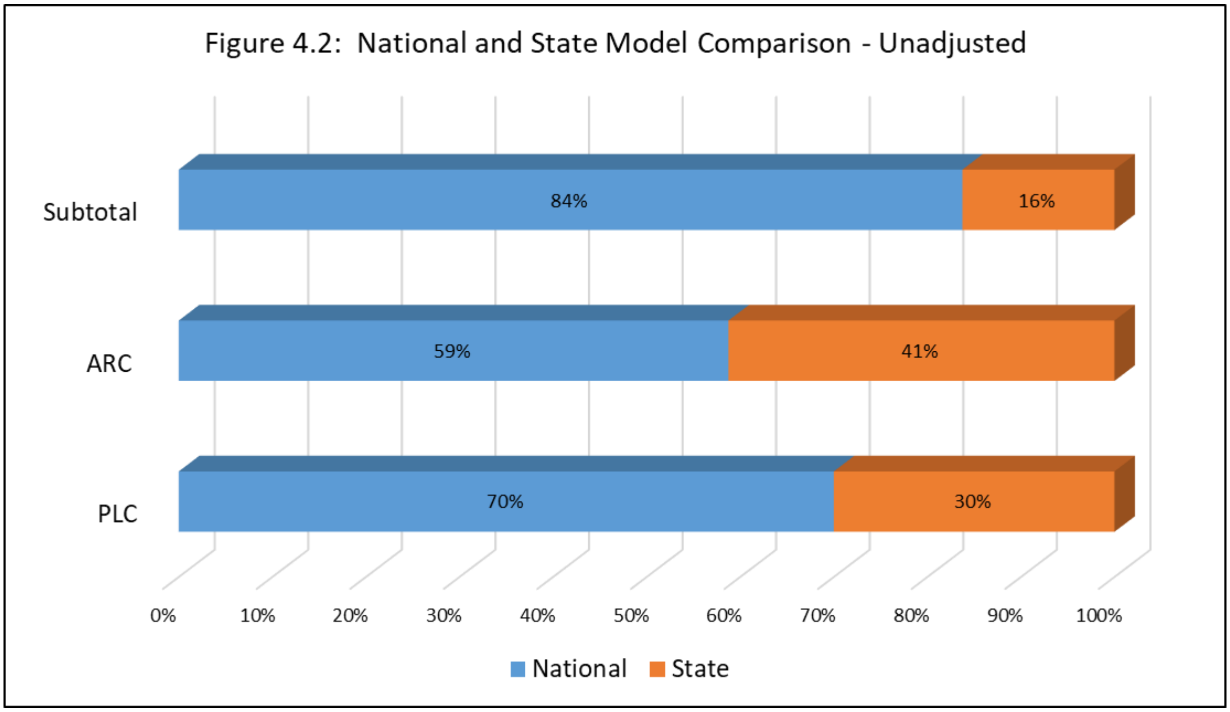
Table 4.7: State Model - Corn Calculated Means

	FY 18	FY 19	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
IOWA												
PLC	43	43	13	388	358	452	427	431	469	525	584	557
ARC	212	0	0	31	27	34	32	34	37	40	42	42
ILLINOIS												
PLC	35	35	11	320	295	373	352	356	387	433	482	460
ARC	347	0	0	36	25	34	35	33	35	36	40	39
NEBRASKA												
PLC	29	29	9	260	240	304	286	289	315	352	392	374
ARC	635	0	0	9	7	10	12	17	19	19	22	20

TABLE 4.8: State Model Mean Projections: Unadjusted												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
CORN												
Total PLC	249	249	76	2255	2084	2636	2486	2512	2734	3058	3402	3246
Total ARC	3406	190	89	172	135	174	175	189	209	223	248	239
Subtotal	3654	439	164	2427	2219	2809	2661	2701	2944	3281	3650	3485
SOYBEANS												
Total PLC	0	0	2	763	575	540	556	470	417	458	492	485
Total ARC	0	78	5	249	167	150	133	106	101	134	138	152
Subtotal	0	78	7	1011	742	690	689	575	518	592	630	637
WHEAT												
Total PLC	1385	670	344	925	1022	1079	1034	993	1001	1023	1017	1040
Total ARC	590	508	60	76	82	89	76	78	86	90	90	90
Subtotal	1975	1178	404	1001	1104	1167	1110	1072	1087	1113	1107	1130
SEEDCOTTON												
Total PLC	0	0	237	1014	975	893	841	755	665	683	644	627
Total ARC	0	0	3	4	4	3	3	2	2	3	3	3
Subtotal	0	0	241	1018	979	897	844	757	667	685	646	630
PEANUTS												
Total PLC	624	340	447	440	432	425	425	420	423	427	440	450
Total ARC	2	0	1	1	1	1	1	1	1	1	1	1
Subtotal	626	341	448	441	433	426	426	421	424	428	442	451
SORGHUM												
Total PLC	337	212	189	276	211	216	207	209	211	210	215	214
Total ARC	35	13	30	28	18	16	13	12	12	13	14	13
Subtotal	373	226	219	304	230	232	220	221	223	223	228	228
ALL RICE												
Total PLC	1026	538	678	717	708	641	604	565	555	544	543	543
Total ARC	5	2	2	2	1	1	1	1	1	1	1	1
Subtotal	1031	540	680	719	710	642	605	567	556	546	544	545
Note: All Figures are in terms of $1,000,000's												

TABLE 4.9: State Model Differences: Unadjusted												
	FY 18	FY 19	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
CORN												
Total PLC	-16	-21	-94	146	378	735	627	592	681	885	794	639
Total ARC	489	-1,036	-492	58	41	48	37	36	36	32	34	25
Subtotal	473	-1,057	-586	204	420	783	664	628	717	918	828	664
SOYBEANS												
Total PLC	-10	-11	-12	216	247	258	295	245	262	280	342	334
Total ARC	-606	-594	-415	13	46	39	36	25	48	65	71	74
Subtotal	-616	-605	-426	229	293	298	331	270	310	345	413	408
WHEAT												
Total PLC	16	-48	-27	197	320	376	329	304	280	333	334	329
Total ARC	79	86	-149	12	15	15	23	19	31	28	25	18
Subtotal	94	38	-176	208	335	392	352	324	311	362	359	346
SEEDCOTTON												
Total PLC	---	---	24	441	461	447	449	418	357	402	383	377
Total ARC	---	---	-41	-12	-16	-15	-13	-12	-13	-12	-12	-12
Subtotal	0	0	-17	429	445	432	436	406	344	390	371	365
PEANUTS												
Total PLC	16	-74	30	53	20	12	19	14	8	1	8	4
Total ARC	2	0	1	1	1	1	1	1	1	1	1	1
Subtotal	18	-73	31	53	21	13	20	15	9	3	9	5
SORGHUM												
Total PLC	-45	-34	10	44	55	69	60	61	65	62	67	66
Total ARC	11	-9	7	9	4	5	4	3	4	4	5	4
Subtotal	-34	-43	16	53	59	74	64	64	69	66	72	70
ALL RICE												
Total PLC	-6	24	-99	-46	-38	-83	-100	-125	-119	-119	-107	-99
Total ARC	-18	-5	-8	-2	-1	-1	-1	-1	-1	-1	-1	-1
Subtotal	-24	19	-107	-48	-39	-85	-101	-126	-120	-120	-109	-100
Note: All Figures are in terms of $1,000,000's												

Unadjusted results for FY 20 – FY 29 were used to compare the national model with the state model results to determine which one more closely matched CBO. The information in Figure 4.2 indicates which model structure did a better job at mimicking CBO.



Based on the above figure, the national model is closer to CBO, especially for PLC. This conclusion makes sense given that CBO uses a nationally based model in their projections.

RAFs were applied to the MYA price distribution using the same methods as the national model to shrink the difference between PLC scores produced by the state model, and the 2019 CBO Baseline. The adjusted results are reported below along with the RAF used for each year for each crop.

Table 4.10: State Model Risk Adjustment Factors

	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
Corn	6.5	0.9413	0.8632	0.7583	0.7763	0.8026	0.78	0.7159	0.7436	0.795
Soybeans	2.95	0.634	0.622	0.616	0.57	0.633	0.608	0.597	0.548	0.568
Wheat	7	0.58	0.472	0.433	0.448	0.467	0.533	0.452	0.448	0.472
Seed Cotton	1	0.35	0.3	0.25	0.2	0.15	0.1	0.23	0.2965	0.334
Peanuts	7	0.55	0.77	0.85	0.8	0.87	0.92	0.98	0.91	0.95
Sorghum	1	0.5	0.38	0.35	0.39	0.4	0.37	0.4	0.373	0.37
Rice	1	0.9	0.9	2.84	2.83	3.28	2.82	2.82	2.35	2.02

TABLE 4.11: State Model Differences: Adjusted												
	FY 18	FY 19	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
CORN												
Total PLC	-16	-21	0	0	0	0	0	0	0	0	0	0
Total ARC	489	-1,036	-298	47	25	17	2	-1	-13	-31	-33	-27
Subtotal	473	-1,057	-299	47	25	17	3	-1	-14	-31	-32	-27
SOYBEANS												
Total PLC	-10	-11	0	0	0	0	0	0	0	0	0	0
Total ARC	-606	-594	-258	-44	-24	-20	-42	-42	-25	-27	-24	-33
Subtotal	-616	-605	-259	-44	-25	-20	-42	-42	-25	-27	-24	-32
WHEAT												
Total PLC	16	-48	0	0	0	0	0	0	0	0	0	0
Total ARC	79	86	-82	-2	-9	-13	-7	-12	-1	-10	-16	-22
Subtotal	94	38	-82	-2	-9	-13	-7	-12	-1	-10	-16	-22
SEEDCOTTON												
Total PLC	---	---	24	409	325	257	189	108	5	0	0	0
Total ARC	---	---	-41	-12	-17	-16	-14	-13	-14	-14	-13	-14
Subtotal	0	0	-17	397	308	241	175	95	-9	-14	-13	-14
PEANUTS												
Total PLC	16	-74	0	32	0	0	0	0	0	0	0	0
Total ARC	2	0	1	0	0	1	1	1	1	1	1	1
Subtotal	18	-73	1	33	1	1	1	1	1	1	1	1
SORGHUM												
Total PLC	-45	-34	10	19	0	0	0	0	0	0	0	0
Total ARC	11	-9	7	10	3	3	2	0	0	0	1	1
Subtotal	-34	-43	16	29	3	3	2	0	0	0	2	1
ALL RICE												
Total PLC	-6	24	-99	-49	-42	0	0	0	1	1	-1	0
Total ARC	-18	-5	-8	-2	-1	-1	-1	-1	0	-1	-1	-1
Subtotal	-24	19	-107	-50	-43	-1	-1	0	0	0	-2	-1
Note: All Figures are in terms of $1,000,000's												

The differences in the PLC scores are all adjusted to the point that they nearly all match the CBO scores in both the national model and the state model. Thus, when comparing the models post-adjustment, the ARC scores and the subtotals indicate that the state model matches CBO more closely in terms of how much the state model differs in absolute value.

Table 4.12 shows the p-values for the state model for each crop. Shading was done in the same way as Table 4.6. Similarly to Table 4.6, the state model RAF's made many of the PLC scores shift from "reject", to "fail to reject." This shift is beneficial because it means that the

RAF's caused many of the scores from the state model to be closer to the CBO Baseline projections.

Table 4.12 : State Model P-Values from One Sample T-test										
	FY 20	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
Corn										
PLC P-Value - Unadj.	0.000	0.276	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLC P-Value - Adj.	0.985	0.981	0.984	0.975	0.974	0.975	0.976	0.970	0.989	0.975
ARC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.003	0.006	0.010	0.023	0.021	0.101
ARC P-Value - Adj.	0.000	0.000	0.013	0.112	0.811	0.900	0.284	0.010	0.010	0.044
Soybeans										
PLC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLC P-Value - Adj.	0.684	0.999	0.997	0.997	0.991	0.984	0.996	0.992	0.976	0.989
ARC P-Value - Unadj.	0.000	0.000	0.000	0.008	0.036	0.331	0.029	0.000	0.000	0.000
ARC P-Value - Adj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.000	0.000
Wheat										
PLC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLC P-Value - Adj.	0.971	0.998	0.998	0.989	1.000	0.993	0.991	0.999	0.996	0.995
ARC P-Value - Unadj.	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARC P-Value - Adj.	0.000	0.386	0.000	0.000	0.004	0.000	0.717	0.000	0.000	0.000
Seed Cotton										
PLC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLC P-Value - Adj.	0.000	0.000	0.000	0.000	0.000	0.000	0.456	0.981	0.988	0.995
ARC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARC P-Value - Adj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Peanuts										
PLC P-Value - Unadj.	0.000	0.000	0.103	0.324	0.131	0.271	0.528	0.909	0.542	0.778
PLC P-Value - Adj.	0.995	0.000	0.972	0.993	0.982	0.973	0.996	0.990	0.993	0.984
ARC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARC P-Value - Adj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sorghum										
PLC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLC P-Value - Adj.	0.000	0.000	0.980	0.972	0.990	0.977	0.953	0.938	0.913	0.983
ARC P-Value - Unadj.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARC P-Value - Adj.	0.000	0.000	0.000	0.000	0.000	0.704	0.910	0.294	0.016	0.076
Note: FY 20 is not empty for any crop because ARC payment occurred in at least one iteration for every crop.										

The differences in the PLC scores are all adjusted to the point that they nearly all match the CBO scores in both the national model and the state model. Thus, when comparing the models post-adjustment, the ARC scores and the subtotals determine that the state model matches CBO more closely in terms of how much the state model differs in absolute value.

CHAPTER V

CONCLUSIONS

Agricultural policy analysis requires timely and accurate research to maintain relevance. With ever-present budgetary pressure, and a population that continues to migrate away from the farm, tools like the ones developed in this study will be needed in the future to defend and improve the programs put in place to protect US producers. Producers and their commodity organizations routinely provide policy suggestions prior to the development of each farm bill. Groups often have several suggestions for potential policy changes, however, without knowing the cost of their policy proposals they have no idea if such changes will be economically feasible. If they ask for a change that is too expensive, it could be quickly dismissed once CBO scores the changes. They may not have the opportunity to propose additional changes and, in essence, they have lost their chance to have a say in agricultural policy reform. Therefore, this scoring tool can be used to assist producers, their associations and other interest groups with developing policy proposals that fit within budget guidelines. This study, in particular, provides a holistic view of the major commodity programs and the projected expenditures on the main commodities produced across the country. These major crops can also be tweaked individually to compare program parameter changes beyond the baseline results that were reported in Chapter IV.

The primary objective of the project was to create a stochastic simulation model that can be used to score ARC and PLC changes for 9 major agricultural commodities. The model used many of the parameters and prices from the Congressional Budget Office (CBO) baseline so that estimates could be expected to approximate the CBO score of the same policy proposals. This analysis compared the CBO baseline projections with the results from two approaches to determine which method provides the most similar payment projections to the CBO baseline.

The first approach of this study was to project scores for the programs based on nationally averaged parameters. The alternative to this approach was to base the program parameters for ARC and PLC on state averages for the states with the highest acres of each crop. The nationally based model was used because it is the understood practice of the CBO. The state based model provided more specific yield variability and history across the analysis which could lead to a more useful model of expected payments. Both approaches were compared to the January 2019 CBO Baseline to see which most closely matched CBO.

The results in Chapter IV show that the unadjusted national model does a better job at mimicking CBO, especially for PLC. This conclusion is based on the fact the national model had a smaller difference from the CBO projection more often than the state based model. This makes sense because CBO uses a nationally based model in their projections.

After the models where adjusted so that the PLC scores are all adjusted to the point that they nearly match the CBO scores, the ARC scores and the subtotals determine that the state model matches CBO more closely.

Future Research

Analytical tools in this field will continue to be vital in helping policy influencers have an educated understanding of any proposed policy changes into the future. In terms of improving the results of the model, more knowledge of any wedges or unique factors used by the CBO would be beneficial when attempting to improve models.

Finally, the state based model could potentially be made more effective by increasing the number of states considered individually. In this model, only 9 states were modeled separately and the remained states were weighted into an *others states* payment. The reasoning behind this was to analyze the major states, while also considering the size of the model. Even though the other states are accounted for the under ‘other states’ umbrella, the yield variability is dampened more than if they were factored in individually.

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APPENDIX

Table A.1: State Model - Corn Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
IOWA												
PLC	43	43	13	388	358	452	427	431	469	525	584	557
ARC	212	0	0	31	27	34	32	34	37	40	42	42
ILLINOIS												
PLC	35	35	11	320	295	373	352	356	387	433	482	460
ARC	347	0	0	36	25	34	35	33	35	36	40	39
NEBRASKA												
PLC	29	29	9	260	240	304	286	289	315	352	392	374
ARC	635	0	0	9	7	10	12	17	19	19	22	20
MINNESOTA												
PLC	24	24	7	219	202	256	241	244	265	297	330	315
ARC	51	0	0	15	14	16	16	17	20	21	24	24
INDIANA												
PLC	17	17	5	155	143	181	171	173	188	210	234	223
ARC	335	0	0	12	8	10	13	13	14	14	16	15
SOUTH DAKOTA												
PLC	13	13	4	116	107	135	128	129	140	157	175	167
ARC	129	87	0	11	8	10	9	10	11	12	14	14
KANSAS												
PLC	14	14	4	125	115	146	138	139	151	169	188	180
ARC	128	103	0	14	11	11	11	11	12	12	14	12
WISCONSIN												
PLC	10	10	3	91	84	106	100	101	110	123	137	131
ARC	91	0	0	6	6	8	7	8	9	10	11	10
TEXAS												
PLC	5	5	2	48	45	57	53	54	59	66	73	70
ARC	111	0	89	5	3	3	4	3	5	5	5	5
OTHER STATES												
PLC	59	59	18	535	494	625	590	596	649	725	807	770
ARC	1367	0	0	33	25	37	38	43	48	54	60	59

Table A.2: State Model - Soybean Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
ILLINOIS												
PLC	0	0	0	112	85	80	82	69	61	67	72	72
ARC	0	0	0	35	25	24	22	17	14	20	20	23
IOWA												
PLC	0	0	0	110	83	78	80	67	60	66	71	70
ARC	0	0	0	31	21	20	17	13	14	20	20	22
MINNESOTA												
PLC	0	0	0	82	62	58	60	51	45	49	53	52
ARC	0	0	0	32	24	19	15	12	11	14	13	15
NORTH DAKOTA												
PLC	0	0	0	45	34	32	32	27	24	27	29	28
ARC	0	0	0	15	11	11	9	8	7	9	9	9
SOUTH DAKOTA												
PLC	0	0	0	49	37	35	36	30	27	29	31	31
ARC	0	38	0	18	13	10	8	6	6	8	8	9
INDIANA												
PLC	0	0	0	59	45	42	43	36	32	35	38	38
ARC	0	0	0	23	13	12	11	9	8	11	11	12
MISSOURI												
PLC	0	0	0	46	35	33	34	28	25	28	30	29
ARC	0	0	3	19	12	12	10	6	7	9	9	10
OHIO												
PLC	0	0	0	49	37	35	36	30	27	30	32	31
ARC	0	40	0	14	8	9	9	8	7	9	9	9
TEXAS												
PLC	0	0	0	1	1	0	0	0	0	0	0	0
ARC	0	0	1	0	0	0	0	0	0	0	0	0
OTHER STATES												
PLC	0	0	1	210	158	149	153	129	115	126	135	134
ARC	0	0	0	62	39	33	30	26	27	35	39	42

Table A.3: State Model - Wheat Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
KANSAS												
PLC	225	109	56	151	167	176	169	162	164	167	166	170
ARC	0	0	8	13	14	18	14	12	15	15	16	16
NORTH DAKOTA												
PLC	201	97	50	135	149	157	151	145	146	149	148	151
ARC	124	113	0	23	18	15	12	15	13	13	14	13
MONTANA												
PLC	131	63	32	87	96	102	97	94	94	96	96	98
ARC	73	66	0	2	3	3	3	4	5	6	5	5
OKLAHOMA												
PLC	126	61	31	84	93	98	94	90	91	93	92	94
ARC	0	39	36	6	7	7	6	5	6	6	6	5
TEXAS												
PLC	91	44	22	60	67	70	68	65	65	67	66	68
ARC	13	20	0	3	3	2	2	2	3	3	3	3
COLORADO												
PLC	57	28	14	38	42	45	43	41	41	42	42	43
ARC	13	0	16	4	4	4	4	3	4	4	4	4
WASHINGTON												
PLC	99	48	25	66	73	77	74	71	72	73	73	74
ARC	55	13	0	4	6	8	7	7	6	7	6	7
SOUTH DAKOTA												
PLC	63	30	16	42	46	49	47	45	45	46	46	47
ARC	35	35	0	5	3	4	3	4	5	5	5	5
NEBRASKA												
PLC	42	20	10	28	31	32	31	30	30	31	31	31
ARC	15	6	0	3	3	3	3	3	3	3	3	3
OTHER												
PLC	350	170	87	234	258	272	261	251	253	258	257	263
ARC	261	215	1	14	20	23	22	23	27	29	29	29

Table A.4: State Model - Seed Cotton Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
TEXAS												
PLC	0	0	66	282	271	249	234	210	185	190	179	175
ARC	0	0	2	1	1	1	1	1	1	1	1	1
MISSISSIPPI												
PLC	0	0	25	108	104	95	90	80	71	73	68	67
ARC	0	0	0	1	1	1	1	0	0	0	0	0
GEORGIA												
PLC	0	0	21	91	88	80	76	68	60	61	58	56
ARC	0	0	0	0	0	0	0	0	0	0	0	0
CALIFORNIA												
PLC	0	0	32	137	131	120	113	102	90	92	87	85
ARC	0	0	0	0	0	0	0	0	0	0	0	0
ARKANSAS												
PLC	0	0	17	73	70	64	61	54	48	49	46	45
ARC	0	0	0	0	0	0	0	0	0	0	0	0
LOUISIANA												
PLC	0	0	15	62	60	55	52	46	41	42	40	39
ARC	0	0	0	0	0	0	0	0	0	0	0	0
NORTH CAROLINA												
PLC	0	0	12	52	50	45	43	38	34	35	33	32
ARC	0	0	0	0	0	0	0	0	0	0	0	0
TENNESSEE												
PLC	0	0	10	44	42	39	37	33	29	30	28	27
ARC	0	0	0	0	0	0	0	0	0	0	0	0
ALABAMA												
PLC	0	0	9	40	38	35	33	29	26	27	25	25
ARC	0	0	0	0	0	0	0	0	0	0	0	0
OTHER												
PLC	0	0	29	125	121	111	104	93	82	84	80	78
ARC	0	0	0	0	0	0	0	0	0	0	0	0

Table A.5: State Model - Peanuts Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
GEORGIA												
PLC	251	137	173	170	167	164	164	162	163	165	170	174
ARC	1	0	0	1	1	1	1	1	1	1	1	1
TEXAS												
PLC	116	63	80	79	77	76	76	75	75	76	79	80
ARC	1	0	0	0	0	0	0	0	0	0	0	0
ALABAMA												
PLC	73	40	56	55	54	53	53	52	53	53	55	56
ARC	0	0	0	0	0	0	0	0	0	0	0	0
NORTH CAROLINA												
PLC	48	26	36	36	35	34	34	34	34	35	36	36
ARC	0	0	0	0	0	0	0	0	0	0	0	0
FLORIDA												
PLC	49	27	37	36	36	35	35	35	35	35	36	37
ARC	0	0	0	0	0	0	0	0	0	0	0	0
OKLAHOMA												
PLC	25	14	19	19	18	18	18	18	18	18	19	19
ARC	0	0	0	0	0	0	0	0	0	0	0	0
SOUTH CAROLINA												
PLC	24	13	18	18	18	17	17	17	17	17	18	18
ARC	0	0	0	0	0	0	0	0	0	0	0	0
VIRGINIA												
PLC	23	12	17	17	17	16	16	16	16	16	17	17
ARC	0	0	0	0	0	0	0	0	0	0	0	0
OTHER												
PLC	15	8	12	11	11	11	11	11	11	11	11	12
ARC	0	0	0	0	0	0	0	0	0	0	0	0

Table A.6: State Model - Sorghum Calculated Means												
	FY 18	**FY 19**	**FY 20**	**FY 21**	**FY 22**	**FY 23**	**FY 24**	**FY 25**	**FY 26**	**FY 27**	**FY 28**	**FY 29**
KANSAS												
PLC	129	81	72	106	81	83	80	80	81	81	83	82
ARC	0	0	0	13	9	8	7	6	5	5	6	6
TEXAS												
PLC	110	69	62	91	69	71	68	69	69	69	71	70
ARC	20	4	19	8	5	4	3	3	4	4	4	4
NEBRASKA												
PLC	24	15	14	20	15	15	15	15	15	15	15	15
ARC	0	0	0	1	1	1	0	0	0	0	1	1
MISSOURI												
PLC	20	13	11	16	12	13	12	12	12	12	13	13
ARC	4	0	2	2	1	1	1	1	1	1	1	1
OKLAHOMA												
PLC	9	6	5	8	6	6	6	6	6	6	6	6
ARC	1	0	1	1	0	0	0	0	0	0	0	0
NEW MEXICO												
PLC	8	5	4	6	5	5	5	5	5	5	5	5
ARC	0	1	1	0	0	0	0	0	0	0	0	0
COLORADO												
PLC	5	3	3	4	3	3	3	3	3	3	3	3
ARC	0	0	0	1	1	0	0	0	0	0	0	0
ARKANSAS												
PLC	8	5	5	7	5	5	5	5	5	5	5	5
ARC	3	2	2	1	0	0	0	0	0	0	0	0
SOUTH DAKOTA												
PLC	6	3	3	4	3	3	3	3	3	3	3	3
ARC	1	1	0	1	0	0	0	0	0	0	0	0
OTHER												
PLC	18	11	10	14	11	11	11	11	11	11	11	11
ARC	6	5	5	1	1	1	1	1	1	1	1	1

Table A.7: State Model - Long Grain Rice Calculated Means												
	FY 18	FY 19	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
ARKANSAS												
PLC	436	248	316	321	313	286	267	250	244	241	240	239
ARC	2	1	1	1	1	1	1	1	1	1	1	1
LOUISIANA												
PLC	173	98	125	127	124	113	106	99	97	95	95	95
ARC	1	1	0	0	0	0	0	0	0	0	0	0
TEXAS												
PLC	145	82	105	106	104	95	89	83	81	80	80	79
ARC	1	0	0	0	0	0	0	0	0	0	0	0
MISSISSIPPI												
PLC	88	50	64	65	64	58	54	51	49	49	49	48
ARC	0	0	0	0	0	0	0	0	0	0	0	0
MISSOURI												
PLC	63	36	46	46	45	41	39	36	35	35	35	35
ARC	0	0	0	0	0	0	0	0	0	0	0	0
CALIFORNIA												
PLC	2	1	2	2	2	2	1	1	1	1	1	1
ARC	0	0	0	0	0	0	0	0	0	0	0	0
OTHER STATES												
PLC	4	2	3	3	3	2	2	2	2	2	2	2
ARC	0	0	0	0	0	0	0	0	0	0	0	0

Table A.8: State Model - Medium Grain and Short Grain Rice Calculated Means												
	FY 18	FY 19	FY 20	FY 21	FY 22	FY 23	FY 24	FY 25	FY 26	FY 27	FY 28	FY 29
ARKANSAS												
PLC	29	17	15	17	17	21	21	21	20	20	19	18
ARC	0	0	0	0	0	0	0	0	0	0	0	0
LOUISIANA												
PLC	3	2	1	2	2	2	2	2	2	2	2	2
ARC	0	0	0	0	0	0	0	0	0	0	0	0
TEXAS												
PLC	0	0	0	0	0	0	0	0	0	0	0	0
ARC	0	0	0	0	0	0	0	0	0	0	0	0
MISSOURI												
PLC	0	0	0	0	0	0	0	0	0	0	0	0
ARC	0	0	0	0	0	0	0	0	0	0	0	0
Temperate Japonica Rice (California Medium Grain)												
CALIFORNIA												
PLC	82	0	0	23	29	92	101	109	99	98	81	76
ARC	1	0	0	0	0	0	0	0	0	0	0	0
Note: California in this table is based on Temperate Japonica Rice.												