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Yield Guarantees and the Producer Welfare Benefits of Crop Insurance

Shyam Adhikari, Thomas O. Knight, and Eric J. Belasco

Farm-level crop insurance guarantees are based on a small sample of historical yields. Two measures enacted by Congress, yield substitution and yield floors, are intended to mitigate the erratic nature of small samples in determining yield guarantees. We examine the impact of small samples and related policy provisions on the producer welfare benefits of individual-level yield insurance. Our findings indicate that sampling variability in Actual Production History (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 mitigate the negative impact of sampling error but also bias guarantees upward, increasing government cost of the insurance programs.

Key words: actual production history, crop insurance, sampling error, yield guarantee

Introduction

Yield Protection is the most common yield insurance product offered by the U.S. Federal Crop Insurance Program (FCIP).¹ Yield Protection bases the insurance guarantee on the USDA's projected price for the year and the simple average of four to ten years of historical yields for the insured unit (the APH yield). Revenue insurance products—including Revenue Protection and Revenue Protection with Harvest Price Exclusion—insure against loss based on projected and harvest prices,² with the yield component of the guarantee computed in the same manner as for Yield Protection. Yield and revenue insurance products based on historical yields dominate the Federal Crop Insurance Program in terms of premiums collected and liability insured. In 2011, Revenue Protection accounted for 69% of insured liability and 78% of premiums, while Yield Protection accounted for 18% of liability and 14% of premiums.

Averaging historical yield samples over a relatively short period of time creates an insurance guarantee with large sampling variance, which can 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 to a predetermined county reference yield and thus are affected by random variation in the yield guarantee. The actuarial problem of using an insurance guarantee based on a small sample of historical yields has surfaced in recent policy debates. In his congressional testimony, Knight (2003) showed that the average cotton yield in Martin County, Texas, during the twenty-four years from 1972 to 1995 was 303 pounds per acre compared with an average of 120 pounds per acre in the seven years from 1996 to 2002. In this case, a recent cluster of low yields significantly lowered most producers' yield guarantees below the trend-

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¹ Referred to as Actual Production History (APH) yield insurance before 2011.

² Prior to 2011, these products were offered under other names, including Crop Revenue Coverage (CRC), Revenue Assurance (RA), and Revenue Assurance Harvest Price Option (RA-HPO).

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

	Texas Cotton	Illinois Corn	Kansas Wheat
Yield substitution	61.7	15.0	45.6
Yield floor	8.1	3.9	4.9

adjusted expected yield. Barnett et al. (2005) showed that errors in calculating expected yields affect both premium rates and the insurance guarantee level. They constructed an example illustrating differences between contracted and effective yield guarantees. The small-sample problem gives rise to nominal- and effective-coverage levels that are sometimes substantially different. Carriquiry, Babcock, and Hart (2008) further examined this issue and found that indemnities are larger and actuarially fair premium rates are higher with a small-sample-based guarantee. They argued that the small-sample APH would mean insureds possess more information than the RMA about their expected farm yield. Farmers who believe that their APH yield is lower than their expected yield would be less likely to insure or would insure at lower coverage levels, while farmers who perceive their APH yield to exceed their expected yield would be more likely to insure or would choose higher coverage. This adverse selection process could increase indemnities and actuarially fair premium rates.

Recognizing that the statistical properties of APH yields result in producers being offered guarantees that are sometimes significantly different from their expected yield, Congress enacted yield substitution and yield floors, two policy measures intended to limit the degree to which these statistical phenomena can reduce the insurance guarantee. Yield substitution allows the producer to use 60% of a prespecified county proxy yield, called a transitional 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 censors the historical yield used for each year in the APH yield calculation at 60% of the pre-established county T-yield for that year. The yield floor sets a minimum APH yield for an insured unit. This minimum is set at 70% of the county T-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 the yield floor sets a minimum on the computed APH yield itself. Both yield substitution and yield floors result in yield guarantees that are biased upward. In the case of yield substitution this bias is due to censoring of individual yields used in the APH yield calculation, while in the case of yield floors it is as a result of censoring of the computed APH yield itself. Risk Management Agency (RMA) yield-history data show that in 2008 approximately 62% of APH yields for dryland cotton in the Texas High Plains made using yield substitution, compared with 15% for Illinois corn and 46% for dryland wheat in Kansas. Yield floors were used to establish insurance guarantees for approximately 8% of Texas dryland cotton units and 4% of Illinois corn and Kansas wheat units (table 1).³

Sampling variability has the potential to affect the producer welfare benefits of yield and revenue insurance products based on APH yields. Furthermore, using yield substitution and yield floors has an asymmetric impact, mitigating the effects of a sample APH yield that is substantially lower than the expected yield, while not dampening the effect of upside sampling error. This paper examines the producer welfare effects of the small-sample problem in APH yields when considering the rigidities associated with yield substitution and yield floors. The analysis is conducted using two broad scenarios: (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

³ In addition to yield substitution and yield floors, other RMA procedures affect the APH guarantee and related premium rates. Specifically, there are limitations on the amount by which APH yields can change from year to year. Second, the convex premium rate function (discussed later in the paper) is constant for insured APH yields below 50% or above 150% of the county reference yield.

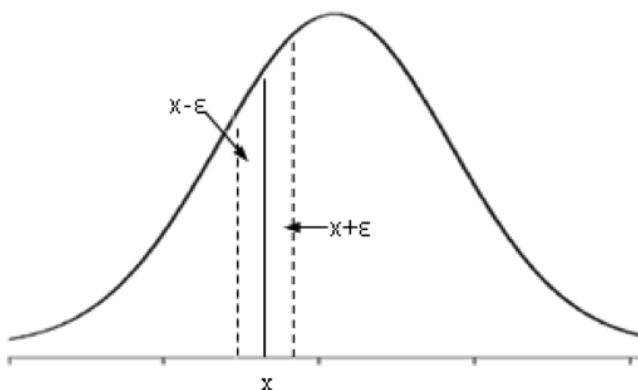


Figure 1. Contracted and Real Guarantee Level

yield floors. This provides significant new insight into the effects of APH yield variability on the effectiveness of the U.S. Federal Crop Insurance Program.⁴

Conceptual Framework

Assume the producer's yield is a random variable y described by a distribution function $f(y)$ with mean μ_y and variance σ^2 . Let the APH yield guarantee have the distribution $f(\alpha y)$ with mean $\alpha\mu_y$ and variance $\alpha^2 \frac{\sigma^2}{n}$, where $\alpha = 0.50$ to 0.85 , in increments of 0.05 , is the insurance coverage level. The APH yield, \bar{y} , is computed using four to ten years of historical yields for the insured unit. If the yield falls below the guarantee level ($\alpha\bar{y}$), the farmer receives an indemnity of $p_G \times (\alpha\bar{y} - y)$ per acre, where p_G is the price guarantee. Small samples, such as a four-year history, will produce larger sample variances than larger samples of, for example, ten years. Consider equal deviations of $\pm\epsilon$ from the expected yield guarantee $\alpha\mu = x$, as shown in figure 1.⁵ Over-insuring at a guarantee level of $x + \epsilon$ increases the expected indemnity relative to the level associated with a fair insurance guarantee of x . Similarly, under-insuring at a level of $x - \epsilon$ decreases the expected indemnity compared with a fair guarantee of x . Given our normality assumption and an insurance guarantee that is at least $\epsilon < \mu_y$, then the expected excess indemnity when over-insuring at a level of $x + \epsilon$ is greater than the expected indemnity shortfall when under-insuring at a level of $x - \epsilon$. The implication is that sampling error in APH yields increases the expected indemnity. That is, when the sample APH is lower than the true APH, a portion of the yield distribution where an indemnity is triggered is lost and no indemnity is paid. When the sample APH is higher than its true value, then a portion of the yield distribution where indemnities would be triggered is added. This phenomenon, which is due to the small-sample problem, results in an increase in expected indemnity. The degree of this error decreases as sample size increases, so that the expected indemnity approaches the true indemnity.⁶

⁴ One reviewer pointed out the importance of acknowledging that our analysis examines the effects of sampling variability, yield substitution, and yield floors under the implicit assumption that no yield trend exists. A positive yield trend, as examined by Adhikari, Knight, and Belasco (2012), could affect the accuracy of APH yields, and trend effects could interact with those arising from sampling variability. Examining these interactive effects is outside the scope of this paper. The RMA recently introduced a trend-adjusted APH yield endorsement for corn and soybeans in the Midwest. It is too early to know how popular this coverage option will become and whether it will be expanded to additional crops and regions. However, the interaction between yield trends and sampling variability will be greatly reduced or eliminated for producers who adopt this endorsement.

⁵ We assume a normal distribution to illustrate this example. However, as we will later show, the assumption of normality is unnecessary and our results are robust to other distributions.

⁶ This result holds not just for normally distributed yields but for any yield distribution that is monotonically increasing over the range from 0 to μ_y .

When crop yields are assumed to have a normal distribution with $y \sim N(\mu_y, \sigma_y)$, the sample mean also has normal distribution with $\bar{y} \sim N(\mu_y, \frac{\sigma_y}{n})$. The yield guarantee is determined as the product of coverage level and expected yield, and the guarantee level is also normally distributed as:

$$(1) \quad \alpha\bar{y} \sim N(\alpha\mu_y, \alpha^2 \frac{\sigma_y}{n}).$$

Consider two cases, each representing an equal deviation from the guarantee level such that the deviation to the right from the mean guarantee is $y_+ = \alpha\mu_y + \varepsilon$, while the deviation to the left of the mean guarantee is $y_- = \alpha\mu_y - \varepsilon$. The indemnity for any coverage level in physical terms is given as:

$$(2) \quad \text{Indemnity}(I) = \max(0, (\alpha\bar{y} - y_i)).$$

The indemnity is zero if the realized yield is larger than the guarantee level. The distribution of the indemnity is censored at zero such that:

$$(3) \quad I = \begin{cases} 0, & \text{if } I^* \leq 0 \\ I^*, & \text{if } I^* > 0 \end{cases},$$

where I^* is the latent indemnity and I is the observed indemnity. Let E_{x+} and E_{x-} be the expected value of the indemnity when the yield guarantee is between $(x, x + \varepsilon)$ and $(x, x - \varepsilon)$. If $E_{x+} > E_{x-}$, then the additional indemnity from a small deviation of the guarantee level to the right of true guarantee is larger than the reduction in indemnity from the same level of deviation of guarantee to the left.

To show this, we define $E_{x+} = \int_{\alpha\mu}^{\alpha\mu+\varepsilon} y f(y) dy$ and $E_{x-} = \int_{\alpha\mu-\varepsilon}^{\alpha\mu} y f(y) dy$. By applying the mean value theorem to both integrals, we obtain the following:

$$(4) \quad E_{x+} = (\alpha\mu + \varepsilon - \alpha\mu)y_+f(y_+) = \varepsilon y_+f(y_+);$$

$$(5) \quad E_{x-} = (\alpha\mu - (\alpha\mu - \varepsilon))y_-f(y_-) = \varepsilon y_-f(y_-);$$

where $y_+ \in [\alpha\mu, \alpha\mu + \varepsilon]$ and $y_- \in [\alpha\mu - \varepsilon, \alpha\mu]$. Since $y_+ > y_- > 0$ and $f(y)$ is positive and monotonic between $[\alpha\mu - \varepsilon, \alpha\mu + \varepsilon]$, then $f(y_+) > f(y_-)$. This immediately implies that $E_{x+} > E_{x-}$.

As indicated earlier, premium rates for Yield Protection, Revenue Protection, and Revenue Protection-Harvest Price Exclusion vary with the ratio of the APH yield to the county reference yield.⁷ The rate curve is convex with respect to the yield ratio. This convexity 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 a smaller rate discount. Both of these factors are important in determining the effect of a small sample on expected indemnities and on producer welfare.

Empirical Implementations

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

$$(6) \quad y_{it} = \mu_i + \beta_i(y_{ct} - \mu_c) + \varepsilon_{it} = \mu_c + \delta_i + \beta_i(y_{ct} - \mu_c) + \varepsilon_{it},$$

⁷ Actually, this component of the rate formula uses 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.

where μ_c and μ_i are the mean county and farm yield, δ_i is the difference between the mean yield for county c and farm i , y_{it} and y_{ct} are the farm and county yield in year t , and ε_{it} is the yield deviation for farm i in year t . It is assumed that $[\varepsilon_{it}] = 0$, $E[y_{it}] = \mu_i$, $E[y_{ct}] = \mu_c$, $\mu_i = \mu_c + \delta_i$, $Cov(\varepsilon_{it}, y_{ct}) = 0$,⁸ $Var(y_{ct}) = \sigma_c^2$, and $Var(y_{it}) = \beta_i^2 \sigma_c^2 + \sigma_\varepsilon^2$. The idiosyncratic shocks ε_{it} are assumed to be characterized by a normal distribution with mean 0 and constant variance $\hat{\sigma}^2$ within a county.⁹ The farm yield variance is estimated from the county yield variance and regression residual ε_{it} variance (σ_ε^2). We use the mean of a statistically significant β_i for a county to estimate the farm yield within that county.

This study uses Texas cotton, Illinois corn, and Kansas wheat because these states are major producers of these crops and yield variability and insurance parameters vary substantially across these states and crops. The specific counties chosen for detailed analysis were Lubbock County, Texas; Adams County, Illinois; and Dickinson County, Kansas. County yield data from 1972 to 2007 were used for the analysis. Farm-level data from 1998 to 2008 were obtained from the RMA. Each county yield series was regressed as a linear function of time for the thirty-six-year period.¹⁰ After estimating the predicted yield, both the farm and county yield series were multiplicatively detrended and normalized to the base year 2007 predicted yield. In order to detrend yield outcomes, the ratio of trended yield for 2007 to any year t was multiplied by the actual yield for the year t , which can be shown as $Y_{ct} \times \frac{\hat{Y}_{c,t=2007}}{\hat{Y}_{ct}}$. The county yield trend was then applied to the farm yield to obtain detrended farm yields. We estimated equation (6) 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 normality was not rejected.

Discussions of appropriate distributional assumptions in crop yield modeling and the implications for crop insurance have received considerable emphasis in the agricultural economics literature (Goodwin and Ker, 1998; Just and Weninger, 1999; Ker and Goodwin, 2000; Atwood, Shaik, and Watts, 2002; Goodwin and Mahul, 2004). Researchers have used the Beta and other parametric distributions, semiparametric distributions, and nonparametric distributions to avoid the conflicting arguments for and against the normal distribution. In areas with high yield variance, such as in case of dryland cotton in Texas, the Beta distribution is often not bell-shaped. Further, a nonparametric distribution needs to have an *a priori* form before simulating values. For this application we assume the censored normal distribution for crop yields. This is the parametric yield distribution used by the RMA in developing Revenue Protection and Revenue Protection with Harvest Price Exclusion rates. Coble et al. (2010) indicate that the RMA uses this distribution, as opposed to a Beta distribution, based on computational ease and some empirical evidence that rates produced by the two distributions are similar. We fitted a censored normal distribution for the county yield and estimated the mean and variance required for the simulation.

For each county, 10,000 observations on each of eleven yield series were simulated from the detrended county yield series using a censored normal cumulative distribution function. The first ten series represented APH yield histories of up to ten years in length, and the eleventh series represented realized yield in the insurance year. The parameter beta that gives the county to farm relationship was simulated by using a normal distribution. The residual from equation (6) by construction assumes a normal distribution. From the simulated county yields, beta, and residuals, we generated farm

⁸ The assumption that $Cov(\varepsilon_{it}, y_{ct}) = 0$ is made in Miranda (1991), Mahul (1999), and Carriquiry, Babcock, and Hart (2008) and assumes that the covariance between county-level yields over time and farm-level idiosyncratic shocks is equal to zero. One reviewer pointed out that individual yield deviations are likely to be larger during periods of exceptionally high or low area yields. If the orthogonality assumption above is violated, then any results based on this assumption would be biased. While this has not been empirically tested, future research should focus on this assumption, given the frequency with which this approach has been used.

⁹ The example farm results generated from this simulation process reflect a farm with average yield variance for the county.

¹⁰ While additional specifications may be used to characterize technological trends in yields over time, we use a linear trend in this application due to the lack of consensus regarding a more complex functional form that may be uniformly applied across crops and regions.

yields for a representative farm for the study counties.¹¹ Price series were constructed assuming a lognormal distribution with the mean price as a FAPRI price projection for 2008 and coefficient of variation of 20%. The correlated yield-price samples were constructed using the Phoon, Quek, and Huang (2004) multivariate simulation method (see also Anderson, Harri, and Coble, 2009). Each observation consists of eleven years of detrended random yield draws, where the eleventh yield draw of each observation is treated as the realized yield in the insurance year and the other yields were used as historical yields to construct APH yields of lengths four and ten years. These yield samples were used to calculate the indemnity for each of the 10,000 yield realizations. Monte Carlo integration has been widely used to approximate expected insurance indemnities, actuarially fair premium rates, and farmer utility and certainty equivalents in the crop insurance literature. We used this approach to obtain indemnity and certainty equivalent estimates.

The indemnity with price guarantee p_G is computed as:

$$(7) \quad I(\alpha) = p_G \times \text{Max}(\alpha\mu_y - y, 0),$$

where 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 paid (γ).

We use an expected utility framework to compute the certainty equivalent for the individual farm at different levels of coverage, where each farmer is assumed to maximize their 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 appropriately reflect farmers' risk aversion (Chavas, 2004). We assume that 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). Given beginning wealth BW for an example farm and production costs c per acre,¹² farm ending wealth EW with insurance and for a given joint observation on the random variables p and y is:

$$(8) \quad EW(\alpha) = BW + p \times y + I(\alpha) - \gamma - c,$$

and the CRRA utility function is:

$$(9) \quad U(\alpha) = -EW(\alpha)^{1-R},$$

where $R > 1$ is the coefficient of relative risk aversion and EW is ending wealth per acre as a function of the APH guarantee level.¹³ Our analysis uses $R = 2$ as a moderate level of risk aversion (Coble, Heifner, and Zuniga, 2000; Coble, Zuniga, and Heifner, 2003). The insurance guarantee level is the product of expected yield and Yield Protection coverage level. Monte Carlo integration is used to obtain the expected utility for alternative coverage levels, and the certainty equivalent is computed as:

$$(10) \quad CE = (-EU)^{1/(1-R)}.$$

The certainty equivalent was estimated for a range of insurance coverage levels under three scenarios: (1) small-sample APH, (2) small sample with yield substitution, and (3) small sample with 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.

¹¹ This process results in a sample with "average" yield variance for farms in the county.

¹² Production costs per acre for cotton, corn, and wheat were taken from Texas A&M University crop-extension budgets, University of Illinois crop budgets, and Kansas State University farm-management guides.

¹³ Under the assumption that $R > 1$, the above utility function is also a decreasing absolute risk aversion (DARA) utility function.

Table 2. Summary Statistics

Parameters	Lubbock County Cotton	Adams County Corn	Dickinson County Wheat
Yield parameters			
Mean	410.42 lb	158.35 bu	40.63 bu
StDev	174.19	31.49	10.39
CV	42.44	19.89	25.56
Beta			
Mean	0.799	0.592	-1.901
StDev	0.482	0.528	3.376
Price	0.59/lb	3.91/bu	6.73/bu

Data Description

For this analysis, county yield data were obtained from NASS website. The data cover the yield history from 1972 to 2008. Individual farm yield data were obtained from the RMA as Type 15 crop insurance data for 2008. APH yield history data for the YP, RA, and RA-HPE insurance products were included in the analysis. These data allow us to determine the frequency with which yield substitutions and yield floors were used. The coefficient of variation of farm level cotton yield in Lubbock County is relatively larger than for the other crops and counties, while Adams County corn has the smallest coefficient of variation (table 2).

Results and Discussion

The insurance indemnity is a function of coverage level, APH yield, actual yield, and projected price. The small sample available for computing the APH yield has an impact on the indemnity expectation because of the higher variability in the sample mean yield from a small sample. Farmers with short yield histories and resultant higher sampling variability in their APH yields are more likely to purchase insurance or to insure at high coverage levels when their APH yield exceeds their true expected yield. Our results reveal that indemnities are larger when APH sample size decreases. Table 3 presents indemnity ratios associated with varying lengths of yield history, by coverage level, for the three example crops and counties. These are the ratios of simulated indemnities for different APH sample sizes (four to ten years) to the indemnity that would be received if the insurance guarantee were based on the true mean yield. For cotton in Lubbock County, Texas, the indemnity ratio is 1.13 when the APH yield is the simple average of four years of historical yields and the coverage level is 50%. This indemnity ratio increases modestly as coverage level increases from 50% to 85%. Furthermore, the indemnity ratio for all coverage levels declines when the sample size is increased to ten years. Indemnity ratios across the three crop and county combinations show that this ratio is smallest for corn, moderate for wheat, and largest for cotton. These results reveal the relationship between yield variance and the effect of sampling variability on indemnities. The small-sample problem has a larger effect on indemnities when the crop yield variance is larger (i.e., cotton versus wheat versus corn). This result, which is consistent with the results reported by Carriquiry, Babcock, and Hart (2008), is not surprising because, as shown earlier, expected indemnities are increased more when over-insuring than they are reduced when under-insuring by an equal amount. However, we extend our study to examine the welfare effects of APH yields based on different sample sizes compared with an APH yield equal to the true mean yield for the farm (i.e., no sampling variability).

Certainty equivalent differences with and without insurance provide the basis for our producer welfare analysis. These simulated differences are shown graphically for the 75% coverage level in figure 2. Several implications can be drawn from these results. First, the benefits of subsidized yield insurance are substantial for all three farms (note comparison with no insurance). Second, the magnitude of the benefit varies directly with yield variability in the county. For example, cotton in

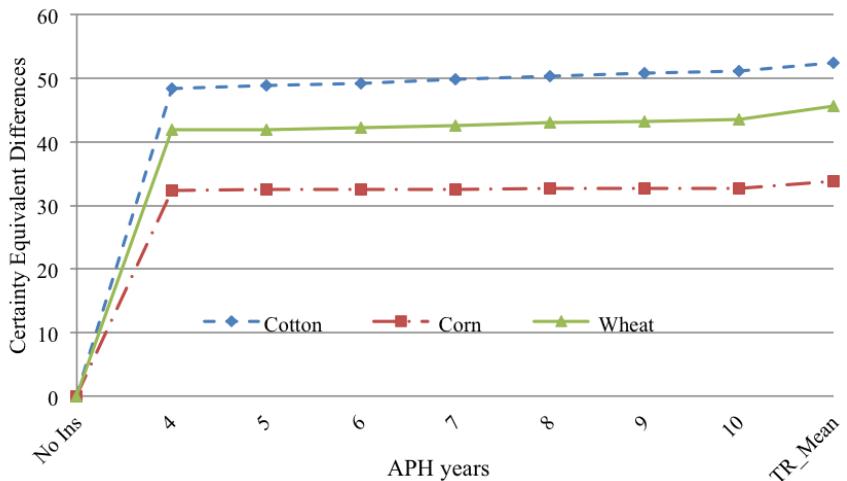


Figure 2. Welfare Effect of Sampling Error at the 75% Coverage Level (Dollars/Acre)

Lubbock County, Texas, ($CV=42.44$) has the largest welfare gain from insurance, followed by wheat in Dickinson County, Kansas, ($CV=25.56$) and then by corn in Adams County, Illinois, ($CV=19.89$). Third, the welfare benefits of insurance increase only modestly as the APH yield sample size increases from four to ten years.¹⁴ Fourth, for the example corn and cotton farms, the benefits of insurance based on the true mean yield are almost fully captured, even when only four years of yield history are used to compute the APH yield. However, the benefits of more years of yield history or a guarantee based on the true mean yield are somewhat larger for wheat farms because the convex yield ratio premium rate function for wheat in Dickinson County is significantly steeper than for the other two county/crop insurance programs.¹⁵ This steep premium rate curve imposes a large premium rate penalty when the APH yield is low due to sampling variability and, as a result, the benefit of a reduced (or no) sampling error is larger.

The results for samples of four years, ten years, and for an APH yield based on the true mean yield are shown for alternative coverage levels in table 4. At the 50% coverage level, a small-sample-based APH yield has almost no impact on producer welfare. However, the effect is more pronounced when the coverage level increases. This pattern holds for all three crops, but the magnitude of the effect is different. As illustrated for the 75% coverage level in figure 2, 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. Additionally, the benefits of insurance increase at a decreasing rate with respect to coverage level for all three 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 2 and show larger gains from increased sample size in Dickinson County wheat, which has a steeper rate curve.

Yield Substitution

APH-based yield and revenue insurance programs allow yield substitution if the farmer's historical yield in any year falls below 60% of the county T-yield. 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, leading to an increase in the certainty equivalent

¹⁴ Recent comments by Worth (2012) indicate that farmers, on average, report five to six years of historical yields in their APH yield records. Given the stability of farm ownership, this raises question as to whether some producers fail to report their full production histories if yields in earlier years are low (perhaps due to trend) and would reduce the APH yield.

¹⁵ 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 Adams County corn, and -1.959 for Dickinson County wheat.

Table 3. Ratio of Expected Indemnity for APH Yield Series of Four and Ten Years Relative to the Expected Indemnity Based on Using True Mean Yield as the APH Yield

Coverage Level	Lubbock County Cotton		Adams County Corn		Dickinson County Wheat	
	4 Years	10 Years	4 Years	10 Years	4 Years	10 Years
50%	1.130	1.080	1.050	1.000	1.110	1.060
65%	1.170	1.102	1.070	1.000	1.160	1.110
75%	1.180	1.105	1.100	1.010	1.160	1.051
85%	1.190	1.110	1.120	1.010	1.170	1.100

Table 4. Certainty Equivalent Differences With and Without Sampling Error (Dollars/Acre)

Coverage Level	Cotton			Corn			Wheat		
	4 Years	10 Years	True Mean	4 Years	10 Years	True Mean	4 Years	10 Years	True Mean
50%	30.37	31.61	31.59	20.11	19.85	20.42	29.39	29.36	30.32
65%	40.99	43.03	44.08	28.03	28.63	29.43	38.45	38.77	40.36
75%	48.47	51.07	52.45	32.29	32.75	33.80	41.89	43.54	45.59
85%	50.14	53.14	54.55	34.31	35.56	37.22	42.42	45.62	49.07

Table 5. Certainty Equivalent Differences with Yield Substitution and Yield Floors (Dollars/Acre)

Coverage Level	Cotton			Corn			Wheat		
	4 Years	10 Years	True Mean	4 Years	10 Years	True Mean	4 Years	10 Years	True Mean
50%	33.69	33.05	31.59	20.58	20.38	20.42	33.81	33.10	30.32
65%	45.97	45.10	44.08	29.30	28.80	29.43	45.19	44.38	40.36
75%	54.75	53.76	52.45	34.15	33.65	33.80	53.17	52.58	47.60
85%	57.70	56.75	54.55	38.02	38.97	37.22	53.75	53.86	49.07

when insured relative to uninsured. Welfare gains for the 75% coverage level, with and without yield substitution, are presented in figure 3. Here the dashed lines represent certainty equivalent gains 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 a lower frequency of yield substitution. The gain for wheat is larger than the gain for cotton, which has higher yield variance and more frequent substitution (see table 1) because the steep slope of the wheat premium rate function with respect to yield ratio, as discussed earlier. Given this steep rate curve, yield substitution reduces the effects of large rate penalties that result when the rate yield is low due to one or more years of exceptionally low yields in the yield history. The producer welfare gain from insurance with a small-sample-based APH yield and yield substitution is larger than the gain that would be achieved with a guarantee equal to the true mean yield. The upward bias in indemnities created by yield substitution more than compensates for the loss of utility due to sampling variability, resulting in a larger benefit than a “perfect” guarantee based on the true mean yield.

Yield Floors

Yield floors and yield substitution do not work simultaneously. Here we assume the insured chooses to use the provision that produces the highest yield guarantee. We analyze the welfare effects of yield floors, assuming that yield substitution provisions are also in effect (i.e., the yield floor is used to establish the insurance guarantee only if it exceeds the APH yield calculated with possible use of

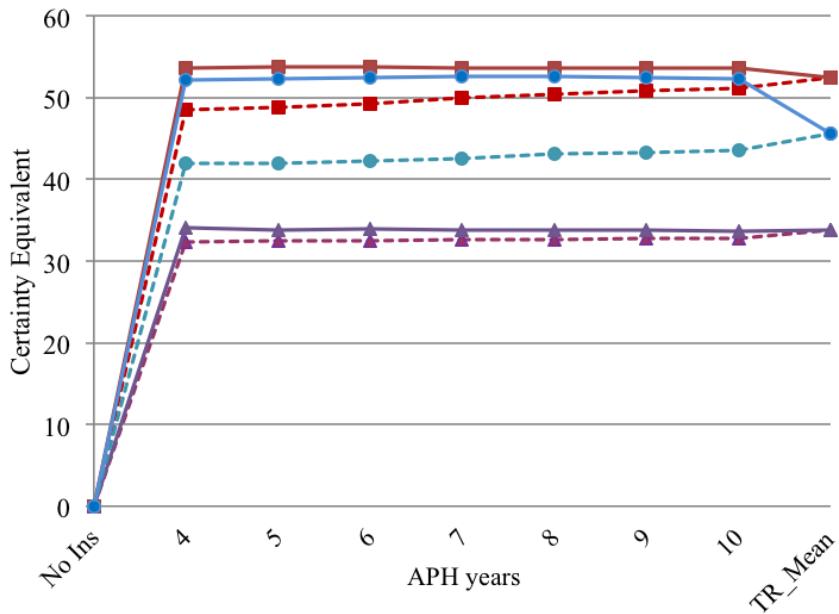


Figure 3. Certainty Equivalent Gain with Yield Substitution at the 75% Coverage Level (Dollars/Acre)

yield substitution). We use a yield floor of 85% of the county T-yield, based on the assumption that five or more years of historical yields are available to support the APH yield calculation. Results shown in table 5 reveal that when the yield floor is used certainty equivalent gains are very large compared to the no insurance case. The gain is largest for our example cotton farm (\$33 to \$58 per acre) and smallest in the case of corn (\$20 to \$39 per acre).

Table 6 isolates 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 using 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 using yield substitution and using 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 results attempt to isolate the marginal effects of yield floors when used in conjunction with yield substitution. These results show that the certainty equivalent gains from using 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 set of results, with both yield substitution and yield floors in place, shows the same pattern, with even larger per acre welfare benefits. Finally, the third set of results, which illustrates the marginal welfare increase due to introducing yield floors, shows that yield floors have relatively modest benefits when the yield substitution provisions are 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.

Welfare Effects in Major Production Areas

The results from the analyses presented thus far focus on the three crop/county examples. To examine the robustness of these results, we conduct analysis for counties in the top ten production states for cotton and corn. We do not include wheat in this analysis due to varied production practices

Table 6. Net Difference in Certainty Equivalent Differences for Alternative Scenarios at the 75% Coverage Level (Dollars/Acre)

Scenario	Years of Yield History						
	4	5	6	7	8	9	10
Cotton							
APH to yield substitution	5.08	4.89	4.40	3.66	3.11	2.80	2.55
APH to yield substitution and yield floor	6.27	5.69	4.93	4.06	3.38	2.99	2.69
Yield substitution to yield floor	1.20	0.80	0.52	0.40	0.27	0.19	0.14
Corn							
APH to yield substitution	1.82	1.39	1.43	1.24	1.19	1.05	0.90
APH to yield substitution and yield floor	1.86	1.41	1.43	1.24	1.19	1.05	0.90
Yield substitution to yield floor	0.04	0.02	0.00	0.00	0.00	0.00	0.00
Wheat							
APH to yield substitution	10.23	10.32	10.47	10.27	9.96	9.45	9.05
APH to yield substitution and yield floor	11.28	11.01	11.28	10.85	10.41	9.82	9.32
Yield substitution to yield floor	1.05	0.69	0.81	0.58	0.46	0.37	0.27

and types of wheat within and across the United States. We use methodology similar to that reported for the three crop/county examples, but we keep initial wealth as net worth per acre constant across the crops. The cost of production is allowed to vary by production region. We use the loss cost ratios obtained from the simulations as actuarially fair premium rates and use RMA's rate-making exponent parameter, which creates rates that decrease at a decreasing rate with respect to yield ratio. In this analysis, we first estimate the welfare loss due to small-sample-based APH yields and then examine the welfare gain due to yield substitution and yield floors. The welfare loss due to a small-sample-based APH was presented for the example counties as differences in certainty equivalents when the insurance guarantee is based on the sample APH yield versus the true mean yield. We also report the welfare effects of sampling variability when yield substitution and yield floor provisions are in effect.

Figures 4a and 4b reveal modest welfare losses for both cotton and corn producers from using an APH yield based on four years of historical yields. In the case of cotton, this analysis was carried out for dryland cotton producing counties of Texas, Arkansas, Georgia, Mississippi, North Carolina, Missouri, Louisiana, Tennessee, Arizona and Alabama. The small sample APH has a detrimental effect on farmers' welfare in all of these states. The per acre welfare loss ranges from less than \$1.50 per acre to \$5.30 per acre. A majority of counties in Texas show a per acre welfare loss from \$2.50 to \$5.30. However, in states like Alabama, Mississippi, Georgia, and South Carolina, the magnitude of loss due to sampling variability is found to be smaller than in Texas (figure 4a).

The welfare analysis for nonirrigated corn was conducted for Iowa, Illinois, Nebraska, Minnesota, Indiana, South Dakota, Kansas, Wisconsin, Ohio, and Missouri (the top ten corn-producing states). Figure 4b reveals that the per acre welfare loss is smaller than for cotton: a majority of counties show welfare losses of \$1.00 to \$3.30 per acre. But in the case of states like Kansas, Nebraska, South Dakota, the welfare loss due to sampling error is either zero or very small—estimated at around \$1.00. In major Corn Belt states such as Illinois, Iowa, Indiana, the small-sample effect is generally larger than in the other corn-growing states. These results are consistent with our sample county results, indicating that sampling variability in APH yield guarantees creates a negative producer welfare effect in the absence of yield substitution and yield floors.

The effect of yield substitution and yield floors was also estimated for the counties in the top ten cotton- and corn-producing states. These yield rigidities were designed to mitigate the adverse effect of a small sample of APH yield. For the example counties, we found that yield substitution and yield floors overcompensate for the small-sample problem and increase farmers' welfare compared to welfare with an insurance guarantee based on the true mean yield. Figures 5a and 5b show the

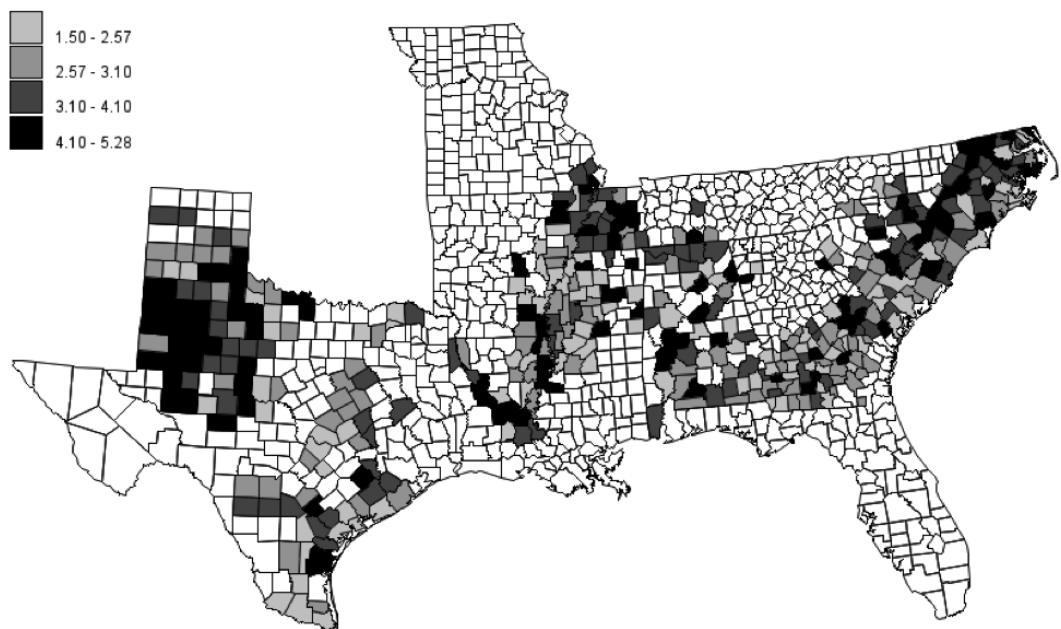


Figure 4a. Welfare Loss in Cotton due to Sampling Error at the 75 % Coverage Level (Dollars/Acre)

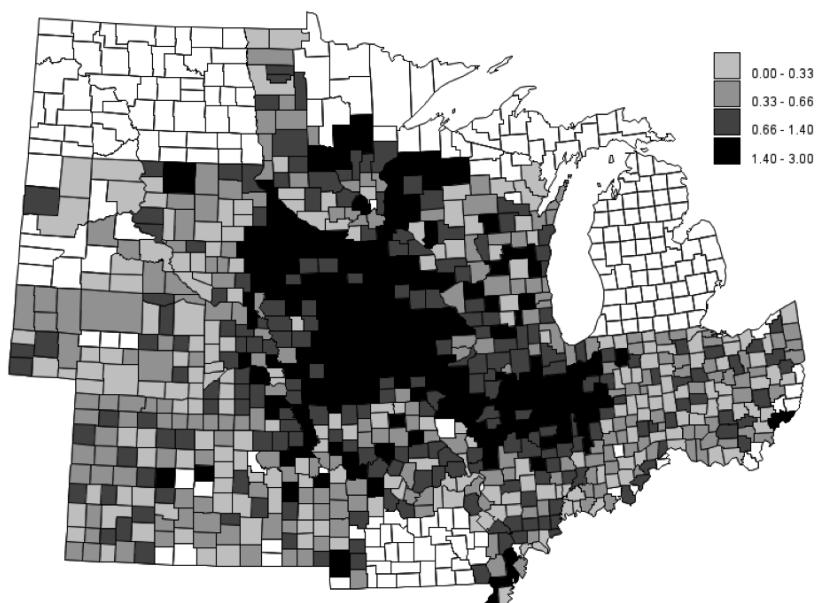


Figure 4b. Welfare Loss in Corn due to Sampling Error at the 75 % Coverage Level (Dollars/Acre)

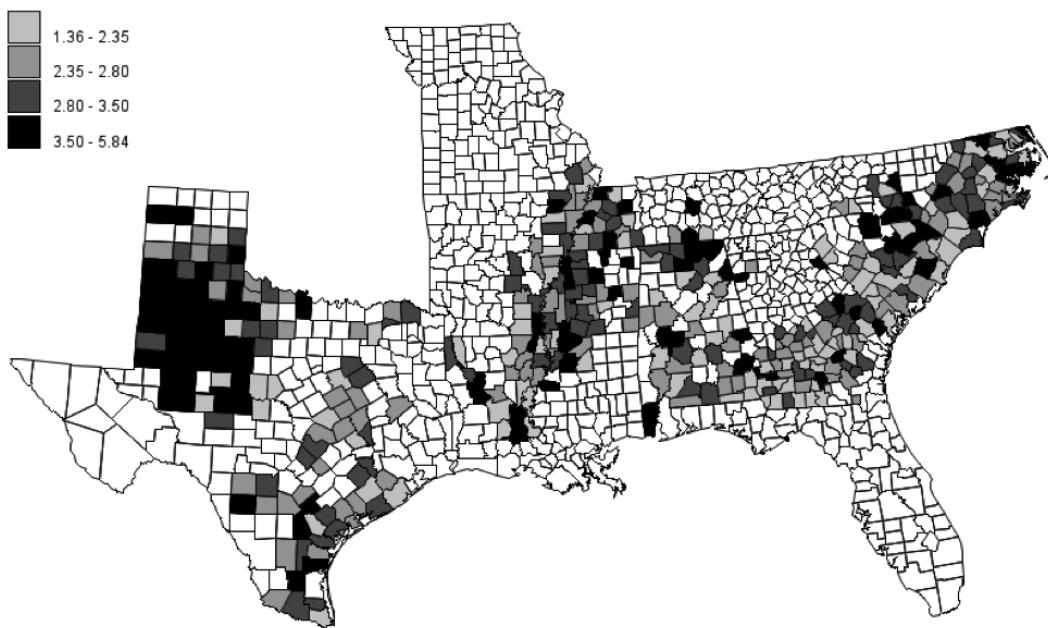


Figure 5a. Welfare Gain in Cotton Due to Using Yield Floor and Yield Substitution at the 75% Coverage Level (Dollars/Acre)

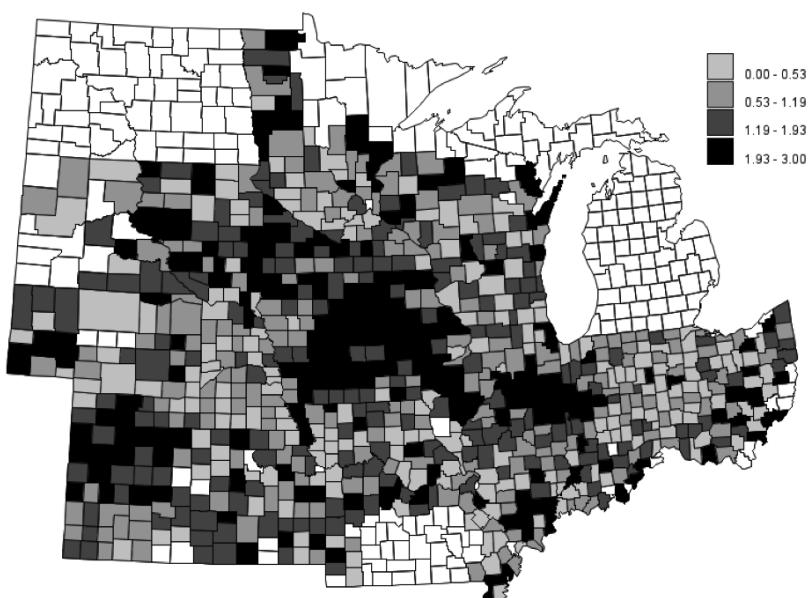


Figure 5b. Welfare Gain in Corn Due to Using Yield Floor and Yield Substitution at the 75% Coverage Level (Dollars/Acre)

welfare gain in dollar terms. For cotton, the gain ranges from \$1.30 to \$5.84 in major cotton-growing states. In general, the effect of yield substitution and yield floors not only compensates for negative effects of variability in small-sample APH yields but also increases farmers' welfare.

In the case of corn, the welfare gain ranges from \$0 to \$3.00 in the ten major corn-producing states. The effect of yield substitution and yield floors does not seem to follow any clear pattern relative to the concentration on corn in the state and counties. In some counties of Iowa, Illinois, and Nebraska, the welfare effect is found to be much larger than in other areas, amounting to \$2.00 to \$3.00. In all other areas the welfare gain after compensating negative effects of small-sample APH yield variability is either smaller than \$0.50 per acre or ranges from \$0.50 to \$2.00 per acre (figure 5b). As in the example counties, the welfare effects of sampling variability, yield substitution, and yield floors are generally smaller for corn than for cotton due to lower yield variability and resulting lower frequency of using yield substitution and yield floor provisions.

Conclusions

Establishing appropriate yield guarantees is important for individual-level yield and revenue insurance programs to function properly. The approach that has been taken in the U.S. crop insurance program is to establish individual yield guarantees using the insured units' historical yields. This is a reasonable approach that takes most or all available information into consideration for the vast majority of insured units. However, guarantees based on average historical yields are subject to sampling variability that 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 downside sampling variability in historical yields. These measures have a left-tail censoring effect on the distribution of the insured yield, which raises the expected guarantee level.

This research analyzed the potential welfare gains and losses associated with sampling error, with and without yield substitution and yield floors. Our results provide the following insights:¹⁶ First, APH yields based on small samples significantly increase expected indemnities and thus increase actuarially fair premiums and premium subsidies. Second, the welfare loss due to sampling variability in APH yields is larger in high-risk areas. Third, both yield substitution and yield floors increase producer welfare, with yield substitution having the larger effect. Finally, the upward bias in insured yields from yield substitution and yield floors more than compensates for the negative effects of sampling variability 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.

Our results indicate that a potential welfare loss is associated with sampling variability in APH yields, but it is more than offset by upward bias in insured yields created using 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. Future research efforts should be directed at investigating alternative mechanisms to mitigate welfare losses from sampling variability while reducing the potential for over-insurance and excessive government cost.

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¹⁶ As one reviewer pointed out, all of our analysis and resulting conclusions are based on an implicit assumption that no significant yield trend affects APH yields and insurance guarantees. A positive yield trend, as examined by Adhikari, Knight, and Belasco (2012), would interact with sampling variability. Specifically, existence of a positive yield trend biases the APH yield downward.

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