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New models to estimate costs of US farm programs

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

ARC	Agriculture Risk Coverage
ARF	Assigned Risk Fund
ARP	Area Revenue Protection
ARP-HPE	Area Revenue Protection with Harvest Price Exclusion
AYP	Area Yield Protection
CBO	Congressional Budget Office
CDF	Cumulative Distribution Function
CF	Commercial Fund
FAPRI	Food and Agricultural Policy Research Institute
FCIC	Federal Crop Insurance Corporation
NASS	National Agricultural Statistics Service
MYA	Market Year Average
PLC	Price Loss Coverage
RMA	Risk Management Agency
RP	Revenue Protection
RP-HPE	Revenue Protection with Harvest Price Exclusion
SCO	Supplemental Coverage Option
SRA	Standard Reinsurance Agreement
YP	Yield Protection

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ABSTRACT

In this study, I extended the stochastic model built by Babcock and Paulson (2012) to conduct a one-year cost projection for crop insurance in order to investigate its feasibility of being solely provided by private firms. Based on the 52 years' yield data from 1961 to 2012, the risk consequences from insuring crop yield and revenue against losses are estimated to be far beyond what private insurers could bear on their own. However, reinsurance from the government provides an attractive incentive to insurance firms. Among the six insurance policies researched in this study, the minimum expected net underwriting gains to private firms with government reinsurance in 2013 was $289.9 million, which is about 9.30% of retained premiums. The maximum loss that firms could have borne in 2013 was $4.9 billion. In addition, the impact of a proposal to eliminate premium subsidy for the harvest price option is also estimated. The total savings for taxpayers are estimated to be $1.3 billion, which is about $400 million more than CBO's estimate in 2013, but only 67% of its estimate in 2015.

Based on the three-crop competitive storage model initiated by Lence and Hayes (2002), I also develop a better approach for a multiple-year cost projection by modeling the demand shock as a random walk. This approach is capable of preserving the correlations between national yields and prices, maintaining the relationships among national, county and farm yields, retaining the spatial correlations of yields across crops, and incorporating inter-temporal price correlations as well. More importantly, this approach is capable of simulating price draws with a desired volatility pattern: increasing over time but at a slower rate than square root of time t, as stated in Lence, Hart and Hayes (2009). Preserving these correlations and price-related features are crucial in conducting precise cost estimations and valid policy analysis. My analysis shows that the payments from Price Loss Coverage (PLC)

with its time-invariant fixed guarantees would be significantly underestimated if both the price serial correlation and the increasing, concave price volatilities are ignored. For Agriculture Risk Coverage (ARC) and Supplemental Coverage Option (SCO), their guarantees are adjusted to reflect market conditions so the difference in estimated payments is modest. An easy fix for estimating the cost of PLC is to inflate the price volatilities used to generate random prices for budget scoring purposes.

CHAPTER 1

INTRODUCTION AND SUMMARY

For policy makers, assessing the taxpayers' monetary cost of an agricultural program is an important stage preceding its implementation. In particular, policymakers would like to estimate this cost not only for a single year but also for the entire horizon of implementation. By comparing those costs associated with various alternatives against the cost of the existing program that is subject to replacement, they can examine whether the new programs, once implemented, can help to reduce taxpayers' spending without undermining the objectives of the programs, which are designed primarily to benefit farmers (Sumner, Smith and Goodwin, 2011).

The 2014 Farm Bill eliminates direct payments, the countercyclical payment program and the Average Crop Revenue Election program. These programs are replaced with two new programs called Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC). Producers were required to make an irreversible decision between the two, with PLC set as the default option. In brief, ARC is a revenue insurance program which covers so-called "shallow losses" and has both county-based and individual-based coverage options. For farmers who sign up for ARC-county, the indemnities are triggered if the actual county revenue falls below 86% of county expected revenue. The expected revnue in a county is defined as the product of the Olympic average[1] of county yields and the Olympic average of national market year average (MYA) prices in last five years. In contrast, PLC is a price insurance program like the counter-cyclical payment program it replaced, but with much higher price guarantees. Payments are made when a commodity's MYA price falls below its statutorily fixed reference price. In addition, for farmers who sign up for PLC, they also have

[1] The Olympic average is to take the average after droping off the maximum and minimum values.

the option to buy yield or revenue insurance that supplements their federal crop insurance. The supplemental insurance is called Supplemental Coverage Option (SCO), which is a county-based insurance policy with 65% premium subsidy. A detailed introduction of these three programs are contained in Chapter 4. The purpose of this research is to develop improved methods to estimate taxpayers' costs of these three programs and the costs of crop insurance. Costs are estimated from an ex ante (to 2014) perspective.

Cost estimation of agricultural programs has long been of interest to agricultural economists. Babcock and Paulson (2012) developed an extensive nationwide model that takes yield and price variability into account to estimate annual payments over 2013-2017 for all the potential new commodity programs. Their results indicated that the proposed farm bill would distort farmers' planting decisions if the payments from the new programs were based on actual planted acreage. Moreover, they found that the impact on the aggregate planted acreage and that on the composition of it is quite different from each other: while the bill has little effect on the former, it could significantly affect the acreage allocated to various crops. Intuitively, the acreage would shift towards the crops that have relative larger returns under the proposed farm bill. As a result, the farmers planting the underlying crops in developing countries would receive lower prices than they would otherwise. Babcock and Paulson's arguments on acreage allocations were consistent with the findings published by Food and Agricultural Policy Research Institute (FAPRI) in June 2015. In FAPRI's report, the actual amount of base acres reallocated to corn, rice and peanut were about 10.39 million acres, 0.69 million acres and 0.53 million acres more than its March 2015 baseline due to the relatively larger projected per-acre payments for these three crops than for most other crops. However, Congress decided to not couple payments to planted acreage, so these programs will not likely have much impact on farmers decisions. Their main impact will be on taxpayers' costs.

Paulson, Woodard and Babcock (2013) adopted the same stochastic model as Babcock and Paulson (2012) to estimate the distribution of payments from the proposed programs in the House and Senate Farm Bills based on the historical county yield data from National Agricultural Statistics Service (NASS), base crop insurance rates from Risk Management Agency (RMA), and the March 2012 Congressional Budget Office (CBO) baseline projections on commodity prices and price volatilities. Their results showed that the expected payment per acre varied significantly across programs, crops and regions, and the Senate's bill was generally preferred over the House's bill from the perspective of corn and soybeans producers, particularly those in the Midwest.

In their stochastic model, price draws were simulated independently from a lognormal distribution with a mean set equal to the corresponding CBO projected price level for each year of 2013-2017. The price volatility was assumed to be the level used for rating 2012 crop revenue insurance policies and stay unchanged over the entire farm bill period, which is exactly in line with what CBO does when scoring new programs. However, their assumption regarding a constant price volatility over time is at odds with the empirical evidence. Lence, Hart and Hayes (2009) found that the volatility of commodity prices tends to increase over time but at a decreasing rate due to mean reversion.

Furthermore, strong serial correlation observed in historical commodity prices is assumed away when prices are simulated independently across different years. Figure 1 depicts the time series of corn, soybeans and wheat price received by U.S. farmers from 1950 to 2014. These series exhibit obvious time trends and significant variations in the amplitude of fluctuations across time, most notably the peak in 2012. Moreover, commodity prices in one year are positively correlated with those in the next. Deviations from quadratic time trends to each of the three price series exhibit strong serial correlation at 0.73 for corn, 0.76 for soybeans and 0.72 for wheat.

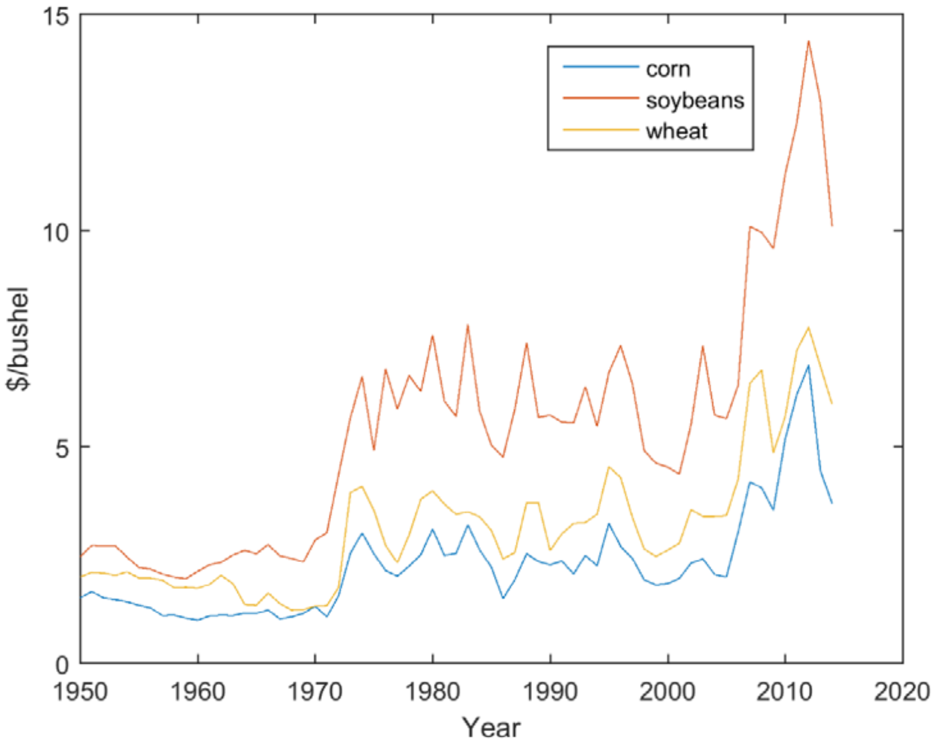

Figure 1. Crop prices received by U.S. farmers over 1950-2014

The fact that CBO does not account for either increasing price volatility or serial correlation raises the question about how accounting for these two market realities will influence cost projections when CBO makes a multiple-year projection of program costs. Thus one objective of this research is to explore the impacts on cost projections after accounting for the increasing price volatilities over time and the serial correlation. Because the main crops affected by the farm bill are storable, a three-crop storage model is employed in this study to simulate price draws with desired properties. These prices are then used to estimate the costs for ARC, PLC and SCO over 2014-2018.

The stochastic model built by Babcock and Paulson (2012) provides an appropriate framework for one-year cost projections. Their model successfully maintains the spatial correlations of yields across different crops and various counties by using Iman and Conover’s resorting method along with empirical yield distributions. To begin my analysis I follow their basic framework and conduct a one-year (2013) cost analysis to examine the taxpayers’ cost of crop insurance programs and to determine the feasibility of private delivery of the program. Specifically, my analysis involves two steps. First I estimate the cumulative distribution function (CDF) of underwriting losses taken by private insurers who provide insurance for corn, cotton, soybeans, spring wheat and winter wheat. Second the distribution of underwriting losses is re-estimated, assuming reinsurance from government is available. As expected, the risk resulted from crop insurance cannot be insured solely by private firms. Reinsurance from government makes it much more attractive to private companies.

I also use the model to estimate taxpayers' cost savings from a proposed reform of the crop insurance program. The reform, proposed by Senators Flake and Shaheen, would eliminate premium subsidy for the so-called harvest price option. I estimate the savings by calculating the difference in taxpayers' costs between the programs with the harvest price option and those without, at various coverage levels. My results indicate that the reform would reduce taxpayers' costs by about $1.33 billion in 2013, which is about $400 million more than CBO's estimate in 2013 but $600 million less than its estimate in 2015. All results from analyzing the crop insurance apply to a single year, 2013. Although it seems straightforward to extend the analysis to multiple years, simply repeating this procedure in a dynamic world may bias our calculations, due to failing to take into account the serial correlation and the fact that price volatilities increase over time.

To estimate costs over a five-year time horizon I employ a three-crop competitive storage model to simulate inter-temporally correlated price draws. The storage model explicitly explains how commodity prices interact with production and storage and, as shown by the existing literature, can be a tool to generate highly auto-correlated prices. However, there are two challenges in this modeling strategy: solving the model and calibrating it to meet price-related targets given the current market environment. In particular, the model is calibrated to meet three market-based targets: (1) the base year (2014) price volatility from the model matches the historical price volatility; (2) the amount of serial correlation in simulated prices is calibrated to what has been observed in historical price data; and (3) price volatility increases over time but at a rate slower than square root of time t, as confirmed by Lence, Hart and Hayes (2009). The two instruments I use to calibrate the model are the standard deviation of a random walk demand shock and the elasticity of demand for the commodity crops. With only two instruments and three targets, I cannot calibrate the model exactly to meet all three targets. I chose to make sure that 2014 price volatilities are set at historical levels and also make sure that price volatilities are an increasing and concave function of time within the five year projection period. The amount of serial correlation in the simulated prices is close to historical levels.

Upon the completion of the simulation from the storage model, I applied a model similar to Babcock and Paulson's stochastic model, to score ARC, PLC and SCO for each year of a five-year projection period, with their model as a benchmark. The results are compared against those from the storage model to study whether the introduction of serial correlations and increasing, concave price volatilities result in any difference in cost estimations. The comparison demonstrates that program payments for PLC will be significantly underestimated if both of the two facts are ignored, but the program payments for SCO and ARC are not. Furthermore, I isolated the impacts of serial dependence alone upon cost estimations and the analysis indicates that most of the variations in program payouts can be attributed to the increasing and concave price volatilities.

The remainder of this dissertation is organized as follows. Chapter 2 gives details about how Babcock and Paulson's stochastic model can be applied to quantify the risk from crop insurance to both taxpayers and private insurers in 2013. Chapter 3 presents the competitive storage model and how it is solved and applied to simulate price draws. The new programs that I evaluate are documented in Chapter 4. The estimated payments for each program over 2014-2018 are shown in that chapter as well.

CHAPTER 2

QUANTIFYING RISK FROM DELIVERING CROP INSURANCE

Policy Background

In this chapter I develop a model of crop insurance to estimate the aggregate amount of risk facing crop insurance companies and the positive impacts of reinsurance from government. The impact of a proposal to eliminate premium subsidy for the harvest revenue option is also investigated.

Compared to the reinsurance simulator built by Vedenov et al. (2004), the model in this study has a much finer calibration of farm-level yields. The farm-level yields are created by shocking the county-level yields rather than the crop reporting district-level yields as they did, so they implicitly assumed all the counties under the same crop district share an exactly same farm-level yield distribution. Moreover, they did not have a scheme to maintain the spatial correlations among crop yields, which is one key factor that differentiates crop insurance from conventional ones[2].

Here, I focus on five crops: corn, upland cotton, soybeans, spring wheat and winter wheat. Together they accounted for 71% of total insured acres in 2013. In total, six crop insurance products are examined: Area Yield Protection (AYP), Yield Protection (YP), Area Revenue Protection (ARP), Area Revenue Protection with Harvest Price Exclusion (ARP-HPE), Revenue Protection (RP) and Revenue Protection with Harvest Price Exclusion (RP-HPE). The first two are yield-based insurance products which set a guarantee for yield, and the last four are revenue-based insurance which provide insurance against losses in revenue.

[2] As stated in Miranda and Glauber (1997), that is, auto collision, workers compensation, homeowners multiple peril, commercial multiple peril, inland marine, fire, group accident and health, allied lines, ocean marine and crop-hail insurance policies

Area Yield Protection (AYP)

The policy pays indemnities when county i's realized yields (y_i) fall below α percent of the expected county yield (Y_i), thus it is possible that farmers who suffered crop losses will not be indemnified if there is no indication of similar loss in the yield at the relevant county level. In particular, per acre indemnities are calculated as

$$\mathrm{I} = \max(0, Y_i - y_i/\alpha) * P_p * \pi \tag{1}$$

where P_p is the projected price, yield coverage α can be chosen from 70% to 90% in 5% increments. Scale π can be selected from 80% to 120% by farmers, with which farmers can better match the county yield insurance indemnities with their individual expected losses.

Yield Protection (YP)

Farmers receive indemnity payment when their yield (y) falls below α percent of the average of their individual production history (Y), which is defined as the average of county-level yields in most recent five years in this analysis and therefore a same yield guarantee is shared among farmers . Per acre indemnities are defined as:

$$\mathrm{I} = \max(0, \alpha\mathrm{Y} - \mathrm{y}) * P_p \tag{2}$$

Farmers can select α, the amount of average yield he or she wishes to insure, from 50% to 85%.

ARP and ARP-HPE

Payments are made to a farmer if the realized average county revenue is less than the revenue guarantee chosen by the farmer. The revenue guarantee for ARP-HPE is equal to the product of the coverage level α selected by the farmer, the expected county yield and the projected price. The ARP policy uses a similar revenue guarantee, except that its price component can be updated to the realized harvest price if the realized price is higher than its projected level. Specifically, per acre indemnities of ARP-HPE can be stated as:

$$I = \max[0, Y_i * P_p - y_i * P_h/\alpha] * \pi \quad (3)$$

Similarly, per acre indemnities of ARP can be written as:

$$I = \max\left[0, Y_i * \max\left(P_p, P_h\right) - y_i * P_h/\alpha\right] * \pi \quad (4)$$

where P_p and P_h are measures of projected and harvest prices. Price P_p (P_h) is the average daily settlement prices in the month prior to planting (harvesting) for the harvest futures contract. For example, the projected (harvest) price for corn is the average daily settlement prices in February (October) for the December corn futures contract. And farmers can choose yield coverage α from 70% to 90% and scale π from 80% to 120%.

RP and RP-HPE

Payments are made to farmers if his or her realized revenue is less than the revenue guarantee. And per acre indemnities of RP are calculated as follows:

$$I = \max[0, \alpha Y * \max(P_p, P_h) - y * P_h] \quad (5)$$

Similarly, the per acre indemnities of RP-HPE are given by:

$$I = \max[0, \alpha Y * P_p - y * P_h] \quad (6)$$

where P_p and P_h are of the same definitions as that under county coverage. And the coverage level α can be selected from 50% to 85%.

Data and Simulation Model

Historical county-level and national-level yield data from 1961-2012 were collected for these five crops from NASS. Counties included in this analysis are those with at least 20 years' yield histories over the time period from 1990 to 2012. Furthermore, I treat counties with yield for both irrigated and non-irrigated practice separately, which involves estimating the payments for each practice type in that county, and then calculating the acreage-weighted payments by using the reported acres on these two practices for that county.

The price component of per-acre indemnities for revenue-based policies is determined by two price levels: projected price (P_p) and harvest price (P_h) as shown in equations (3)-(6). Both of these prices are set based on commodity futures markets to calculate the actual indemnities. Table 1 below lists the commodity exchange price information used to set those levels for each of the five crops investigated in this study. For example, the projected (harvest) price of corn is the average daily settlement price of its December futures contract in February (October). Moreover, in order to project the 2013 total indemnities for each of the four revenue-based policies, the harvest prices are assumed to be log-normally distributed with the mean set to their respective projected levels $\vec{\mu}$, and volatility $\vec{\sigma}$ set to the levels used for the rating of 2013 crop revenue insurance policies, where $\vec{\mu} = (\$5.65/bu,\ \$12.87/bu,\ \$0.81/lb,\ \$8.44/bu,\ \$8.78/bu)$, and $\vec{\sigma} = (20\%,\ 17\%,\ 17\%,\ 15\%,\ 24\%)$ for corn, soybeans, cotton, spring wheat and winter wheat, respectively. In addition, the projected prices and harvest prices for the period of 2000-2012 are collected from RMA to measure the historical price-yield correlations among the five crops, which will be imposed on the simulated harvest prices.

Table 1. Commodity exchange price provisions (CEPP) 2012 and succeeding crop years

			Projected price discovery period		Harvest price discovery period	
Contract commodity	Commodity exchange	Contract Month	Starting date	Ending date	Starting date	Ending date
Corn	CBOT	December	Feb-1	Feb-28	Oct-1	Oct-31
Cotton	ICE	December	Feb-1	Feb-28	Oct-1	Oct-31
Soybeans	CBOT	November	Feb-1	Feb-28	Oct-1	Oct-31
Spring Wheat	MGE	September	Feb-1	Feb-28	Aug-1	Aug-31
Winter Wheat	KCBT	July	Aug-15	Sep-14	Jun-1	Jun-30

Note: Risk Management Agency provides CEPP on a state basis, so for each crop I only list the discovery periods for the state that has most production for that crop in 2012. Specifically, the CEPP is for corn of Iowa, cotton of Texas, soybeans of Illinois, spring wheat of North Dakota and winter wheat of Kansas.

Simulating harvest prices

Before the national-level and county-level yield histories can be employed, they have to be adjusted for positive trends, thus a simple OLS regression is implemented:

$$\ln(y_{USt}) = \beta_0 + \beta_1 t + \varepsilon_t \tag{7}$$

$$\tilde{y}_{USt} = \exp\left(\hat{\beta}_0 + \hat{\beta}_1 t\right) \tag{8}$$

$$y_{USt} = \alpha\tilde{y}_{USt} \tag{9}$$

$$y_{USt}^{tre} = \hat{y}_{USt} = \hat{\alpha}\tilde{y}_{USt} \tag{10}$$

where y_{USt}^{tre} is the trended national-level yield at time t.

Equation (11) below gives the specific formula to calculate the historical correlations between prices and national-level yields. Yield deviate is defined as the percentage change of yield from its trend, and price deviate is calculated as the percentage change in prices from the projected to the harvest. And I further assume the correlation structure among the most recent time period would reflect the current and future price-yield relationships more precisely, so that is why only twelve most recent years of data are used to estimate correlation.

$$\hat{\rho}_{P_h y_{US}} = \frac{\frac{1}{13}\sum_{t=2000}^{t=2012} \frac{P_{ht} - P_{pt}}{P_{pt}} \frac{y_{USt} - y_{USt}^{tre}}{y_{USt}^{tre}}}{\sqrt{\frac{1}{13}\sum_{t=2000}^{t=2012} [\frac{P_{ht} - P_{pt}}{P_{pt}}]^2}\sqrt{\frac{1}{13}\sum_{t=2000}^{t=2012} [\frac{y_{USt} - y_{USt}^{tre}}{y_{USt}^{tre}}]^2}} \tag{11}$$

The estimates for own price-yield correlation coefficients are -0.59, -0.24, -0.42, -0.29 and -0.31 for corn, cotton, soybeans, spring wheat and winter wheat, respectively. Note that all of them are negative, which is consistent with the fact that U.S. is a large country with respect to the international trade of these crops.

Following Babcock and Paulson (2012), the empirical yield distribution is generated by vertically stacking the national-level yield deviates from 1961-2012 500 times to create a yield sample with 26,000 observations (Goodwin and Ker, 1998; Ker and Coble, 2003; Vedenov et al., 2004). In contrast to the parametric distribution of yield, the empirical distribution naturally captures the historical spatial correlations of yields across crops and counties, which may not be fully reflected in the parametric specifications. Moreover, it avoids the potential misspecification that the marginal distribution of yield is parametrically Beta or Weibull.

As for the simulation of prices, I start the process by simulating 26,000*5 independent draws from a standard uniform distribution. Then I employ the resorting method introduced in Iman and Conover (1982) to impose the historical correlations upon the simulated prices. Their method is straightforward and relatively easy to implement. The only operation on the data is resorting. This method is based on rank correlations, because, as Iman and Conover pointed out, the Pearson correlation coefficients can be misleading if the underlying data is not normal or it contains outliers. Below is the specific procedure:

1) Create a matrix C with the desired rank correlation coefficients, which can be achieved by the following sub steps.
    a. Denote the historical rank correlation matrix as T. Since it is positive-definite, there exists a unique upper triangular matrix P such that $T = P' * P$ (where P' is the transpose of P and can be obtained by Cholesky factorization).
    b. Let A be a 26000*10 matrix with all of its elements drawn from a standard normal distribution. Its correlation coefficient matrix is denoted as D and decomposed to $Q' * Q$.
    c. Let $S = Q^{-1} * P$, and $C = A * S$. The transformed matrix C should have a rank correlation matrix close to the target T.
2) Combine 26000*5 uniform-distributed draws with the 26000*5 empirical yield deviates into a 26000*10 matrix J. Rearrange elements in each column of J to match the order of the elements in the corresponding column of the matrix C so that J will have the same rank correlation matrix as C, which is close to the target T. However, yield deviates are left unsorted so as to preserve the spatial correlations of the empirical yield distributions. The resorted 26000*5 draws from uniform distributions are then transformed into five

lognormal distributions with a different target of mean and volatility. As a result, for each crop, this stacking will generate 500 harvest price realizations for each specific year of the 52-year histories.

The target and simulated sample rank correlations are listed in Tables 2 and 3. The first 5x5 elements in the target rank correlation matrix are replaced with the actual rank correlations of the 26000*5 U.S. yield deviates in order to maintain the year-to-year yield correlations across crops. The Iman and Conover approach does a good job in matching the target rank correlation matrix, with the maximum difference between the target and simulated sample rank correlations being merely 0.02[3].

Calibrating the farm-level yield variability

Following Vedenov et al. (2004), all county-level yield histories (y_{it}) are detrended to 2013-equivalent yields (y_{it}^{det}).

$$y_{it}^{det} = \frac{y_{it} * y_{i2013}^{tre}}{y_{it}^{tre}} \text{ , t} = 1961, \ldots, 2012 \tag{12}$$

where y_{i2013}^{tre} is the trended yield of county i in 2013.

For individual-based policies, I simulate 100 farm-level yields for each county and year over 1961-2012, which is achieved by adding 100 normal deviates to county-level yields. The normal deviates are drawn from a normal distribution with mean zero and some pre-specified value of standard deviation, which is assumed to be accurately calibrated by RMA base crop insurance rates for 2013 crop year reported in RMA's Actuarial Data Master. Specifically, an implied premium rate for 65% coverage of YP from the simulated farm-level yields across all available years with county yield realizations match exactly the 2013 RMA 65% base rate in the county for YP.

[3] Since I need to freeze the yield deviates, the maximum difference between the target and simulated rank correlation matrix is 0.04 instead of 0.02.

For revenue-based insurance policies, the 52-year detrended county-level yields are vertically stacked 500 times in order to maintain the spatial correlation across crops and counties. The spatial correlations among county yields have large effects on the cumulative distribution function of private insurance companies' underwriting losses. If there is no spatial correlation among crops, that is, county yields are independent from each other, then the county yield risks can be pooled and eliminated by a well-diversified portfolio. On the other hand, if the county yields are perfectly correlated, the county yield risks can be hedged via futures and options markets. Furthermore, every row (year) of yield realization is matched with the corresponding row of harvest price draws so as to keep the historical correlations between national-level yields and prices. Preserving the price-yield correlations is crucial in conducting a valid revenue-based program analysis.

All the policies in this analysis are defined to cover losses from 70% to 85% of expected yield or revenue. In each scenario, I consider only one available policy, say RP, and all the contracts are assumed to be insured under the same coverage level. As a result, I will get 26,000 simulated indemnities per acre for each crop/county and calculate the 26,000 indemnities in dollars using the 2012 county-level harvested acre data. Summing them up across different crops and counties will yield the total indemnities in dollars across crops and counties. Finally, the distributions for loss ratios and for underwriting losses can be computed, where the loss ratio and the underwriting losses are defined as $\text{Loss Ratio}^{4} = \frac{Indemnity}{Premium}$, $Underwriting\ losses = Indeminity - Premium$[5]. The yield-based policies are much simpler to simulate because their indemnities do not rely on the harvest prices. Thus there are 52 simulated indemnities per acre for each county and crop. Similarly, the total indemnities in dollars across counties and crops for a given coverage level can be calculated.

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4 Premium is calculated as the expected indemnities, that is equal to setting expected net income from insurance is zero for private companies.

5 Underwriting Gain=Premium-Indemnity.

Table 2. Rank correlation matrix for U.S. yield deviates and price deviates over 2000-2012

	corn yield	soybean yield	cotton yield	swheat yield	wwheat yield	corn price	soybean price	cotton price	swheat price	wwheat price
corn yield	1	0.58	0.16	0.54	0.30	-0.62	-0.40	0.00	-0.59	-0.24
soybean yield		1	0.32	0.26	0.07	-0.23	-0.27	-0.04	-0.07	0.10
cotton yield			1	0.15	-0.20	-0.21	-0.03	-0.38	0.14	0.36
swheat[6] yield				1	0.31	-0.15	0.03	0.15	-0.26	-0.48
wwheat yield					1	-0.42	-0.19	-0.13	-0.48	-0.29
corn price						1	0.64	0.48	0.70	-0.12
soybean price							1	0.66	0.82	-0.46
cotton price								1	0.44	-0.42
swheat price									1	-0.02
wwheat price										1

Table 3. Rank correlation matrix for U.S. yield deviates and simulated price draws over 1961-2012

	corn yield	soybean yield	cotton yield	swheat yield	wwheat yield	corn price	soybean price	cotton price	swheat price	wwheat price
corn yield	1	0.58	0.16	0.54	0.30	-0.59	-0.36	0.00	-0.59	-0.26
soybean yield		1	0.32	0.26	0.07	-0.25	-0.28	-0.05	-0.10	0.08
cotton yield			1	0.15	-0.20	-0.20	-0.02	-0.35	0.15	0.36
swheat yield				1	0.31	-0.14	0.05	0.14	-0.25	-0.46
wwheat yield					1	-0.40	-0.16	-0.14	-0.48	-0.28
corn price						1	0.61	0.47	0.67	-0.11
soybean price							1	0.65	0.80	-0.44
cotton price								1	0.42	-0.41
swheat price									1	0.01
wwheat price										1

[6] swheat and wwheat stand for spring wheat and winter wheat, respectively.

Assigning the policies to reinsurance funds

After simulating the distribution of indemnities, I also estimate how much protection private insurers would receive from the Federal Crop Insurance Corporation (FCIC) through the Standard Reinsurance Agreement (SRA). The SRA is a cooperative financial assistance agreement between FCIC and private companies to subsidize the delivery and reinsurance of crop insurance to eligible crops. Specifically, insurance companies may place eligible contracts they sell and serve with high expected loss ratios in the Assigned Risk Fund (ARF) while retaining contracts with relatively low risk in the Commercial Fund (CF). The non-proportional shares of losses and gains are outlined in Table 4. The shares of losses taken by FCIC and companies vary by loss ratio, reinsurance fund and State group. As companies' loss ratios go up, FCIC will assume a larger amount of shares in losses. In the extreme case, FCIC assumes 100% of losses if the loss ratio exceeds 500% in a state. In the case of underwriting gains, FCIC takes more gains as loss ratio decreases.

Following Mason, Hayes and Lence (2003), I use the 2012 state-level premium allocations between ARF and CF which are available from RMA[7] to mimic the 2013 state-level allocations, and then assign the contracts from each county to ARF based on the risk they present to private insurers. The procedure is as follows. First, for each state, I calculate the dollar amounts of premiums that are allocated to ARF by assuming the proportion of premiums assigned to ARF is same as that in 2012 for that state. Second, I rank counties' contracts for a particular state by the standard deviations of their loss ratios. I assign policies to ARF from counties with the largest standard deviation until the total premium reaches the state's share of premiums that are allocated to ARF for 2013. The process is repeated for every remaining state. How I allocated policies to reinsurance funds differs from how private insurers allocate policies. Private companies typically will designate all contracts

7 http://www3.rma.usda.gov/apps/reins_public/

Table 4. Companies' shares in underwriting losses and gains under SRA

	Losses		Gains	
State Group Reinsurance Fund	State group 1[8]	State group 2[9] and 3[10]	State group 1	State group 2 and 3
	Loss ratio between 100% and 160%		*Loss ratio between 65% and 100%*	
Commercial Fund	65.0%	42.5%	75.0%	97.5%
Assigned Risk Fund	7.5%	7.5%	22.5%	22.5%
	Loss ratio between 160% and 220%		*Loss ratio between 50% and 65%*	
Commercial Fund	45.0%	20.0%	40.0%	40.0%
Assigned Risk Fund	6.0%	6.0%	13.5%	13.5%
	Loss ratio between 220% and 500%		*Loss ratios less than 50%*	
Commercial Fund	10.0%	5.0%	5.0%	5.0%
Assigned Risk Fund	3.0%	3.0%	3.0%	3.0%

Note: FCIC will assume 100% of that portion of the underwriting loss amount for which the company's loss ratio exceed 500% of total retained premium in a given state and fund for given reinsurance year.

[8] State group 1 means Illinois, Indiana, Iowa, Minnesota, and Nebraska.

[9] State group 2 means Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Kansas, Kentucky, Louisiana, Michigan, Missouri, Mississippi, Montana, North Carolina, North Dakota, New Mexico, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Virginia, Washington, and Wisconsin.

[10] State group 3 means Alaska, Connecticut, Delaware, Hawaii, Maine, Massachusetts, Maryland, Nevada, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Utah, Vermont, West Virginia, and Wyoming.

from a county to CF if they are able to estimate the distribution of its loss ratio, and allocate the contracts to ARF if they do not have enough related information or they know it would be quite risky to retain those contracts based on their operating experience. Thus I am likely to underestimate the amount of underwriting losses that the private industry cedes to the government in the ARF. In addition, my approach may overestimate aggregate underwriting losses for private companies because of the possible benefits of retaining counties with high variance if they have a lack of correlation in losses with other counties. It is not practical for me to try to more closely mimic how private companies allocate their policies because I assume that premiums for all policies are set at actuarially fair levels.

After the county-level allocation is completed, I apply the terms of the SRA to calculate the amount of underwriting losses retained by insurance companies, and sum them across counties, which results in 26,000 (52) simulated total underwriting losses for revenue-based policies (yield-based policies).

Eliminating premium subsidies for harvest price option

One proposed reform of crop insurance programs is to remove harvest price option (HPO) on revenue-based policies. The rationale for this proposal is that many believe that HPO over-compensates farmers for losses because liability is increased if the harvest price is higher than the insured planting price. According to the Harvest Price Subsidy Prohibition Act introduced by Senate Jeff Flake and Senate Jeanne Shaheen on February 12, 2015, the elimination of HPO would save taxpayers $19 billion over the next 10 years. Note that was not the first time that reform of this type has been discussed. In 2013 Senate Flake offered the same proposal as an amendment to the farm bill. At that time, CBO projected that the amendment would have saved taxpayers $9 billion over 10 years. Thus it will be interesting to estimate the amount of savings using the extended stochastic model built in this study.

Results and Discussions

Table 5 below displays the statistics of underwriting losses under four coverage levels for six insurance policies before applying the SRA. The expected underwriting loss is zero for all the cases, as the premium is always set to be equal to the expected indemnities.

Table 5. Statistics of the underwriting losses by policy and coverage level

	Coverage Level	70%	75%	80%	85%
YP	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2482.9	3001.8	3577.3	4196.9
	Minimum	-2490.8	-3037.2	-3669.0	-4380.3
	Maximum	8962.8	10752.0	12669.0	14655.0
AYP	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2015.3	2648.7	3377.7	4187.1
	Minimum	-1431.0	-1905.7	-2511.3	-3253.3
	Maximum	8367.1	11051.0	13887.7	16729.9
RP	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2764.3	3463.0	4261.3	5138.1
	Minimum	-3419.3	-4469.7	-5764.8	-7315.2
	Maximum	18951.0	22432.7	25826.7	29019.7
RP-HPE	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2353.9	3012.7	3797.3	4700.2
	Minimum	-3421.8	-4510.0	-5887.8	-7590.1
	Maximum	19313.3	22956.3	26556.3	30005.0
ARP-HPE	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2441.1	3254.1	4230.6	5345.3
	Minimum	-1931.9	-2824.5	-4043.9	-5622.4
	Maximum	28117.3	32560.1	36366.0	39424.2
ARP	Mean	0.0	0.0	0.0	0.0
	Standard Deviation	2895.8	3787.5	4816.6	5941.2
	Minimum	-2485.6	-3477.0	-4858.7	-6681.9
	Maximum	27840.6	32121.3	35703.9	38483.6

Note: Results of YP and AYP are based on 52 underwriting losses observations while results of RP, RP-HPE, ARP-HPE and ARP are based on 26000 simulated underwriting losses. All values are expressed in millions of dollars.

If all the crops are insured under YP at the 85% coverage levels, the insurance companies would face a maximum of underwriting losses of $14.655 billion and obtain a maximum underwriting gain of $4.38 billion. As the coverage level decreases, the maximum underwriting losses (gains) decrease, as does the standard deviation. Moreover, these variables follow the same pattern under all other policies. And among all the policies, the standard deviation of underwriting losses are largest for ARP under each of the four coverage levels. In other words, the private companies bear most risk if all the crops are insured under ARP. The reason for this is that the amount of diversification is higher under farm-level insurance because of the distribution of farm yields around the county average yield in each.

Table 6. Coefficients of variation of total indemnities by policy and coverage level

Coverage Level	70%	75%	80%	85%
No SRA:				
YP	45.99%	44.86%	43.37%	41.51%
AYP	131.55%	125.43%	117.84%	109.00%
ARP	111.86%	101.73%	91.45%	81.41%
ARP-HPE	126.07%	114.61%	103.60%	93.31%
RP-HPE	50.14%	49.92%	49.25%	48.16%
RP	48.76%	47.37%	45.53%	43.30%
Apply SRA:				
YP	15.29%	15.61%	15.92%	16.08%
AYP	17.57%	19.39%	21.16%	22.20%
ARP	18.03%	19.88%	21.49%	22.54%
ARP-HPE	17.48%	19.81%	22.05%	23.85%
RP-HPE	15.49%	16.61%	17.79%	18.75%
RP	15.54%	16.30%	17.01%	17.55%

I also calculate the coefficients of variation[11] of total indemnities under different coverage levels for each policy. They are listed in Table 6 above. If all crops are insured with 70% coverage and without reinsurance from government, the coefficients of variation of total indemnities paid by private crop insurers range from 46.0% to 131.6%. According to Miranda and Glauber (1997), the variations of total indemnities paid by conventional insurers[12] range from 5.3% to 14.9%. Thus the risk from insuring crop yields and revenues are far beyond the level that private crop insurers can solely bear. However, with the reinsurance from government, the coefficients of variation of total indemnities are significantly lower, ranging

[11] Coefficients of variation $= Standard\ deviation/Mean$

[12] As stated in Miranda and Glauber (1997), that is, auto collision, workers compensation, homeowners multiple peril, commercial multiple peril, inland marine, fire, group accident and health, allied lines, ocean marine and crop-hail insurance policies.

from 15.3% for YP at the 65% coverage level to 23.85% for ARP-HPE at the 85% coverage level. Lowering the coefficient of variation of indemnities to these levels is what incentivizes private companies to get involved in the crop insurance business.

Figure 2 below shows the cumulative distribution function of the underwriting losses under different coverage levels if all crops are insured under yield protection and without reinsurance from government. As coverage level increases, the CDF of the underwriting losses rotates clockwise, which means the risk level goes up as coverage level increases. This is a quite intuitive result because the frequency of indemnities increases and so too does their magnitude. This conclusion also holds true when crops are insured under the other five policies. I only list the corresponding estimated CDF of the underwriting losses for RP in Figure 3, because all revenue-based policies have similar charts as that of RP while the CDF of the underwriting losses for AYP is close to that of YP. The CDF of the underwriting losses for RP shares the same pattern with that for YP, but the curve is much smoother because of the additional simulations required to capture the price variation for the revenue-based policies.

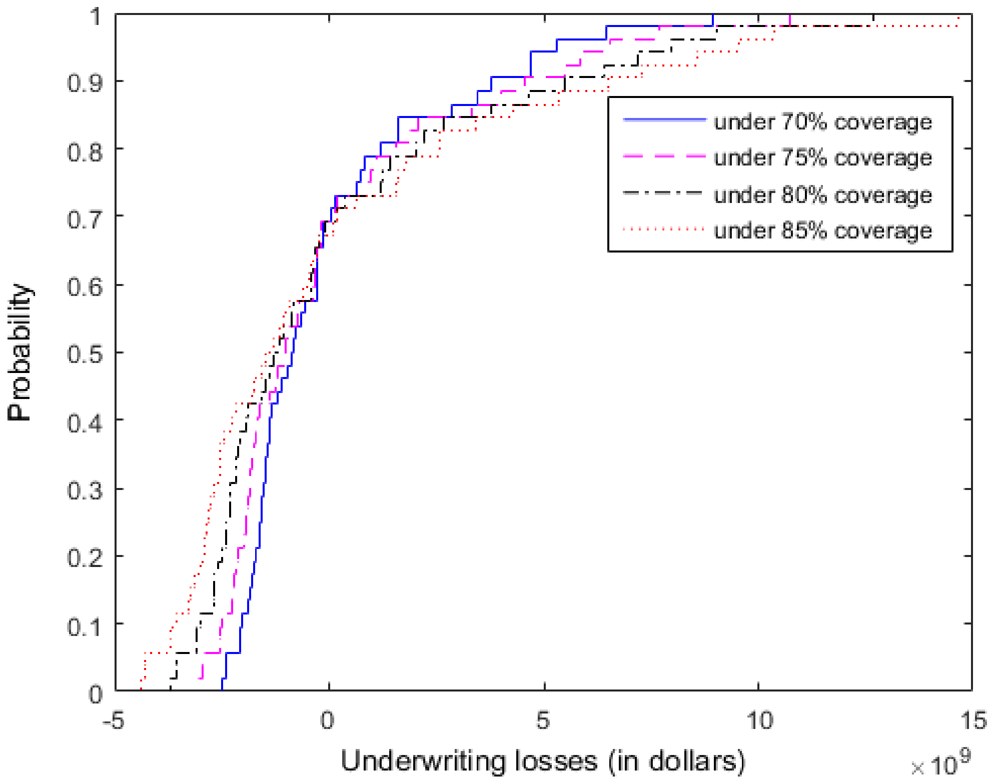

Figure 2. CDF of the underwriting losses by coverage level for YP

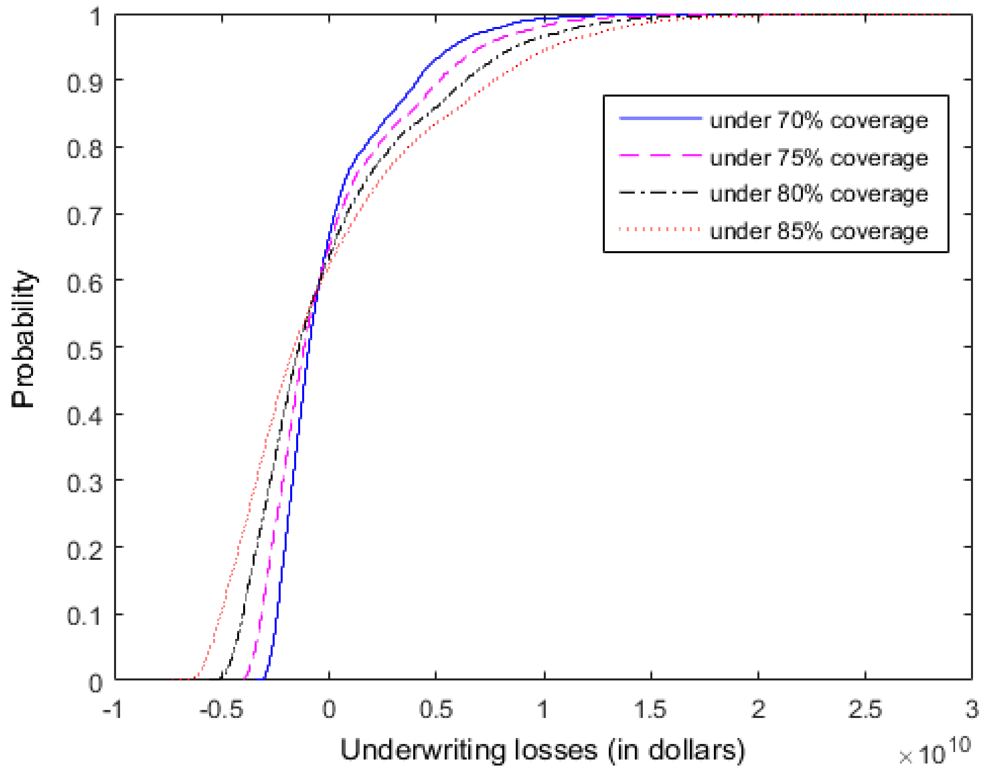

Figure 3. CDF of the underwriting losses by coverage level for RP

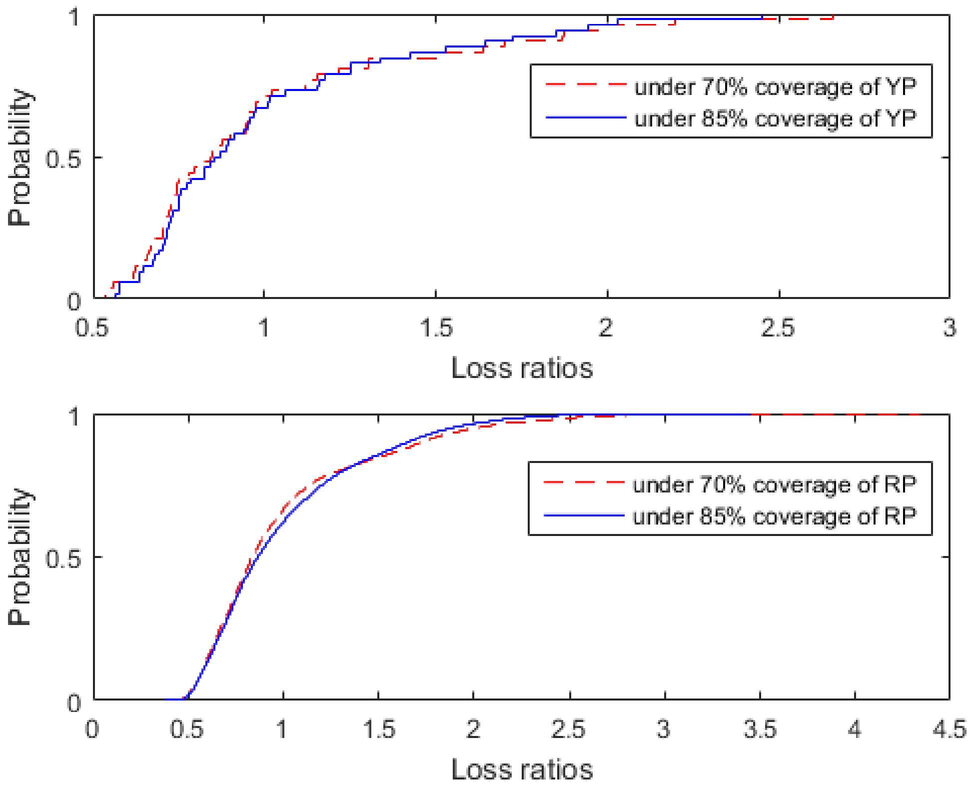

Figure 4. CDF of loss ratios by policy and coverage level

Figure 4 above presents the CDFs of loss ratios under different coverage levels if all crops are insured under yield protection or revenue protection. The distribution of loss ratios does not change much as coverage level changes. The maximum and minimum of loss ratios with 70% coverage under YP are 2.66 and 0.54, respectively, while those under RP are 4.34 and 0.40, respectively. Together Figure 3 and Figure 4 indicate that while the coverage level affects both the absolute value of loss and its expected value, the effects tend to be in a similar proportion, which shifts the distribution of their difference, but leaves that of their ratio almost unchanged.

Table 7. Statistics of loss ratios of corn vs. of all crops by policy and coverage level if no SRA

	Coverage Level	70%	75%	80%	85%
YP	Corn only:				
	Standard Deviation	0.6837	0.6624	0.6354	0.6031
	Minimum	0.42	0.43	0.43	0.44
	Maximum	3.35	3.25	3.13	2.99
	All crops:				
	Standard Deviation	0.4599	0.4486	0.4337	0.4151
	Minimum	0.54	0.55	0.56	0.57
	Maximum	2.66	2.61	2.54	2.45
RP	Corn only:				
	Standard Deviation	0.7725	0.7373	0.6962	0.6508
	Minimum	0.25	0.24	0.24	0.25
	Maximum	6.22	5.61	4.99	4.43
	All crops:				
	Standard Deviation	0.4876	0.4737	0.4553	0.4330
	Minimum	0.40	0.39	0.38	0.38
	Maximum	4.34	4.07	3.76	3.45

Note: Results of YP (RP) are based on 52 (26000) underwriting losses observations. The expected loss ratio is equal to 1 by construction.

Table 7 above lists the respective summary statistics of loss ratios from insuring only corn and insuring all crops under YP or RP if reinsurance is not available. The results for other policies are not displayed since they exhibit similar patterns. The corresponding CDFs of loss ratios with 85% coverage are depicted in Figure 5. Compared to the case of providing insurance to all the five crops, insuring only corn yield or revenue gives a much larger standard deviation and larger maximum loss ratios under each coverage level. Therefore, private insurers derive some benefit from diversifying across crops. However, diversification across crops is clearly limited because other crop yields and prices are correlated with corn yields and prices, together with the fact that corn represents a large portion of total planted acreage.[13]

[13] In 2013, the US total acreage planted for corn, cotton, soybeans, spring wheat and winter wheat are 95.34 million acres, 10.34 million acres, 76.49 million acres, 11.60 million acres and 43.09 million acres, respectively.

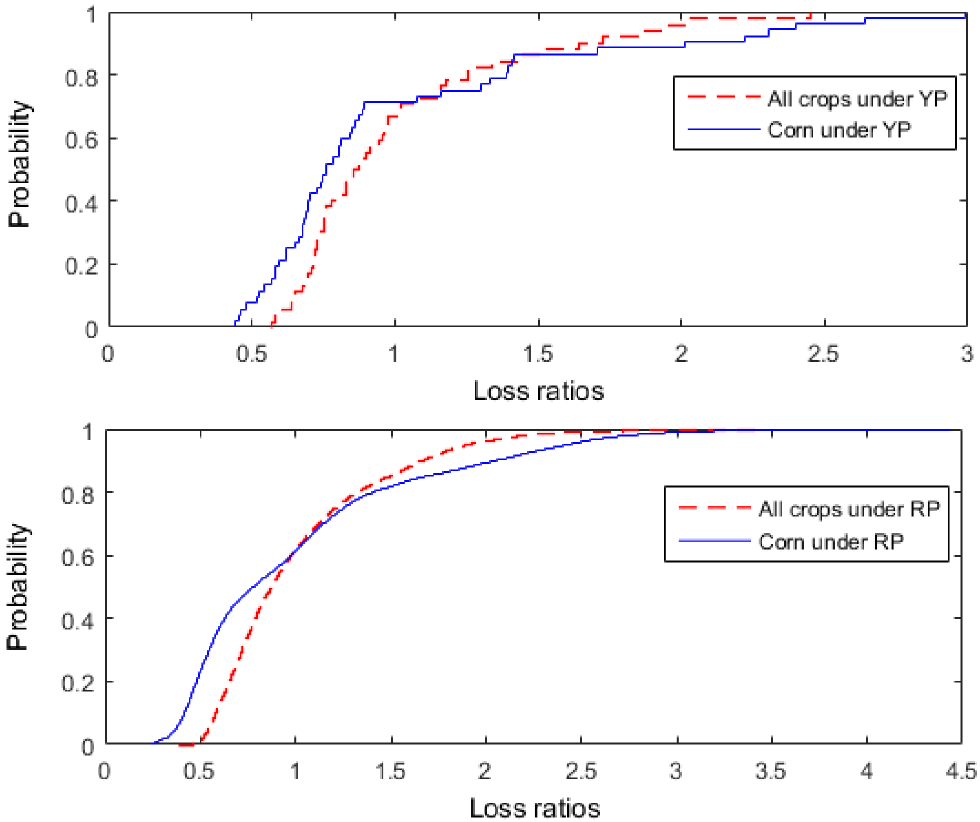

Figure 5. CDF of loss ratios for corn and for all crops under 85% coverage of YP or RP

The statistics of underwriting losses paid by insurance firms are summarized in Table 8. Compared to the "No SRA" scenario, reinsurance from the government does a very good job in reducing the risk faced by private companies from offering crop yield and revenue insurance. Instead of being actuarially fair, the SRA creates an expected underwriting gain to insurance companies of up to \$673.5 million per year. This is in addition to the amount these companies receive to cover the costs of servicing crop insurance policies. Moreover, the SRA decreases the standard deviations of insurers' underwriting losses by more than 70 percent under every coverage level. The reduced risk is also reflected in smaller range of the underwriting losses. The maximum observed underwriting loss of ARP-HPE is \$39.4 billion before reinsurance and only \$2.8 billion after reinsurance. Reinsurance also improves VAR(95%)[14] and VAR(90%). There is 5 percent probability that private firms would lose at

[14] VAR(95%) is the vaule V such that prob(underwriting losses $\leq$ V) = 95%.

least \$11.9 billion under ARP if no reinsurance available. However, the amount reduces to \$1.6 billion after applying the SRA.

Table 8. Summary statistics of companies' underwriting losses before and after applying SRA[15]

Policy	YP	AYP	RP	RP-HPE	ARP-HPE	ARP
No SRA:						
Mean	0.0	0.0	0.0	0.0	0.0	0.0
Standard Deviation	4196.9	4187.1	5138.1	4700.2	5345.3	5941.2
Minimum	-4380.3	-3253.3	-7315.2	-7590.1	-5622.4	-6681.9
Maximum	14655.0	16729.9	29019.7	30005.0	39424.2	38483.6
VAR(95%)	9444.1	8798.3	10419.6	9073.7	11011.9	11924.5
VAR(90%)	6727.0	7437.7	7725.7	6131.5	6744.9	8674.2
Apply SRA:						
Mean	-629.8	-521.5	-673.5	-552.9	-554.2	-640.0
Standard Deviation	1121.0	531.1	1454.9	1272.1	904.9	1110.6
Minimum	-2014.1	-1014.4	-2849.6	-2537.2	-1641.0	-1996.5
Maximum	2347.3	1036.9	4873.2	3981.4	2775.6	3579.7
VAR(95%)	1667.3	656.3	2209.1	2004.3	1469.9	1610.6
VAR(90%)	1036.1	378.5	1563.4	1361.0	855.5	1007.3

Note: Results of YP and AYP are based on 52 underwriting losses observations while results of other policies are based on 26000 simulated underwriting losses. All values are expressed in millions of dollars. And it is under 85% coverage level.

Figure 6 below compares the CDFs of the underwriting losses paid by private companies before and after government reinsurance given all the contracts are insured with 85% coverage level of YP. The blue solid line is the CDF of the underwriting losses without applying SRA. The red dotted line stands for the CDF after applying SRA. Without involvement of the government, the probability of obtaining underwriting gains from insuring crop yields is about 67 percent, that is, losses occur at 33 percent of time for private insurance companies. However, if the private insurers get reinsurance from government through SRA, not only the chance of suffering a loss will decrease, but also the risk (in terms of standard deviations) will decline. Also notice that the expected underwriting gain increases to \$629.8 million, which is about 7.75% of retained premiums.

[15] Under the reinsurance scenario, I take into account the net book quota share, which is to cede 6.5% of companies' cumulative underwriting gain or loss to FCIC.

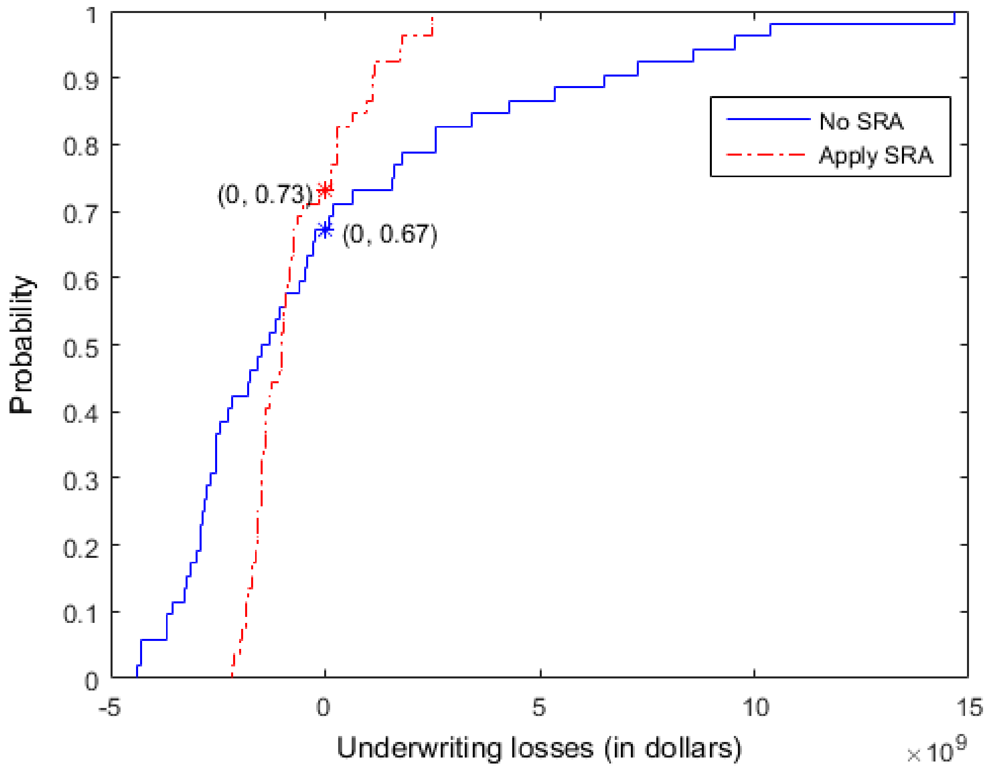

Figure 6. CDF of the underwriting losses under 85% coverage of YP

The corresponding comparison for RP is listed in Figure 7. Without reinsurance from the government, the private firms would suffer a loss about 38 percent of time, which is higher than the situation where all the crops are insured under yield protection. However, with reinsurance from government, not only the chance of suffering a loss declines to 29%, but also the risk would be eliminated to a great extent, from $5.1 billion to $1.5 billion (shown in Table 8). And the expected underwriting gain has increased to $673.5 million, which accounts for 7.02% of retained premiums.

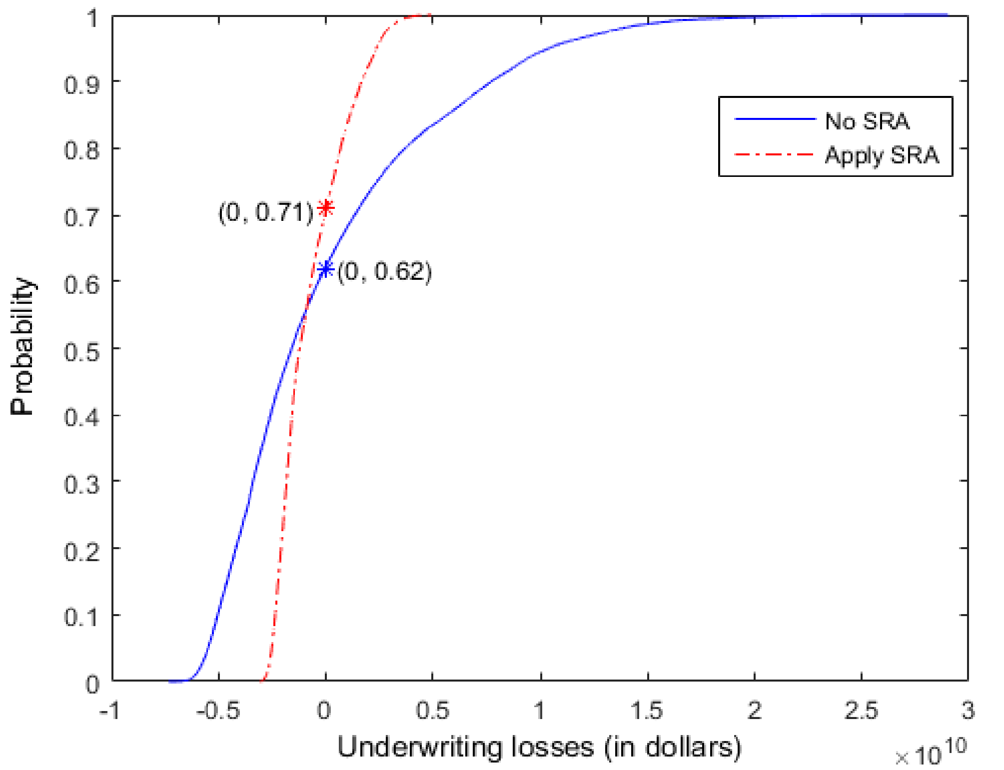

Figure 7. CDF of the underwriting losses under 85% coverage of RP

Summary statistics of program costs paid by taxpayers are contained in Table 9. For each policy, as coverage level goes up, all the variables (mean, standard deviation etc.) increase. ARP turns out to be the riskiest policy for taxpayers as well. If all crops are insured under ARP, taxpayers are expected to pay at least $416.8 million. Under 85% coverage, the maximum underwriting losses (gains) is $35.2 ($4.7) billion. And there is a 5 percent chance that taxpayers would pay at least $10.6 billion.

The corresponding CDFs of the underwriting losses that taxpayers incur from crop yield or revenue insurance are shown in Figure 8. The distribution rotates clockwise as coverage level increases, which indicates taxpayers are exposed to higher level of risk with the increase in coverage.

Table 9. Statistics of underwriting costs paid by taxpayers by policy and coverage level

	Coverage Level	70%	75%	80%	85%
YP	Mean	395.4	468.8	545.4	629.8
	Standard Deviation	1959.5	2328.5	2717.2	3112.3
	Minimum	-1421.4	-1726.6	-2076.5	-2453.7
	Maximum	7939.1	9387.8	10858.5	12307.7
	VAR(95%)	4243.8	5143.9	6145.7	7197.4
	VAR(90%)	3619.7	4299.3	4981.5	5690.9
AYP	Mean	289.9	366.0	441.1	521.5
	Standard Deviation	1870.9	2422.6	3031.9	3681.7
	Minimum	-1011.8	-1331.6	-1750.1	-2253.0
	Maximum	8154.5	10649.1	13203.1	15693.1
	VAR(95%)	4424.2	5263.0	6425.0	8105.4
	VAR(90%)	2817.8	3974.7	5513.7	7063.8
RP	Mean	432.1	513.7	593.6	673.5
	Standard Deviation	2218.1	2704.5	3222.4	3741.4
	Minimum	-2113.3	-2759.0	-3549.4	-4465.7
	Maximum	17174.9	19993.9	22529.8	24658.2
	VAR(95%)	5013.6	6068.0	7215.0	8328.8
	VAR(90%)	3690.3	4488.4	5336.7	6209.3
RP-HPE	Mean	351.4	419.6	489.6	552.9
	Standard Deviation	1915.7	2388.9	2915.8	3487.7
	Minimum	-2283.8	-3014.2	-3932.7	-5074.2
	Maximum	17857.3	20953.6	23835.2	26394.9
	VAR(95%)	3860.1	4822.3	5954.4	7152.8
	VAR(90%)	2515.4	3175.9	3964.3	4812.3
ARP-HPE	Mean	328.0	413.3	496.5	554.2
	Standard Deviation	2263.0	2942.4	3699.2	4492.2
	Minimum	-1380.2	-2017.1	-2873.0	-3981.5
	Maximum	27410.3	31433.4	34631.9	36864.7
	VAR(95%)	4169.2	5744.8	7587.2	9569.0
	VAR(90%)	2292.8	3262.3	4510.7	5914.7
ARP	Mean	416.8	511.3	589.8	640.0
	Standard Deviation	2638.6	3359.5	4125.6	4883.4
	Minimum	-1764.7	-2454.7	-3424.0	-4704.0
	Maximum	26876.3	30615.8	33457.6	35234.3
	VAR(95%)	5988.6	7491.1	9061.6	10579.2
	VAR(90%)	3891.4	5133.7	6400.4	7669.1

Note: Results of YP and AYP are based on 52 underwriting losses observations while results of RP, RP-HPE, ARP-HPE and ARP are based on 26000 simulated underwriting losses. All values are expressed in millions of dollars.

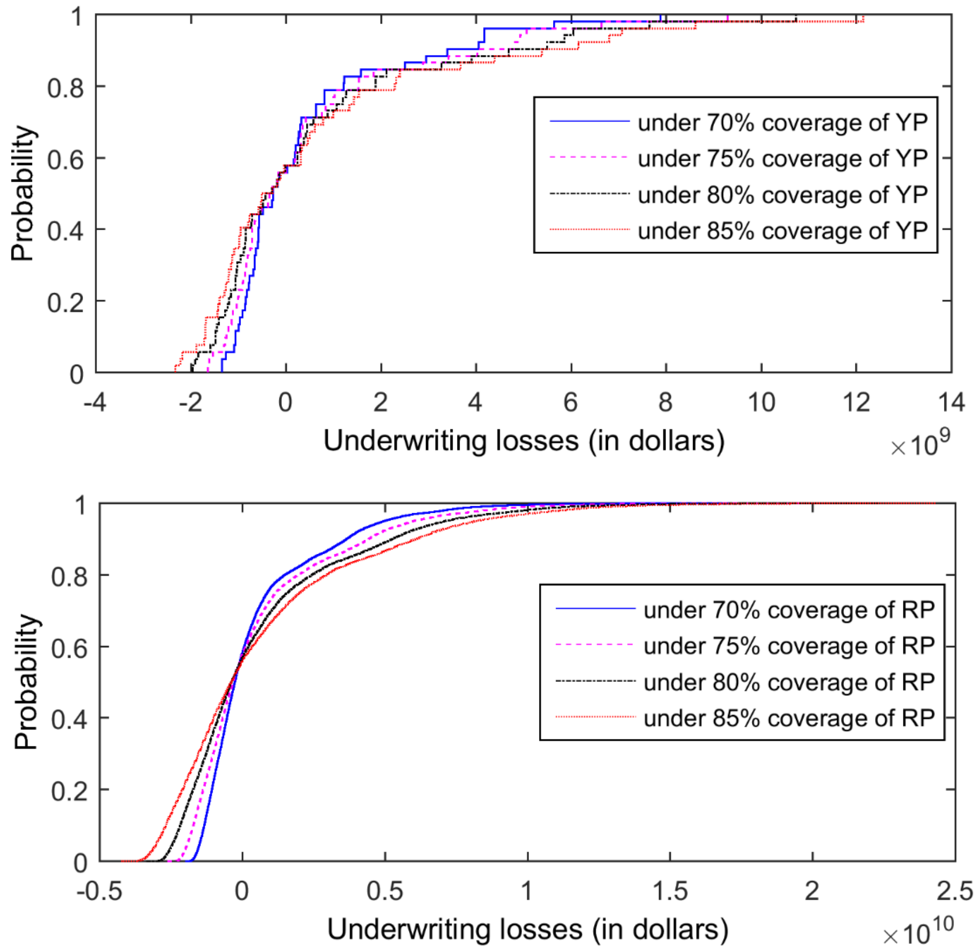

Figure 8. CDF of the costs paid by taxpayers by policy and coverage level

Evaluation of proposal to eliminate subsidies for harvest price option

Eliminating subsidies on harvest option policies can save taxpayers in three aspects. First, it can reduce the amount of underwriting loss sharing. If we assume that all farmers switch to RP without harvest option due to the removal of subsidies on RP, it would be reasonable to calculate the differences in the amount of underwriting gains and losses paid by taxpayers between RP and RP-HPE. The calculated difference would be the estimated savings for taxpayers due to changes in the amount of underwriting gains that private companies obtain. Table 10 displays the per acre cost comparison between RP and RP-HPE. If all the contracts are insured under RP with 85% coverage level, taxpayers are expected to pay $3.40 for each acre insured, which is about 60 cents more than the case where only

RP-HPE is available for farmers. On average, the saving is about 40 cents to 60 cents. However, when losses are very high, say at its 90% quantile, this difference can be as large as $6.50 per acre. The dollar amount of annual savings would range from $74 million to $110 million, given 180 million of acres insured under RP in 2013.

Table 10. Statistics of per acre underwriting losses cost paid by taxpayers by policy and coverage level

	Coverage Level	70%	75%	80%	85%
RP	Mean	2.2	2.6	3.0	3.4
	Standard Deviation	10.3	12.5	14.9	17.2
	Minimum	(9.6)	(12.5)	(16.1)	(20.2)
	Maximum	80.7	93.8	105.5	115.2
	VAR(95%)	23.5	28.4	33.6	38.8
	VAR(90%)	17.3	21.0	25.0	28.8
RP-HPE	Mean	1.8	2.1	2.5	2.8
	Standard Deviation	8.9	11.1	13.5	16.1
	Minimum	(10.4)	(13.8)	(18.0)	(23.2)
	Maximum	84.0	98.5	111.9	123.7
	VAR(95%)	18.1	22.5	27.8	33.2
	VAR(90%)	11.8	14.9	18.4	22.3
Difference (RP - RP-HPE)	Mean	0.4	0.5	0.5	0.6
	Standard Deviation	1.4	1.4	1.4	1.1
	Minimum	0.9	1.3	1.9	3.0
	Maximum	(3.3)	(4.7)	(6.4)	(8.5)
	VAR(95%)	5.4	5.9	5.9	5.6
	VAR(90%)	5.5	6.2	6.5	6.5

Note: Results are based on 26000 simulated underwriting losses. All values are expressed in dollars.

Table 11. Premium and premium subsidies for RP and RP-HPE by coverage level

	Coverage Level	70%	75%	80%	85%
Premium	RP	5.67	7.31	9.36	11.87
	RP-HPE	4.69	6.04	7.71	9.76
Premium Subsidies	Subsidy factor	0.59	0.55	0.48	0.38
	RP	3.34	4.02	4.49	4.51
	RP-HPE	2.77	3.32	3.70	3.71
	Difference in subsidies	0.57	0.70	0.79	0.80

Note: Values are in billions of dollars. Premium for each insurance plan is the sum amount for five crops: corn, soybeans, cotton, spring wheat and winter wheat.

Second, since all the insurance policies are heavily subsidized in premium, elimination of premium subsidies would be the biggest portion of the total savings. As shown in Table 11, the total premium is about $11.87 billion if all the contracts are insured with 85% coverage of RP, $4.51 billion of which is paid by taxpayers. If all the contracts are insured under RP-HPE, then the taxpayers' cost would be down to $3.71 billion, which is $800 million less.

Third, FCIC also subsidizes the insurance firms for the administrative and operating expenses, which are about 20% of the total premium for each policy. Due to the lower premiums for RP-HPE, the shift from RP to RP-HPE would save taxpayers another $195 million to $421 million. So taking into account the savings in underwriting loss sharing, premium subsidies, and subsidies for operating expenses, replacing RP with RP-HPE would save taxpayers $1.33 billion in total given all the contracts are insured with 85% coverage level, which is about $400 million more than CBO's estimate in 2013, but only 67% of its estimate in 2015.

Conclusions

Based on the stochastic model developed by Babcock and Paulson (2012), the risk from providing crop yield and revenue insurance can be quantified and is found to be far greater than the level of risk in conventional private insurance markets. As a result, crop insurance would not be active without government's involvement. After obtaining reinsurance from FCIC, insurance firms are expected to extract positive net underwriting gains under all six insurance policies. Furthermore, the elimination of premium subsidies on harvest price option and the anticipated shift of producers to RP-HPE would have saved taxpayers up to $1.33 billion per year given all the RP farmers switch to RP-HPE, which is about $400 million more than CBO's estimate in 2013 but $600 million less than its estimate in 2015.

Note that all this analysis conducted on crop insurance is a one-year cost projection. Thus, a natural, but quite crucial, question arises: what is an appropriate way of analyzing agricultural programs in a dynamic setting, as most policies are implemented for many years. At first look, extending the analysis to multiple years seems straightforward, but simply repeating this procedure in a dynamic world may bias our calculations, due to lack of consideration of serial correlation and increasing price volatilities over time. To formally explore this question, a three-crop storage model is adopted, which is discussed in the next chapter, as a better approach for the multiple-year projections.

CHAPTER 3

THE STORAGE MODEL

Introduction

The competitive storage model under rational expectations has attracted great attention from economists, because its derivation is based on a microeconomic foundation that incorporates demand, supply and storage. The model has been widely adopted to understand the complexity of commodity price dynamics. Deaton and Laroque (1992) made the first attempt to estimate the serial dependence among twelve major commodity prices by using the storage model. Their paper concluded that the storage model could introduce some autocorrelation of price but the degree was far below what was actually observed in price data. However, based on Deaton and Laroque’s work, Cafiero et al. (2011) showed that employing a much finer grid to approximate the equilibrium price function would produce quite different results. They conclude that the storage model is capable of explaining the high serial correlations observed in price data for the twelve major commodities under study.

The storage model is increasingly used to simulate the impacts of alternative policy scenarios. Miranda and Helmberger (1988) developed a one-commodity storage model to analyze the long-run impacts of price stabilization programs on soybean market prices. They found that the programs would essentially decrease the long-run market price of soybeans and also destabilize producers’ revenue even though they were initiated to support and stabilize price. Roberts and Tran (2012) researched the impacts of a large and permanent demand shift on food prices by using a one-crop storage model. They argue that about 11% to 30% of the increase in food price is the result of U.S. ethanol mandate which shifted the world demand by more than 5%.

Lence and Hayes (2002) were the first to generalize the storage model to a three-commodity framework which allows output substitution effects among crops. Their two-period generalized model was then used to solve the equilibrium variables, such as production, price, planted acres and storage, under three different policy scenarios: a free-market regime, the Federal Agricultural Improvement and Reform (FAIR) Act of 1996 regime and the regime that preceded the FAIR Act. Their results showed that FAIR Act could not account for the significant increases in long-run price volatility or revenue volatility. In this chapter, I present a three crop storage model that can be used to generate serially correlated price deviates that are used to provide better estimates of the cost of agricultural commodity programs.

Model Setup

Unlike Chapter 2, the focus of this chapter is restricted to three storable commodities: corn, soybeans and wheat, because the reference price for Price Loss Coverage (PLC), one of the programs that will be evaluated, does not differentiate between spring and winter wheat. Reducing the number of crops from four to three also makes the model more computationally tractable because it reduces the "curse of dimensionality" (Judd, 1998).

At any time period t, the total available amount of commodity j ($\mathrm{j} = 1, 2, 3$), denoted as TA_{jt}, is composed of the inventory carried over from previous year I_{jt-1}, the new production Q_{jt}, which equals the product of the acreage planted at time $\mathrm{t}-1$ A_{jt-1} and the yield y_{jt}

$$\mathrm{TA}_{jt} = \mathrm{I}_{jt-1} + \mathrm{Q}_{jt} = \mathrm{I}_{jt-1} + A_{jt-1}y_{jt} \tag{13}$$

Part of the total supply is used for current consumption c_{jt} and the rest is saved for next period I_{jt}

$$\mathrm{TA_{jt}} = \mathrm{c_{jt}} + \mathrm{I_{jt}} \tag{14}$$

The demand function for commodity j is assumed to be the following:

$$\mathrm{c_{jt}} = \mathrm{D}(\mathrm{p_{jt}}) = (\frac{\mathrm{p_{jt}}}{\alpha_{\mathrm{jd}}\mathrm{e_{jt}}})^{\gamma_{\mathrm{jd}}} \tag{15}$$

$$\mathrm{p_{jt}} = \alpha_{\mathrm{jd}}\mathrm{e_{jdt}}(\mathrm{c_{jt}})^{1/\gamma_{\mathrm{jd}}} \tag{16}$$

where $\alpha_{\mathrm{jd}} > 0, -1 < \gamma_{\mathrm{jd}} < 0$ and $|\gamma_{\mathrm{jd}}|$ is the demand elasticity. $\mathrm{e_{jdt}}$ is the demand shock, which is assumed to be a random walk. The error term ε_{jdt} of demand shock is independently and normally distributed with mean zero and variance σ_{jd}^2. Formally,

$$e_{jdt} = e_{jdt-1} + \varepsilon_{jdt},\ \varepsilon_{jdt} \sim N(0, \sigma_{jd}^2) \tag{17}$$

$$e_{jdt} = e_{jd0} + \sum_{i=1}^{t} \varepsilon_{jdi} \tag{18}$$

I further assume the error term at time 0 (year 2013) is realized and equal to 1, that is

$$e_{jd0} = 1 \tag{19}$$

Therefore e_{jdt} , the demand shock at time t, is normally distributed with mean 1 and variance $t * \sigma_{jd}^2$.

The planting decisions are made one period ahead and based on per acre expected revenues in the next period. If there is no constraint for total acreage planted, then acreage supply for commodity j is given as follows

$$lnA_{jt}^{un} = ln\alpha_{js} + \sum_{k=1}^{3} \beta_{jks} \ln(E_t(p_{kt+1}y_{kt+1}))\,, \mathrm{j} = 1, 2, 3 \tag{20}$$

In equation (20), $\beta_{jjs} > 0$ for $\mathrm{j} = 1, 2, 3$ ensures that the acreage responds positively to its own per acre revenue; $\beta_{jks} < 0$ for $j \neq \mathrm{k}$ reflects the substitution effects among crops; $\sum_{k=1}^{3} \beta_{jks} > 0$ makes sure that the acreage planted for commodity j would increase if all the commodities' per acre expected revenues increase by the same proportion.

As in Lence and Hayes (2002), I restrict total acreage to be A and assume the constrained acreage supply A_{jt}^{con} is proportional to the unconstrained supply A_{jt}^{un}. That is

$$\frac{A_{jt}^{con}}{A} = \frac{A_{jt}^{un}}{\sum_{i=1}^{3} A_{it}^{un}} \tag{21}$$

Combined with equation (20), I have

$$\ln A_{jt}^{con} = ln\alpha_{js} + \sum_{k=1}^{3} \beta_{jks} \ln(E_t(p_{kt+1}y_{kt+1})) + lnA - \ln\left(\sum_{i=1}^{3} A_{it}^{un}\right), \tag{22}$$

$$\mathrm{j} = 1, 2, 3$$

$$\begin{aligned} \ln A_{jt}^{con} = ln\alpha_{js} + \sum_{k=1}^{3} \beta_{jks} \ln(E_t(p_{kt+1}y_{kt+1})) + lnA \\ - \ln\{\sum_{i=1}^{3} \alpha_{is} \prod\nolimits_{k=1}^{3} E_t(p_{kt+1}y_{kt+1})^{\beta_{iks}}\} \end{aligned} \tag{23}$$

I include convenience yield to account for the reality that some inventories are carried even when the expected price increase is not enough to cover conventional storage costs. This stockholding activity is explained by the benefit of physically holding the commodity. With storage, stockholders can use the commodity as needed. For example, the inventory can be used to make profits from temporary shortage or keep a production process running smoothly.

Furthermore, by incorporating convenience yield, Rui and Miranda (1995) were able to explain the high serial correlation observed in primary commodity prices based on Deaton and Laroque's model, which instead assumed a constant return to the storage[16] and failed to generate highly auto-correlated prices. As Rui and Miranda (1995) pointed out, the assumption that a fixed portion of inventory depreciated over time is equivalent to imposing a decreasing function of the marginal storage cost in the stock level, which results in a failure to explain the observed high autocorrelation of prices.

[16] A constant return to the storage means one unit of storable commodity at time t will be $(1-\delta)$ remained if carried over to $t+1$.

Convenience yield can be modeled as an unobservable negative storage cost. Thus the storage cost per unit consists of the marginal physical storage cost and the marginal convenience yield (MCY). MCY is assumed to be large when the inventory is small, ultimately leading to a negative storage cost per unit and decreases as inventories increase. Following Kaldor (1939), Rui and Miranda (1995), and Tomek (1997), I assume MCY of commodity j has the following form[17]:

$$MCY_{jt} = MCY(I_{jt}) = \alpha_{jc}\exp(-\beta_{jc}I_{jt}) \tag{24}$$

where $\alpha_{jc} > 0,\ \beta_{jc} > 0$ captures that MCY is decreasing in the stock level.

The intertemporal arbitrage conditions for competitive and risk-neutral storers are given as following:

$$\frac{E_t(p_{jt+1})}{1+r} + MCY_{jt} = p_{jt} + m_j \quad j = 1, 2, 3 \tag{25}$$

In equation (25), $E_t(p_{jt+1})$ is the price expectation for the next period from the standpoint of time t, m_j is the marginal storage cost of commodity j assumed to be a constant, and r is the interest rate. Equation (25) says that, if the benefit of storing an additional unit of commodity for the next period is greater than the current price plus the marginal storage cost, then stockholders would increase the amount carried to the next period. Such storage would lead to a decrease in current consumption, and therefore, an increase in the current price. When the current price increases, the difference between the marginal benefit and current price shrinks until it equals the unit storage cost. Similarly, if the benefit of carrying one more unit of commodity is less than the current price plus the marginal storage cost, then storers will store less, resulting in an increase in current consumption and thus a decline in the current price utill the marginal benefit equals the current price plus the

[17] The function form that adopted in Rui and Miranda (1995) for MCY is: $\mathrm{MCY} = {}^{\beta}/_{I_t}$, where β is a constant that needs to be calibrated.

marginal storage cost. So in the equilibrium, the benefit of storing an extra unit of commodity is equal to the cost of that. Furthuermore, possibilities of stockouts are eliminated because of the convenience yield.

Solving the Storage Model

Solving the storage model (13)-(25) requires stochastic dynamic programming. As documented in the literature, more than one way can be used to solve the rational expectation storage model. Following Deaton and Laroque (1992, 1995 and 1996), I approximate optimal storage as a function of the state variables[18]. The natural state variables are the total amount available for each crop. Specifically,

$$I_{jt} = g_j(TA_{1t}, TA_{2t}, TA_{3t}) \quad j = 1, 2, 3 \tag{26}$$

In general, the closed form of g_j cannot be derived. However, numerical methods can be used to approximate the function. Here I adopt the collocation method. The basic idea is to approximate the unknown function g_j using a linear combination of $\mathrm{n} = \prod_{k=1}^{3} n_k$ known independent basis functions

$$\begin{aligned} g_j(TA_{1t}, TA_{2t}, TA_{3t}) &\approx \hat{g}_j(TA_{1t}, TA_{2t}, TA_{3t}) \\ &= \sum_{i_1=1}^{n_1} \sum_{i_2=1}^{n_2} \sum_{i_3=1}^{n_3} c^j_{i_1 i_2 i_3} \phi_{1i_1}(\mathrm{TA}_{1t}) \phi_{2i_2}(\mathrm{TA}_{2t}) \phi_{3i_3}(\mathrm{TA}_{3t}) \end{aligned} \tag{27}$$

where $\{(\phi_{k1}, \dots, \phi_{kn_k}) | \mathrm{k} = 1, 2, 3\}$ is a $1 \times n_k$ vector of univariate basis functions. For each commodity j, eight Chebychev nodes are used to solve the storage model. As a result, there are $\mathrm{n} = 8^3 = 512$ coefficients $\{c^j_{i_1 i_2 i_3}\}_{i_1=1,\dots,n_1; i_2=1,\dots,n_2; i_3=1,\dots,n_3}$ to be determined for each commodity j. I solve for these coefficients by an iteration process described later. Equation (25) can be rewritten as

[18] Lence and Hayes (2002) approximated price expectations as a function of inventories.

$$\frac{E_t\{\alpha_{\mathrm{jd}}\mathrm{e}_{\mathrm{jdt+1}}[\mathrm{TA}_{jt+1} - g_j(TA_{1t+1}, TA_{2t+1}, TA_{3t+1})]^{1/\gamma_j}\}}{1+r} + MCY_{jt}(I_{jt})$$
$$= \alpha_{\mathrm{jd}}\mathrm{e}_{\mathrm{jdt}}(\mathrm{TA}_{jt} - I_{jt})^{1/\gamma_j} + m_j \tag{28}$$

The uncertainty in equation (28) comes from future random yields $(y_{1t+1}, y_{2t+1}, y_{3t+1})$ and demand shocks $(e_{1dt+1}, e_{2dt+1}, e_{3dt+1})$. Thus calculating expected prices requires multi-dimensional integration over all possible yield and demand shock values. Empirical yield distributions are used in this analysis. Yields are assumed to be independent from demand shocks. Monte Carlo methods are applied to integrate over the yield distributions. For each demand shock, ten Gaussian quadrature nodes and their corresponding weights are generated from a normal distribution with a specified mean and a calibrated variance. Equations (29) and (31) below give the specific expressions of the approximated expected price and the approximated per acre expected revenue in terms of 53*3 empirical yield draws, the generated ten Gaussian quadrature nodes and their corresponding weights.

$$E_t(p_{jt+1}) = E_t\{\alpha_{\mathrm{jd}}\mathrm{e}_{\mathrm{jdt+1}}[\mathrm{TA}_{jt+1} - g_j(TA_{1t+1}, TA_{2t+1}, TA_{3t+1})]^{1/\gamma_j}\}$$
$$\approx \widehat{E_t}(p_{jt+1})$$
$$= \sum_{i=1}^{10} w_i\, \alpha_{\mathrm{jd}} z_{jdi} \left\{\frac{1}{53}\sum_{k=1}^{53}[\mathrm{I}_{jt} + A_{jt}y_{jk} \right. \tag{29}$$
$$\left. - g_j(\mathrm{I}_{1t} + A_{1t}y_{1k}, \mathrm{I}_{2t} + A_{2t}y_{2k}, \mathrm{I}_{3t} + A_{3t}y_{3k})]^{1/\gamma_j}\right\}$$

$$E_t(p_{jt+1}y_{jt+1})$$
$$= E_t\left\{\alpha_{\mathrm{jd}}\mathrm{e}_{\mathrm{jdt+1}}\left[\mathrm{TA}_{jt+1} - g_j(TA_{1t+1}, TA_{2t+1}, TA_{3t+1})\right]^{1/\gamma_j} y_{jt+1}\right\} \tag{30}$$

$$\widehat{E_t}(p_{jt+1}y_{jt+1})$$
$$= \sum_{i=1}^{10} w_i\, \alpha_{\mathrm{jd}} z_{jdi} \left\{ \frac{1}{53} \sum_{k=1}^{53} [\mathrm{I}_{jt} + A_{jt}y_{jk} \right. \tag{31}$$
$$\left. - g_j(\mathrm{I}_{1t} + A_{1t}y_{1k}, \mathrm{I}_{2t} + A_{2t}y_{2k}, \mathrm{I}_{3t} + A_{3t}y_{3k})]^{1/\gamma_j} y_{jk} \right\}$$

where $\{z_{jdi}|i = 1, \ldots, 10\}$ are the ten Gaussian quadrature nodes for the demand shock of commodity j, $\{w_i|i = 1, \ldots, 10\}$ are the associated weights. $\{(y_{1k}, y_{2k}, y_{3k})|k = 1, \ldots, 53\}$ are 53 sets of empirical yield draws. They are drawn from the same historical year to maintain the spatial correlations among crop yields.

Substitution of equation (29) into (25) yields

$$\frac{\widehat{E_t}(p_{jt+1})}{1+r} + MCY_{jt}(I_{jt}) = D^{-1}(TA_{jt} - I_{jt}) + m_j \tag{32}$$

The acreage supply in equation (23) can be rewritten as

$$\mathrm{ln}A_{jt}^{con} = ln\alpha_{js} + \sum_{k=1}^{J} \beta_{jks} \mathrm{ln}(\widehat{E_t}(p_{kt+1}y_{kt+1})) + lnA \tag{33}$$
$$- \mathrm{ln}\{\sum_{i=1}^{J} \alpha_{is} \prod_{k=1}^{J} \widehat{E_t}(p_{kt+1}y_{kt+1})^{\beta_{iks}}\}$$

Equation (32) and (33) are then used to solve the undetermined 512*3 coefficients $\{c_{i_1 i_2 i_3}^{j}\}_{i_1=1,\ldots,n_1; i_2=1,\ldots,n_2; i_3=1,\ldots,n_3;\ j=1,2,3}$. The specific iteration process is listed in the following:

1. Define the domain of function $\hat{g}$ as $[TA_{1min}, TA_{1max}] \times [TA_{2min}, TA_{2max}] \times [TA_{3min}, TA_{3max}]$ and then construct $1 \times n_k$ vector of Chebychev nodes $x_k = (x_{k1}, \ldots, x_{kn_k})$ over the interval $[TA_{kmin}, TA_{kmax}]_{k=1,2,3}$ for the state variable $\mathrm{TA}_k|_{k=1,2,3}$.

$$x_{ki} = \frac{TA_{kmin} + TA_{kmax}}{2} + \frac{TA_{kmax} - TA_{kmin}}{2} cos\left(\frac{n_k - i + 0.5}{n}\pi\right), \quad (34)$$
$$k = 1, 2, 3;\ i = 1, \dots, n_k$$

A grid of $\mathrm{n} = \prod_{k=1}^{3} n_k$ interpolation nodes can be formed by Cartesian product[19] of the univariate interpolation nodes $\{x_k\}_{k=1,2,3}$

$$\{(x_{1i_1}, x_{2i_2}, x_{3i_3}) | i_k = 1, \dots, n_k, k = 1, \dots, 3\} \quad (35)$$

where $[TA_{jmin}, TA_{jmax}]$ is the range of total amount available (new production + inventory) for commodity j, defined as $[10, 20] \times [2.6, 7] \times [2.5, 4]$ in this study for corn, soybeans and wheat with the values in billions of bushels.

2. Construct the $\mathrm{n} = \prod_{k=1}^{3} n_k = 8^3 = 512$ independent Chebychev polynomials $\{\phi_{1i_1}\phi_{2i_2}\phi_{3i_3}\}_{i_k=1,\dots,n_k; k=1,\dots,3}$ using the tensor product[20] of the univariate interpolation polynomials, which are defined on the domain $[-1, 1]$.
3. Define Z_{ki} below to normalize the domain to the interval $[-1, 1]$.

$$\{Z_{ki} = \frac{2(x_{ki} - TA_{kmin})}{TA_{kmax} - TA_{kmin}} - 1 |\ k = 1, 2, 3;\ i = 1, \dots, n_k\ \} \quad (36)$$

Evaluate the n independent Chebychev polynomials $\{\phi_{1i_1}\phi_{2i_2}\phi_{3i_3}\}_{i_k=1,\dots,n_k; k=1,\dots,3}$ at normalized node $(Z_{1i_1}, Z_{2i_2}, Z_{3i_3})$, which produces a $1 \times \mathrm{n}$ matrix.

4. Given an arbitrary starting value c^{0j} $(\mathrm{n} \times 1$ matrix$)$ for coefficients, I obtain

$$\hat{g}_j(Z_{1i_1}, Z_{2i_2}, Z_{3i_3}), = \sum_{i_1=1}^{n_1}\sum_{i_2=1}^{n_2}\sum_{i_3=1}^{n_3} c^{0j}_{i_1 i_2 i_3} \phi_{1i_1}(Z_{1i_1})\phi_{2i_2}(Z_{2i_2})\phi_{3i_3}(Z_{3i_3}) \quad (37)$$

5. Substitute equation (37) into both non-arbitrage conditions (32) and acreage supply functions (33).
6. Plug in the first Chebychev node $Z^1 = (Z_{11}, Z_{21}, Z_{31})$ defined based on current total

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[19] Cartesian product is a mathematical operation which returns a set from multiple sets. That is, for sets A and B, the Cartesian product $A \times B$ is the set of all ordered pairs (a, b) where $a \in A$ and $b \in B$.

[20] Tensor product denoted by $\otimes$, If $A = [1\ \ x_1\ x_1^2]$, $B = [1\ x_2]$, then $A \otimes \mathrm{B} = [1\ \ x_1\ x_1^2\ x_2\ x_1x_2\ x_1^2x_2]$, which has 6 columns.

supplies, solve for $I_t = (I_{1t}, I_{2t}, I_{3t})$ and $A_t = (A_{1t}, A_{2t}, A_{3t})$, denoted as I_t^1 and A_t^1.

7. Repeat step 6 for all the remaining Chebychev nodes, then I have n values of I_t, $\begin{pmatrix} I_t^1 \\ \vdots \\ I_t^n \end{pmatrix}$,

   which corresponds to $\begin{pmatrix} Z^1 \\ \vdots \\ Z^n \end{pmatrix}$, and get the updated coefficient $c^1 = \Phi^{-1}\begin{pmatrix} I_t^1 \\ \vdots \\ I_t^n \end{pmatrix}$, where Φ is a $\mathrm{n} \times \mathrm{n}$ matrix, obtained by evaluating the n independent Chebychev polynomials $\{\phi_{1i_1}\phi_{2i_2}\phi_{3i_3}\}_{i_k=1,\dots,n_k; k=1,\dots,3}$ at each of the n interpolation nodes $\begin{pmatrix} Z^1 \\ \vdots \\ Z^n \end{pmatrix}$.

8. Replace c^0 with c^1 and repeat step 5-7 until coefficients c converge[21] to c^*

   Then I have

$$I_{jt}^* = \sum_{i_1=1}^{n_1} \sum_{i_2=1}^{n_2} \sum_{i_3=1}^{n_3} c_{i_1 i_2 i_3}^{j*} \phi_{1i_1}(Z_{1i_1}) \phi_{2i_2}(Z_{2i_2}) \phi_{3i_3}(Z_{3i_3}) \tag{38}$$

   where $Z_{ji_j}|_{j=1,2,3}$ is the normalized total supply of commodity j at time t built in equation (36).

The Chebychev nodes and polynomials are calculated by using the Matlab package developed by Miranda and Fackler (2002). The full Matlab codes implemented to solve the storage model are attached as an appendix to this chapter.

Data and methodology

Historical county-level and national-level yield data over 1961-2013 were collected for corn and soybeans from NASS. For wheat, the same periods of national-level yields were also assembled, but the county-level yields are not available for 2008-2013 from NASS. As a result, county-level production and acreage planted data on spring and winter wheat over 1961-2013 were collected to calculate the corresponding county-level yields on wheat.

[21] The tolerance for convergence is 10^{-7}.

As in Chapter 2, I only include counties with at least 20 years' historical yield data over 1990-2013 into the analysis. Irrigated and non-irrigated practices are treated separately in calculating the program payments, which are then averaged by their respective acreage to obtain the averaged payments. However, the farm-level yield variabilities are not calibrated, because individual-based ARC is not a main focus in this analysis as it was rarely selected by farmers. In 2015, only 1% of base acres are enrolled under ARC-individual while 76% of base acres are enrolled under ARC-county. The remaining 23% of base acres are enrolled under PLC[22]. In order to compare with county-based ARC, the program background on individual-based ARC will be provided in Chapter 4.

A big difference from Chapter 2 lies in the model adopted to simulate price draws. To my knowledge, the present study is the first one that employs a three-crop rational expectation storage model to simulate intertemporally correlated prices and then apply them to evaluate commodity programs.

Calibrating model parameters

Yield Distribution. For each commodity j, the historical national-level yield draws are detrended to their 2014-equivalents:

$$Y_{jt}^{det} = \frac{Y_{jt} * Y_{j2014}^{tre}}{Y_{jt}^{tre}}, \mathrm{t} = 1961, \dots, 2013; \mathrm{j} = 1, 2, 3. \tag{39}$$

where Y_{j2014}^{tre} is U.S. trended yield in 2014.

The detrended national corn yield Y_{1t}^{det} has a mean of 169.01 bushel per acre and standard deviation of 16.65, while the detrended national soybeans yield Y_{2t}^{det} has a mean of 44.96 and standard deviation of 3.08. For wheat, the mean and the standard deviation are 47.38 and 3.33, respectively.

[22] https://www.fsa.usda.gov/programs-and-services/arcplc_program/index

Demand Function. The demand shock for each crop is assumed to be a random walk: $e_{jdt} = e_{jdt-1} + \varepsilon_{jdt}$, $\varepsilon_{jdt} \sim N(0, \sigma_{jd}^2)$, where σ_{jd} is calibrated with demand elasticities to achieve the three price-related targets which are discussed in the following section. The calibrated standard deviations are 0.15 for corn, 0.14 for soybeans and 0.13 for wheat. The respective demand elasticities for corn, soybeans and wheat are calibrated to be (-0.56, -0.45, -0.15). Furthermore, the total usage and average prices received by farmer in 2013 marketing year are collected to calibrate the constants $\{\alpha_{jd}\}_{j=1,2,3}$ in the demand functions. The total usage of corn, soybeans and wheat are 13.454 billion bushels, 3.478 billion bushels and 2.436 billion bushels, respectively. The average prices received by farmers are $4.46 per bushel for corn, $13 per bushel for soybeans and $6.87 per bushel for wheat. Thus the parameters in equation (14) are: $\alpha_{1d} = 462.5, \alpha_{2d} = 207.4, \alpha_{3d} = 2598.9$.

Acreage Supply. For illustration purposes, the own supply elasticities β_{jjs} for $\mathrm{j} = 1, 2, 3$ are assumed to be 0.2 and the cross elasticities β_{jks} for $j \neq \mathrm{k}$ are assumed to be -0.08. The constant parameter in the acreage supply function of commodity j is set to a level such that given this parameter, the supply elasticities and expected revenue for the 2014 market year of commodity j, the producers would plant the acreage that matches the observed planted acre of commodity j in 2014. The own price-yield correlations are needed to calculate the expected revenue $\mathrm{E_t(p_{kt+1} y_{kt+1})}$:

$$\mathrm{E_t(p_{kt+1} y_{kt+1}) = E_t(p_{kt+1}) E_t(y_{kt+1}) + COV(p_{kt+1}, y_{kt+1})} \tag{40}$$

Similar to Chapter 2, the projected prices and harvest prices for the period of 2000-2012 were collected from RMA to measure the historical price-yield correlations among corn, soybeans, spring wheat and winter wheat. Wheat price-yield correlation is the production-weighted average of that for spring and winter wheat. Expected price for each crop is obtained from its corresponding futures market. For corn, I use the average daily settlement price of December

2014 corn futures contract over the 2013 market year[23] to approximate the expected price for the 2014 market year. Expected yield for each crop is set to its average detrended yield in 2014. For wheat, I get the expected revenue by averaging the expected revenue of spring wheat and winter wheat using their respective outputs. In addition, following Lence and Hayes (2002), the total planted acreage in 2014 for these three crops is assumed to be 98% of the land that could be planted to these three crops in order to calibrate the constant parameters. Thus I have $\alpha_{1s} = 0.0644$, $\alpha_{2s} = 0.0660$, and $\alpha_{3s} = 0.0507$.

Marginal Convenience Yield. MCY is calibrated using storers' non-arbitrage conditions: $\frac{E_t(p_{jt+1})}{1+r} + MCY_{jt} = p_{jt} + m_j \;\; j = 1, 2, 3$. Averaged prices received by farmers in both crop year 2002/03 and 2012/13 are collected as spot prices. The average daily settlement prices over the same crop years of harvest futures contract are assembled as expected prices. For wheat, I average the expected price of spring and winter wheat using their production as weights. Annual storage cost is assumed to \$0.36 per bushel for all three crops. The interest rate is set to be 5.26% to allow a depreciation rate of 95%. Below are the calibrated constants:

$$(\alpha_{1c}, \alpha_{2c}, \alpha_{3c}) = (190.025, 158.148, 9.432) \tag{41}$$

$$(\beta_{1c}, \beta_{2c}, \beta_{3c}) = (5.638, 29.272, 5.542) \tag{42}$$

The calibrated MCY for corn, soybeans and wheat are shown in the following three figures. Dots marked in red are the two crop years used for calibration while the blue ones present the 2014 stock level. The charts below indicate that there is almost no convenience benefit to store any additional units of corn for 2015 while it is worth 59 cents and 15 cents respectively for soybeans and wheat farmers to carry one more unit to the 2015 crop year.

[23] Since I am using market year average price as the spot price, so it is better to be consistent to take the average daily settlement price of harvest furtures contract over the same market year.

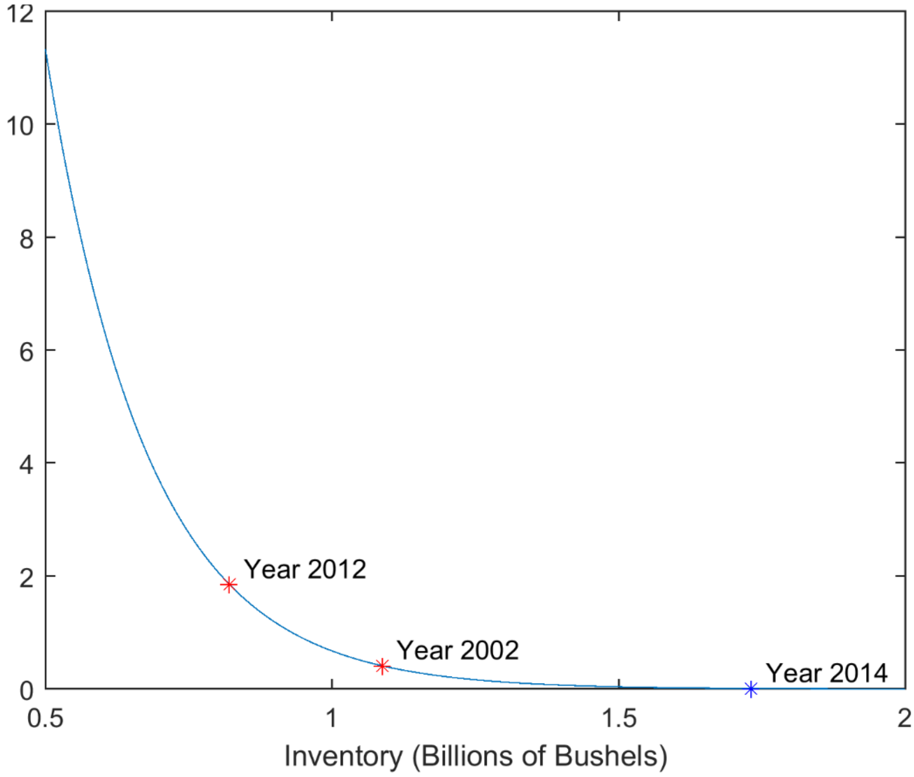

Figure 9. Marginal convenience yield for corn ($/Bushel)

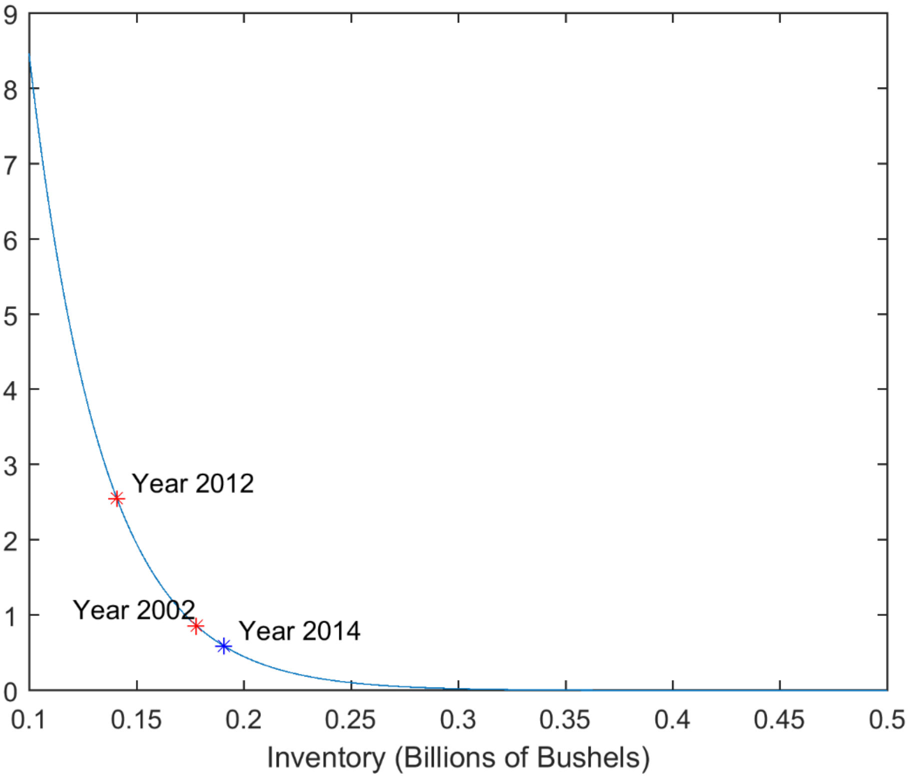

Figure 10. Marginal convenience yield for soybeans ($/Bushel)

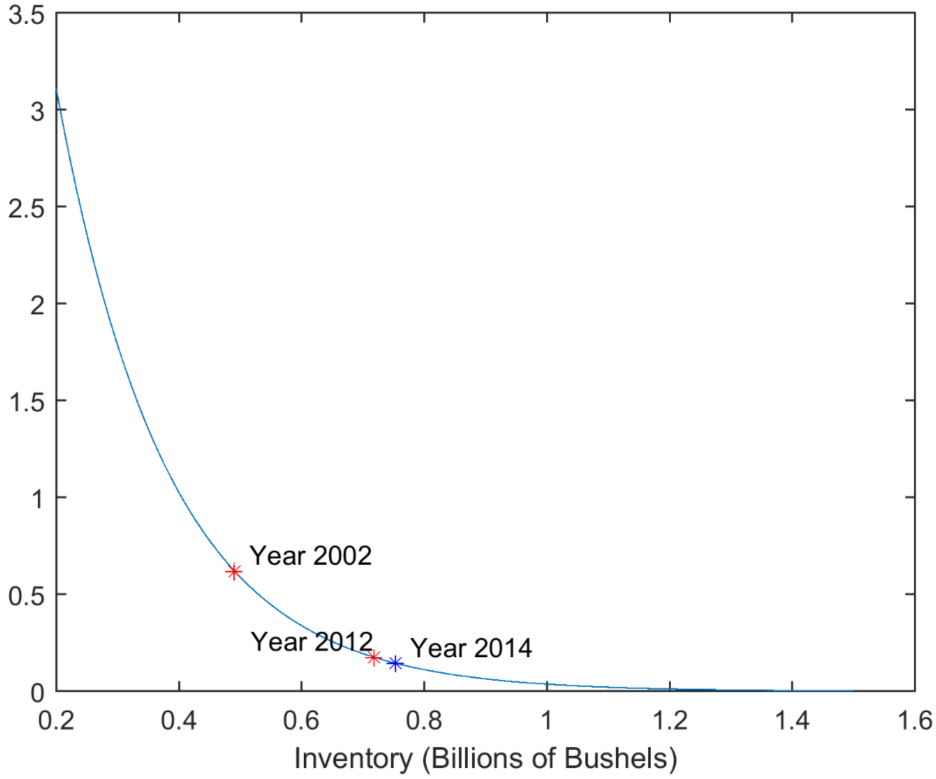

Figure 11. Marginal convenience yield for wheat ($/Bushel)

Figure 12 below displays the approximated optimal storage function for corn given low supply of both soybeans and wheat. The corresponding charts are listed in Figure 13 and 14 for soybeans and wheat. All of them show that the optimal storage is an increasing function of the crop's total supply. Given a positive crop yield shock, the total supply of that crop would increase, which would then lead the current price for that crop to decline, and therefore incentivize the storers to carry more to the next period until the new equilibrium is restored.

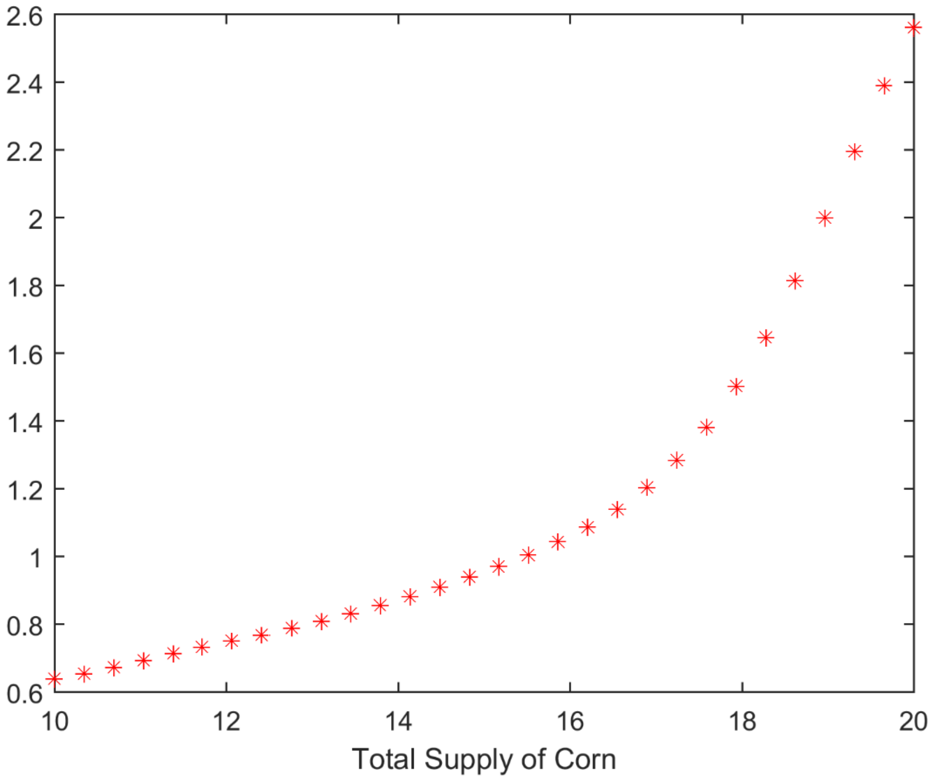

Figure 12. Optimal storage for corn (Billions of Bushels)

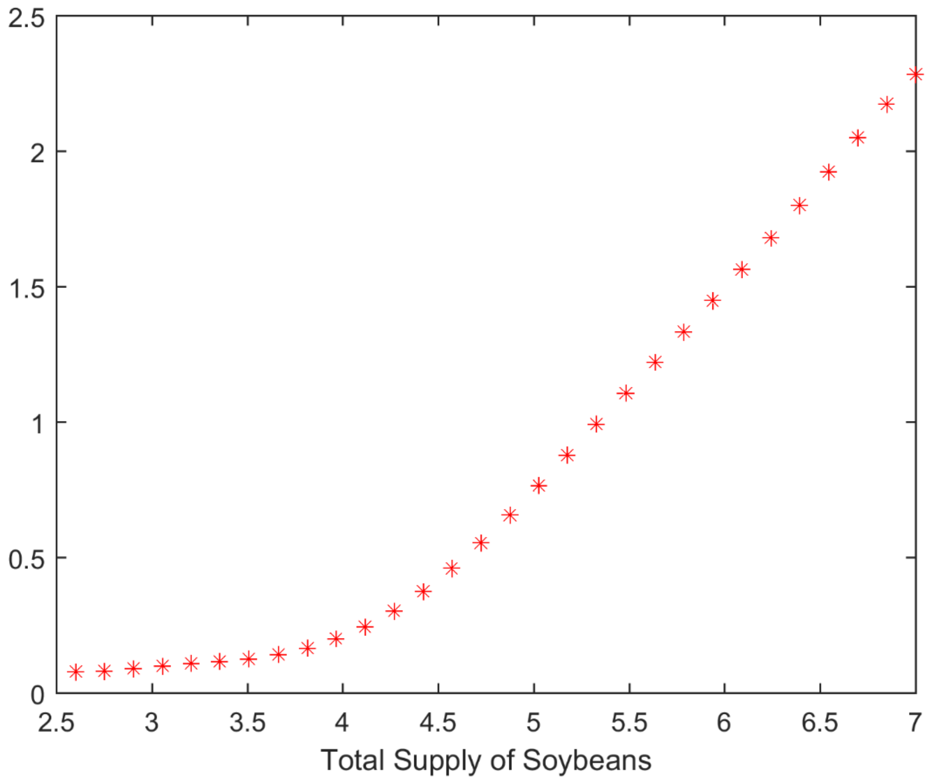

Figure 13. Optimal storage for soybeans (Billions of Bushels)

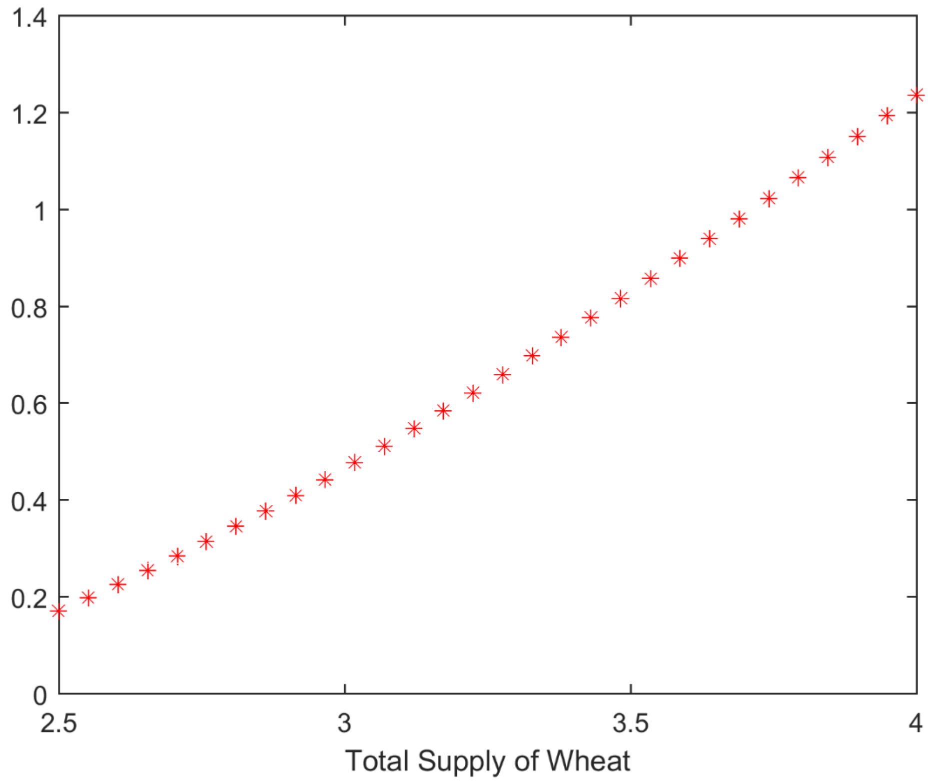

Figure 14. Optimal storage for wheat (Billions of Bushels)

Simulating harvest prices

Since this study is to project five-year (2014-2018) program payments from the perspective of the crop year 2013, I randomly draw a five-year national yield series from the 53 detrended histories with replacement and repeat the process 5000 times to create enough yield samples for each crop. In the meanwhile, in order to maintain the spatial correlations among crops, yields are drawn from the same random years across crops. For example, if the first five yields are drawn from years (1961, 2004, 2010, 1980 and 1961) for corn, then the same five-year yields are selected for both soybeans and wheat. As a result, 5000 five-year sequences of national yields are generated for each crop and applied to the solved storage model to simulate expected harvest prices. Below is the detailed procedure.

1) Input year 2013 ending stock, year 2014 planted acreage and simulated year 2014 national yield draw (the first element in the first five-year yield draws) into the

equation below to calculate TA_{j2014}, the total amount of supply for commodity j in 2014.

$$\mathrm{TA}_{jt} = \mathrm{I}_{jt-1} + A_{jt-1} y_{jt} \quad j = 1, 2, 3. \tag{43}$$

2) Solve for these three variables for each commodity: the ending stock in 2014, the price realized in 2014, and the optimal acreage planted in 2015, which depends on expected price.
3) The solved storage and acreage are then combined with simulated year 2015 yield (the second element in the first five-year yield draws) to get total amount of supply in 2015, and repeat step 2 to solve the corresponding three variables for crop year 2015.
4) Continue the process for 2016-2018 until the first sequence of five yields are all adopted, which would generate a series of five-year prices for each crop.
5) Repeat steps 1-4 with the remaining 4999 five-year yield draws to simulate the corresponding 4999 five-year price series. As a result, 5000 prices will be simulated for each crop and year of 2014-2018.

My purpose in using the storage model to generate prices is to have the prices reflect three market realities. The first is the level of annual (one year ahead) price volatility exhibited by corn, soybean, and wheat prices. Second, as shown by Lence, Hart and Hayes (2009), price volatility increases at a decreasing rate, but slower than at a rate equal to the square root of time due to mean reversion. And third, prices are serially correlated. The instruments I use to calibrate the model are the demand elasticity and the standard deviation of the demand random walk term. More inelastic demand increases price volatility and decreases serial correlation. A larger standard error increases price volatility and increases serial correlation. Because I have only two instruments and three targets, I cannot hit all the targets exactly. The target for base year price volatilities are to match their historical levels, which are 22% for corn, 20% for soybeans and 19% for wheat. These volatilities equal the standard deviation of the annual percentage change in prices over 1980-2014. Second, the amount of serial correlations can be quite close to the levels observed in the historical prices. The price data over 1950-2014 are assembled and fitted with a second degree polynomial time trend. The Pearson correlation between the residual and its lag is calculated to approximate the serial correlations in prices. The estimated autocorrelations are 0.73 for corn, 0.76 for soybeans and 0.72 for wheat. The third target, how much price volatility should deviate from increasing at a rate equal to the square root of time is rather poorly defined. Given the short time period (five years) of this analysis, I deem to have hit this third target as long as price volatility is a concave function of time t, as stated in Lence, Hart and Hayes (2009).

Discussions

As there is no closed form of price volatilities in terms of the two instruments that I manipulate to achieve those three targets, I tried about 250 combinations of those parameters to find a ideal set. I found the following:

1. Larger demand elasticity or more elastic demand would produce a lower base year (2014) price volatility and a stronger price serial correlation. The reason is that with a more elastic demand, prices are less sensitive to the changes in quantities, and therefore given a same yield shock, elastic demand would respond with a smaller change in prices, which results in a lower price volatility and stronger serial dependence.
2. Larger standard deviation of the error term in demand shock increases the base year (2014) price volatility but also the serial correlation. It is one of the two sources that bring in the uncertainty to the model. If the demand shock is more volatile, then it is natural to observe more variable prices. Furthermore, the demand shock is modeled to

be a random walk which accumulates the impacts over periods and therefore increases serial correlations. In addition, larger standard deviation would also increase the likelihood of price volatility to be concave due to the concavity in the variance of the random walk.

Table 12 reports the mean and volatility of simulated prices under three different sets of parameters. The corresponding charts of price volatilities are displayed in Figures 15 - 17. The serial correlations under each set of parameters are presented in Table 14, which are obtained by two steps: 1) line up the first price draw of 2014 with that of 2015 until the 5000th draw of 2017 is paired with 5000th draw of 2018; 2) calculate the Pearson correlation between these 20,000 price pairs and take it as an approximation of serial correlation in simulated prices.

Parameter Set I is the ideal set and will be applied to evaluate ARC, PLC and SCO in the next chapter. It achieved both the target on the base year volatilities and that on increasing and concave pattern of volatilities. Although it did not exactly meet the desired level of serial correlation, it came close. The level of serial correlation for soybeans and wheat are a bit higher than their targets.

Compared to Set I, Set II changes the corn demand elasticity from 0.56 to 0.6. This leads to a slight decrease in base year volatility (22.3% to 21.6%). However, the increase in demand elasticity improves the serial correlations in corn prices (0.728 to 0.75).

The comparison of Set I versus Set III demonstrates the impacts on price volatility and serial dependence from adjusting the standard deviation of the error term in corn demand shock. The result shows higher standard deviation leads to higher base year volatility (22.3% to 26%) and also strengthens the serial correlations in corn prices (0.728 to 0.815).

Instead of having two instruments, I also investigate the possibility of having only one instrument and fixing the demand elasticities at their conventional levels[24]. The results are displayed in Table 13. It shares the same pattern as that in Table 12 regarding standard deviation. However, Set IV fails to meet all three targets. In particular, a more inelastic corn demand, holding the standard deviation of the random walk term constant, results in a near-constant price volatility over time. With higher standard deviation in corn, it starts to show concavity in price volatility, but the base year volatility is too high for corn. Furthermore, the serial correlation for wheat is way too far from its historical level while that for corn is relatively low compared to its historical value. This last example shows the difficulty in calibrating the storage model and the interdependence of the demand elasticity, demand shocks, and yield volatilities in determining how prices behave over time.

[24] The conventional levels are taken from the current literature. I calculate the production-weighted elasticity based on the literature's elasticity for each demand component. For example, corn demand elasticity is the production-weighted average of that for export demand, feed demand, food demand and ethanol demand.

Table 12. Simulated crop prices and their volatilities by different sets of parameters

Parameter Set I:

Demand elasticities=[-0.56; -0.45; -0.15] for corn, soybeans and wheat, respectively;

Sigma=[0.15, 0.14, 0.13] for corn, soybeans and wheat demand shock, respectively;

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.602	22.3%	10.863	19.6%	4.781	19.2%
2015	3.628	27.1%	10.508	23.7%	4.860	25.2%
2016	3.628	31.1%	10.423	27.4%	4.879	28.5%
2017	3.637	34.4%	10.446	30.8%	4.888	31.7%
2018	3.624	37.6%	10.392	33.6%	4.894	34.2%

Parameter Set II:

Demand elasticities=[-0.6; -0.45; -0.15] for corn, soybeans and wheat, respectively;

Sigma=[0.15, 0.14, 0.13] for corn, soybeans and wheat demand shock, respectively;

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.639	21.6%	10.891	19.6%	4.807	19.2%
2015	3.668	26.4%	10.533	23.6%	4.887	25.2%
2016	3.668	30.5%	10.448	27.4%	4.907	28.4%
2017	3.677	33.9%	10.471	30.8%	4.916	31.7%
2018	3.665	37.1%	10.416	33.5%	4.922	34.2%

Parameter Set III:

Demand elasticities=[-0.56; -0.45; -0.15] for corn, soybeans and wheat, respectively;

Sigma=[0.2, 0.14, 0.13] for corn, soybeans and wheat demand shock, respectively;

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.606	26.0%	10.861	19.6%	4.788	19.2%
2015	3.633	32.9%	10.506	23.7%	4.867	25.2%
2016	3.635	38.7%	10.422	27.5%	4.886	28.5%
2017	3.643	43.4%	10.444	30.8%	4.895	31.7%
2018	3.632	47.8%	10.390	33.6%	4.901	34.2%

Note: Sigma is the standard deviation of the error term in demand shocks. And units are $/bu for expected prices, which are the simple averages over 5000 simulated prices for each year and crop.

Table 13. Simulated crop prices and their volatilities under conventional demand elasticities

Parameter Set IV:
Demand elasticities=[-0.36; -0.58; -0.46] for corn, soybeans and wheat, respectively;
Sigma=[0.01, 0.16, 0.17] for corn, soybeans and wheat demand shock, respectively;

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.461	24.0%	11.212	19.5%	5.574	18.6%
2015	3.457	24.4%	10.953	25.0%	5.675	25.6%
2016	3.445	24.4%	10.903	29.6%	5.708	30.6%
2017	3.460	25.0%	10.932	33.6%	5.724	35.1%
2018	3.438	24.7%	10.887	36.9%	5.734	38.9%

Parameter Set V:
Demand elasticities=[-0.36; -0.58; -0.46] for corn, soybeans and wheat, respectively;
Sigma=[0.10, 0.16, 0.17] for corn, soybeans and wheat demand shock, respectively;

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.469	26.2%	11.212	19.5%	5.574	18.6%
2015	3.467	28.3%	10.953	25.0%	5.675	25.6%
2016	3.458	30.3%	10.903	29.6%	5.708	30.6%
2017	3.471	32.0%	10.932	33.6%	5.724	35.1%
2018	3.451	33.5%	10.887	36.9%	5.734	38.9%

Note: Sigma is the standard deviation of the error term in demand shocks. And units are $/bu for expected prices, which are the simple averages over 5000 simulated prices for each year and crop.

Table 14. Serial correlations by different sets of parameters

	Corn Price	Soybeans Price	Wheat Price
Parameter Set I	0.728	0.795	0.804
Parameter Set II	0.750	0.796	0.805
Parameter Set III	0.815	0.795	0.804
Parameter Set IV	0.155	0.873	0.944
Parameter Set V	0.425	0.873	0.944
Historical	0.725	0.762	0.717

Note: Historical serial correlations are derived from crop price data over 1950-2014 available on NASS.

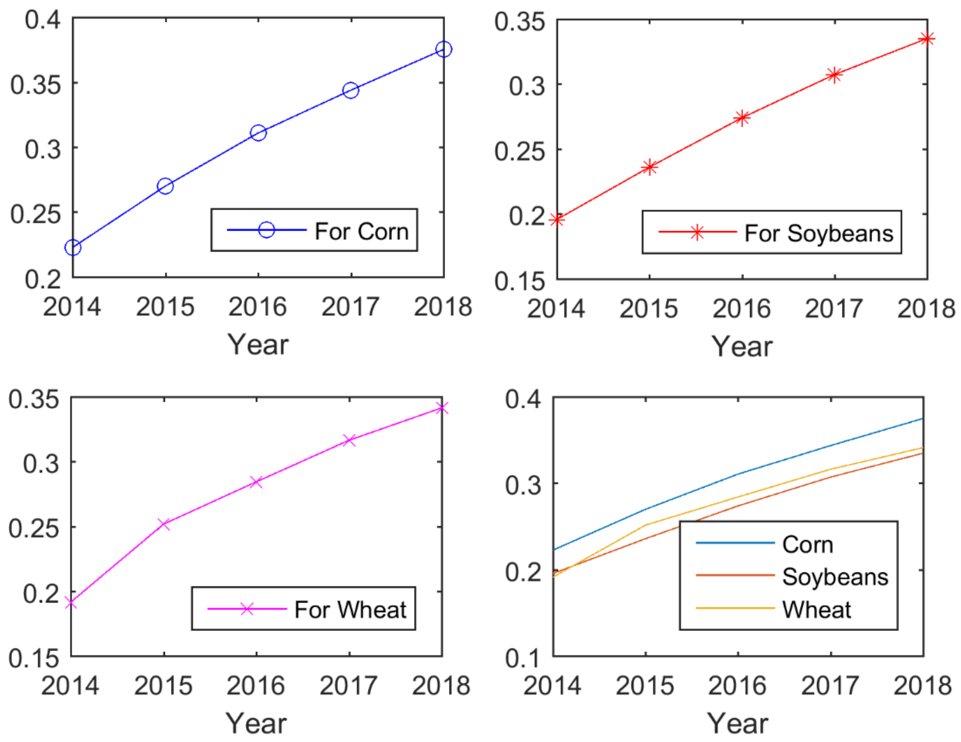

Figure 15. Crop price volatility over 2014-2018 under Parameter Set I

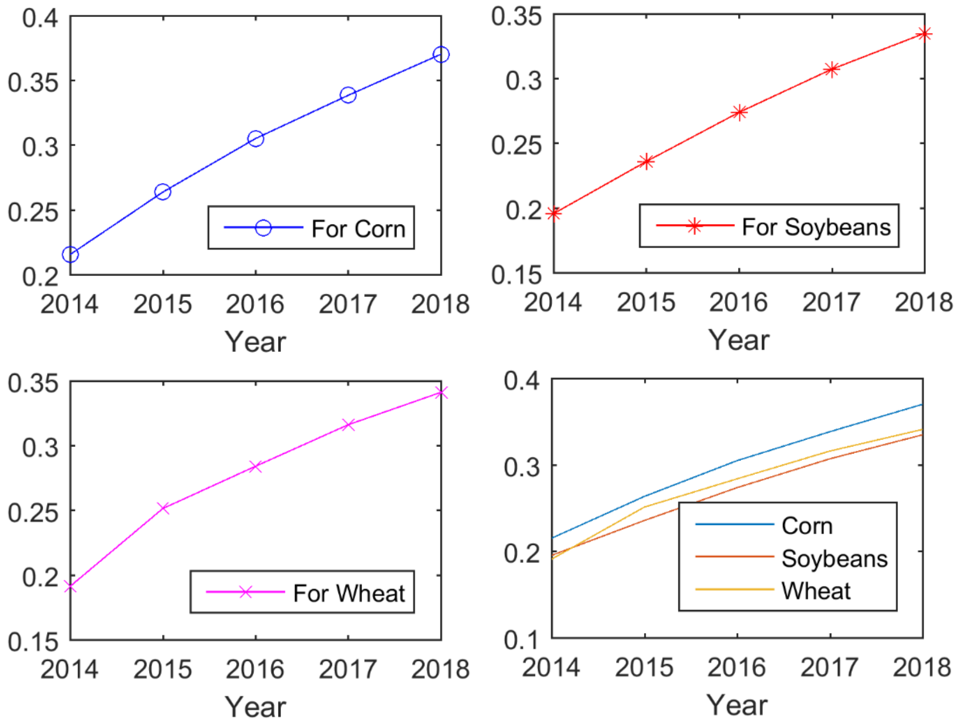

Figure 16. Crop price volatility over 2014-2018 under Parameter Set II

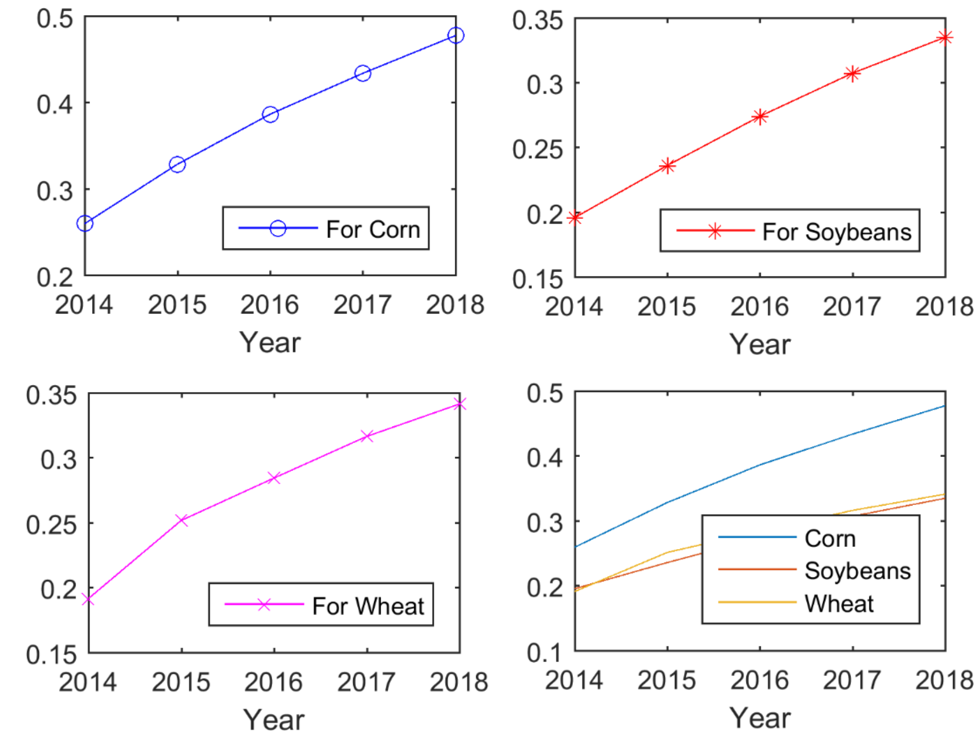

Figure 17. Crop price volatility over 2014-2018 under Parameter Set III

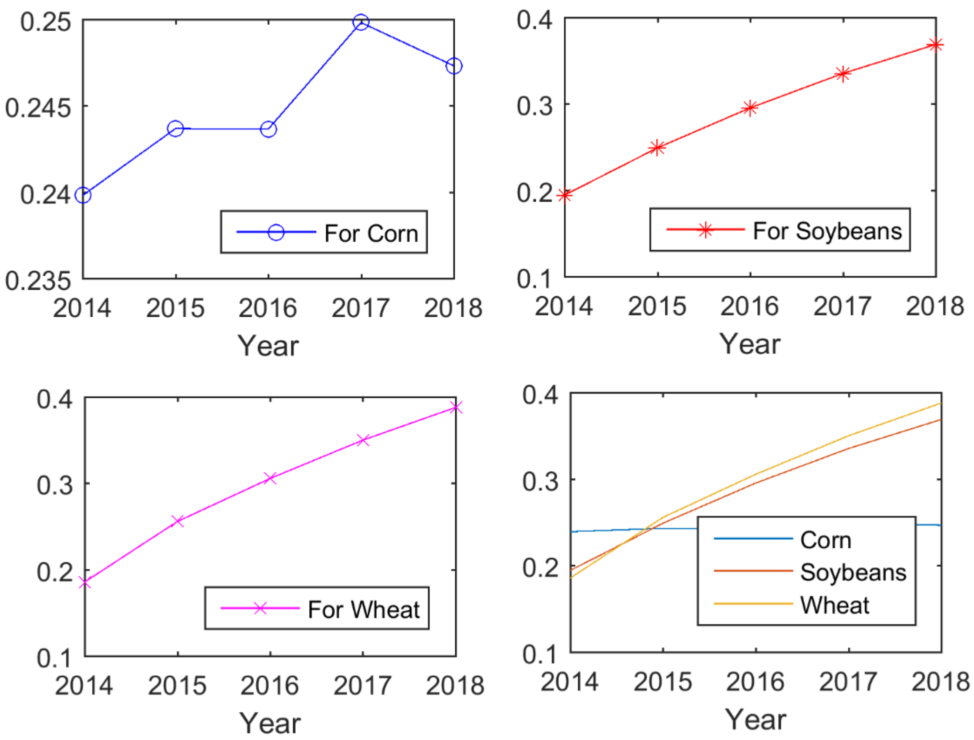

Figure 18. Crop price volatility over 2014-2018 under Parameter Set IV

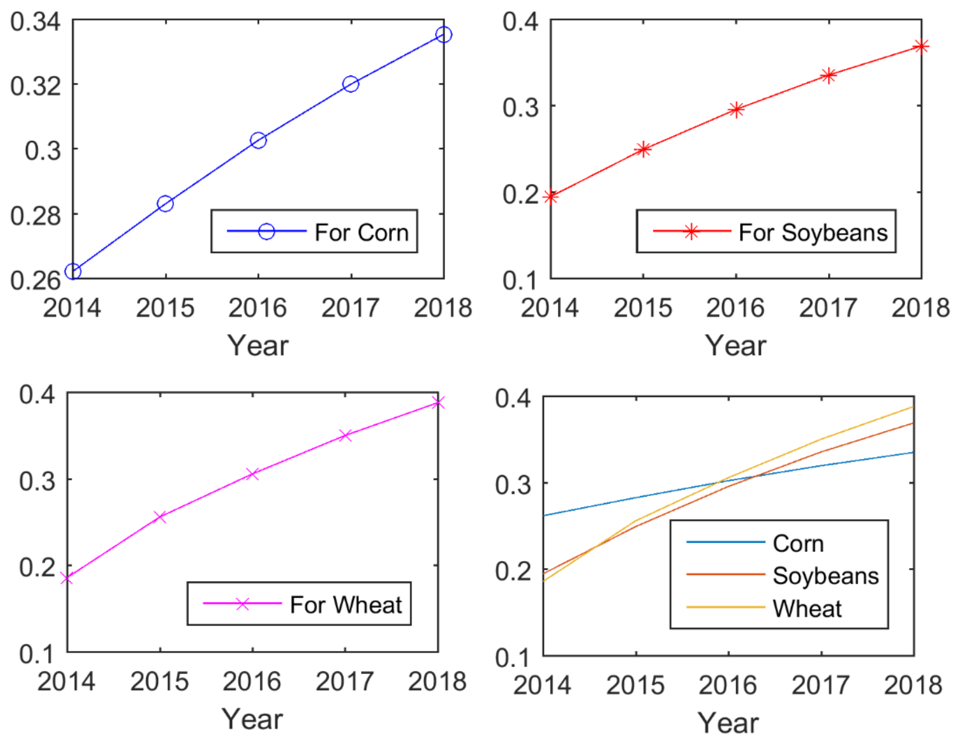

Figure 19. Crop price volatility over 2014-2018 under Parameter Set V

Conclusions

The storage model is capable of simulating serially correlated price draws with price volatilities that increase at a decreasing rate given the demand shock is modeled as a random walk. The results show that if the corn demand elasticity is set too low, then price volatility can increase over time, but only at a cost of having too high price volatility in the base year. However, if demand elasticities are added as another dimension of parameters to be calibrated, then both the base year volatility target and the increase in price volatility target can be met, although the serial correlations observed in wheat is still a little bit higher than its historical level. The storage model successfully incorporates serial dependence into the simulated prices. One potential way of improving the model performance on the second target is to have supply elasticities to be calibrated as well. And this could be explored as future work since there are many acreage combinations of supply elasticities functions that would need to be explored. The price draws are created while maintaining the correlations between yields shocks because I use empirical yield distributions that maintain the spatial correlations of yield across different crops to simulate prices.

CHAPTER 4

NEW COMMODITY PROGRAMS UNDER 2014 FARM BILL

Introduction

The simulated price draws and empirical yield distributions generated in Chapter 3 are used to estimate the cost of the new safety net programs passed by Congress as part of the new farm bill. The safety net programs that will be examined include Agriculture Risk Coverage (ARC), Price Loss Coverage (PLC) and Supplemental Coverage Option (SCO).

Farmers had to make a one-time, irrevocable decision between PLC and ARC, and then stick to their choice for the entire farm bill period. For those who failed to make a final decision, PLC was their default option. Congress passed these new programs ostensibly to save money. CBO estimated the cost of the program using their now standard way of stochastic scoring. CBO assumes a constant level of price volatility and makes projections about mean commodity prices. Price draws from year to year are independent. This method of estimating costs is not consistent with the fact that prices are serially correlated over time. Furthermore, the assumption of constant price volatility ignores the fact that serial correlation in price creates commodity price volatility that increases over time, albeit at a decreasing rate. One justification for using CBO's assumption of constant price volatility is that conditional on a given level of expected price in a given year, price volatility in the next year may be approximately constant. However, the unconditional price volatility at the beginning of the projection period must increase over time because the level of expected price in the future is not known. As such, the CBO assumption should underestimate the actual expected costs of farm programs. The objective of this chapter is to estimate the magnitude of this underestimation and to determine whether there exists an easy fix for CBO to correct its method of estimating farm program costs.

Besides CBO, the other important estimator of farm program costs is the Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri. FAPRI maintains two separate but related U.S. crops models: a deterministic U.S. crops model and a stochastic U.S. crops model. The deterministic model is used primarily to develop baseline while the stochastic model is calibrated to the deterministic baseline. Specifically, the demand curve was shocked by an i.i.d error term to generate 500 sets of 10-year price projections from their stochastic model. The simulated prices might have some serial correlation because of the structure of the model. But their model is not a storage model and it does not have a random walk in terms of a demand shock. That is each demand shock occurs off a known mean demand and are i.i.d from year to year. Furthermore, the FAPRI model only shocks export demand. So price volatility does not increase over time. So although both CBO and FAPRI use stochastic scoring methods to determine expected program costs, neither use a method that accounts for increasing price volatility and serial correlation in prices.

Overview of Programs

ARC is a revenue insurance program that covers ‘shallow losses’. It has both county-based and individual-based options and covers per acre revenue shortfalls between 76 percent and 86 percent coverage. For those who sign up for the ARC program, no premium would be charged for the coverage, and a payment would be made on 85 percent (65 percent) of the sum of base acres and generic acres planted to covered crops for county-based ARC (individual-based ARC). The payment for producers enrolled in county ARC is described as follows

$$\mathrm{PAY}_{ARC,Co} = 0.85A_{farm}\min\{\max[(0.86ExpRev - ActRev)\,,0]\,,0.1ExpRev\} \qquad (44)$$

where A_{farm} is the base acre. $ExpRev$ is the expected county revenue or the benchmark revenue defined as the product of the following (A) and (B):

(A) Olympic average of county yields over the most recent five crop years, which is obtained by excluding the highest and lowest yields and then taking the average;

(B) Olympic average of national market year average (MYA) prices in last five crop years, which is similarly obtained as that for yield;

According to 2014 Farm Bill, if the yield for any of the most recent five years is less than 70% of the transitional yield, it will be replaced with 70% of the transitional yield to construct the Olympic average in subparagraph (A). In this study, I replaced it with 70% of the county trend yield.

In subparagraph (B), if the national MYA price for any of the most recent five years is lower than the reference price set for the covered commodity, it will be replaced with the corresponding reference price. The reference price is \$3.70 per bushel for corn, \$8.40 per bushel for soybeans and \$5.50 per bushel for wheat.

$ActRev$ is the actual county revenue, which is the product of these two items:

(C) The actual average county yield for the covered commodity;

(D) The higher of

i. The national average market price received by producers during the 12-month marketing year for the covered commodity;

ii. The national average loan rate (\$1.95 per bushel for corn, \$5.00 per bushel for soybeans and \$2.94 per bushel for wheat) for a marketing assistance loan for the covered commodity in effect for that crop year;

As for those producers enrolled in individual ARC, their payments are given by

$$\text{PAY}_{ARC,Ind} = 0.65A_{farm}\min\{\max[(0.86ExpRev - ActRev), 0], 0.1ExpRev\} \quad (45)$$

In equation (45), A_{farm} is the base acre. $ExpRev$ is the expected farm revenue or benchmark revenue for the farm, which is determined as follows:

(A) For each covered commodity and each of the most recent five years, the revenue is calculated by multiplying the yield of the covered commodity by the national MYA price for that covered commodity;

(B) For each covered commodity, the benchmark revenue is obtained by calculating its Olympic average, which is the average revenue after excluding the highest and lowest values among the most recent five years.

(C) The benchmark revenue for the farm is obtained by weighting the amounts in subparagraph (B) using their planted acreage.

Likewise, the low yield for any of the five most recent years will be updated to the 70 percent of the trend yield if it is less than 70% of the trend yield. The national MYA price in last five years will be replaced with the reference price if it is lower than that. $ActRev$ is the realized farm revenue, which is determined by:

(D) For each covered commodity, the realized revenue is the product of

i. The total production of the covered commodity on such farms;

ii. The higher of

a. The national average market price received by producers during the 12-month marketing year;

b. The national average loan rate for a marketing assistance loan for the covered commodity in effect for that crop year;

(E) The sum of the amounts got from subparagraph (D) for all covered commodity on such farms;

(F) The quotient obtained by dividing the amount determined in subparagraph (E) by the total planted acres of all covered commodities on such farms.

PLC is a price support program like the eliminated counter cyclical program but with much higher target prices for most commodities. The target or reference prices are \$3.70 per bushel for corn, \$8.40 per bushel for soybeans, and \$5.50 per bushel for wheat. Farmers who enroll in PLC would receive a payment when the effective price of a crop is less than its reference price p_{ref}. The effective price is defined as the higher of the following two items:

(A) The national average market price received by farmers during the 12-month marketing year p_{mkt};

(B) The national average loan rate p_{loan}, which is fixed at \$1.95 per bushel for corn, \$5.00 per bushel for soybeans and \$2.94 per bushel for wheat.

The payment is calculated as follows:

$$\mathrm{PAY}_{PLC} = 0.85 A_{farm} y_{PLC} \max[p_{ref} - \max(p_{mkt}, p_{loan}), 0] \tag{46}$$

where A_{farm} denotes the base acre. y_{PLC} is the payment yield used for calculating counter cyclical program payments and it can be updated to 90 percent of the farm's average yield per planted acre over the 2008-2012 crop years, excluding the crop year with zero acreage planted. And I assume all the farmers would update their payment yields to 90% of the average yield over 2008-2012.

SCO is a county-based insurance program that farmers can buy if they sign up for PLC. It will cover revenue losses between the coverage level chosen for farm-level revenue insurance and 86 percent coverage, so it is not overlapping with crop insurance. Farmers who sign up for ARC are not eligible to buy SCO. SCO premiums are subsidized at a 65 percent rate. Thus farmers who buy SCO only need to pay 35 percent premium in order to get a SCO payment which is listed in the following

$$\mathrm{PAY}_{SCO} = A_{farm} \min\left(\max\left[\frac{\left(0.86 - \frac{ActRev}{ExpRev}\right)}{(0.86 - CL)}, 0 \right], 1 \right) * (0.86 - CL) * ExpRev \tag{47}$$

where $ExpRev$ is the expected county revenue calculated as the product of projected price and expected county yield. $ActRev$ is the realized county revenue. CL is the producer's coverage level for farm-level revenue insurance. A_{farm} is the planted acre for covered commodities. The above formula says that if a producer selects a coverage of 75 percent, and if the actual county revenue is above 75 percent but less than 86 percent of expected county revenue, then he will be paid the difference between 0.86*ExpRev and ActRev, that is $0.86 * \text{ExpRev} - \text{ActRev}$, otherwise, he will be paid $0.86 * \text{ExpRev} - 0.75 * \text{ExpRev}$.

As a benchmark, Babcock and Paulson's stochastic model in 2012 is adopted to simulate serially uncorrelated price draws and then applied to ARC, PLC and SCO to estimate the program costs. It is denoted as the CBO scenario in this research because they were trying to emulate how CBO scores farm programs. In order to be comparable with the results from the storage model, the national yields that are used to simulate price draws are also randomly generated from the 53 yield histories with replacement. Furthermore, the resorted uniformly distributed draws are transformed to lognormal-distributed harvest price draws with mean and volatilities set equal to the corresponding levels projected by the storage model. The statistics (expected prices and volatilities) of the simulated prices from the storage model are listed in Table 15. For each commodity, the change in expected prices is limited over periods due to the "stationary" world built into this study. By "stationary" I mean that the average demand curve and the average supply curve are same across the five-year simulation. Furthermore, the yield distribution is held constant because I use the same empirical yield distribution for each year of the simulation.

Table 15. The statistics of simulated prices from storage model by crop and year

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.602	22.3%	10.863	19.6%	4.781	19.2%
2015	3.628	27.1%	10.508	23.7%	4.860	25.2%
2016	3.628	31.1%	10.423	27.4%	4.879	28.5%
2017	3.637	34.4%	10.446	30.8%	4.888	31.7%
2018	3.624	37.6%	10.392	33.6%	4.894	34.2%

Note: Units are $/bu for expected prices, which are the simple averages over the 5000 simulated prices for each year and crop.

Table 16. The statistics of simulated prices under CBO scenario by crop and year

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.611	22.0%	10.812	19.4%	4.770	19.1%
2015	3.638	22.5%	10.478	19.8%	4.855	19.3%
2016	3.649	22.3%	10.407	19.2%	4.866	19.3%
2017	3.633	22.8%	10.449	19.7%	4.878	19.3%
2018	3.624	22.5%	10.374	19.5%	4.903	19.2%

Note: Units are $/bu for expected prices. They are set according to the storage model in order to be comparable.

Table 17. The statistics of simulated prices with increasing volatility under CBO scenario by crop and year

	Corn		Soybeans		Wheat	
Year	Expected Price	Volatility	Expected Price	Volatility	Expected Price	Volatility
2014	3.611	22.0%	10.812	19.4%	4.770	19.1%
2015	3.641	27.2%	10.473	23.8%	4.854	25.5%
2016	3.656	31.2%	10.396	26.8%	4.861	28.7%
2017	3.633	35.2%	10.453	31.0%	4.872	31.9%
2018	3.626	37.9%	10.359	33.2%	4.910	34.1%

Note: Units are $/bu for expected prices. They are set according to the storage model in order to be comparable.

Table 18. Serial correlations under CBO scenario

	Corn Price	Soybeans Price	Wheat Price
Fixed Price Volatilities	-0.005	-0.005	0.003
Concave Price Volatilities	-0.003	-0.005	0.003

Table 16 presents the corresponding summary of the simulated prices under CBO scenario assuming that the price volatilities are fixed at the 2014 level of the storage model. Even though I am targeting the same magnitude of expected prices according to the storage model, the resulted expected prices using CBO method will still be slightly different from that in the storage model due to pseudorandom number generator in Matlab. Since I am also interested in isolating the impacts of serial correlation from increasing and concave price volatilities, another set of prices are simulated for CBO scenario by imposing the same magnitude of price volatilities as that under the storage model. The simulated prices will be applied to PLC only. The statistics are provided in Table 17. As shown in Table 18, there is almost zero serial dependence among simulated prices using Babcock and Paulson’s method.

Results and Discussions

For both the storage model and CBO scenario, 5000 five-year yield series are generated from the empirical distributions of national yields for each crop. The county-level yields over the same period are collected and detrended to 2014 equivalents:

$$y_{ijt}^{det} = \frac{y_{ijt} * y_{ij2014}^{tre}}{y_{ijt}^{tre}} \text{ , t} = 1961, \dots, 2013, \text{j} = 1, 2, 3. \tag{48}$$

where y_{ij2014}^{tre} is the trend yield of county i in 2014. County yields from the same years as the drawn national yields are drawn not only to maintain the national and county yield correlations, and to preserve the spatial correlation among crops and counties, but also to be able to estimate price-yield correlations at the county level in a natural way. Specifically, if the first five-year sequence of national yields are selected from (1961, 2009, 2000,1988, 2009), then the same five year yields are picked for each county in the same order. As a result, 5000 five-year yield samples are created for each county. Moreover, the historical correlation between national-level yields and prices are preserved by matching every row (year) of county yield with the corresponding row of harvest price draws.

For ARC-county, two different ways of constructing price guarantees are investigated. One is to build a draw-specific price guarantee and therefore 5000 different price guarantees are created for 2015. Similarly, I would have 5000 price guarantees the remaining three years. As a result, the price guarantee is not only annually adjusted but also draw-specific. The other is to have one common price guarantee for the 5000 price draws by calculating the Olympic average of the historical and averaged simulated prices. For example, the Olympic average of 2010-2013 historical prices and averaged simulated price in 2014 would produce one common price guarantee for 2015.

Table 19 displays the expected payments per base acre for county-based ARC by crop and scenario assuming the same price guarantee is shared among the 5000 draws for a given crop year. For a corn farmer, if he chose to enroll in ARC-county, he would expect to receive $57.18/base acre in 2014 but much less payments in the remaining four years, which is mainly due to the drop in price guarantees year over year. Because ARC uses a five-year Olympic average of prices and yields, historical price data over 2009-2013 (listed in Table 20) is assembled to build 2014 price guarantees. The price guarantees for 2015 are constructed by historical price data over 2010-2013 and 5000 simulated prices for 2014.

Table 19. Expected county-based ARC payments with common price guarantee for a given crop year

Year	Corn		Soybeans		Wheat	
	Storage Model	CBO Scenario	Storage Model	CBO Scenario	Storage Model	CBO Scenario
2014	57.18	55.59	13.69	15.29	16.63	16.46
2015	53.43	53.94	18.44	17.92	16.71	16.51
2016	40.64	40.08	19.33	17.34	16.21	16.07
2017	23.00	18.93	17.25	13.92	13.31	12.67
2018	21.59	15.89	15.90	11.58	10.72	9.21

Note: All units are $/base acre. The payment for each year and crop is based on 5000 simulated prices and fixed price guarantees.

Table 20. Historical and projected crop prices

Year	Corn	Soybeans	Wheat
2009	3.70	9.59	5.50
2010	5.18	11.30	5.70
2011	6.22	12.50	7.24
2012	6.89	14.40	7.77
2013	4.50	12.30	6.80
2014	3.60	10.86	4.78
2015	3.63	10.51	4.86
2016	3.63	10.42	4.88
2017	3.64	10.45	4.89
2018	3.62	10.39	4.89

Note: All units are $/bu. Prices for 2014-2018 are projected by the storage model, simply averaging over 5000 simulated prices for the corresponding year.

Table 20 lists the historical crop prices over 2009-2013 and projected prices over 2014-2018. For corn and wheat, the simulated prices on average are much lower than their historical levels. Consequently, the price guarantees would decrease over time, which would therefore induce smaller payments year over year.

As shown in Table 19, if the price guarantee is not draw specific, then payments under storage model are substantially higher than using the CBO method. In other words, ignoring serial dependence and keeping price volatility constant would underestimate the payments for ARC-county. However, as displayed in Table 21, there is no obvious difference in expected payments between prices generated by the storage model and prices generated using the CBO method. Because positive cost effects from serial dependence and increasing price volatility are offset by more volatile price guarantees. Given a negative demand shock or a positive supply shock in 2016, the market price would be low in 2016. Due to the price serial correlations, the market price in 2017 would be low as well, If the price guarantee is draw specific, then the lower market price would result in a relatively lower price guarantee and therefore a smaller amount of payments, but if a constant price guarantee is used as in PLC, then the payments will be high in 2017.

Table 21. Expected county-based ARC payments by crop and scenario with draw-specific price guarantees

Year	Corn		Soybeans		Wheat	
	Storage Model	CBO Scenario	Storage Model	CBO Scenario	Storage Model	CBO Scenario
2014	57.18	55.59	13.69	15.29	16.63	16.46
2015	54.11	54.70	19.16	19.52	16.84	16.77
2016	44.42	45.80	18.91	20.07	16.69	16.79
2017	26.35	27.18	15.25	17.82	14.14	13.86
2018	24.67	24.31	11.35	14.48	11.56	10.62

Note: All units are $/base acre. The payment for each year and crop is based on 5000 simulated prices and 5000 price guarantees.

Similarly as for county-based ARC, two different sets of price guarantees are constructed for SCO. The per acre SCO payments that are calculated using a constant price guarantee for a given crop year are listed in Table 22 for corn, Table 23 for soybeans and Table 24 for wheat. As expected, for each crop, no matter which coverage level farmers choose, they would receive more payments if they have Revenue Protection instead of Revenue Protection with harvest price exclusion in place to insure their crop revenue.

Furthermore, as the coverage level for the underlying crop insurance product increases, payments under both RP and RP-HPE decline. Because SCO program only covers losses that fall between the coverage level of the underlying policy and 86% of expected revenue. A full amount of SCO coverage is paid when the county average revenue falls to the coverage level of the underlying policy. Corn farmers would receive $22.52 per planted acre if they choose 70% coverage of Revenue Protection in 2014, while they receive only $2.59 per planted acre if insured under 85% coverage for the same crop year.

In addition, given a certain coverage level, payments would grow significantly over time under the storage model while the payments using CBO method are stationary across years. Compared to 2014 crop year, the per acre payments are expected to increase at least 27% for RP and 31% for RP-HPE in 2018. To sum up, ignoring both intermporal price correlations and increasing price volatilities would lead to an underestimate of the costs for SCO if a same price guarantee is adopted for a given crop year.

Table 22. Expected SCO payments for corn by policy and scenario with common price guarantee for a given crop year

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	22.52	18.07	11.67	2.59
	2015	28.16	22.03	13.80	2.93
	2016	31.40	24.14	14.86	3.09
	2017	34.22	26.05	15.88	3.24
	2018	35.48	26.79	16.18	3.28
	CBO Scenario:				
	2014	23.00	18.48	11.92	2.63
	2015	23.82	19.11	12.31	2.70
	2016	23.21	18.64	12.02	2.65
	2017	24.19	19.40	12.47	2.72
	2018	23.46	18.80	12.09	2.66
RP-HPE	Storage Model:				
	2014	16.47	13.35	8.70	2.02
	2015	21.88	17.12	10.70	2.33
	2016	24.84	19.02	11.63	2.46
	2017	27.46	20.75	12.51	2.60
	2018	28.78	21.55	12.86	2.64
	CBO Scenario:				
	2014	18.11	14.63	9.45	2.15
	2015	18.80	15.14	9.76	2.20
	2016	18.15	14.66	9.47	2.15
	2017	18.92	15.25	9.82	2.22
	2018	18.42	14.82	9.54	2.16

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 23. Expected SCO payments for soybeans by policy and scenario with common price guarantee for a given crop year

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	17.13	14.00	9.17	2.13
	2015	20.33	16.16	10.28	2.29
	2016	22.68	17.69	11.04	2.40
	2017	24.94	19.24	11.86	2.53
	2018	25.81	19.71	12.04	2.55
	CBO Scenario:				
	2014	17.68	14.31	9.28	2.12
	2015	17.28	13.99	9.06	2.08
	2016	16.62	13.51	8.80	2.04
	2017	17.52	14.16	9.17	2.10
	2018	16.71	13.55	8.81	2.03
RPHPE	Storage Model:				
	2014	12.74	10.48	6.93	1.69
	2015	16.05	12.72	8.08	1.85
	2016	18.29	14.16	8.78	1.95
	2017	20.39	15.57	9.51	2.06
	2018	21.35	16.11	9.72	2.09
	CBO Scenario:				
	2014	14.52	11.76	7.64	1.80
	2015	14.23	11.53	7.48	1.77
	2016	13.62	11.10	7.25	1.73
	2017	14.37	11.63	7.54	1.78
	2018	13.74	11.16	7.26	1.73

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 24. Expected SCO payments for wheat by policy and scenario with common price guarantee for a given crop year

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	9.57	7.66	4.97	1.28
	2015	11.77	9.24	5.85	1.42
	2016	12.86	9.98	6.24	1.48
	2017	13.80	10.61	6.57	1.53
	2018	14.41	10.99	6.76	1.56

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 24 continued

	Coverage Level	0.7	0.75	0.8	0.85
RP	CBO Scenario:				
	2014	9.72	7.74	5.00	1.27
	2015	9.78	7.79	5.03	1.28
	2016	9.84	7.84	5.05	1.28
	2017	9.83	7.84	5.06	1.29
	2018	9.84	7.84	5.07	1.29
RPHPE	Storage Model:				
	2014	7.43	5.97	3.89	1.07
	2015	9.36	7.34	4.64	1.19
	2016	10.37	8.01	4.99	1.24
	2017	11.17	8.52	5.24	1.28
	2018	11.74	8.87	5.40	1.30
	CBO Scenario:				
	2014	8.09	6.43	4.15	1.11
	2015	8.14	6.48	4.18	1.12
	2016	8.20	6.51	4.19	1.12
	2017	8.18	6.51	4.20	1.12
	2018	8.18	6.51	4.20	1.12

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 25 gives the per acre SCO payments for corn farmers if price guarantee is draw specific, and the corresponding results for soybeans and wheat farmers are listed in Table 26 and Table 27. These sets of results are how program costs should be calculated because the guarantee reflects market conditions, which is how the programs are supposed to work. For each year's simulation under the storage model, I am able to obtain 5000 actual price realizations and 5000 expected price realizations using the storer's non-arbitrage conditions. The 5000 price guarantees in 2015 are simulated in 2014 and so on. Since 2014 is the year that started the simulation, no corresponding expected prices could be simulated, so I am still using a constant averaged price as the price guarantee.

Similarly as ARC-county, for all three crops, payments with draw-specific price guarantee tend to be stable across years due to the offsetting effects from more volatile price guarantees. However, the payments under the storage model with draw-specifice price guarantees would be much lower than that under CBO scenario. One possible explanation is that the storage model can rationally and more accurately adjust its expectation on prices given any market environment.

Table 25. Expected SCO payments for corn by policy and scenario with draw-specific price guarantees

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	22.52	18.07	11.67	2.59
	2015	16.42	13.35	8.89	2.11
	2016	15.88	12.89	8.58	2.06
	2017	16.24	13.16	8.76	2.08
	2018	15.77	12.80	8.54	2.05
	CBO Scenario:				
	2014	23.00	18.48	11.92	2.63
	2015	23.82	19.11	12.31	2.70
	2016	23.21	18.64	12.02	2.65
	2017	24.19	19.40	12.47	2.72
	2018	23.46	18.80	12.09	2.66
RPHPE	Storage Model:				
	2014	16.47	13.35	8.70	2.02
	2015	10.49	8.75	6.01	1.57
	2016	10.01	8.34	5.75	1.52
	2017	10.21	8.49	5.85	1.53
	2018	10.04	8.36	5.77	1.52
	CBO Scenario:				
	2014	18.11	14.63	9.45	2.15
	2015	18.80	15.14	9.76	2.20
	2016	18.15	14.66	9.47	2.15
	2017	18.92	15.25	9.82	2.22
	2018	18.42	14.82	9.54	2.16

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 26. Expected SCO payments for soybeans by policy and scenario with draw-specific price guarantees

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	17.13	14.00	9.17	2.13
	2015	12.71	10.57	7.16	1.79
	2016	11.96	9.95	6.75	1.71
	2017	11.94	9.91	6.71	1.69
	2018	11.62	9.66	6.56	1.67
	CBO Scenario:				
	2014	17.68	14.31	9.28	2.12
	2015	17.28	13.99	9.06	2.08
	2016	16.62	13.51	8.80	2.04
	2017	17.52	14.16	9.17	2.10
	2018	16.71	13.55	8.81	2.03
RPHPE	Storage Model:				
	2014	12.74	10.48	6.93	1.69
	2015	9.24	7.81	5.42	1.45
	2016	8.50	7.20	5.02	1.38
	2017	8.39	7.09	4.93	1.35
	2018	8.31	7.02	4.90	1.35
	CBO Scenario:				
	2014	14.52	11.76	7.64	1.80
	2015	14.23	11.53	7.48	1.77
	2016	13.62	11.10	7.25	1.73
	2017	14.37	11.63	7.54	1.78
	2018	13.74	11.16	7.26	1.73

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices..

Table 27. Expected SCO payments for wheat by policy and scenario with draw-specific price guarantees

	Coverage Level	0.7	0.75	0.8	0.85
RP	Storage Model:				
	2014	9.57	7.66	4.97	1.28
	2015	8.21	6.63	4.38	1.18
	2016	8.14	6.57	4.35	1.17
	2017	8.12	6.56	4.33	1.16
	2018	8.06	6.51	4.31	1.16
	CBO Scenario:				
	2014	9.72	7.74	5.00	1.27
	2015	9.78	7.79	5.03	1.28
	2016	9.84	7.84	5.05	1.28
	2017	9.83	7.84	5.06	1.29
	2018	9.84	7.84	5.07	1.29
RPHPE	Storage Model:				
	2014	7.43	5.97	3.89	1.07
	2015	6.09	4.95	3.31	0.97
	2016	6.07	4.93	3.28	0.96
	2017	6.04	4.91	3.27	0.96
	2018	6.00	4.87	3.25	0.96
	CBO Scenario:				
	2014	8.09	6.43	4.15	1.11
	2015	8.14	6.48	4.18	1.12
	2016	8.20	6.51	4.19	1.12
	2017	8.18	6.51	4.20	1.12
	2018	8.18	6.51	4.20	1.12

Note: All units are $/planted acre. The payment for each crop and year is based on 5000 simulated prices.

Table 28. Expected PLC payments by crop and scenario

Year	Corn		Soybeans		Wheat	
	Storage Model	CBO Scenario I	Storage Model	CBO Scenario I	Storage Model	CBO Scenario I
2014	48.95	48.45	2.66	3.32	33.13	33.39
2015	55.40	47.59	8.30	4.59	34.58	31.10
2016	61.70	46.45	13.03	4.41	35.59	30.83
2017	65.30	48.17	16.24	4.58	36.62	30.62
2018	69.19	48.56	19.40	5.05	37.38	29.74

Note: All units are $/base acre. The payment for each crop and year is based on 5000 simulated prices. In addition, the price volatilities for CBO scenario are fixed at the 2014 levels projected by the storage model.

Table 28 displays the expected payments per base acre for PLC. The payments under CBO Scenario I are based on the assumption that the price volatilities are constant over the five-year simulation for each crop and fixed at 2014 levels projected by the storage model. Corn farmers would receive most payments under PLC beacuse the simulated prices for corn is further below its reference price ($3.70/bushel) than the other two crops. Furthermore, PLC payments under the storage model increase dramatically over periods while they stay steady if using CBO method. The most notable increase is observed in soybeans. Soybeans farmers would receive a payment of $19.4 per acre in 2018 which is only $2.66 per acre in 2014. Alike as ARC and SCO, the payments would be underestimated if serial correlation and increasing price volatility are ignored.

As is mentioned in the beginning of this chapter, another set of CBO prices are simulated by incorporating the same magnitude of price volatilities as that under the storage model. The simulated prices are then applied to PLC to isolate the impacts on cost estimatons of serial correlations. The results are listed in Table 29. After imposing the increasing price volatilities, a similar pattern of the payments as that under the storage model is found for CBO secenario, that is the payments grow significantly over time, which indicates that increasing price volatility accounts for the most part of the increase in program costs. The mild differences in the payments between the storage model and CBO scenario are attributed to the fact that the expected prices and volatities using CBO method are slightly different from that under the storage model (refer to Table 15 and Table 17). Instead of using a complicated storage model, CBO could inflate the price volatilities over periods and come up with a more accurate program cost estimations.

Table 29. Expected PLC payments by crop and scenario

Year	Corn		Soybeans		Wheat	
	Storage Model	CBO Scenario II	Storage Model	CBO Scenario II	Storage Model	CBO Scenario II
2014	48.95	48.45	2.66	3.32	33.13	33.39
2015	55.40	55.97	8.30	7.97	34.58	34.83
2016	61.70	61.49	13.03	11.24	35.59	36.59
2017	65.30	69.05	16.24	14.82	36.62	38.48
2018	69.19	73.77	19.40	18.22	37.38	38.58

Note: All units are $/base acre. The payment for each crop and year is based on 5000 simulated prices. In addition, the price volatilities are also increasing and concave for CBO scenario.

Conclusions

Program payments for PLC are underestimated if both price serial correlations and increasing price volatilities are ignored. Furthermore, the impacts from serial correlations are isolated by a further test on PLC. After imposing the same level of price volatility as generated by the storage model but maintaining the assumption of no serial correlation, there is no apparent differences in program costs between the storage model and CBO method. In other words, the increase in estimated PLC payments can be attributed to differences in price volatilities, rather than serial correlation. Instead of using the complicated storage model, CBO could simply inflate the price volatilities by a reasonable range to obtain more accurate estimations of PLC payments.

For ARC-county, the payments under the storage model and CBO scenario are similar when program guarantees are adjusted to reflect market conditions in the simulated draws. Even though unconditional price volatilities increase over time, program costs do not because conditional price volatilities (conditional on market conditions) do not increase over time. For example, given a positive yield shock in 2015, the increase in the supply would drive down the market price. As prices are serially correlated, the market price for 2016 would be lower as well. So if a constant price guarantee is used, farmers may get a positive payment due to lower market price, however, if the price guarantee is adjusted to be draw-specific, then the payments would decrease due to lower price guarantee.

Unlike ARC-county, the payments for SCO are lower under the storage model than under the CBO method when allowing draw-specific price guarantees. Besides the compensation effect of serial dependence, another reason that may explain the different pattern observed in ARC-county and SCO is the way of constructing their price guarantees. ARC-county use the Olympic average of prices in last five years. So it constructs its 2014 price guarantee totally based on historical 2009-2013 prices and gradually takes in the prices simulated from the storage model to build the guarantees for the remaing four years. Even for 2018, the historical prices of 2013 are used to calculate the price guarantees. But for SCO, the price guarantee has only one period dependence. The storage model would give lower payments because of its internal structure, which enables it to make rational and accurate expections on prices.

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APPENDIX MATLAB CODE USED TO SOLVE STORAGE MODEL

```
clc
clear all
tic
global mu_2014 std_2014 y_emp betaacre alphaacre acreplanted alphacon acretotal elasd
fspace n alpha_cy beta_cy r m sigma1 eta_cur acre_por;

% all the parameters
n1=8;
n=n1^3;
n3=5000;
n4=5;
r=0.0526;
m=0.36;
% the range of total amount available for three crops
tacmax=20;
tacmin=10;
tasmax=7;
tasmin=2.6;
tawmax=4;
tawmin=2.5;
% acre planted in 2014
acreplanted=[0.0906;0.0833;0.0568];
acretotal=sum(acreplanted);
acre_por=0.98;
betaacre=[0.2 -0.08 -0.08;-0.08 0.2 -0.08; -0.08 -0.08 0.2];
sigma1=[0.15,0.14,0.13];
elasd=[-0.56;-0.45;-0.15];

% demand shock
eta_cur=1;
eta_t=zeros(n3,3,n4+1);
for i=1:(n4+1)
    for j=1:3
        rng('default')
        eta_t(:,j,i)=normrnd(eta_cur,sqrt(i)*sigma1(j),n3,1);
    end
end

% demand function calibrated using 2013/2014 data
pricecurrent=[4.46;13;6.87];
consum=[13.454;3.478;2.436];
alphacon=pricecurrent./(eta_cur*consum.^(1./elasd));

cornyield = dataset('XLSFile','corn-national yield.xlsx');
nyield=length(cornyield.year);
X=[ones(nyield,1),cornyield.year];

% log-linear trending
```

```
[b1,bint1,r1] = regress(log(cornyield.yield),X);

% detrended yield
cornyield.trend1=exp(X*b1);
alpha_corn=regress(cornyield.yield,cornyield.trend1);
cornyield.trend=alpha_corn*cornyield.trend1;
cornyield_2014=exp([1, 2014]*b1)*alpha_corn;
cornyield.detrend=cornyield.yield*cornyield_2014./cornyield.trend;

% soybeans yield
soybeansyield = dataset('XLSFile','soybeans-national yield.xlsx');

% log-linear trending
[b2,bint2,r2] = regress(log(soybeansyield.yield),X);

% detrended yield
soybeansyield.trend1=exp(X*b2);
alpha_soy=regress(soybeansyield.yield,soybeansyield.trend1);
soybeansyield.trend=alpha_soy*soybeansyield.trend1;
soybeansyield_2014=exp([1, 2014]*b2)*alpha_soy;
soybeansyield.detrend=soybeansyield.yield*soybeansyield_2014./soybeansyield.trend;

% wheat yield
wheatyield = dataset('XLSFile','wheat-national yield.xlsx');
[b3,bint3,r3] = regress(log(wheatyield.yield),X);
wheatyield.trend1=exp(X*b3);
alpha_wheat=regress(wheatyield.yield,wheatyield.trend1);
wheatyield.trend=alpha_wheat*wheatyield.trend1;
wheattrend_2014=exp([1,2014]*b3)*alpha_wheat;
wheatyield.detrend=wheatyield.yield*wheattrend_2014./wheatyield.trend;

mu_2014=[mean(cornyield.detrend),mean(soybeansyield.detrend),mean(wheatyield.detrend)]
;
std_2014=[std(cornyield.detrend),std(soybeansyield.detrend),std(wheatyield.detrend)];

% using empirical yield data
y_emp=[cornyield.detrend, soybeansyield.detrend, wheatyield.detrend];

% approximate acreage supply function as a function of expected revenue
options1=optimset('Display','iter','MaxIter',5000, 'TolFun',1e-10,'TolX',1e-10);
[alphaacre,alphaacrefval]=fsolve(@(x) acre(x),[10;10;10], options1);

% Marginal conveience yield
% using 2002/03 and 2012/13 data to calibrate marginal conveience yield functions
% assume alpha*exp(-beta*I)
[c_cy,fvalc_cy]=fsolve(@(x) cyc(x),[10,10], options1);
% for soybeans and wheat(using output-averaged price data)
[s_cy,fvals_cy]=fsolve(@(x) cys(x),[10,10], options1);
[w_cy,fvalw_cy]=fsolve(@(x) cyw(x),[10,10], options1);
alpha_cy=[c_cy(1);s_cy(1);w_cy(1)];
```

```
beta_cy=[c_cy(2);s_cy(2);w_cy(2)];

fspace=fundefn('cheb', [n1 n1 n1], [tacmin, tasmin, tawmin], [tacmax, tasmax, tawmax]);
ta=funnode(fspace);
B=funbas(fspace,ta);
% B is equivalent to kron(kron(B3,B2),B1)
fspace1=fundefn('cheb', n1, tacmin, tacmax);
fspace2=fundefn('cheb', n1, tasmin, tasmax);
fspace3=fundefn('cheb', n1, tawmin, tawmax);
ta1=funnode(fspace1);
ta2=funnode(fspace2);
ta3=funnode(fspace3);
B1=funbas(fspace1,ta1);
B2=funbas(fspace2,ta2);
B3=funbas(fspace3,ta3);

TA1=kron(ones(n1^2,1),ta1);
TA2=repmat(kron(ta2,ones(n1,1)),n1,1);
TA3=kron(ta3,ones(n1^2,1));
TA=[TA1,TA2,TA3];

st=zeros(n,6);
c0=ones(n,3);
c1=zeros(n,3);
options=optimset('Display','off','MaxFunEvals',1000, 'TolFun',1e-6,'TolX',1e-6);
x0=[0.8, 0.07, 0.4, 0.09,0.08,0.05];
while max(max(abs(c0-c1)))>1e-6
    c0=c1;
    for i=1:n
    [st(i,:),fval(i,:)]=fsolve(@(x) storage(x,TA(i,:)',c0),x0, options);

    end
    c1=inv(B)*st(:,1:3);
    max(max(abs(c0-c1)))
end
toc


function L=acre(x)
global mu_2014 std_2014 acreplanted betaacre acre_por
pnext=[4.568, 11.606, 7.191];
volat3=[0.19, 0.13, 0.18];
pricestd=volat3.*pnext;
% py_cor=[-0.59, -0.42, -0.3125];
load('wheat own price_yield correlation.mat','py_cor')
% calculate covariance
py_cov=pricestd.*std_2014.*py_cor;
% calculate the expected revenue for corn, soybens, and wheat
exprev3=pnext.*mu_2014+py_cov;
L=log(x)+betaacre*log(exprev3')+log(acre_por)-log(acreplanted);
```

```
function L=cyc(theta)
global r m
L=[theta(1)*exp(-theta(2)*1.087)+2.385/(1+r)-m-2.32;theta(1)*exp(-theta(2)*0.821)+5.678/(
1+r)-m-6.89];

function L=cys(theta)
global r m
L=[theta(1)*exp(-theta(2)*0.178)+5.291/(1+r)-m-5.53;theta(1)*exp(-theta(2)*0.141)+12.852/
(1+r)-m-14.4];

function L=cyw(theta)
global r m
L=[theta(1)*exp(-theta(2)*0.491)+3.473/(1+r)-m-3.56;theta(1)*exp(-theta(2)*0.718)+8.372/(
1+r)-m-7.77];

% three-crop storage model
function L=storage(theta,xx,c0)
% theta 1*6 vector, xx 3*1 vector
global y_emp betaacre alphaacre alphacon acretotal elasd fspace n alpha_cy beta_cy r m
sigma1 eta_cur;
nn1=10;

[etanext1,wetanext1] = qnwnorm(nn1,eta_cur,sigma1(1)^2);
[etanext2,wetanext2] = qnwnorm(nn1,eta_cur,sigma1(2)^2);
[etanext3,wetanext3] = qnwnorm(nn1,eta_cur,sigma1(3)^2);
wetanext=[wetanext1,wetanext2,wetanext3];
% equation for expected price of corn
tanext=zeros(size(y_emp,1),3);
for j1=1:3
    tanext(:,j1)=theta(1,j1)+theta(1,j1+3)*y_emp(:,j1);
end
Bnext=zeros(size(y_emp,1),n);
for j2=1:size(y_emp,1)
    Bnext(j2,:)=funbas(fspace,tanext(j2,:));
end

f_etanext=zeros(length(etanext1),3);
for j3=1:length(etanext1)

f_etanext(j3,1)=mean((tanext(:,1)-Bnext*c0(:,1)).^(1/elasd(1))*alphacon(1)*etanext1(j3));

f_etanext(j3,2)=mean((tanext(:,2)-Bnext*c0(:,2)).^(1/elasd(2))*alphacon(2)*etanext2(j3));

f_etanext(j3,3)=mean((tanext(:,3)-Bnext*c0(:,3)).^(1/elasd(3))*alphacon(3)*etanext3(j3));
end
EP=zeros(3,1);
for i=1:3
    EP(i)=f_etanext(:,i)'*wetanext(:,i);
end
```

```
g_etanext=zeros(length(etanext1),3);
for j4=1:length(etanext1)

g_etanext(j4,1)=mean(((tanext(:,1)-Bnext*c0(:,1)).^(1/elasd(1))*alphacon(1)*etanext1(j4)).*
y_emp(:,1));

g_etanext(j4,2)=mean(((tanext(:,2)-Bnext*c0(:,2)).^(1/elasd(2))*alphacon(2)*etanext2(j4)).*
y_emp(:,2));

g_etanext(j4,3)=mean(((tanext(:,3)-Bnext*c0(:,3)).^(1/elasd(3))*alphacon(3)*etanext3(j4)).*
y_emp(:,3));
end
Exrev=zeros(3,1);
for i=1:3
    Exrev(i)=g_etanext(:,i)'*wetanext(:,i);
end
L=[(1/(1+r))*EP-(xx-theta(1,1:3)').^(1./elasd).*alphacon-m*ones(3,1)+alpha_cy.*exp(-beta_
cy.*theta(1,1:3)');...

log(alphaacre)+betaacre*log(Exrev)-log(alphaacre'*prod((ones(3,1)*Exrev').^betaacre,2))+lo
g(acretotal)-log(theta(1,4:6)')];

end
```