Comparison of County ARC and SCO

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The Agricultural Act of 2014 transforms agricultural commodity programs and crop insurance. The new law removes fixed, direct payments and replaces them with an option between price (Price Loss Coverage) or revenue (Agriculture Risk Coverage) based programs. Those choosing not to enroll crops in ARC have the opportunity to purchase additional crop insurance, the Supplemental Coverage Option (SCO). SCO allows producers who select PLC to still obtain shallow loss coverage similar in some respects to ARC. Yet, the two programs have distinct features that make them imperfect substitutes. Therefore, we undertake analysis that compares and contrasts SCO and ARC through county level models to determine expected benefits and risk protection.

Program descriptions

Agriculture Risk Coverage is a Title I program that provides free shallow loss protection to producers. Enrollees can choose between farm and county level coverage. The latter can choose between ARC and PLC for each crop with base acres on their farms. For commodities in county ARC, the benchmark guarantee is set by the product of the five year Olympic average (average of the set after excluding the high and low) national farm price and five year Olympic average yield per planted acre. If historical prices fall below the reference price set in law, the reference price may be used in place of the farm price in determining the benchmark. Current year revenue is calculated as the product of the higher of the farm price or loan rate and the county average yield per planted acre. If the current year revenue falls below 86 percent of the benchmark, the payment rate per payment acre is the difference between the two, but cannot exceed 10 percent of the benchmark. Payments are made on 85 percent of the base acres in the crop plus any allocated generic base.

Farm level ARC also provides shallow loss coverage. The principal difference is that it operates on a whole farm basis instead of a crop by crop basis at the county level. Benchmarks are determined similar to county ARC, only using farm instead of county yields, except that each crop is weighted by actual plantings to obtain a farm benchmark and revenue averaged across all crops. Payments are made on 65 percent of farm base acres plus generic base.

Conversely, the Supplemental Coverage Option is a Title XI crop insurance program that producers must purchase to participate. It also covers 86 percent of a benchmark, but the benchmark is defined differently than the ARC benchmarks. An individual insurance policy must be bought to be eligible for SCO, and the SCO policy operates in the same manner as the individual policy. Most acres are insured with a Revenue Protection plan, which insures revenues and uses the higher of the planting and harvest price. The limit on payments is the difference between 86 percent and the individual policy coverage level. For example, if the underlying policy has an 80 percent coverage level SCO would protect between 80 and 86 percent of the benchmark. The payment rate is adjusted based upon the ratio of the yield in the underlying plan to the SCO county (region) yield. The plan is intended to be rated actuarially fair and have a 65 percent subsidy rate.

While there are definite similarities between county ARC and SCO, important differences do exist. SCO uses a county trend yield while ARC uses a moving Olympic average yield. ARC utilizes a moving Olympic average price with floors while SCO utilizes a planting price determined by the futures market. This should cause the ARC benchmark values to react more slowly to market movements, so there will be times when ARC will make a payment when there is no SCO indemnity and vice-versa. The programs have different caps on payments, which can drastically affect results. Furthermore, producers must pay 35 percent of the SCO premium while

ARC enrollees do not have to pay to enroll. ARC pays on fixed based acres while SCO pays on actual planted (or prevented planted) acres.

Given the similarities and important differences, we have constructed county level models for all counties with adequate data to compare and contrast PLC with SCO against county level ARC for corn, soybeans and wheat. Given the data necessities and operational difference of individual ARC, the program has been excluded from this analysis. When program enrollment begins, producers must make a one-time decision to enroll in ARC or PLC for the life of the farm bill. As a result, this analysis, which to our knowledge is the first to delve into such detail in comparing the two programs, provides timely results that can be used by agents making decisions.

Methodology

Assumptions

Several simplifying assumptions are necessary to make the models tractable. Below are the assumptions, along with corresponding impacts.

1) **Each county is represented by a single farm**

   Gerlt, et al. (2014) analyzes the effects of using inflated county data in place of farm data. The direction of the bias is dependent upon the underlying farm distributions, but is generally found to be small at high coverage levels, such as those in the programs under study. While SCO makes payments adjusted to the farm yield from the county, this assumption renders the adjustment unnecessary.

2) **Planted and base area are equal**

Given that county level base area is not available, this assumption is necessary. In aggregate across all crops for the country as a whole, base is about equal to plantings. However, for individual crops and farms, this is not necessarily true. However, given that the 2014 farm bill allows base to be reallocated, on average this assumption should not be too limiting. Individual cases could vary widely, though. For example, some landowners will rationally choose to maintain prior base area if that yields larger expected payments than would occur under a base reallocation.

3) **All Payment yields are updated**

   Again, since this data is not available at the county level, this assumption is necessary. The 2014 farm bill allows landowners to retain their counter cyclical payment yields or to update based on the average of 90% of the 2008 to 2012 yields for PLC. Given that farmers will likely only update if the new yields exceed the old, this assumption may underestimate true yields and therefore underestimate PLC payments. However, it is also possible that some landowners will lack the records needed to update their program yields, or may fail to do so for other reasons even if updated yields would be higher than current program yields.

4) **Underlying crop insurance participation levels do not change**

   In reality, producers may have incentives to reduce coverage levels for underlying policies given that SCO and ARC provide coverage at high levels at a lower marginal cost. O'Donoghue (2014) shows that producers do respond to subsidy levels. Given that the changes are likely to be small and the effect is beyond the scope of this analysis, the changes will be ignored. This may result in understated SCO subsidies as the coverage for the program increases as the coverage level for the underlying level decreases.

Mitigating this effect is the demonstrated preference of most producers for individual policies that make indemnity payments tied to farm level losses rather than area-level coverage, even when the latter is more heavily subsidized (Bulut, et al. (2012)).

5) **All crop insurance policies are Revenue Protection**

   Revenue protection (RP) is overwhelmingly the most popular crop insurance product. For example, 87% percent of insured corn acres in 2013 were insured with RP (RMA). While extending RP for corn to the other 13% of acres is a small extension, it will increase SCO indemnities. SCO operates like the underlying insurance policy and RP has the most generous payout, so SCO indemnities and premium subsidies should increase.

Analytical methods

SCO and ARC are new programs, so analysis is lacking. However, previous research has analyzed similar programs. Coble and Dismukes (2008) studied revenue programs at the county, state and national level with revenue insurance wrapped around the programs. They found that corn, soybean and wheat producers would benefit from the program with wrapped insurance while cotton would not. They also found the lower levels of aggregation were more beneficial to producers. Cooper et al. (2012) analyzed the 2012 Senate proposed ARC program and found that producers were likely to favor farm level payments over county level payments. Additionally, many studies have estimated crop insurance premiums (Barnett et al, 2005, Coble and Barnett, 2008, Coble and Dismukes, 2008, Carriquiry et al., 2008, Deng et al., 2007).

SCO analysis is simplified by the fact that bills passed by both chambers of Congress mandate that SCO should target a loss ratio of one. In other words, the program is intended to operate in a manner such that the total premiums are equal to expected losses. Therefore, calculating the expected indemnities yields the program premiums, assuming RMA estimates would match our own.

This analysis estimates revenues, SCO premium, PLC payments and ARC payments for corn, soybeans and wheat over the projection period of 2014 to 2018, the scheduled life of the farm bill. USDA National Agricultural Statistics Service (NASS) production data was obtained for each crop from the years 1980 to 2013. However, NASS does not have data for all counties, crops and years. Several steps were taken to address this issue. First, the USDA Farm Service Agency (FSA) reports yields per planted acre by county for the ACRE program. Their county coverage is more extensive than NASS's, so it was used to augment the NASS data. If, after that, the county did not have yields for at least 15 of the last 20 years, it was dropped from the analysis.

A simple linear trend was estimated for each county and state yield per planted acre for soybeans, while yield per harvested acre data was used for corn and wheat. Silage and grazing are excluded when calculating yields per planted acre for ARC and SCO purposes, so the yield per harvested acre is generally a closer proxy for the yield per planted acre than is the simple result of dividing total grain production by total planted area. The residuals for each county were regressed on the state residuals. The predicted values of this regression were used to fill in missing county residuals. By using Latin Hypercube, 500 normally distributed draws for each county and year in the forecast were created based upon the residuals. This explicitly assumes that county yields are normally distributed. The literature on the appropriate distribution for farm yields is mixed about normality (Atwood, Shaik, and Watts, 2003; Claasen and Just, 2011; Goodwin and Ker, 1998; Harri et al., 2011; Just and Weninger, 1999; Ker and Coble, 2003; Ker and Goodwin, 2000; Koundouri and Kourogenis, 2011; Ramirez et al., 2003; Sherrick et al., 2004). However, since the county yield is an aggregation of farm yields, it is more likely to be normally distributed. Furthermore, the RMA assumes normality of farm yields when calculating Revenue Protection and Revenue Protection with Harvest Price Exclusion (RMA 2009). Therefore, this assumption should be in line with actual rating procedures.

FAPRI's stochastic model results were used for the price projections. The model generates500 sets of prices for each crop and year. The model consists of approximately 2000 equations that estimate production, prices and a variety of other variables of interest for a wide range of crop, livestock and biofuel commodities. The stochastic estimates are developed by using 500 sets of correlated draws on a number of exogenous variables, including growing conditions, energy prices, and a variety of other factors that affect both the supply and demand for crop and livestock products. The models are solved for each of the 500 sets of exogenous assumptions, generating internally consistent distributions of prices, production and other endogenous variables. Table 1 contains the average prices for these outcomes.

Proper analysis of SCO and ARC must take into account the relationship between yields of different counties and national prices used for crop insurance and marketing year average prices. The correlation of yields between counties can be easily derived from the detrended yield residuals. However, determining the correlations between the county yields and national price is not straightforward. Since this analysis uses FAPRI estimates of prices, the proper correlation is between the county yields residuals and the FAPRI price residuals.

The first step is to obtain the correlations between state yields and the national price. For corn, soybeans and wheat, the FAPRI model generates state yields for Arkansas, California, Georgia, Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Montana, Nebraska, North Dakota, Ohio, South Dakota and Texas. The correlations between the state yields and national price were obtained from the last year of the FAPRI stochastic baseline for each of the three aforementioned crops. The correlations between all the states that produced the crop were also obtained from the NASS data residuals.

The missing state correlations for corn, soybeans and wheat were obtained by utilizing the following correlation matrix, $\boldsymbol{\Omega}$:

(1) $$\Omega_{17x17} = \begin{bmatrix} 1 & v_i' & \rho_{1,17} \\ v_i & m & p \\ \rho_{17,1} & p' & 1 \end{bmatrix}$$

where p is a 15x1 vector of state yield to national price correlations from the FAPRI model, m is the 15x15 matrix of state yield correlations from the FAPRI baseline, v_i 15x1 vector of state yield correlations between state i and the states in the FAPRI model from the detrended NASS data and $\rho_{1,17}$ is the unknown correlation between the yield for state i and the national price for the crop. By the symmetry requirement of a correlation matrix, $\rho_{1,17} = \rho_{17,1}$. By assuming that the partial correlation between state i yield and the national price is zero, $\rho_{1,17}$ can be solved for by finding the value of $\rho_{1,17}$ that sets the (1,17) minor (or cofactor) to zero. This can be written mathematically as:

(2) $$\text{Solve } det\begin{bmatrix} v_i & m \\ \rho_{17,1} & p' \end{bmatrix} = 0 \text{ for } \rho_{17,1}.$$

The proof of this property is in Appendix 1 of Gerlt and Westhoff (2013). This imposes the assumption that the relationship between the state yield i and national price is determined entirely by the other correlations in the matrix. While this may not be true, without more information, a partial correlation of zero is the midpoint of possibilities. This process is repeated for every state for which the model has counties for which SCO payments are estimated.

Table 2 displays the resulting state yield to national price correlations for all three crops. The county residual to national farm price correlation still needs to be obtained. This is done by multiplying the state residual to national price correlation by the county residual to state residual correlation. The method demonstrated in Appendix 1 of Gerlt and Westhoff (2013) does not work well for matrices that have multiple missing values. Instead, suppose there are three random variables $\{x_1, x_2, x_3\}$ with correlations $\rho_{1,2}$, $\rho_{1,3}, \rho_{2,3}$. Furthermore, suppose that $\rho_{1,3}$ is unknown while the other two are known. x_2 can serve as a bridge variable to help provide an estimate of the unknown correlation. The midpoint of the potential range for $\rho_{1,3}$ is $\rho_{1,2} * \rho_{2,3}$, which also happens to correspond to a partial correlation of zero. These properties are proven in Appendix 2 of Gerlt and Westhoff (2013). In this case, the state yield residuals acts as a bridge between the county yield deviates and the national farm price.

Once this is done, a correlation matrix for each crop can be composed consisting of the inter-county yield correlations and the yield to national price correlations. This can be used to properly correlate the county yield deviates and FAPRI farm prices. Iman and Conover's (1982) procedure accomplishes this. Their method reorders the deviates to impose the correlation matrix. While copulas have been increasing in prominence, they generate data while Iman and Conover's method reorders existing data, making it suitable for our application. The only issue is that for their method, the correlation matrix must be factored. Since correlation matrices must be positive semidefinite, this is usually not a problem. However, since our correlation matrices are generally both overspecified and combine different data series, this requirement often fails. To overcome this, we use spectral decomposition to decompose the matrix. We then set any negative eigenvalues to zero and recompose the correlation matrix. This is the first step in

Higham's (2002) algorithm to find the nearest correlation matrix if the target matrix is the identity matrix.

These steps produce the following for corn, soybeans and wheat for each year of the forecast: trend county yields, 500 yield deviates for each county based upon historical variation and 500 prices that are correlated with the county deviates. Note that the structure imposed does not correlate across crops. A basis is added to the farm price to achieve a harvest futures price. For corn, \$0.103 per bushel is added to the farm price, and the assumed basis is \$0.067 per bushel for soybeans and for wheat, the basis is \$0.209 per bushel, based on data for 1980 to 2012. The standard deviation of the relative deviate for each crop between the planting period and harvested period was calculated based upon data from 1980 through 2012 to generate an implied volatility. The result is .1899 for corn, .1730 for soybeans and .1844 for wheat. This volatility factor is used to create a stochastic futures planting price from the futures harvest price.

These data can be used to calculate SCO indemnities under each bill. We assumed that participation across coverage levels of crop insurance in 2012 would continue (Table 3). The average SCO indemnities, ARC payments and PLC payments across participants and enrolled acres were calculated for each of the 500 market outcomes. The national average was obtained by multiplying each county by the ratio of its sum of 2010 to 2012 planted acres to the 2010 to 2012 total planted acres.

Last of all, revenues per acre were calculated at the county level. Since the county is a representative farm for the farms within the county, its standard deviation was inflated by a factor of 1.3 (Gerlt, et al (2014)). An extra deviate was generated around the random county draw to add the extra uncertainty.

Results

Average payments

The following results present averages across all counties, with a particular set of price assumptions. Note that these national average comparisons will not hold for particular farms in particular counties. Additionally, different projected price assumptions could significantly alter the outcomes.

Tables 4 through 9 contain average payments and frequency of payments. Average payments are presented for corn, soybeans and wheat for ARC, SCO, PLC and PLC+SCO. Note that ARC and PLC payments include the 15% reduction for payment acres and SCO is net indemnities (indemnities minus producer paid premiums). Corn ARC payments start at $33.79 per acre in 2014 and continue at approximately this level until 2017 (Table 4). In that year, payments drop to $19.94 as historically high prices no longer hold up the benchmark. While corn ARC payments are triggered with a frequency of 61.9% in 2014, this amount drops to 35.8% by 2018 as the benchmark drops (Table 5).

Corn SCO payments also drop through time as prices decline in the FAPRI-MU baseline, but since SCO is based upon intra-year volatility only, the effect is muted. The ARC benchmark is held high at first due to the five year Olympic average of prices, but since SCO has no inter-year price component, it is not propped up at the beginning of the baseline. The result is that SCO payment levels exhibit less movement. While SCO net indemnities start tat $17.55, they end at $14.76. Payment frequency only moves from 29.7% to 28.7%. For corn, ARC county has both higher average payments and pays more frequently.

Corn PLC exhibits the opposite pattern as ARC. PLC payments rise as prices fall, so payments start at $15.94 and end at $30.01 with the frequency increasing from 30.6% to 40.8%.

When PLC and SCO are combined, payments start at $31.09 and end at $40.25. The only year that average ARC payments exceed the combination of the other two is 2014. However, ARC payments still trigger more often in the first three years.

Soybeans and wheat exhibit similar payment patterns to corn as all three have declining prices in the FAPRI-MU baseline. However, on average corn payments exceed soybean payments which are higher than wheat payments. This is due to their relative revenues per acre. Soybean ARC payments exceed both SCO and PLC payments every year except PLC in 2018 (Table 6). However, SCO+PLC payments are higher than ARC in 2016 through 2018. The frequency of soybean payments is very close to those of corn, except PLC which is slightly higher for corn (Table 7). This is caused by projected prices that are higher relative to the reference price for soybeans than corn.

While wheat does have generally declining prices in the FAPRI-MU baseline, ARC county payments actually peak in 2016 (Table 8). This is due to generally low county yields in 2010 that drop out of the benchmark while revenues decline from the previous year. Otherwise, payments follow the same patterns of movement as corn and soybeans. Wheat ARC payments always exceed SCO payments, but PLC payments are always larger than ARC, sometimes substantially. As a result, SCO+PLC payments always exceed ARC payments. ARC frequency of payments exceeds SCO in every year and PLC in the first three years (Table 9). SCO+PLC payments have a higher frequency of payments in every year than ARC.

Revenue distributions

While average and frequency of payments are useful metrics, both overlook the effect of the programs on profitability. As crop insurance and costs of production are exogenous to our models, revenues plus program net benefits are the relevant measure of profitability.

Additionally, program payments and revenues are correlated, so just reporting average payments can hide important information. The programs are intended to help producers manage uncertainty, so it is not sufficient to consider expected payment levels without also considering the ability of the programs to mitigate financial risk.Figures 1 through 6 display revenues plus relevant program benefit at the mean, 10^{th} percentile and 90^{th} percentile. The difference in means signifies the average wealth transfer. The difference in 90^{th} percentiles displays the net benefits in a good year, while the differences in the 10^{th} percentiles displays the net benefits in a bad year. Note that the percentiles are sorted on the variables including program benefits (if relevant), and not just revenue. For example, the 10^{th} percentile of revenue and revenue plus ARC may not correspond to the same iteration.

Figure 1 contains revenue, revenue plus SCO and revenue plus ARC for corn. Note that at the mean, revenue plus ARC payments are the highest, followed by revenue plus SCO, consistent with Table 4. At the 90^{th} percentile, there is no discernible difference between revenues with or without any of the programs. In other words, the top end of the distribution remains essentially unchanged. At the 10^{th} percentile, revenue with ARC exceeds revenue with SCO and market revenue alone by an even wider margin. This indicates that ARC provides better risk protection, in addition to higher average benefits.

Figure 2 is the same as Figure 1, except that PLC payments have been added to SCO net indemnities. The 90^{th} percentile remains relatively unchanged from Figure 1. Mean revenue with SCO and PLC now exceeds mean revenue with ARC starting in 2016. At the 10^{th} percentile, revenue with SCO and PLC is about equal to revenue with ARC in 2014, but exceeds it in all other years. In other words, SCO with PLC provides at least as good as risk protection as ARC for the average producer given all of the assumptions of this analysis.

Figures 3 and 4 are similar to Figures 1 and 2, except for soybeans. Again, the patterns remain the same. The 90th percentiles across all options are virtually the same, as ARC and PLC payments and SCO net indemnities are zero in most cases. Mean revenue with ARC still exceeds mean revenue with SCO. At the 10th percentile, revenue with ARC is significantly higher than revenue with and without SCO. Adding PLC to SCO largely has the same results for soybeans as it did for corn. The 90th percentiles remain largely the same and the means become ambiguous between ARC and SCO with PLC. At the 10th percentile, revenue with SCO and PLC remains about equal to revenue with ARC during 2014 and 2015 but exceeds it in later years.

Figures 4 and 5 are also similar to Figures 1 and 2, only for wheat. The 90th percentile levels are practically the same for all programs, or lack thereof. The means and 10th percentiles favor SCO with PLC, ARC, SCO and then no program in all years.

In all cases, results are very sensitive to the means of projected prices. All else equal, higher average prices result in lower average PLC payments. The effects on ARC benefits may differ across time, as higher prices reduce ARC payments in the short run, as actual county revenues are less likely to fall below the benchmark. In the longer run, however, the benchmark itself is higher if average prices are persistently higher than assumed in this analysis. If the volatility of prices is unchanged, average ARC payments could actually increase in later years of the analysis.

Conclusions

Several conclusions can be drawn from this analysis. First, on average any of the programs is better than no program for corn, soybeans and wheat. With the exception of SCO, the programs are free. While producers may pay an SCO premium without getting an indemnity payment in most years, subsidized premiums suggest net indemnities should be positive on average if policies are rated properly.

In general, we find that ARC provides better revenue protection than SCO considered alone. We propose two reasons for this result. The first is that the projected prices used in the analysis decline from recent highs. The ARC benchmark incorporates these recent higher prices for several years leading to higher payments in the first years of the farm bill. The second is that ARC pays on 85% of (base) acres, while SCO has a 65% subsidy rate. Even if the raw payment rates were the same across all iterations, ARC enrollees would receive 85% of the raw payments while SCO would receive only 65% if SCO is rated actuarially fair.

However, adding PLC to SCO elevates the program's performance to generally exceed ARC, in both risk and average payments. , PLC with SCO generally provides greater average net benefits over the next five years for the crops examined, and provide greater average benefits when market revenues are low, given all the assumptions of the analysis.

Commodities with base acreage will have to choose between ARC and PLC. PLC with SCO may look attractive relative to ARC for many producers. For particular producers in particular counties, the expected benefits of the two programs will depend on recent county yields, price expectations, and many other factors. For example, some counties have had abnormally high or abnormally low yields in recent years, which could have a large effect on expected ARC payments, especially in the next two or three years. SCO and PLC benefits would not be affected in the same way, so producers in different counties may have different optimal choices, even when they share common assumptions about future prices.

Due to the base update allowance of the 2014 farm bill, producers may have the option to include (or not) a crop in base. If it is not in ARC base, the crop can still be in SCO. Our analysis shows that the producer would still benefit with only SCO, but not as much as with ARC (or PLC with SCO).

This analysis is limited by the fact that it uses averages. Local yields could significantly alter expected payments and conclusions. Furthermore, the payments are strongly dependent upon future price paths. A declining price path, as used in this analysis, will help ARC relative to PLC, while SCO will only move by small amounts. Reversing the price path would have the opposite effect. Last of all, we do not consider the risk protection effect of PLC alone as we are comparing the revenue programs. Future analysis addressing these shortcomings would be beneficial.

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Table 1: FAPRI-MU mean annual farm price projections (March baseline), marketing year, dollars per bushel

	14/15	15/16	16/17	17/18	18/19	19/20	20/21	21/22	22/23	23/24
Corn	4.17	4.09	4.07	4.06	4.04	4.02	3.97	3.93	3.92	3.87
Soybeans	9.84	9.80	9.68	9.68	9.77	9.85	9.87	9.94	9.89	9.88
Wheat	5.55	5.37	5.32	5.31	5.28	5.26	5.25	5.23	5.23	5.21

Table 2: Estimated state yield to national price correlations

	Corn	Soybeans	Wheat
Alabama	-0.20	-0.06	-0.09
Arizona	0.15	n.a.	-0.10
Arkansas	-0.22	-0.22	0.04
California	-0.11	n.a.	0.01
Colorado	-0.24	n.a.	-0.11
Delaware	-0.20	-0.01	0.09
Florida	-0.05	-0.09	-0.13
Georgia	-0.10	-0.21	-0.02
Idaho	-0.30	n.a.	0.01
Illinois	-0.36	-0.30	-0.10
Indiana	-0.34	-0.29	-0.10
Iowa	-0.42	-0.36	-0.10
Kansas	-0.35	-0.32	-0.25
Kentucky	-0.32	-0.14	0.03
Louisiana	-0.16	-0.12	-0.08
Maryland	-0.23	-0.02	0.04
Michigan	-0.19	-0.09	-0.14
Minnesota	-0.44	-0.27	-0.22
Mississippi	-0.09	-0.18	-0.05
Missouri	-0.35	-0.34	-0.03
Montana	-0.08	n.a.	-0.03
Nebraska	-0.43	-0.25	-0.23
Nevada	n.a.	n.a.	0.05
New Jersey	-0.33	-0.10	-0.03
New Mexico	0.05	n.a.	-0.17
New York	-0.26	-0.07	-0.11
North Carolina	-0.09	-0.22	0.01
North Dakota	-0.19	-0.18	-0.24
Ohio	-0.45	-0.35	-0.18
Oklahoma	-0.05	-0.09	-0.17
Oregon	-0.23	n.a.	0.09
Pennsylvania	-0.38	-0.26	-0.02
South Carolina	-0.18	-0.13	0.03
South Dakota	-0.44	-0.32	-0.23
Tennessee	-0.25	-0.05	0.01
Texas	-0.16	-0.16	-0.16
Utah	-0.17	n.a.	-0.10
Virginia	-0.15	-0.10	0.14
Washington	0.04	n.a.	0.05
West Virginia	-0.17	n.a.	-0.04
Wisconsin	-0.34	n.a.	-0.13
Wyoming	-0.13	n.a.	-0.13

Table 3: 2013 crop insurance participation rates across coverage levels

Coverage level	Corn	Soybeans	Wheat
50%	6.6%	8.5%	9.0%
55%	0.3%	0.4%	0.6%
60%	1.9%	1.8%	4.8%
65%	6.8%	7.0%	15.0%
70%	20.1%	21.2%	35.0%
75%	29.2%	31.3%	24.6%
80%	22.1%	20.5%	6.5%
85%	10.9%	7.6%	4.1%
90%	2.1%	1.7%	0.4%

Table 4: Corn average payments per base or planted acre

	2014	2015	2016	2017	2018
ARC	$33.79	$35.98	$31.49	$19.94	$15.99
SCO	$17.55	$15.16	$14.27	$14.33	$14.76
PLC	$15.94	$25.12	$29.76	$30.35	$30.01
SCO+PLC	$31.09	$36.50	$39.53	$40.10	$40.25

Table 5: Corn frequency of payments

	2014	2015	2016	2017	2018
ARC	61.9%	63.5%	57.5%	41.3%	35.8%
SCO	29.7%	28.2%	27.8%	26.8%	28.7%
PLC	30.6%	36.8%	39.2%	40.4%	40.8%
SCO+PLC	44.4%	50.5%	52.4%	53.2%	53.6%

Table 6: Soybean average payments per base or planted acre

	2014	2015	2016	2017	2018
ARC	$20.98	$21.93	$20.91	$17.39	$12.57
SCO	$9.09	$8.99	$8.93	$8.79	$9.25
PLC	$9.99	$12.79	$14.96	$16.10	$15.73
SCO+PLC	$17.59	$19.87	$21.65	$22.49	$22.64

Table 7: Soybean frequency of payments

	2014	2015	2016	2017	2018
ARC	58.5%	59.3%	57.1%	49.7%	39.3%
SCO	26.2%	26.1%	26.1%	25.9%	26.4%
PLC	24.6%	31.2%	30.6%	33.8%	30.4%
SCO+PLC	41.6%	46.9%	45.0%	46.9%	46.0%

Table 8: Wheat average payments per base or planted acre

	2014	2015	2016	2017	2018
ARC	$10.42	$12.88	$13.02	$10.98	$8.55
SCO	$8.48	$8.19	$7.90	$7.95	$7.69
PLC	$11.46	$19.14	$19.33	$20.07	$21.03
SCO+PLC	$18.24	$24.47	$24.34	$25.02	$25.57

Table 9: Wheat frequency of payments

	2014	2015	2016	2017	2018
ARC	53.7%	62.3%	61.8%	56.5%	48.0%
SCO	31.9%	32.4%	32.5%	31.3%	31.6%
PLC	46.8%	57.2%	59.4%	60.0%	59.2%
SCO+PLC	57.7%	65.9%	69.4%	68.1%	68.7%

Figure 1: Corn distributions

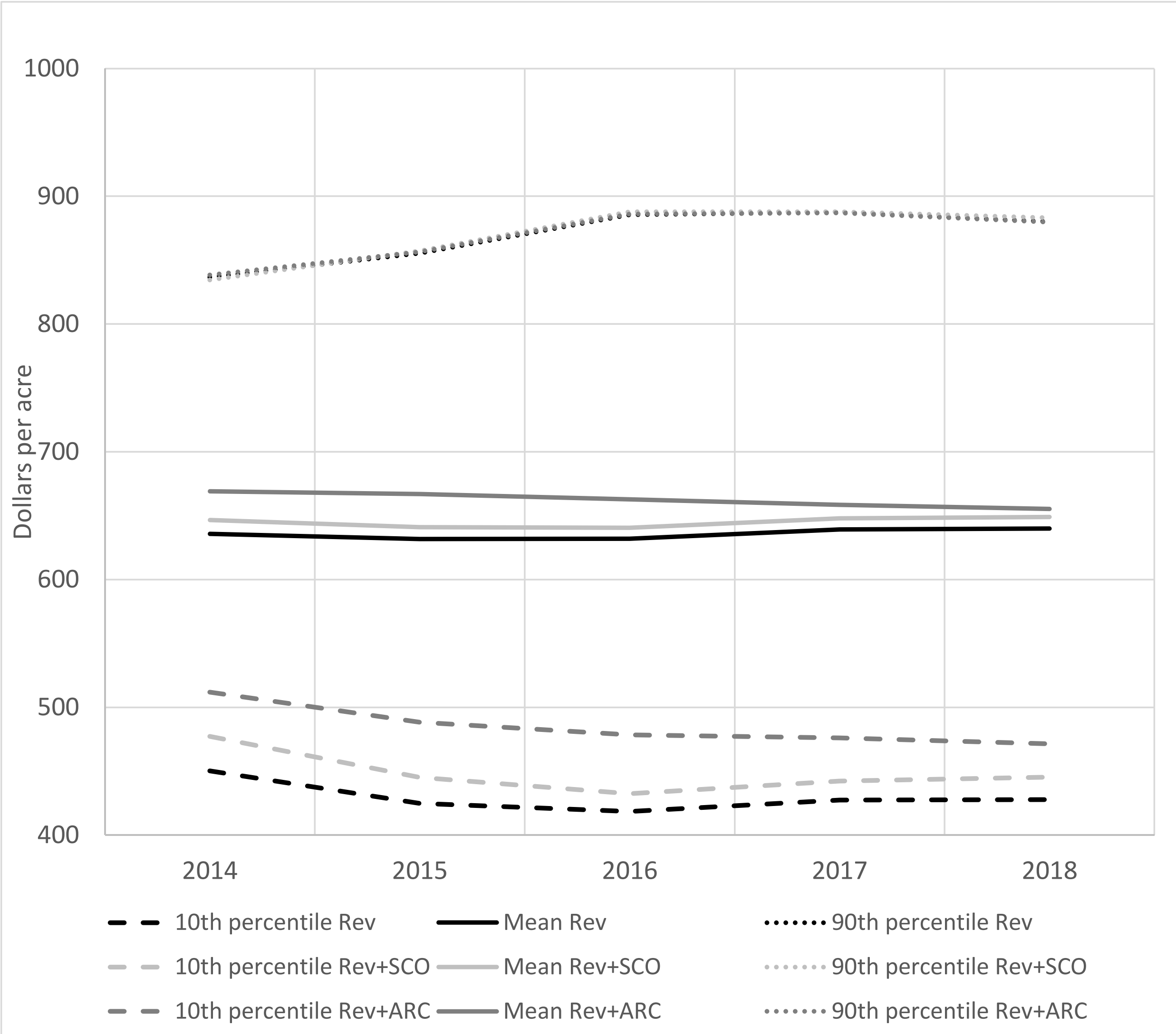

Figure 2: Corn distributions with PLC

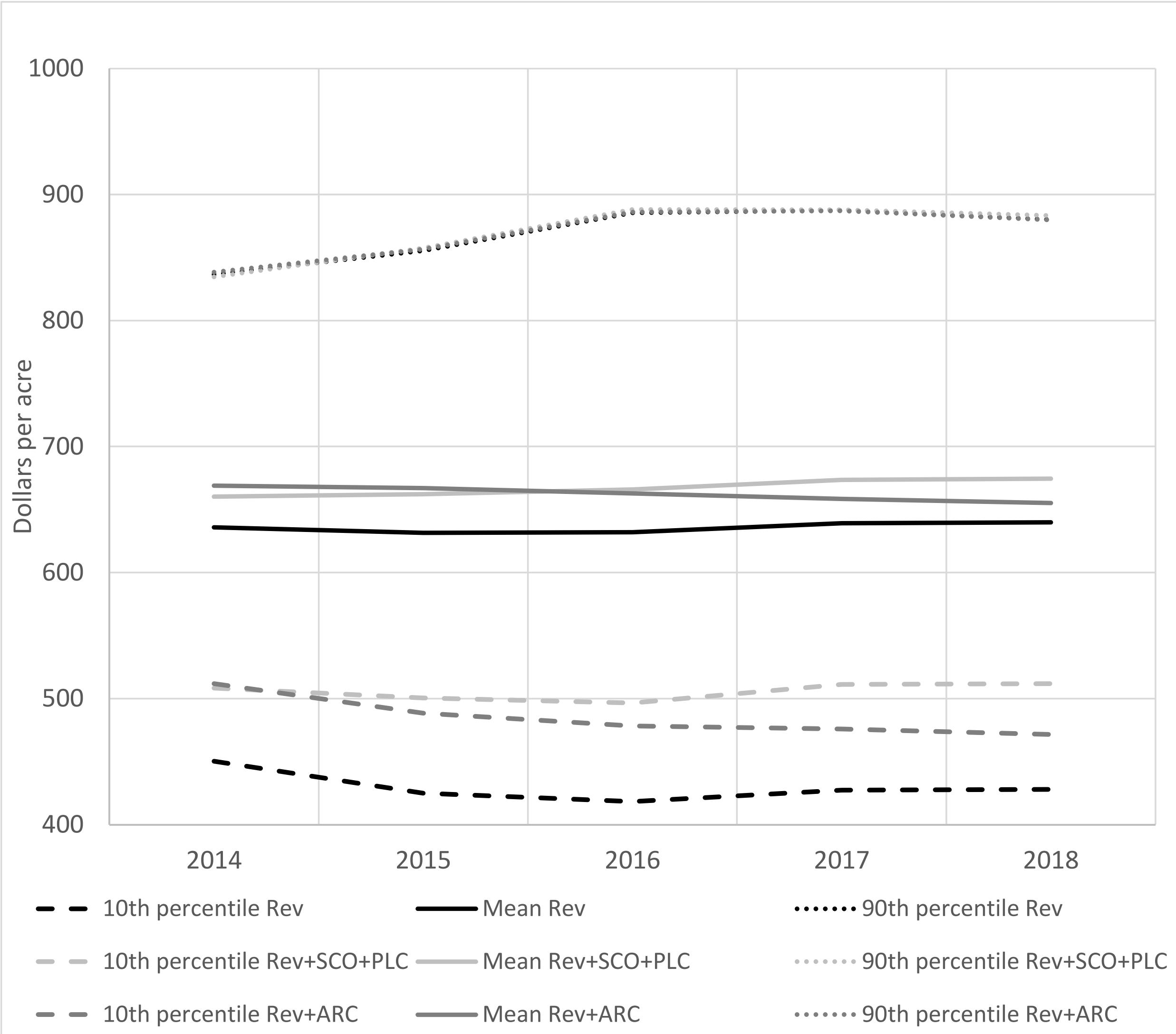

Figure 3: Soybean distributions

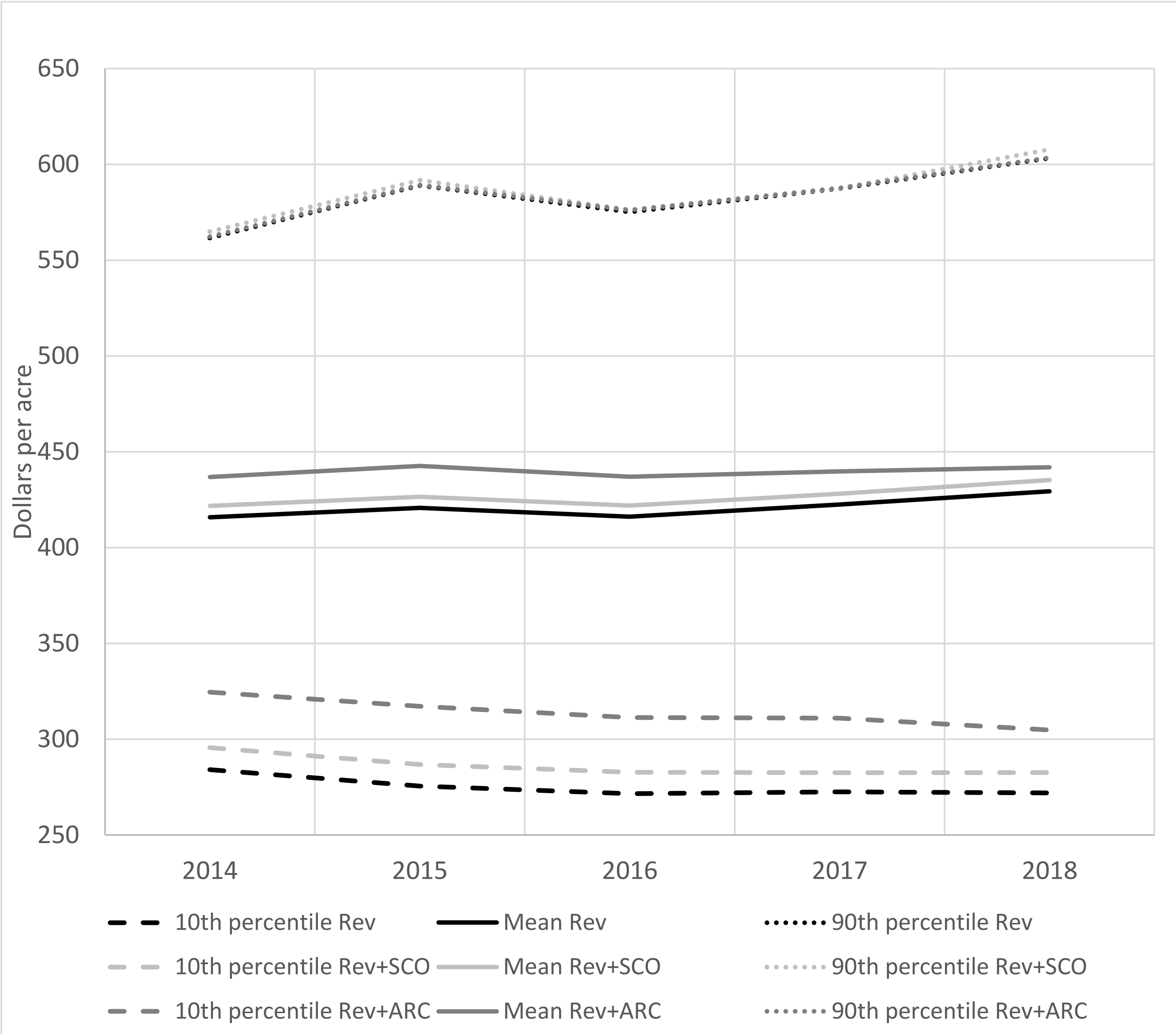

Figure 4: Soybean distributions with PLC

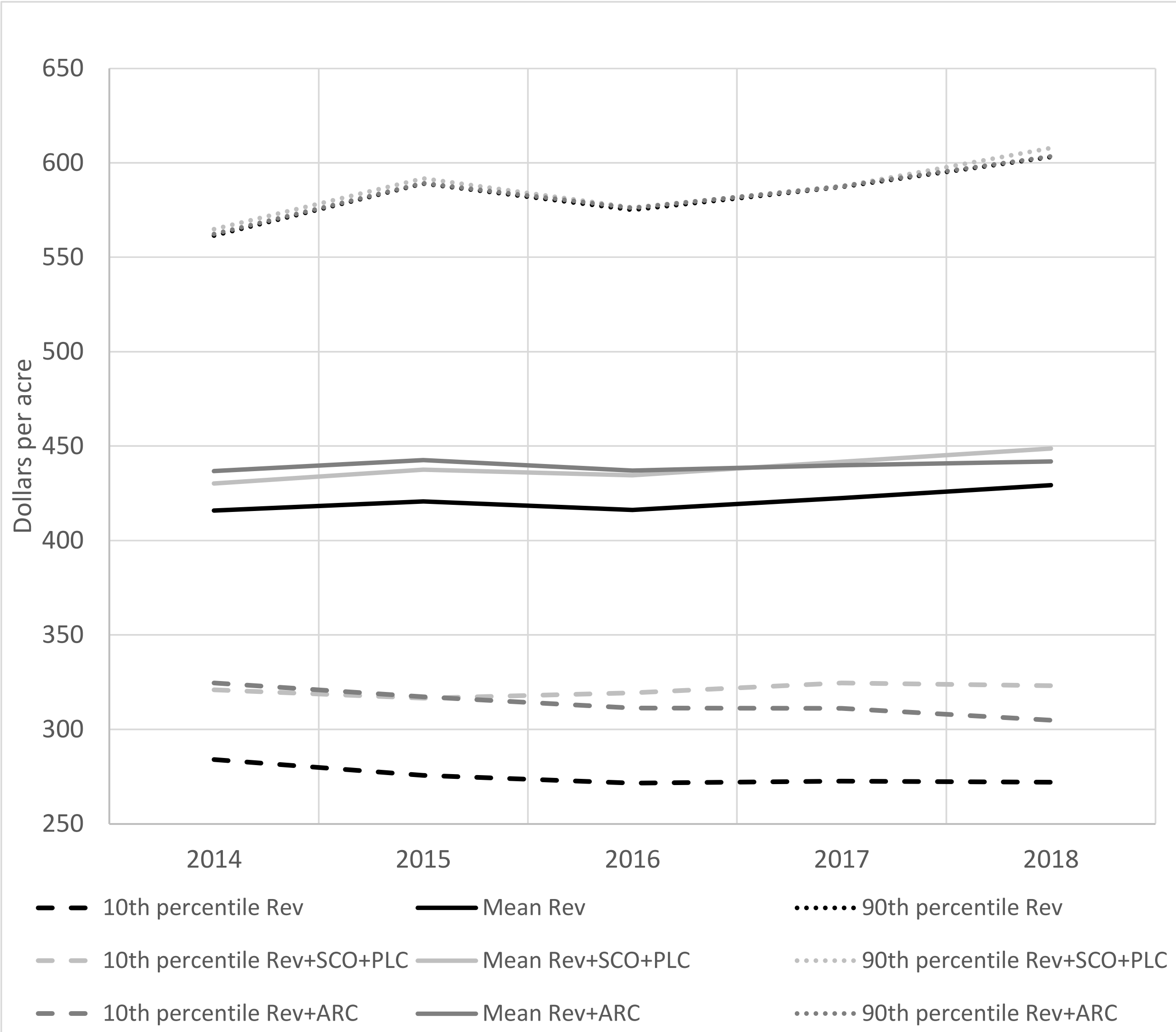

Figure 5: Wheat distributions

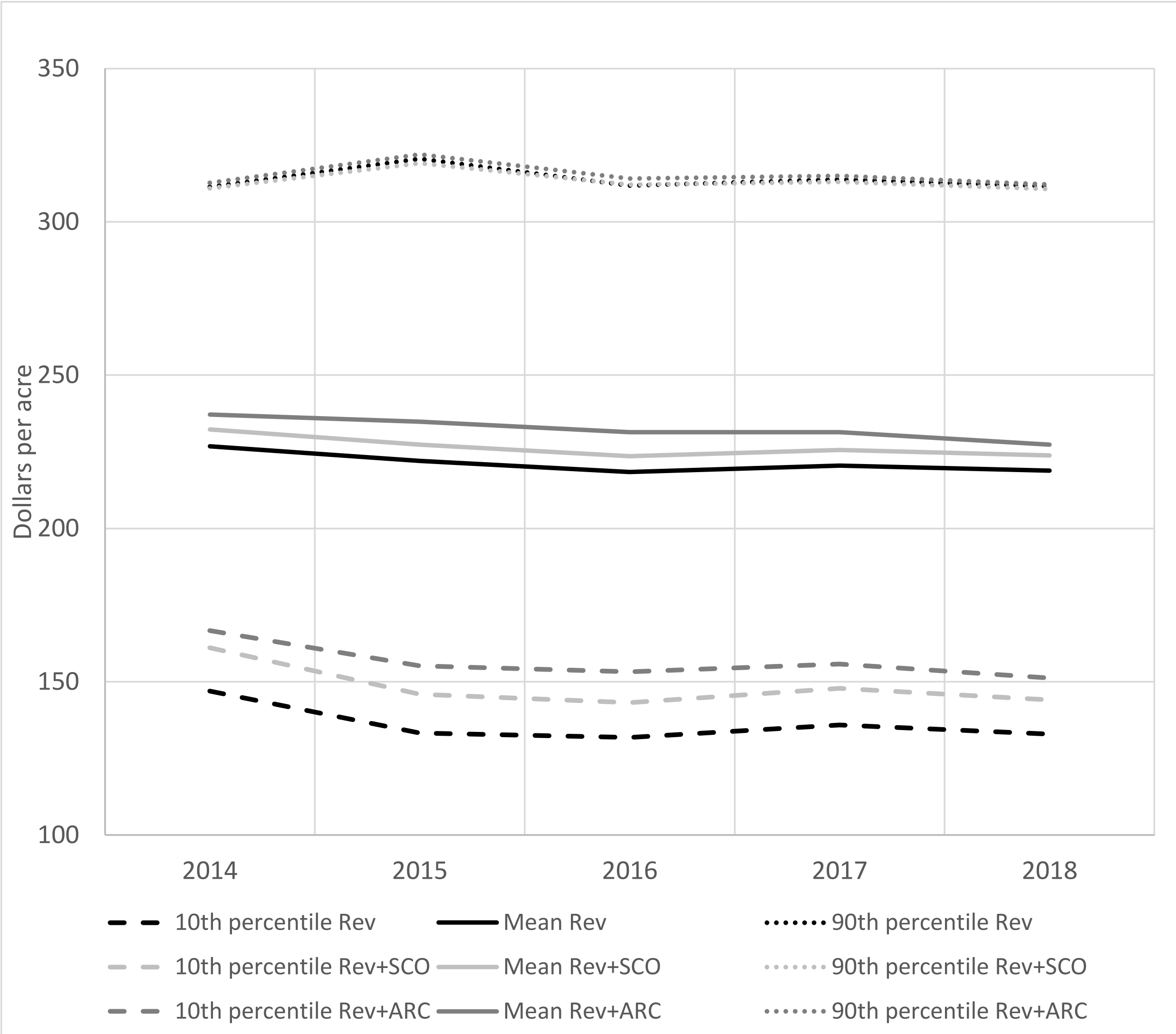

Figure 6: Wheat distributions with PLC