An Analysis of Factors Affecting Bias and Inefficiency in Area Yield Indexes Based on Aggregated Farm Yields

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U.S. agriculture makes extensive use of crop insurance to manage yield or revenue risk. In 2015, more than 297 million acres of farmland were protected through the Federal Crop Insurance Program (FCIP) (USDA/RMA, 2015). The FCIP is administered by the Risk Management Agency (RMA) of the United States Department of Agriculture (USDA), on behalf of the Federal Crop Insurance Corporation (FCIC) under the Federal Crop Insurance Act. The RMA works with private sector insurance companies (known as "approved insurance providers" or AIPs) that sell and service policies. Crop insurance is made more affordable to farmers by federal premium subsidies. The federal government also provides administrative and operating (A&O) expense reimbursements to AIPs to offset the cost of delivering FCIP policies.

For most major field crops, the FCIP offers two types of insurance: yield-based or revenue-based. Crop insurance products can also be offered at the farm-level or the area-level. Yield-based, farm-level, insurance provides an indemnity when the actual farm yield falls below the guarantee (known as the trigger yield). This insurance product is known as Yield Protection (YP). Revenue-based, farm-level, insurance provides an indemnity when an estimate of farm-level revenue (actual yield × a price derived from the futures market) falls below the revenue guarantee (known as the trigger revenue). The FCIP offers two types of revenue insurance. The Revenue Protection (RP) product allows the dollar amount of insurance protection (known as the liability) to increase if price increases during the growing season. For the Revenue Protection with the Harvest Price Exclusion (RP-HPE) product, liability does not increase if price increases during the growing season. Yield-based, area-level, insurance provides an indemnity when the estimated county average yield falls below the county-level trigger yield. This insurance product

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is known as Area Yield Protection (AYP). Revenue-based, area-level, insurance provides an indemnity when the estimated county average revenue (county average yield estimate × a price derived from the futures market) falls below the county-level trigger revenue. This insurance product is known as Area Revenue Protection (ARP).

The 2014 farm bill (P.L. 113-79) increased funding for crop insurance by an additional $5.7 billion over 10 years. This increase was mainly due to two new insurance products: the Supplemental Coverage Option (SCO) and the Stacked Income Protection Plan (STAX). Both SCO and STAX are considered shallow-loss products because they are designed to provide county-level coverage for a portion of the deductible on the underlying farm-level YP, RP, or RP-HPE policy. The amount of SCO liability depends on the coverage level and approved yield for the underlying YP, RP or RP-HPE policy. STAX is similar to SCO but is available only for producers of cotton. SCO is yield-based or revenue-based depending on whether the underlying policy is yield insurance or revenue insurance while STAX is always revenue-based. SCO purchasers must have an underlying YP, RP, or RP-HPE policy whereas this is not required for STAX purchasers.

Area-level products have existed within the FCIP since the early 1990s (Skees, Black, and Barnett 1997). However, growers previously had to choose either a farm-level product or an area-level product. The same acreage could not be insured with more than one FCIP product. With the introduction of the shallow-loss products in the 2014 farm bill, two crop insurance policies can now be purchased for the same acreage: an underlying farm-level, YP, RP, or RP-HPE policy and a shallow-loss, area-level, SCO or STAX policy.

Previously, the area-level insurance products administered by the RMA depended on the availability of county yield estimates from USDA's National Agricultural Statistics Service

(NASS). Yet, NASS does not report yield data for every county where a crop is produced – although yield data for the crop may still be available at a higher level of aggregation (e.g., the crop reporting district or state levels). Thus, limited availability of NASS county yield estimates restricted the counties where area-level insurance products could be offered. In addition, in recent years, NASS has significantly reduced the number of counties for which yield estimates are reported (Dismukes et al., 2013). While the lack of NASS yield data would affect all SCO and STAX crops, it is particularly problematic for cotton since, as a result of the 2014 farm bill, STAX is the primary mechanism for providing federal support to cotton producers.

For specified crops, SCO and/or STAX are offered wherever YP, RP, and RP-HPE products are offered. Thus, rather than having some SCO and STAX policies based on NASS yield data and other SCO and STAX policies based on another estimator of county yield (due to a lack of NASS county yield estimates), RMA decided to move away from basing area-level insurance products on NASS data. Instead, yield data collected from underlying YP, RP, and RP-HPE policies are used to generate a unique county yield estimate that serves as the basis for settling RMA administered area-level insurance products.

This study investigates the potential implications of this decision. In particular, this study investigates the potential for bias and inefficiency in county-level yield estimates derived from farm-level yields reported on underlying YP, RP, and RP-HPE policies. The preliminary analysis reported here is for selected corn counties in Iowa, wheat counties in Kansas, and a soybean county in Mississippi.

Literature Review

Because the products have only recently been introduced, the literature on SCO and STAX is currently quite limited. However, an extensive literature exists on county-level, yield and revenue insurance products.

Dismukes et al. (2013) analyzed how the purchase of a shallow-loss, county-level, insurance product would affect the optimal coverage for underlying, farm-level, crop insurance products. They found that shallow-loss, county-level, insurance designs have some potential for causing producers to reduce coverage levels for underlying farm-level crop insurance.

Many studies have suggested that farm-level FCIP products have been plagued with adverse selection and moral hazard problems (Quiggin, Kiragiannis, and Stanton, 1993; Smith and Goodwin 1996; Coble et al. 1997; Just, Calvin, and Quiggin 1999; Barnett 2000). Farm-level products are susceptible to these problems because farmers often have better information about their yield distributions than an insurer would have and can also influence yield outcomes after the insurance has been purchased (Wang et al. 1998). In contrast, county-level insurance products are far less susceptible to adverse selection and moral hazard problems (Chambers 1989; Barnaby and Skees 1990; Miranda 1991; Quiggin, Kiragiannis, and Stanton, 1993; Smith and Goodwin 1996; Coble et al. 1997; Just, Calvin, and Quiggin 1999; Skees and Barnett 1999; Barnett 2000). Individual farmers are unlikely to have better information than the insurer about county yield distributions and (assuming that each insured farmer constitutes a relatively small proportion of planted acreage in the county) cannot significantly affect county yield outcomes.

The primary shortcoming of county-level products is that they are subject to basis risk (Skees, Black, and Barnett 1997). Basis risk is caused by less than perfect dependency between county yields and farm yields which means that farm-level losses may not be fully covered by a

county-level insurance product. In an extreme case, a farm can experience a yield shortfall and receive no indemnity from a county-level insurance product. It is also possible that a farm may experience no yield shortfall but receive an indemnity from a county-level insurance product.[1]

Systematic (sometimes called "systemic") yield risk is the portion of farm-level yield risk that is positively, spatially, correlated with other farms in the county. The idiosyncratic (sometimes called nonsystematic or nonsystemic) yield risk is the portion of farm-level yield risk that is due to the unique circumstances of the individual farmer (Bulut, Schnapp, and Collins, 2011). Farms that are characterized by yield risk that tends to be more systematic (idiosyncratic) should experience less (more) basis risk with county-level insurance products (Skees, Black, and Barnett, 1997). Thus, conceptually it seems likely that basis risk varies directly with the heterogeneity of soil and climatic conditions faced by producers within a county (Miranda 1991; Smith, Chouinard, and Baquet 1994; Skees, Black, and Barnett 1997).

It is also important to note that, due to the lack of perfect correlation in yields across farms in a county, yield variability is generally lower at the county level than at the farm level. Cooper et al. (2009) found that while county yield standard deviations are generally smaller than farm yield standard deviations, the difference between these measures varies significantly across crops and regions. Claasen and Just (2011) found that county yield variation understates farm yield variation by approximately 50 percent for corn grown in the Northern Plains and Corn Belt. This implies that if the coverage level is constrained to be the same for both products, a farm-level insurance product will provide much greater risk protection than an area-level insurance product.

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[1] Barnett et al. (2005) argued that farm-level insurance products are also subject to basis risk due to sampling and measurement errors in the estimates of the expected and realized farm-level yields.

Miranda (1991) noted that since county-level insurance products are not subject to adverse selection and moral hazard problems, they can be offered with much lower deductibles (higher coverage levels) than farm-level insurance products. As a result, county-level insurance products can provide better coverage of systematic yield risk than farm-level insurance products. This improved coverage of systematic yield risk may outweigh the lack of idiosyncratic yield risk coverage resulting in better farm-level yield risk protection relative to farm-level insurance product that require higher deductibles.

Mahul (1999) expanded on this idea by noting that since county-level insurance products are not subject to adverse selection and moral hazard problems there is conceptually no reason that the trigger yield on county-level insurance products could not exceed the expected yield for the county (i.e., county-level insurance could be offered with coverage levels in excess of 100 percent). This would allow farmers to use county-level insurance products to obtain even better protection against systematic risk.[2]

Smith, Chouinard, and Baquet (1994), Wang et al. (1998), Barnett et al. (2005), and Deng, Barnett, and Vedenov (2007) each conducted empirical analyses comparing the performance of county-level insurance products with farm-level insurance products. Generally, these studies found that the extent to which county-level insurance products can provide risk reduction that is competitive with farm-level insurance products varies across crops and regions. However, consistent with the insights of Miranda (1991) and Mahul (1999), county-level insurance products were much more competitive if restrictions on coverage were relaxed such

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[2] Mahul also noted that with farm-level insurance products, deductibles reduce the transaction costs associated with high numbers of claims. For county-level insurance products, this is much less of a concern since the marginal transaction costs of settling a claim is very small.

that deductibles were low or even negative (i.e., trigger yields in excess of expected county yields).

County-level Shallow-loss Products

SCO must be purchased as an endorsement to an underlying YP, RP, or RP-HPE policy. If the underlying policy is yield based (revenue based), SCO provides yield coverage (revenue coverage). SCO provides a layer of coverage from 86% of the expected county yield or revenue down to the coverage level on the farmer's underlying YP, RP, or RP-HPE policy. For example, if the farmer purchased Yield Protection (YP) insurance at the 65% coverage level, SCO covers losses between 86% and 65% of the county's expected yield.

For SCO with an underlying YP policy, SCO liability per acre on insured unit i located in county c is calculated as:

(1) $Liability\ per\ Acre_{it} = E(y_{it}) \times PP_{ct} \times (86\% - Coverage\%_{it})$

where $E(y_{it})$ is the expected yield on insured unit i in year t (the approved yield on the underlying YP policy), PP_{ct} is the projected price determined by RMA for the insured crop in the county where insured unit i is located, and $Coverage\%_{it}$ is the coverage level for the underlying YP policy. As with most other FCIP revenue insurance products, projected (and realized) prices for SCO are based on prices derived from futures markets. The indemnity per acre is calculated as:

(2) $Indemnity_{it} = max\left(\left(min\left(\frac{Trigger\ Yield_{ct} - Yield\ to\ Count_{ct}}{Trigger\ Yield_{ct} - (Coverage\%_{it} \times E(y_{ct}))}\right), 1\right), 0\right) \times$
        $Liability\ per\ Acre_{it}$

where $E(y_{ct})$ is the expected county yield for year t in the county where insured unit i is located, $Yield\ to\ Count_{ct}$ is the realized county yield in year t, and

(3) $Trigger\ Yield_{ct} = 86\% \times E(y_{ct}).$

For SCO with an underlying RP-HPE policy, liability per acre is calculated as in equation (1) but indemnity per acre is calculated as:

(4) $$Indemnity_{it} = max\left(\left(min\left(\frac{Trigger\ Revenue_{ct}-(Yield\ to\ Count_{ct}\times RP_{ct})}{Trigger\ Revenue_{ct}-(Coverage\%_{it}\times E(y_{ct})\times PP_{ct})}\right),1\right),0\right)\times$$
$$Liability\ per\ Acre_{it}$$

where RP_{ct} is the realized price determined by RMA for the insured crop in the county where insured unit i is located, and

(5) $$Trigger\ Revenue_{ct} = 86\% \times E(y_{ct}) \times PP_{ct}.$$

For SCO with an underlying RP policy, liability per acre is calculated as:

(6) $$Liability\ per\ Acre_{it} = E(y_{it}) \times (max(PP_{ct}, RP_{ct})) \times (86\% - Coverage\%_{it})$$

and indemnity per acre is calculated as

(7) $$Indemnity_{it} =$$
$$max\left(\left(min\left(\frac{Trigger\ Revenue_{ct}-(Yield\ to\ Count_{ct}\times RP_{ct})}{Trigger\ Revenue_{ct}-\left(Coverage\%_{it}\times E(y_{ct})\times (max(PP_{ct},RP_{ct}))\right)}\right),1\right),0\right)\times$$
$$Liability\ per\ Acre_{it}$$

where

(8) $$Trigger\ Revenue_{ct} = 86\% \times E(y_{ct}) \times \left(max(PP_{ct}, RP_{ct})\right).$$

STAX is similar to SCO but available only for cotton growers. It may be purchased either with or without an accompanying YP, RP, or RP-HPE policy. A STAX indemnity is triggered whenever the county realized revenue falls below 90 percent of its expected level. STAX provides a layer of coverage that extends from 90 percent to the greater of 70% or the coverage level on any underlying YP, RP, or RP-HPE policy. For example, if the farmer purchased YP at a 65 percent coverage level, STAX would cover losses between 90 percent and 70 percent of the county's expected revenue. If the farmer purchased YP at a 75 percent coverage level, STAX would cover losses between 90 percent and 75 percent of the county's expected revenue. STAX

is only available as revenue insurance. Other minor differences exist between STAX and SCO but they are not relevant to the analysis presented here.

Following Miranda (1991), the relationship between insured unit yield deviations from expectation and county yield deviations from expectation is assumed to be linear:

(9) $\quad y_{it} - E(y_{it}) = \beta_i(y_{ct} - E(y_t)) + \varepsilon_{it}$

where β_i measures the sensitivity of the insured unit's yield deviations from expectation to the systematic factors that affect the county yield deviations from expectation and ε_{it} is an error term that measures idiosyncratic risk. Clearly, higher values of β_i imply that more of the yield variability on the insured unit is explained by county yield variability and thus, a county-level insurance product will be more effective in providing risk protection for the farm.

RMA estimates y_t for SCO and STAX as an acreage-weighted average:

(10) $\quad y_t = \frac{\sum_{i=1}^{n} a_{it} y_{it}}{\sum_{i=1}^{n} a_{it}}$

where y_{it} are farm level yields from the available sample of YP, RP, and RP-HPE purchasers in year t, n is the sample size in the county, and a_{it} is the acreage for farm i in year t.

As with any statistical estimate, y_t is measured with some uncertainty. However, there is no definitive mathematical formula for the standard error of the weighted average of a sample. Gatz and Smith (1995) have proposed several formulas which all assume that the sample observations are uncorrelated. Unfortunately, such an assumption is almost certainly not valid for yields. However, it does seem reasonable to assume that, *ceteris paribus*, the standard error would be decreasing in the sampling density. The extent to which changes in the sampling density impact the standard error of the estimation of y_t likely depends on both the current level of the sampling density and the heterogeneity of the production region.

This study uses farm-level data to investigate how differences in sampling density and the heterogeneity of the production region impact the variability of the county yield estimate. Higher variability in the estimate of the county yield would be expected to increase basis risk and thus reduce the effectiveness of a county-level, shallow-loss products.

Data and Methods

The analysis uses yield data at the insured unit level that were obtained several years ago from RMA. These data are the 10-year yield histories from 1999 to 2008 that were used to establish expected yields for 2009 purchasers of yield and revenue insurance policies. Only insured units which reported actual yields for the entire 10 year yield history were included in the analysis.

As an initial test of concept, crops and counties were analyzed from Iowa, Kansas, and Mississippi. Specifically, Fremont and Humboldt Counties in Iowa were analyzed for corn, Reno and Rush Counties in Kansas were analyzed for wheat, and Bolivar County, Mississippi was analyzed for soybeans. For this initial test of concept, counties were selected based on two primary criteria. First, each crop-county combination included in the analysis was required to have at least 100 insured units that met the criteria of having actual yields for the entire 10 year yield history. Second, for each crop-state combination, an attempt was made to identify a county with less heterogeneous yield risk and a county with more heterogeneous yield risk (where heterogeneity of yield risk within the county was assumed to reflect heterogeneity of growing conditions).

To estimate the heterogeneity of yield risk within a county, a linear yield trend was first estimated at the county level using all of the available 10-year farm-level yield histories for the crop in the county. This county-level yield trend was then used to detrend all of the farm-level

yields for the crop in the county.[3] A coefficient of variation was then estimated for each of the farm-level, detrended, 10-year, yield histories. This coefficient of variation can be thought of as a farm-level measure of relative yield risk. Histograms of these farm-level coefficients of variation are shown in Figures 1-5. As a proxy for yield risk heterogeneity within the county, a coefficient of variation was estimated across all the farm-level yield coefficients of variation within the county. This measure is used as a proxy for yield risk heterogeneity for the crop in the county with higher (lower) values indicating more (less) yield risk heterogeneity.

As shown in table 1, for each crop-state combination except for Mississippi soybeans, a county was selected with a relatively high yield coefficient of variation (more yield risk heterogeneity within the county) and a county was selected with a relatively low coefficient of variation (less yield risk heterogeneity within the county). The yield coefficients of variation for Mississippi soybeans were similar across counties, so only one county was included in the analysis.

The empirical analysis assumes that for a given year, the number of insured units (N) contained in the database for a specific crop in a county constitutes all of the farms that produce the crop in the county (see table 1). While this assumption is clearly counterfactual (it is unlikely that 100% of farmers actually purchased YP, RP, or RP-HPE policies), it allows us to establish a population from which we can examine the impact on y_t of different sampling densities. This is important because while national average crop insurance participation is above 80% for many of the major field crops (corn, cotton, soybeans, wheat), participation rates vary a great deal at the county level.

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[3] With only 10 years of available yield data there is too much noise to estimate yield trends at the farm level.

The acreage-weighted average yield μ_t^p for each crop/county for each of the $t = 10$ years was calculated over the assumed population of (N) observations

(11) $\quad \mu_t^p = \frac{\sum_{i=1}^{N} a_{it} y_{it}}{\sum_{i=1}^{N} a_{it}}$

where the superscript p indicates the population and other variables are as previously defined. Random sampling without replacement was then used to draw samples of n observations from the population for each year t. For each random sample size, an acreage-weighted average yield μ_{tj}^s was calculated for each of the $t = 10$ years

(12) $\quad \mu_{tj}^s = \frac{\sum_{i=1}^{n} a_{it} y_{it}}{\sum_{i=1}^{n} a_{it}}$

This process was repeated for 5,000 iterations. The subscript j in equation 12 indicates the jth iteration. The average across the iterations was calculated as

(13) $\quad \mu_t^s = \frac{1}{5000} \sum_{j=1}^{5000} \mu_{tj}^s$

Thus, for a specified sampling density μ_t^s is the average over 5,000 iterations of the acreage-weighted sample average yield for each year t.

For each crop and county, different sampling densities were used to reflect the fact that crop insurance participation varies across counties. Specifically, n was set to a level that was equal to sampling densities of 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90% of N for each crop/county.

For each sampling density and year t, an estimate of bias δ_t and root mean square error ϑ_t were calculated:

(14) $\quad \delta_t = \mu_t^p - \mu_t^s$

(15) $\quad \vartheta_t = \delta_t^2 + s_t^2$

where s_t^2 is the variance (across iterations) of the sample acreage-weighted average yield μ_t^s. To facilitate comparison across crops, regions, and years, the root mean square errors were normalized by dividing by the acreage-weighted average yield μ_t^p for each year t. Thus,

(16) $norm\_\vartheta_t = \dfrac{\vartheta_t}{\mu_t^p}$

Results

In tables 2-4 results are presented for the selected Iowa, Kansas, and Mississippi counties, respectively. In these tables the first column contains the sampling density as a percentage of N. The second column is the number of times that the null hypothesis $\left(Ho: \mu_t^p - \mu_t^s = 0\right)$ is rejected at the one percent level of significance over the 10 years. In other words, it is the number of times (over the 10 year period) that the bias δ_t was statistically different from zero. The third column is the average normalized root mean square error. The two last columns are respectively, the minimum and the maximum normalized root mean square error over the 10 year period.

At low sampling densities, the null hypothesis of no bias (equality between the sample mean and the population mean) is rejected frequently for Bolivar County, Mississippi soybeans. Only for sampling densities in excess of 60% is the null hypothesis rejected for fewer than half of the 10 years. Sampling densities of at least 80% are required before the null hypothesis is not rejected for any of the 10 years. In contrast, for Iowa corn, the null hypothesis is never rejected for more than one year. For Kansas wheat, the null hypothesis is rejected occasionally at lower sampling densities but never for sampling densities of 60% or higher. In general, the null hypothesis is rejected more often in more heterogeneous counties than in less heterogeneous counties.

Though not shown in the tables, the average bias (and even the maximum bias) over the 10 year period was very small relative to the 10 year average of the population acreage-weighted average yield μ_t^p. In other words, though statistical tests did not always reject the null hypothesis of no bias, the magnitude of any bias for these crops and counties (even at low sampling densities) was trivial relative to the expected yield. This is not all that surprising given that μ_t^s was calculated as an average over 5,000 iterations.

Of more interest is the normalized RMSE $norm\_\vartheta_t$ which measures the variability in the difference between the sample estimate county average yield and the population average yield. For all crops and counties, the average of the normalized RMSE (over the 10 years) decreases as the sampling density increases. Furthermore the spread between the minimum normalized RMSE and the maximum normalized RMSE decreases as the sampling density increases. However, there are important differences across crops and counties. The highest normalized RMSE measures occur for soybeans in Bolivar County, Mississippi while the lowest occur for corn in Humboldt County, Iowa and wheat in Reno County, Kansas. In addition, the spread between the minimum and maximum normalized RMSE measures is largest for soybeans in Bolivar County, Mississippi and smallest for corn in Humboldt County, Iowa and wheat in Reno County, Kansas. These findings indicate that the potential magnitude of error in a sample based estimate of the county yield is higher in more heterogeneous counties compared to less heterogeneous counties. In other words, less heterogeneous counties have higher spatial correlation of yields between farms within the county which reduces the potential magnitude of error in a sample based estimate of the county yield.

These results seem to suggest that more heterogeneous counties may have higher basis risk for area-based crop insurance products such as SCO and STAX due to sampling errors in the

estimate of the county yield. This is especially true if the percentage of growers purchasing YP, RP, or RP-HPE (the sampling density) is small. The potential basis risk is further amplified for STAX since, unlike SCO, STAX purchasers are not required to purchase an underlying YP, RP, or RP-HPE policy. This implies that the pool of people purchasing STAX policies may be quite different than the pool of people purchasing YP, RP, or RP-HPE policies. But despite this, the weighted average yield for YP, RP, and RP-HPE purchasers will serve as the estimate of the county yield on which the STAX policy will make payments. Similarly, for crops other than cotton, all SCO purchasers are required to also purchase YP, RP, or RP-HPE though the converse is not true (YP, RP, and RP-HPE purchasers are not required to purchase SCO). This implies that the pool of people purchasing SCO will be a subset of the pool of people purchasing YP, RP, and RP-HPE. Basis risk will be increased if the yield experience of the subset of SCO purchasers varies significantly from the aggregated yield experience of all YP, RP, and RP-HPE purchasers.

Conclusion

This paper presents findings from a "test of concept" analysis of farm-level yield data from five counties. While the analysis is still in preliminary stages, the findings presented here suggest that basis risk for SCO and STAX is likely to be higher (lower) in more (less) heterogeneous counties. This is especially true if the percentage of growers purchasing YP, RP, or RP-HPE is small.

Future efforts will expand the analysis to more crops and regions. In addition, we will examine the implications of non-random sampling on the estimate of the county yield and basis risk for SCO and STAX. For example, what if larger producers are more inclined to purchase YP, RP, or RP-HPE compared to smaller producers? How might this affect basis risk for SCO

and STAX? We will also attempt to simulate how all of these factors affect the welfare benefits

that growers can obtain from SCO and STAX purchasing.

Table 1: Number of Farms and CV of Farm-level Yield CVs, by Crop and County

State	Crop	Counties	Number of farms (*N*)	CV of Farm-level Yield CVs
Iowa	Corn	Fremont	406	24.66
		Humboldt	440	9.52
Kansas	Wheat	Rush	416	24.85
		Reno	698	12.54
Mississippi	Soybean	Bolivar	118	29.56

Table 2: Iowa Corn Bias and Root Mean Square Error by Sampling Density

Sampling density	Rejection of Ho	Normalized Average RMSE	Normalized Minimum RMSE	Normalized Maximum RMSE
		Freemont County		
0.2	1	9.81%	3.02%	20.57%
0.3	0	5.08%	1.60%	10.85%
0.4	0	2.86%	0.91%	6.15%
0.5	0	1.70%	0.54%	3.62%
0.6	0	0.99%	0.32%	2.19%
0.7	1	0.55%	0.17%	1.19%
0.8	1	0.28%	0.09%	0.58%
0.9	0	0.10%	0.03%	0.22%
		Humboldt County		
0.2	0	2.13%	1.17%	3.24%
0.3	1	1.13%	0.59%	1.73%
0.4	1	0.62%	0.33%	0.94%
0.5	0	0.37%	0.19%	0.58%
0.6	0	0.21%	0.11%	0.33%
0.7	0	0.12%	0.06%	0.19%
0.8	0	0.06%	0.03%	0.09%
0.9	0	0.02%	0.01%	0.03%

Table 3: Kansas Wheat Bias and Root Mean Square Error by Sampling Density

Sampling density	Rejection of Ho	Normalized Average RMSE	Normalized Minimum RMSE	Normalized Maximum RMSE
		Rush County		
0.2	2	6.18%	1.95%	19.79%
0.3	4	3.25%	0.99%	10.34%
0.4	2	1.89%	0.59%	5.99%
0.5	0	1.11%	0.34%	3.53%
0.6	0	0.65%	0.20%	2.06%
0.7	0	0.36%	0.11%	1.17%
0.8	0	0.17%	0.05%	0.55%
0.9	0	0.06%	0.02%	0.20%
		Reno County		
0.2	1	1.82%	1.28%	3.14%
0.3	1	0.95%	0.67%	1.65%
0.4	1	0.54%	0.37%	0.95%
0.5	1	0.32%	0.22%	0.55%
0.6	0	0.18%	0.13%	0.31%
0.7	0	0.10%	0.07%	0.17%
0.8	0	0.05%	0.04%	0.09%
0.9	0	0.02%	0.01%	0.03%

Table 4: Mississippi Soybeans Bias and Root Mean Square Error by Sampling Density

Sampling density	Rejection of Ho	Normalized Average RMSE	Normalized Minimum RMSE	Normalized Maximum RMSE
		Bolivar County		
0.2	7	23.54%	4.73%	100.27%
0.3	7	12.91%	2.31%	61.44%
0.4	5	7.45%	1.28%	37.68%
0.5	6	4.56%	0.75%	23.85%
0.6	1	2.71%	0.43%	14.61%
0.7	4	1.55%	0.24%	8.36%
0.8	0	0.76%	0.12%	4.09%
0.9	0	0.27%	0.04%	1.47%

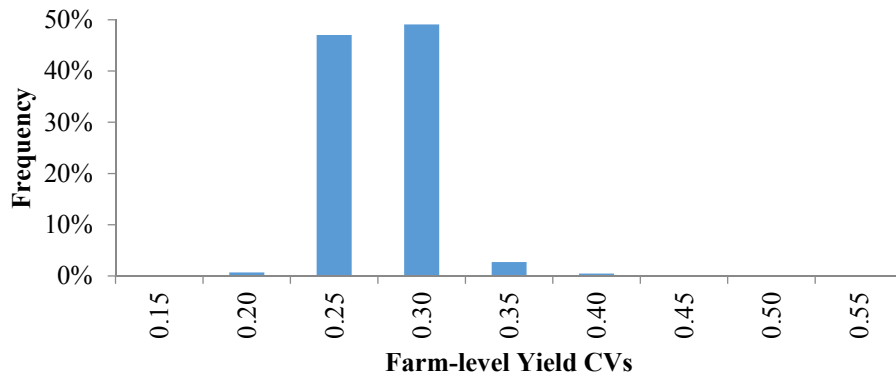*Figure 1: Fremont County, Iowa Histogram of Farm-level Corn Yield CVs*

Figure 2: Humboldt County, Iowa Histogram of Farm-level Corn Yield CVs
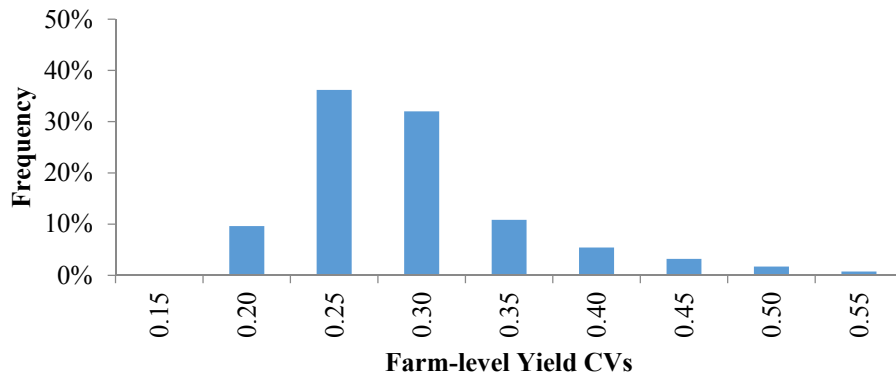

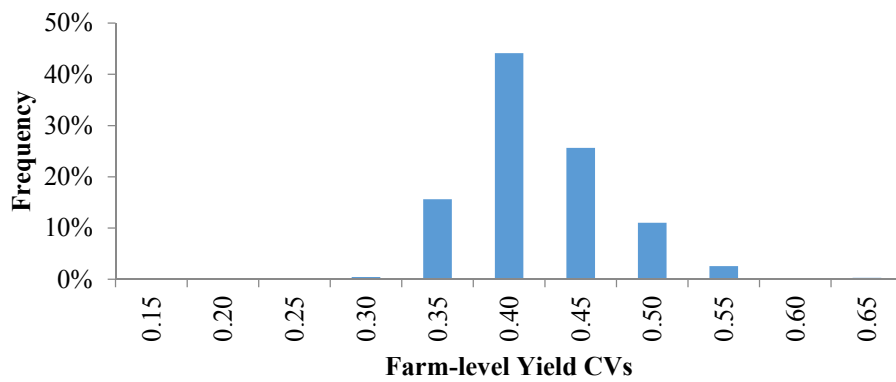*Figure 3: Reno County, Kansas Histogram of Farm-level Wheat Yield CVs*

Figure 4: Rush County, Kansas Histogram of Farm-level Wheat Yield CVs
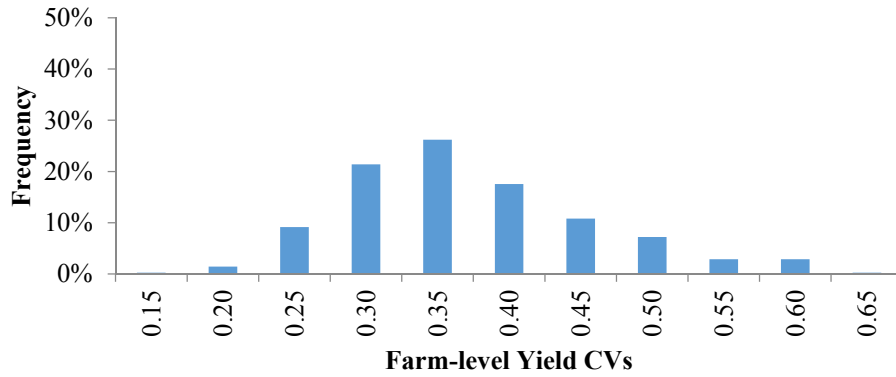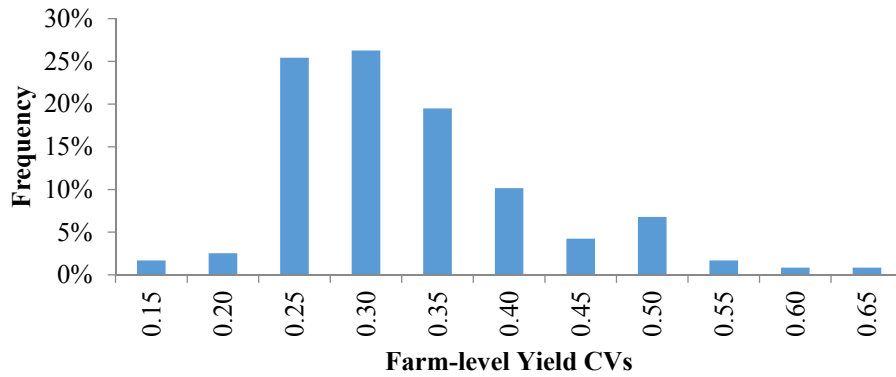

Figure 5: Bolivar County, Mississippi Histogram of Farm-level Cotton Yield CVs

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