YIELD GUARANTEES AND THE PRODUCER WELFARE BENEFITS OF CROP INSURANCE

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Yield Guarantees and the Producer Welfare Benefits of Crop Insurance

Abstract

Crop yield and revenue insurance products with coverage based on actual production history (APH) yields dominate the U.S. Federal Crop Insurance Program. The APH yield, which plays a critical role in determining the coverage offered to producers, is based on a small sample of historical yields for the insured unit. The properties of this yield measure are critical in determining the value of the insurance to producers. Sampling error in APH yields has the potential to lead to over-insurance in some years and under-insurance in other years. Premiums, which are in part determined by the ratio of the APH yield to the county reference yield, are also affected by variations in APH yields. Congress has enacted two measures, yield substitution and yield floors, that are intended to limit the degree to which sampling error can reduce the insurance guarantee and producer welfare. We examine the impact of sampling error and related policy provisions for Texas cotton, Kansas wheat, and Illinois corn. The analysis is conducted using county level yield data from the National Agricultural Statistics Service and individual insured-unit-level yield data obtained from the Risk Management Agency's insurance database. Our findings indicate that sampling error in APH yields has the potential to reduce producer welfare and that the magnitude of this effect differs substantially across crops. The yield substitution and yield floor provisions reduce the negative impact of sampling error but also bias guarantees upward, leading to increased government cost of the insurance programs.

Key Words: Actual Production History, Crop Insurance, Sampling Error, Yield Guarantee

Introduction

Actual Production History (APH) yield insurance was the dominant insurance product offered under the U.S. federal crop insurance program prior to the mid-1990s. The APH yield insurance guarantee is based on a fixed price and the simple average of from four to ten years of historical yields for the insured unit. Yield guarantees for the Revenue Assurance (RA) and Crop Revenue Coverage (CRC) revenue insurance products are determined in the same manner. These APH-yield-based yield and revenue insurance products continue to dominate the crop insurance program in terms of premium collected and liability insured.

The actual production history yield guarantee is based on a 4 to 10 year average of historical yields for the insured unit. Sampling error in APH yields has the potential to lead to over-insurance in some years (relative to the chosen coverage level) and under-insurance in other years. Furthermore, premium rates vary substantially based on the ratio of the APH yield for an insured unit to a predetermined county reference yield and thus are affected by sampling error. The problem of errors in APH yields and resulting insurance guarantees has surfaced in recent policy debates. In the early part of the current decade, many farmers in the Western Corn Belt and Plains States believed that a multi-year drought was undermining the effectiveness of their insurance coverage by biasing their yield guarantees downward and their premium rates upward (Knight, 2003, High Plain/Mid West Ag Journal, 2004). In his Congressional testimony on this issue, Knight (2003) showed that the average yield of cotton during the 24 years period from 1972-1995 was 303 pounds per acre in Martin County, Texas compared with an average of 120 pounds per acre in the 7 year period from 1996 to 2002. These recently clustered low yields significantly lowered most producers yield guarantees below the trend-adjusted expected yield.

In addition to affecting insurance guarantees, premium rates, and producer welfare, sampling error in APH yields also has the potential to contribute to adverse selection. Adverse selection occurs when farmers are better informed than the insurer about their yield and indemnity distributions. Farmers who recognize that they have an opportunity to over-insure, due to positive sampling error, are more likely to insure and to choose high coverage levels. Similarly, farmers who believe that their yield guarantee is too low are less likely to insure or, if insuring, to choose lower coverage levels (Carriquiry, Babcock and Hart, 2008, henceforth CBH). Given a premium structure that would otherwise be actuarially fair, this selection process will result in the collection of premiums that are inadequate to cover expected indemnities.

Recognizing that the statistical properties of APH yields result in producers being offered guarantees that are sometimes significantly different from their expected yield, Congress has enacted two measures that are intended to limit the degree to which these statistical phenomena can reduce the insurance guarantee. These two policy provisions are yield substitution and yield floors. Yield substitution allows the producer to use 60% of a specified county proxy yield (T-yield) as a substitute for the actual historical yield in any year when the actual yield falls below 60% of the T-yield. This causes the historical yield used for each year in the APH yield calculation to be censored at 60% of the pre-established county T-yield for that year. Use of yield substitution varies substantially based on variability of crop yields in different regions. For example, the Risk Management Agency (RMA) yield history data show that, in 2008, 62% of APH yields for dryland cotton in the Texas High Plains made use of yield substitution compared with 15% for Illinois corn and 46% for dryland wheat in Kansas.

Yield floors set minimum APH yields for an insured unit in the insurance year. The basic provisions relating to yield floors set a minimum on the APH yield for an insured unit equal to 70% of the county T-yield yield if only one year of actual historical yields is provided. This increases to 75% if 2-4 years of historical yields are provided and 80% when 5-10 years of actual yields are used. Thus, yield substitution sets a minimum value for any single year's yield used in the APH yield calculation, while yield floors set minimums on the APH yield itself. In 2008, yield floors were used in establishing insurance guarantees for 8.12% of Texas dryland cotton units, 3.94% of Illinois corn units, and 4.89% of insured Kansas wheat units (Table 1).

Table 1. Percent of Units Using Yield Substitution or Yield Floors in 2008

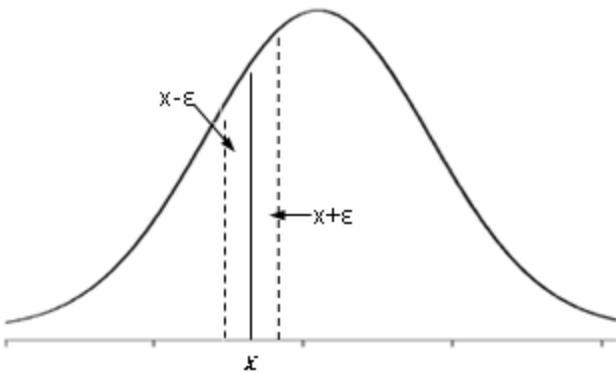| Yield limitation	Cotton	Corn	Wheat
	Texas	Illinois	Kansas
Yield floor	8.12	3.94	4.89
Yield substitution	61.69	14.99	45.56

It is clear that sampling error has the potential to affect the producer welfare benefits of yield and revenue insurance products that are based on APH yields. Furthermore, it is also clear that use of yield substitution and yield floors mitigates the effects of a sample (APH) yield that is substantially lower than the expected yield while not dampening the effect of upside sampling error. The objective of this paper is to examine the producer welfare effects of sampling error in APH yields when considering the rigidities associated with yield substitution and yield floors. The analysis is conducted (1) assuming that there are no legislative restrictions (such as yield floors and substitutions) and that APH yields are simple averages of different lengths of historical yield series for the insured unit and (2) imposing the current legislative restrictions of yield substitution and yield floors. CBH used the expected indemnity to measure the effect of APH yields that are subject to sampling error. We extend beyond the expected indemnity and evaluate producer welfare effects based on certainty equivalent differences. This provides significant new insight into the effects of APH yield variability on the effectiveness of the U.S. Federal Crop Insurance program.

Conceptual Framework

The producer's yield is a random variable y described by a distribution function $f(y)$ with mean μ_y and variance σ_y^2. Let the APH yield have the distribution $\alpha f(y)$ with mean $\alpha \mu_y$ and variance $\alpha^2 \sigma_y^2$, where $\alpha = 0.50$ to 0.85, in increments of 0.05, is the insurance
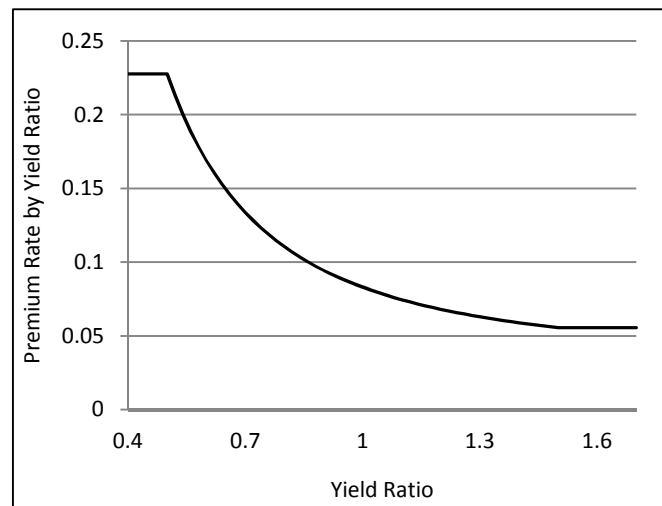
coverage level. If the yield falls below the guarantee level$(\alpha\bar{y})$, the farmer receives an indemnity of $p_G * (\alpha\bar{y} - y)$ per acre, where, p_G is the price guarantee. The APH yield, $\bar{y}$, is computed using from 4 to 10 years of historical yields for the insured unit. Small samples such as 4 year history will produce larger variance than larger samples of say 10 years. Let us assume the expected yield guarantee is distributed normally with mean $\alpha\mu$ and variance $\alpha^2\sigma_y^2$. Consider equal deviations of $\pm\varepsilon$ from the expected yield guarantee $\alpha\mu = x$, as shown in Figure 1. Over-insuring at a level $x + \varepsilon$ increases the expected indemnity relative to the level associated with a fair insurance guarantee of x. Similarly, under insuring at a level $x - \varepsilon$ decreases the expected indemnity compared with a fair guarantee of x. Given an insurance guarantee that is in the left tail of a bell shaped yield distribution, the probability mass between $x + \varepsilon$ and x is greater than that between $x - \varepsilon$ and x. The implication of this is that the effect of sampling error is to increase the expected indemnity. Also, it is important to note that the degree of sampling error increases as sample size decreases so that the expected indemnity decreases with sample size.

Figure 1. Contracted and Real Guarantee Level

As indicated earlier, premium rates for APH yield insurance, CRC, and RA vary with the ratio of the APH yield to the county reference yield.[1] This is illustrated if Figure 2, which shows an example premium rate curve which is convex in the yield ratio (insured unit yield divided by county reference yield). It is clear that this convex component of the rate structure imposes large rate "penalties" when sampling error leads to an APH yield substantially below the expected yield for an insured unit. This relationship is not symmetric in that positive sampling error of the same magnitude results in smaller rate "discount."

Figure. 2 Premium Rate as Function of Yield Ratio

Both of the above factors are important in determining the effect of sampling error on expected indemnities and on producer welfare. Those effects are examined in the sections that follow.

Empirical Implementation

Farm level yield data are required to support the empirical analysis. We decompose National Agricultural Statistics Service (NASS) county yield data into systemic and idiosyncratic components in order to approximate the farm yield. We use the decomposition given by Miranda (1991), Mahul (1999) and Carriquiry, Babcock and Chad (2008) as:

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[1] Actually, this component of the rate formula utilizes the rate yield rather than the APH yield. The rate yield is the simple average of the historical yields without incorporation of yield substitutions and yield floors.

$$y_{it} = \mu_i + \beta_i(y_{ct} - \mu_c) + \varepsilon_{it} = \mu_c + \delta_i + \beta_i(y_c - \mu_c) + \varepsilon_{it} \qquad (1)$$

where μ_c and μ_i are the mean county and farm yield, δ_i is the difference between county mean yield and farm mean yield, y_{it} and y_{ct} are the farm and county yield in year t and ε_{it} is the farm yield deviation in year t. It is assumed that $E[\varepsilon_{it}] = 0, E[y_{it}] = \mu_i, \;E[y_{ct}] = \mu_c \, , \mu_i = \mu_c + \delta_i,$ $Cov(\varepsilon_{it}, y_{ct}) = 0, Var(y_{ct}) = \sigma_c^2 \;$ and $Var(y_{it}) = \beta_i^2\sigma_c^2 + \sigma_c^2$. We assume the variance of the idiosyncratic shock is uniform across the insured units within a county. The regression residual ε_{it} is used to estimate the variance as a weighted average of the error variance $(\hat{\sigma}^2)$ estimated for each of the insured farm units. We used the mean of statistically significant β_i for a county to estimate the farm yield within that county.

Texas cotton, Illinois corn, and Kansas wheat were chosen for this study because these states are major producing states for these crops and yield variability and insurance parameters vary substantially across these states and crops. In evaluating the impact from sampling error and yield rigidities, we use these different areas to examine differences in impacts by crop and region. County yield data from 1972 to 2007 were used for the analysis. Farm level data from 1998 to 2007 were made available by RMA of the United States Department of Agriculture. Both farm and county level data were detrended. Each county yield series was regressed as a linear function of time for the 36 year period. After estimating the predicted yield, both the farm and county level yield series were multiplicatively detrended and normalized to the base year 2007 predicted yield such that

$$County\; yield\; at\; the\; t\; year = y_{ct} * (\frac{\hat{y}_{c,07}}{\hat{y}_{c,t}})$$

$$Farm\; yield\; at\; the\; t\; year = y_{it} * (\frac{\hat{y}_{i,07}}{\hat{y}_{i,t}})$$

We estimated equation (1) using the detrended data series. The mean and variance of β_i were estimated. The normality of the distribution of β_i was tested and failed to reject the null hypothesis of normality. The residual ε_{it} is assumed to have normal distribution with mean 0 and variance $\hat{\sigma}^2$.

Debate regarding the distributional assumptions for crop yield distributions and the implications for crop insurance has received great emphasis in the agricultural economics literature (Goodwin and Ker, 1998, Ker and Goodwin, 2000, Atwood, Shaik, Watts, 2002, Goodwin and Mahul, 2004). Researchers have used the Beta and other parametric distributions, semi-parametric distributions and non-parametric distributions in order to avoid the conflicting arguments for and against the normal distribution. At high levels of yield variance, such as in case of dryland cotton in Texas, the Beta distribution often is not bell shaped. Further, a nonparametric distribution needs to have an a priori form before simulating values. Therefore, we assume the censored normal distribution for crop yields as discussed in Coble et. al, (2010).

For each county, 10,000 simulated observations were constructed from the detrended yield series for the county using a censored normal cumulative distribution function. Price series were constructed by assuming a lognormal distribution with the mean price and coefficient of variation for 2008. The correlated yield-price samples were constructed using the Phoon, Quek, and Huang (PQH) multivariate simulation method (Phoon, Quek, and Huang, 2002; Anderson, Harri, and Coble, 2009). The residuals (ε_{it}) and β_i were also simulated based on normal distributions with the mean and standard deviation for respective counties. Each yield series consists of 11 years of detrended random draws, where years 1 to 10 were used to construct expected yield and the 11th year was used as the realized yields. These yield samples were used to simulate the actuarially fair premium rate and indemnity for each of the yield realizations.

Monte Carlo integration has been widely used to approximate the insurance indemnity, farmers'

utility and certainty equivalents in the crop insurance literature. We used this approach to obtain

indemnity and certainty equivalent approximations.

The indemnity with APH is computed as:

$$I(\beta) = p_G * Max(\beta\mu_y - y, 0)$$

where, p_G is the price guarantee, μ_y is the APH expected yield and y is the realized farm yield.

We refer to farm revenue as the crop revenue (the product of random yield and random price)

plus the insurance indemnity, minus premium (γ) paid.

Our analysis uses an expected utility framework to compute the certainty equivalent for

the individual farm at different levels of coverage. A risk averse farmer maximizes expected

utility of wealth. We assume that farmers' risk preferences are represented by a power utility

function which implies Constant Relative Risk Aversion (CRRA). The CRRA utility function

requires initial wealth in order to reflect appropriate risk aversion of farmers (Chavas, 2004). We

assume the initial wealth is the net worth per acre of the Agricultural and Food Policy Center

(AFPC) representative farm that is located closest to our study counties (Richardson et. al, 2008).

Let initial wealth be w and c is the production cost[2] per acre. Farm revenue with insurance is:

$$\pi_i(\beta) = w + p * y + I(\beta) - \gamma - c$$

and the CRRA utility function is:

$$U_i(\beta) = -\pi_i(\beta)^{1-R}$$

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[2] Production cost per acre for cotton, corn, and wheat was taken from crop budget of Texas A and M University, crop extension budget, University of Illinois, crop budget and Kansas State University, farm management guide respectively for the counties under this study.

where, R > 1 is the coefficient of relative risk aversion and π_i is revenue per acre as a function of the APH guarantee level. Coble, Heifner, and Zuniga (2000) and Coble, Zuniga, and Heifner (2003) have used R = 2. The insurance guarantee level is the product of expected yield and APH coverage level. Assuming that a farmer chooses the APH insurance coverage level to maximize his/her expected utility, the farmer's decision problem as given by Mitchell and Knight (2008) is:

$$\max_\beta EU_i(\beta) = \max_\beta \int_\pi -\pi(\beta)^{1-R} dF(\pi_i | \beta)$$

The maximized expected utilities are converted into associated certainty equivalents for each case:

$$CE^* = (-EU_i^*)^{1/(1-R)}$$

The certainty equivalent was estimated for a range of levels of guarantee of APH insurance under three different major scenarios: for small sample APH, for the small sample and yield substitution, and for small sample and yield floor. Our welfare measure is based on the difference in the certainty equivalent per acre for each policy regime compared with the per acre certainty equivalent for the uninsured case.

Data Description

For this analysis, county yield data were obtained from NASS website. The data covers the yield history from 1972 to 2008. Individual farm yield data were obtained from RMA as Type15 crop insurance data for 2008 cotton, corn, and wheat. APH yield history data for the APH, RA , and CRC insurance products were included in the analysis. These data allow us to determine the frequency with which yield substitutions and yield floors were used in 2008. We selected Lubbock County, Texas for cotton, Adam County, Illinois for corn and Dickinson County,

Kansas for wheat in our analysis. The coefficient of variation of farm level cotton yield in Lubbock County is relatively larger than for the other crops and counties. Adam County corn has the smallest coefficient of variation (Table 2).
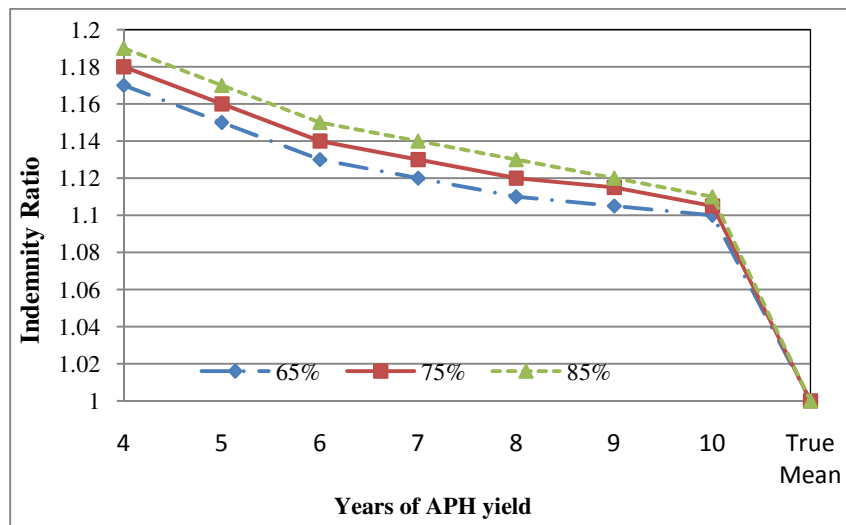
Table 2. Summary Statistics

Parameters		Cotton	Corn	Wheat
		Lubbock, TX	Adam, Ill	Dickinson, KS
Yield parameters	Mean	410.42	158.35	40.63
	StDev	174.19	31.49	10.39
	CV	42.44	19.89	25.56
	Min	160.87	68.99	13.35
	Max	833.99	204.29	63.58
Beta	Mean	0.79996	0.592	-1.901
	StDev	0.48153	0.528	3.376
Weighted variance		49312.6	562.613	187.516
Price		0.59/lb	3.91/bu	6.73/bu

Results and Discussion

The expected insurance indemnity is a function of coverage level, APH yield, actual yield realizations and random price of the commodity. The small sample available for computation of the APH yield has an impact on the indemnity expectation because of the higher variability in the expected yield from a small sample. Farmers with short yield histories have larger sampling error in their APH yields and are more likely to purchase insurance and to insure at high coverage levels when their APH yield exceeds their expected yield. This positive sampling error results in a higher likelihood of collecting an insurance indemnity. Our results reveal that indemnities are larger when APH sample size decreases. Figure 3 presents the indemnity ratios associated with varying levels of yield history, by coverage level. These are the ratios of simulated indemnities for different APH sample sizes (4 to 10 years) to the indemnity that would have been received if the insurance guarantee had been based on the true mean yield. For cotton in Lubbock County,
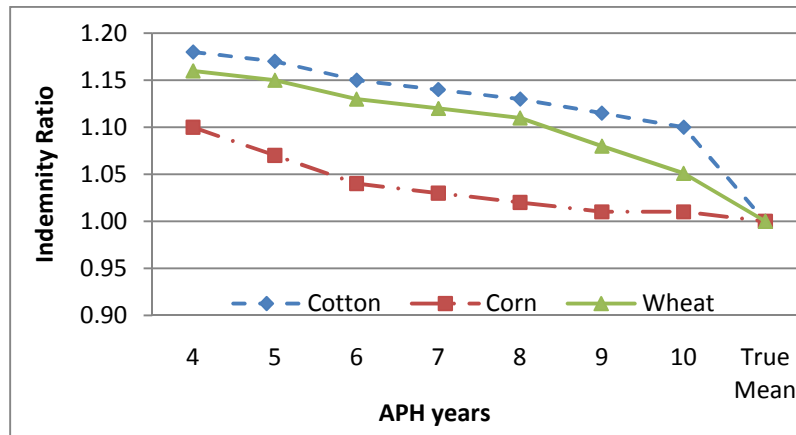
Texas, the indemnity ratio is 1.19 when the APH yield is the simple average of 4 years of historical yields and the coverage level is 85%. This indemnity ratio decreases modestly as coverage level decreases from 85% to 65%. Furthermore, the indemnity ratio for all coverage levels declines at a similar rate when sample size increases from 4 to 10 year.

Figure 3. Ratio of Expected Indemnity by Coverage Levels for Cotton

Indemnity ratios were also evaluated across the three crop/county combinations in Figure 4. These results show that this ratio is smallest for corn, moderate for wheat and largest for cotton. What this reveals is the relationship between yield variance and the effect of sampling error on indemnities. Sampling error has larger effect on indemnities when the crop yield variance is larger. This result, which is consistent with the CBH results, is not surprising because of higher incidence of over-insurance than under-insurance. However, we extended our study to examine welfare effects with different sizes of sample and without sampling error.
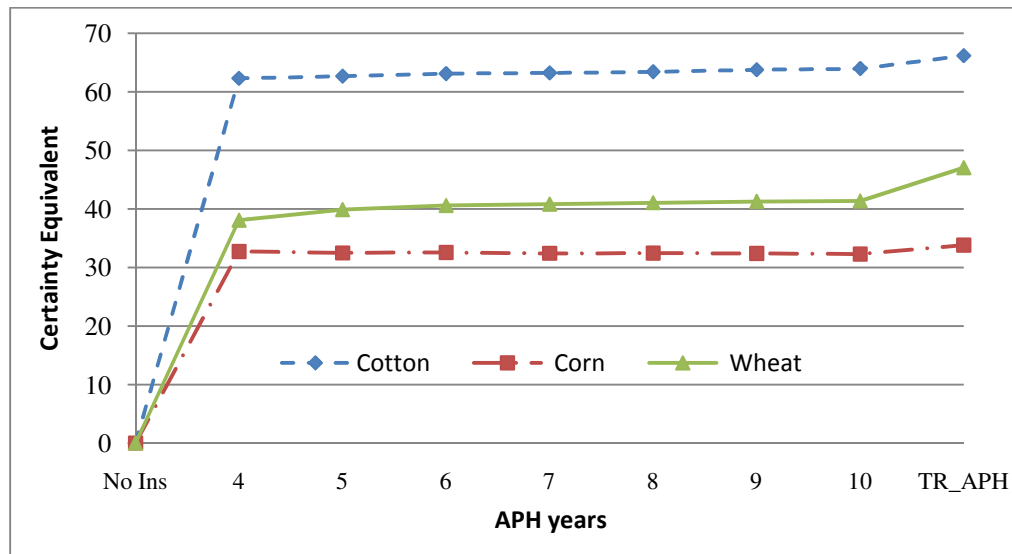
Figure 4. Indemnity Ratio at 75% Coverage by Crop

Certainty equivalent differences with and without insurance (CE with insurance – CE without insurance) provide the basis for our producer welfare analysis. These simulated differences are shown graphically for the 75% coverage level in Figure 5. Several implications can be drawn from these results. First, the benefits of the subsidized yield insurance are substantial for all three example farms. Second, the magnitude of the benefit varies inversely with yield variability in the county. Cotton in Lubbock County, Texas (CV=42.44) has the largest welfare gain from insurance, followed by wheat in Dickenson County, Kansas (CV=25.56), and then by corn in Adam County, Illinois (CV=19.89). Third, the welfare benefits of insurance increase only modestly as the sample size increases from 4 to 10 years of APH yield history. Fourth, for the example corn and cotton farms, the benefits of insurance based on the true mean yield are almost fully captured, even with only four years of yield history to support the APH yield calculation. However, for the example wheat farm the benefits of more years of yield history are somewhat larger with perfect information, as reflected in the results for an APH yield equal to the true mean yield. The reason for this last result is that the concave yield ratio premium rate function for wheat in Dickenson County (see Figure 2) is significantly steeper than for the other example county/crop insurance programs. This steep premium rate curve imposes a

large premium rate penalty when the APH yield is low due to sampling error and, as a result, the benefit of reduced (or no) sampling error is larger.

Figure 5. Effect of Sampling Error at 75% Coverage

The results for samples of 4 years, 10 years, and for an APH yield based on the true mean yield are shown for alternative coverage levels in Table 3. At the 50% coverage level, sampling error has almost no impact on producer welfare. Little impact is observed at the 65% coverage level but the effect is more pronounced when the coverage level increases. A similar trend is found for all three crops, but the magnitude of effect is different. As illustrated in Figure 5, the benefit from crop insurance is largest for cotton, moderate for wheat and smallest for corn. Moving from lower coverage to higher coverage, cotton has the largest gain followed by wheat and corn. Also, the benefits of insurance increase at a decreasing rate with respect to coverage level for all of these crops. Gains from larger sample size are negligible at the 50% coverage level but are substantial at higher coverage levels. The results in Table 3 are consistent with

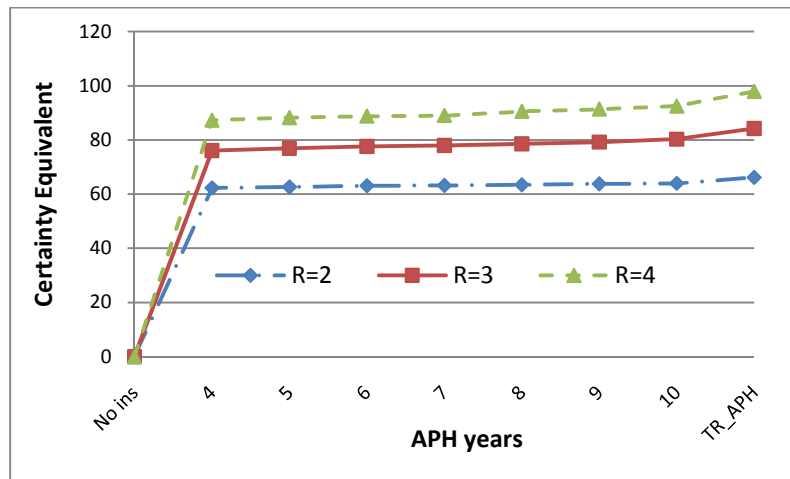Figure 5 in showing larger gains from increased sample size in Dickinson County wheat which has a steeper rate curve.[3]

Table 3. Certainty Equivalent Differences With Sampling Error

Coverage	Cotton			Corn			Wheat		
level	4	10	True APH	4	10	True APH	4	10	True APH
50%	42.09	41.87	42.24	20.11	19.85	20.42	31.45	31.37	32.83
65%	54.75	54.83	55.60	28.38	27.87	28.81	37.26	38.44	41.66
75%	62.29	63.95	66.15	32.73	32.27	33.80	38.07	41.34	47.03
85%	65.81	67.50	69.54	34.31	35.56	37.22	39.98	46.35	52.13

We further examine the case of cotton by conducting a sensitivity analysis in order to determine the effect of sampling error across different levels of risk aversion. Risk aversion levels represented by a CRRA coefficient of 2, 3, and 4 were chosen for analysis. Figure 6 shows the sensitivity of sampling error at these alternative levels of risk aversion. At the higher levels of risk aversion, the changes in certainty equivalent are larger as sample size increases. However, the difference in the effect of sampling error is very modest over the range of risk aversion evaluated.

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[3] The exponent giving rise to the negative slope and convexity of the yield ratio curve is -1.369 for Lubbock County cotton, -1.926 for Adam County corn, and -1.959 for Dickinson County wheat.

Figure 6. Sensitivity Analysis of Sampling Error with Alternative Risk Aversion Levels for Cotton
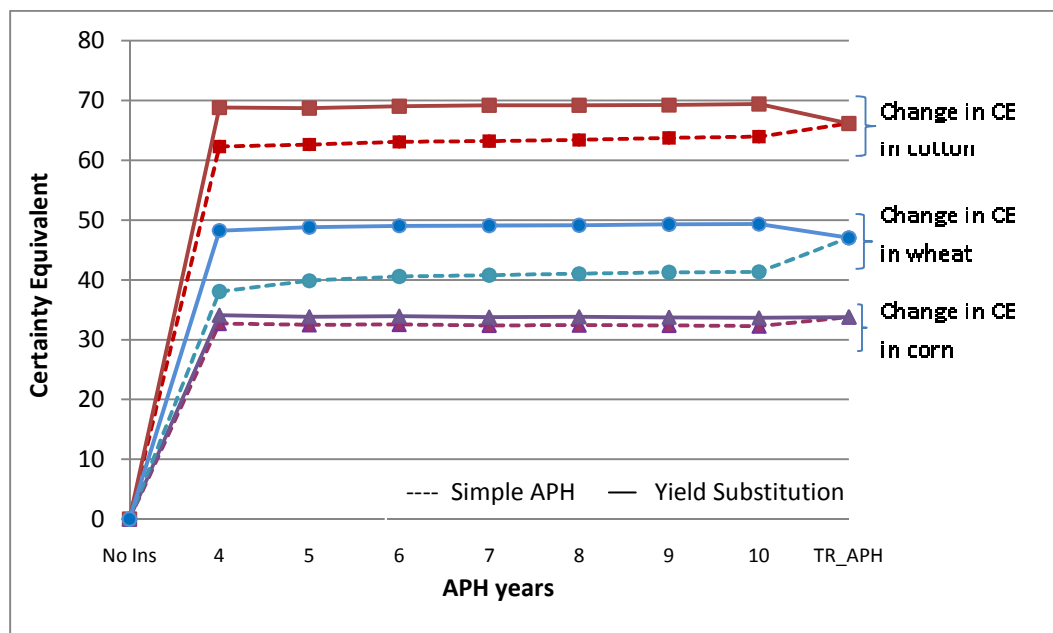

Yield Substitution

APH-based yield and revenue insurance programs allow yield substitution if the farmers' realized yield falls below 60 percent of the county T-yield. This provision was created by Congress to mitigate the effects of a catastrophic event in one year on APH yield guarantees in subsequent years. When the guarantee level is determined using one or more substitute yields, the expected APH yield is biased upward relative to the true mean. This increases the probability of collecting an indemnity and the expected indemnity, and also reduces yield variance, leading to an increase in the certainty equivalent when insured relative to uninsured.

The analysis of welfare gains with and without yield substitution is presented in Figure 7. Here the dashed lines represent certainty equivalent gains from insurance (CE with insurance – CE without insurance) with no yield substitution and the corresponding solid lines represent certainty equivalent gains with yield substitution. Corn has the smallest net welfare gain from yield substitution because it has low yield variance and lower frequency of yield substitution. Net welfare gains for cotton and wheat are substantial. The gain for wheat is larger than the gain

in cotton, which has higher yield variance. The reason for this is the steep slope of the wheat premium rate function with respect to yield ratio as discussed earlier. Given this steep rate curve, yield substitution prevents some occurrences of large rate penalties associated with one or more years of exceptionally low yields. It should be noted that the producer welfare gain from insurance with sampling error and yield substitution is larger than the gain that would be achieved with a guarantee equal the true mean yield. Thus, the upward bias in indemnities created by yield substitution more than compensate for the loss of utility due to sampling error in the insurance guarantee. This gain to producers is at least in part supported by increased premium subsidies.

Figure 7: Certainty Equivalent Gain with Yield Substitution at 75% Coverage

Yield Floors

Yield floors and yield substitution do not work simultaneously; rather the maximum of these two is used. The yield floor has been used less frequently than yield substitution. Here we analyze the welfare effects of yield floors, assuming that yield substitution provisions are also in effect. We

use a yield floor of 85 percent of the county T-yield, based on the assumption that 5 or more years of historical yields are available to support the APH yield calculation. Results shown in Table 4 reveal that certainty equivalent gains compared to the no insurance case are very large when the yield floor was used. The gain is largest for our example cotton farm, ranging from $46 to $76 per acre, and smallest in case of corn ranging from $20 to $38 per acre.

Table 4. Certainty Equivalent Differences with Yield Substitution and Yield Floors

Coverage	Cotton			Corn			Wheat		
level	4	10	True APH	4	10	True APH	4	10	True APH
50%	46.52	45.63	42.24	20.58	20.38	20.42	35.85	35.21	32.83
65%	61.29	60.31	55.60	29.30	28.80	28.81	44.79	44.54	41.66
75%	70.52	69.68	66.15	34.15	33.65	33.80	48.80	49.34	47.03
85%	75.87	74.93	69.54	38.02	38.97	37.22	39.50	42.30	52.13

In Table 5 we attempt to isolate the effects of yield substitution and yield floors. The reported values are differences in certainty equivalent gains for each scenario (i.e., differences in certainty equivalent differences relative to the uninsured case). For each crop, we report three results: (1) the difference associated with use of yield substitution compared with a guarantee based on the simple average APH yield; (2) the difference when using both yield substitution and yield floors relative to the simple average yield; and (3) the difference between use of yield substitution and use of yield floors in conjunction with substitution. The first results isolate the effects of yield substitution; the second results show the combined effects of yield substitution and floors; and the third result attempts to isolate the effects of yield floors when used in conjunction with yield substitution. These results show that the certainty equivalent gains from use of yield substitution are substantial compared with APH yields based on the simple average of historical yields. These benefits are largest for wheat, but also substantial for cotton, and much

smaller for corn. The second results, with both yield substitution and yield floors in place, show the same pattern, with even larger per acre welfare benefits. Finally, the third set of results, which show the marginal welfare increase due to introduction of yield floors show that yield floors have relatively modest benefits when yield substitution is already in effect. These final results indicate that the marginal benefit of yield floors is strongly related to sample size, with greater benefits when the sample size is small.

Table 5. Net Difference in Certainty Equivalent Differences for Alternative Scenarios (75% Coverage Level)

Crop	Scenario	4	5	6	7	8	9	10	TR_APH
Cotton	APH to yield substitution	6.53	6.08	5.97	5.98	5.79	5.48	5.48	0.00
	APH to yield substitution and yield floor	8.23	7.22	6.77	6.54	6.21	5.82	5.73	0.00
	APH to yield floor	1.71	1.14	0.80	0.56	0.42	0.35	0.25	0.00
Corn	APH to yield substitution	1.38	1.36	1.39	1.38	1.38	1.35	1.38	0.00
	APH to yield substitution and yield floor	1.42	1.38	1.39	1.38	1.39	1.35	1.38	0.00
	APH to yield floor	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Wheat	APH to yield substitution	10.18	8.94	8.48	8.28	8.11	8.02	7.99	0.00
	APH to yield substitution and yield floor	10.73	9.25	8.66	8.36	8.15	8.04	8.00	0.00
	APH to yield floor	0.55	0.30	0.17	0.08	0.04	0.02	0.01	0.00

Conclusion

Establishing appropriate yield guarantees is important to the effective functioning of individual level yield and revenue insurance programs. The approach that has been taken in the U.S. crop insurance program is to use historical yields for the insured unit to establish individual yield guarantees. This is a reasonable approach which takes into consideration most or all information that is available for the vast majority of insured units. However, guarantees based on average historical yields are subject to sampling error which can lead to over- or under-insurance. Policy

provisions, including yield substitution and yield floors, have been put in place to mitigate the effect of down-side sampling error. These measures have a left-tail censoring effect on the insured yield which raises the expected guarantee level.

This study analyzed the potential welfare gains/losses associated with sampling error, with and without yield substitution and yield floors. Our results provide the following insights.

- Sampling error significantly increases expected indemnities and thus increases actuarially fair premiums and premium subsidies.

- The welfare loss due to sampling error is larger in high risk areas and especially in areas where premium rates are highly sensitive to differences in producers' yields relative to a predetermined county yield.

- Both yield substitution and yield floors increase producer welfare, with yield substitution having the larger of the two effects.

- The upward bias in insured yields from yield substitution more than compensates for the negative effects of sampling error and provides producer welfare in excess of an "accurate" guarantee with no sampling error. This upward bias increases actuarially fair premium rates and associated government premium subsidies.

These results indicate that there is a potential welfare loss associated with sampling error but this potential welfare loss is more than offset by upward bias in insured yields created through use of yield substitution and yield floors. This welfare gain to producers comes, at least in part, at the expense of taxpayers in the form of increased premium subsidies. We believe that future research efforts should be directed at investigating alternative mechanisms to mitigate

welfare losses from sampling error while reducing the potential for over-insurance and excessive government cost.

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