Premium Estimation Inaccuracy and the Distribution of Crop Insurance Subsidies

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Background

- In 2012, the U.S. crop insurance program covered close to 265 million acres, assuming nearly $110 billion in liabilities through 1.14 million policies insuring about 500,000 farms
- High participation has been achieved through large subsidies, with farmers as a whole now paying less than 50% of the total amount of premiums required to keep the program solvent

Background

- Recent research suggests that the need to discount producer premiums in order to achieve substantial rates of producer participation, and the resulting high loss ratios and government subsidy levels, can be fully explained by the sizable error in the RMA's premium estimates
- Producer error in premium estimation could have as much of a negative impact on program performance as insurer error

Objective

- This study explores the impact of the inaccuracies in RMA and producer premium estimation on the distribution of the premiums paid and thus the subsidies received by the participating farmers
- Specifically, given an "intended" subsidy level of 50%, it estimates the probabilities that a producer would end up paying various percentages of the AFP and thus receiving different effective subsidy levels

Part I Procedures

- First, the AFPs corresponding to prototypical Midwest corn yield distributions are computed through standard procedures
- The first set of distributions (A) is assumed to be normal with a mean of 180 bushels /acre and standard deviations of 30, 35, 40 45 and 50 bushels/acre
- The second set (B) is assumed to have the same mean and standard deviations but exhibit substantial left-skewness

Part I Procedures

- Next, a large number of small samples are drawn from each of those distributions and premium estimates are computed
- The distribution of the estimates is then compared with the AFP using the Percentage Bias (PBIAS) and Percentage Mean Absolute Deviation (PMAD) statistics
- The PBIAS and PMAD statistics corresponding to the selected distributions for a coverage level of 65% are presented in Table 1

Table 1	Normal Distribution - Mean = 180				
STD	AFP	APE	MAD	PBIAS	PMAD
30.00	0.97	1.38	0.96	41.58	98.46
35.00	2.50	3.12	1.89	24.96	75.70
40.00	4.93	5.71	3.08	15.80	62.39
45.00	8.26	9.26	4.47	12.18	54.13
50.00	12.37	13.52	5.95	9.30	48.06
	Non-Normal Distribution - Mean = 180				
STD	AFP	APE	MAD	PBIAS	PMAD
30.00	7.14	8.73	5.57	22.36	78.07
35.00	10.20	11.67	6.82	14.38	66.86
40.00	13.70	14.70	8.02	7.27	58.55
45.00	17.29	17.84	9.20	3.19	53.22
50.00	21.17	21.20	9.92	0.17	46.87

Part II Procedures

- The distribution of the premiums paid by participating farmers is generated under a set of plausible behavioral assumptions and various levels of insurer premium estimation error
- Specifically, it is assumed that both the farmer and the insurer (RMA) do not know what the AFP is and thus have to estimate it with various degrees of error (PMAD and PBIAS).

Part II Procedures

- The producer and insurer premium estimates are denoted by PPE and IPE, respectively, and risk-averse producers are willing to pay a risk-protection premium (RPP) in excess of their PPE
- A farmer’s decision rule for participating, thus, is PPE+RPP≥IPE, i.e. that his/her own premium estimate plus any risk protection premium he/she is willing to pay is greater than the insurer’s quote

Part II Procedures

- For each scenario in the analysis, it is assumed that 10,000 identical producers are eligible to participate in the program
- Alternatively, this could be interpreted as conducting repeated outcome draws from a single producer
- Each outcome (i) is characterized by a set of two premium estimates, one by the producer (PPE_i) and one by the insurer (IPE_i), which are randomly drawn as follows:

Part II Procedures

1) $PPE_i = AFP + PB + U_{iP}$, and 2) $IPE_i = AFP + IB + U_{iI}$, where AFP=10 in all cases, PB and IB are the levels of bias in the producer and insurer premium estimates, respectively, and U_{iP} and U_{iI} are draws from uniform distributions with zero mean and whatever range is required to achieve the desired PMAD for PPE and IPE

For some of the scenarios, the resulting PPE and IPE draws are partially correlated using the standard Cholesky decomposition approach.

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Part II Procedures

- The statistics presented in Table 2 can then be easily computed given the 10,000 PPE and IPE draws and the participation rule (PPE+RPP≥IPE)
- Table 3 contains similar statistics under an adjusted participation rule that allows for subsidized premiums (PPE+RPP≥ (1-GSR)IPE) where GSR is the Government Subsidy Rate

Table 2

PBIASI	0.00	0.00	0.00	0.00	0.00	-15%	15%
RPP	0.00	0.00	0.00	10%	15%	15%	15%
PMADI	30%	40%	40%	50%	50%	50%	50%
PMADP	30%	40%	40%	50%	50%	50%	50%
CORR	0.00	0.00	0.60	0.60	0.60	0.60	0.60
GSR	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PPR	0.500	0.499	0.500	0.558	0.589	0.679	0.502
PPG	0.200	0.266	0.100	0.145	0.133	0.263	0.009
20%	1.000	1.000	1.000	0.861	0.864	0.784	0.977
30%	1.000	0.878	0.915	0.796	0.799	0.721	0.904
40%	1.000	0.765	0.833	0.730	0.736	0.662	0.833
50%	0.840	0.660	0.756	0.668	0.675	0.603	0.764
60%	0.694	0.563	0.680	0.608	0.616	0.547	0.698
70%	0.562	0.473	0.607	0.551	0.561	0.491	0.634
80%	0.444	0.391	0.537	0.496	0.506	0.438	0.573
90%	0.341	0.317	0.471	0.443	0.452	0.387	0.515
100%	0.252	0.251	0.407	0.392	0.401	0.338	0.460
110%	0.173	0.192	0.345	0.343	0.351	0.291	0.406
120%	0.111	0.141	0.287	0.296	0.304	0.246	0.354
130%	0.062	0.098	0.231	0.251	0.259	0.202	0.305

Table 3

PBIASI	0.00	0.00	0.00	0.00	0.00	-15%	15%
RPP	0.00	0.00	0.00	10%	15%	15%	15%
PMADI	30%	40%	40%	50%	50%	50%	50%
PMADP	30%	40%	40%	50%	50%	50%	50%
CORR	0.00	0.00	0.60	0.60	0.60	0.60	0.60
GSR	0.520	0.650	0.520	0.570	0.520	0.440	0.570
PPR	0.902	0.897	0.901	0.896	0.898	0.901	0.898
PPG	0.538	0.665	0.502	0.555	0.507	0.521	0.492
20%	0.985	0.742	0.881	0.787	0.805	0.756	0.863
25%	0.889	0.644	0.823	0.731	0.756	0.711	0.807
30%	0.793	0.550	0.763	0.676	0.706	0.665	0.751
35%	0.696	0.457	0.701	0.619	0.656	0.620	0.694
40%	0.601	0.369	0.638	0.562	0.604	0.574	0.637
45%	0.507	0.283	0.575	0.503	0.552	0.528	0.579
50%	0.416	0.200	0.510	0.445	0.499	0.483	0.519
55%	0.329	0.120	0.443	0.385	0.447	0.437	0.459
60%	0.248	0.045	0.375	0.324	0.394	0.392	0.398
65%	0.168	0.000	0.305	0.263	0.340	0.346	0.336
70%	0.095	0.000	0.234	0.202	0.286	0.299	0.274
75%	0.025	0.000	0.163	0.140	0.232	0.253	0.210
80%	0.000	0.000	0.092	0.077	0.178	0.207	0.146
85%	0.000	0.000	0.021	0.013	0.123	0.160	0.081

Conclusions

- The probability distribution of the premiums paid and the subsidies received by participating farmers is highly disperse even when the premium estimation errors (PMAD and PBIAS) are in the low range of those found in the first part of the study
- It is quite likely that a producer could receive more than a 75% premium subsidy while another with an identical risk profile gets less than a 25% subsidy just as a result of the expected errors in premium estimation

Premium Estimation Inaccuracy and the Distribution of

Crop Insurance Subsidies across Participating Producers

For many decades, the Federal government has recognized the extreme and uncontrollable revenue risks associated with many of our agricultural production systems and the need to provide a financial safety net that keeps farmers afloat after catastrophic events and ensures a stable food supply for our nation's consumers. Beginning with a few select crops in the early 1980's, the US crop insurance program has increasingly become a major tool for the government to help producers deal with severe yield shortfalls due to natural disasters such as drought, floods and hail, pest epidemics, or extraordinary declines in the prices of agricultural commodities. In fact, it appears that the next Farm Bill will rely heavily on an expanded crop insurance program as the primary and in many cases only source of income support for US farmers.

Over the years, however, academicians, legislators, commodity group representatives and producers have pointed out important drawbacks and articulated significant criticisms of the US crop insurance programs, which can be summarized as follows:

1) In its current form, the program is not an adequate risk management tool for all crops and production systems **(references)**.
2) The program has systematically favored certain crops and regions with relatively low premiums while penalizing others with "unfairly high" premiums **(references)**.
3) Extremely high government subsidy levels have been needed to keep the program solvent **(references)**.
4) Many producers feel that their crop insurance premiums are much higher that what they should be **(references)**.

A less discussed but equally important issue is how the subsidies to the Crop Insurance program are distributed across individual producers. Specifically it can be argued that if the producer and/or the insurer are not certain about what the actuarially fair premium is, due to random error on what they perceive or estimate it to be, some will receive more generous subsidies than others. For example, the simulation analyses presented in this paper suggest that, assuming an average premium estimation error of just ±25% and that the government pays for 50% of the effective premium, there is a 15% probability that the subsidized premium paid by the producer is 33% or less of what is actuarially fair and a 15% probability that it is 66% or more of what is actuarially fair. That is, just by chance, it is not unlikely that a producer will receive less than half as much premium payment support from the government as another "identical" operator. Since both face the same yield and revenue risk, this is clearly not an optimal safety net scheme.

The results of the simulation analyses are presented in the next two sections. The first section entitled "Yield Variability and Premium Estimation Error" establishes a range of plausible levels of crop insurance premium estimation error corresponding to typical corn production scenarios in the Midwestern US. The second section entitled "Distribution of Crop Insurance Subsidies" assesses the potential impact of such levels of premium estimation error on the distribution of the Crop Insurance subsidies across participating corn producers.

Yield Variability and Premium Estimation Error

The yield simulation scenarios are designed to resemble the case of corn production in the Midwestern US. Specifically, prototypical farms yields with a mean of 180 bushels/acre and standard deviations ranging from 30 to 50 bushels/acre are simulated. In the first part of the analysis (Scenario A), yields are assumed to be normally distributed. At the lowest standard deviation of 30 bushels/acre the probability of a yield value under 130 bushels/acre or over 230 bushels/acre is only 10% (5% under and 5% over). This would have to be a superior farmer with limited downside and substantial upside yield potential. At the highest standard deviation of 50 bushels/acre the 5% probability bounds are 97.5 and 262.5 bushels/acre. This could be farmer with a fair downside but an unrealistically high upside yield potential.

In the second part of the analysis (Scenario B), yields are assumed to follow a substantially left skewed SU distribution (Ramirez, Carpio and Rejesus 2011). At the lowest standard deviation of 30 bushels/acre and skewness and kurtosis values of -3.25 and 23.5, the 5% probability boundaries are 125 and 207 bushels/acre (Figure 1). These expand to 88.5 and 225 bushels/acre at the highest standard deviation of 50 bushels/acre (Figure 2). In other words, the upside yield potential from the mean of 180 bushels/acre less than half as much as the downside potential. It is believed that these distributions are more consistent with the likely behavior of farm-level corn yields in the Midwestern US.

The actuarially fair premiums (AFP) corresponding to each of the above yield distributions for the Actual Production History (APH) farm-level yield insurance program under a price guarantee of \$5/bushel and 60, 65, 70, 75 and 80% coverage levels are then computed using standard simulation methods. Specifically, 10 million random yield observations (Y_i) are simulated from the appropriate distribution (normal or SU) given the assumed parameter values (for a description of the procedure to simulate draws from an SU distribution, please see Ramirez, Misra and Field 2003). Each of those values is compared with CL times the known mean of the distribution (M=180), where CL is the coverage level (0.60, 0.65, 0.70, 0.75 or 0.80). If the simulated yield value is lower than CL*x*M the difference (CL*x*M-Y_i) is multiplied by the assumed price guarantee (\$5/bushel), otherwise the observation is discarded. The sum of all the non-discarded values divided by 10 million is thus the expected indemnity associated with that specific yield distribution and, therefore, the actuarially fair premium that needs to be charged.

In the case of the normal distributions (Table 1), at the most common 65% coverage level, the AFP range from \$0.97/acre when the standard deviation is 30 bushels/acre to \$12.37/acre when the standard deviation is 50 bushels/acre. At the mid-point of 40 bushels/acre the AFP is \$4.93/acre. This begins to illustrate the problem faced by the RMA. If the correct standard deviation of a farmer's yield distribution was 40 bushels/acre but the insurer estimated it at 45 bushels/acre, the premium estimate for 65% coverage would be \$8.26/acre instead of \$4.93/acre. Unfortunately, as shown later because the limited amount of data available for rating, an estimation error of that magnitude might not be uncommon. Alternatively, the insurer could choose to charge all farmers the average premium for the most likely standard deviation value (e.g. 40 bushels/acre). In this case, however, farmers with only slightly lower or higher than average levels of yield variability (e.g. 35 or 45 bushels/acre) would pay quite more ($4.93 versus $2.50/acre) or less ($4.93 versus $8.26/acre) than what they actually should.

The situation is not much different when the yield distribution is assumed to be left-skewed (Table 1). Under this distributional assumption, at the 65% coverage level a producer who is able to maintain a 5% lower bound of 125 bushels/acre (Figure 1) should only pay a $7.14/acre premium. In contrast, a farmer whose 5% lower-bound is 88.5 bushels/acre (Figure 2) should be charged $21.17/acre. Unfortunately again, because of the limited amount of yield data available for participating producers, it is impossible to reliably estimate the correct location of the far left tail of the yield distribution and, as shown in the next section, errors of this magnitude might not be uncommon.

Distribution of Crop Insurance Subsidies

The distribution of the estimated premiums (and thus of the crop insurance subsidies) under any given yield distribution can be obtained by simulation methods as well. Specifically, 10,000 small samples of size n=20 are drawn from the underlying distribution and the distributional parameters are estimated based on each sample. In the case of a normal, the usual estimates for the mean and standard deviation are utilized. In the case of an SU, Maximum Likelihood methods are used to estimate the four distributional parameters (Ramirez, Misra and Field 2003). Once the parameter estimates corresponding to each of the 10,000 samples are available, the same procedure utilized to compute the actuarially fair premiums (AFP) is applied to obtain premium estimates. Those 10,000 premium estimates represent (i.e. are draws from) the statistical distribution of the estimated premiums associated with that particular yield distribution.

Key summary statistics describing the distribution of the premium estimates corresponding to each the 10 assumed yield distributions are presented in Tables 1 and 2. In the case of an underlying normal with a mean of 180 and a standard deviation of 40 bushels/acre, the average of the 10,000 premium estimates (labeled as APE in Table 1) at 65% coverage is $5.71/acre versus the AFP of $4.93/acre. In other words, the premium estimates exhibit a 16% upward bias in this particular instance. In addition, the average of the absolute differences between the estimated premiums and the AFP (labeled as MAD in Table 1) is $3.08/acre. This means that premium estimates that are several dollars apart from the AFP of $4.93/acre are fairly common, with a strong tendency for the estimates to be higher rather than lower than the AFP. When the underlying yield distribution is an SU with the same mean (180 bushels/acre) and standard deviation (40 bushels/acre), the APE is $14.70/acre versus the AFP of $13.70/acre, and the MAD stands at $8.02/acre. This means that premium estimates that are more than 50% lower or higher than the AFP are fairly common. The column labeled PMAD (percentage MAD) in Table 1 is obtained by multiplying the MAD by 100 and dividing by the AFP, which expresses it as a percentage of the AFP. Note that, in all cases, the PMAD decreases with the coverage level and when the yield distribution has a higher standard deviation. Generally on a relative basis the MAD is lower at higher AFP. At the most common 65% coverage level, the PMAD ranges from 98.5 to 48.1 percent for the normal and 78.1 to 46.9 percent for the SU distributions.

While such PMAD levels are high by any standards, as previously suggested, it might be possible to improve premium estimation accuracy by incorporating information from other farms that are believed to exhibit somewhat similar yield distributions. Specifically, the premium estimate for a particular farm could be computed as a weighted average of the estimate obtained based on the available individual farm yield data and the average of the premium estimates for the other farms. The previous procedures are used to assess the potential effectiveness of this strategy as well.

For this purpose, however, a somewhat different underlying yield distribution has to be assumed for each sample. Specifically, for the baseline scenario, the mean and standard deviations are assumed to randomly and uniformly (i.e. with equal probability) range from 160 to 200 bushels/acre and 30 to 50 bushels/acre, respectively. Likewise the skewness and kurtosis parameters (S and K) of the data-generating SU distributions are set to range from 0 to -5 and 0 to 0.75 respectively. On one extreme (S=K=0) the yield distribution would be normal and on the other (S=-5, K=0.75) it would exhibit the same asymmetry characteristics of the SU distributions assumed previously.

Each simulation event then starts with a set of four randomly drawn parameter values. Those “originating” values are used to simulate 10 million yield draws form an SU distribution and compute the AFP for the desired coverage levels. A small sample of 20 observations is then extracted from those yield draws and used to estimate the values of the originating parameters, as described in the previous section. A second batch of 10 million yield draws is obtained on the basis of the small sample parameter estimates and utilized to compute the corresponding estimated premiums.

This process is repeated 10,000 times, which results on 10,000 sets of AFP and premium estimates associated with 10,000 somewhat different underlying yield distributions. The final premium estimates are computed as a weighted average of the mean of all estimates and each of the 10,000 individual estimates, with the weights ranging from 0.0 to 1.0 in increments of 0.10. Thus, in one extreme all 10,000 estimates are the same and equal to the overall average and on the other they are just the individual premium estimates. Key statistics summarizing the results if this analysis at the 65% coverage level and the baseline scenario are presented in the first panel of Table 2.

As expected, the mean of the final premium estimates is the same regardless of the weights being applied, so in all cases there is a 13.5% bias in premium estimation. In addition, if the premiums are estimated individually (weight 0.0/1.0), the PMAD is nearly 70%. On the other extreme, if the average of the 10,000 premiums is used as the estimate (weight 1.0/0.0) the PMAD is reduced to 46%. Finally, for this particular mix of distributions, the optimal weight is approximately 70% of the overall average plus 30% of the individual premium estimate (weight 0.70/0.30), which lowers the PMAD to 41%.

The scenario presented in the second panel of Table 2 assumes a much more compact set of mean (170 to 190 bushels/acre) and standard deviation (35 to 45 bushels/acre) values across the underlying distributions. The optimal weighting in this scenario is approximately 80% of the overall average plus 20% of the individual premium estimate (weight 0.80/0.20), which yields a PMAD of 32% and a bias of 11%. Alternatively, when the potential ranges for the mean and standard deviation are expanded to 150 to 210 bushels/acre and 20 to 60 bushels/acre (third panel of Table 2), the optimal weighting is 0.40/0.60 and the minimum PMAD balloons to 50%.

In short, although the strategy of compressing the individual premium estimates towards the average of all producers with somewhat similar yield distributions seems effective in reducing the PMAD, its efficacy depends on identifying a relatively homogeneous group of producers and being able to ascertain what the appropriate weighting should be. This might be difficult since, in practice, the mean and variance of the individual farm-level yield distributions are unknown and, as previously noted, very difficult to estimate with any degree of precision.

While the yield distributions underlying the previously discussed bias and PMAD statistics are hypothetical in nature, they are by no means unrealistic representations of possible corn production scenarios in the Midwest. In addition, note that the premium estimates used to compute those statistics are obtained under the following "optimistic" conditions:

1) There are 20 yield observations available for each farm and the probability distribution generating them is not changing over time, therefore, there is no need to estimate time trends for the mean or the variance of the distribution (which would increase the levels of inaccuracy in premium estimation).
2) The general form (normal or SU) of the underlying distribution is assumed to be known, therefore, there is no risk of model misspecification and the parametric methods utilized for premium estimation are asymptotically the most efficient.

In practice, the RMA cannot assume that the means and variances of the farm-level yield distributions are constant over time. Thus, (arguably) to avoid the need to model mean and variance trends, it limits the number of observations used for premium estimation to 10 years. In addition, the

RMA does not know what the underlying yield distribution looks like. Thus, it uses non-parametric methods for premium estimation. In other words, the PMAD levels reported in Table 2 are likely lower than what can be accomplished in practice.

Impacts of Premium Estimation Inaccuracy:

While it is not claimed that the RMAD and bias magnitudes discussed in the previous section are necessarily characteristic of the RMA premium estimates for corn production in the Midwestern US, in this section they will be used to explore the potential impacts of analogous levels of premium estimation inaccuracy on the distribution of crop insurance subsidies across farmers who produce the same crop and (unknown to the insurer) exhibit identical yield risk profiles.

Specifically, it is assumed that both the farmer and the insurer (RMA) do not know what the AFP is and thus have to estimate it with various degrees of error (PMAD and bias). The producer and insurer premium estimates are denoted by PPE and IPE, respectively, and risk-averse producers are willing to pay a risk-protection premium (RPP) in excess of their PPE. A farmer's decision rule for participating in the program, thus, is PPE+RPP≥IPE, i.e. that his/her own premium estimate plus any risk protection premium he/she is willing to pay is greater than the insurer's quote.

For each scenario in the analysis, it is assumed that 10,000 identical producers are eligible to participate in the program. Alternatively, this could be interpreted as conducting repeated outcome draws from a single producer. Each outcome (i) is characterized by a set of two premium estimates, one by the producer (PPE_i) and one by the insurer (IPE_i), which are randomly drawn as follows:

1) $PPE_i = AFP + RPP + PB + U_{iP}$
2) $IPE_i = AFP + IB + U_{iI}$

where AFP=10 in all cases, PB and IB are the levels of bias in the producer and insurer premium estimates, respectively, and U_{iP} and U_{iI} are draws from uncorrelated uniform distributions with zero mean and whatever range is required to achieve the desired PMAD for PPE and IPE. In the first scenario (S1), for example, it is assumed that PB, IB and RPP are all zero and a relatively low PMAD of 2.0 is desired for both PPE and IPE. Thus, both U_{iP} and U_{iI} are set range between -4 and 4. As expected in this scenario $PPE_i \geq IPE_i$ in just about 50% of the 10,000 simulated outcomes, which means that only half of the eligible producers would voluntarily participate.

A more interesting question, however, is: what is the distribution of the premiums paid by the participating producers relative to the AFP, i.e. to what they should in fact be paying? This question can be answered by comparing their IPE_i (i.e. what they ended up paying) with the AFP. Surprisingly, even at these relatively low PMAD levels, nearly 25% of participating producers end up paying 25% or more than what they should (i.e. the AFP) while another 25% pays less than 70% of the AFP. In addition, it is noted that because only farmers for whom $PPE_i \geq IPE_i$ participate in the program and there is no RPP or any positive bias on the producer's premium estimate, the sum of their IPE_i (i.e. what they actually pay) is only 86.6% of the sum of their AFP, which means that this particular scheme could not operate without a substantial external subsidy.

In practice, the RMA provides subsidized premiums to promote higher levels of participation. Mathematically, this alters the participation rule to $PPE_i \geq (1\text{-}PPS) x IPE_i$ where PPS is the percentage premium subsidy. For instance, if PPS=0.30 (30 percent), the insurer's quote would be 0.70x IPE_i. Table 3 presents additional results under the same scenario (PB= IB=RPP=0 and PMAD=2.0) and select PPS values. At PPS=0.37, for example, $PPE_i \geq (1\text{-}PPS) x IPE_i$ in 9,020 of the 10,000 cases, i.e. the producer participation rate (PPR) is 90.2 percent. In addition, at this PPS, the sum of $(1\text{-}PPS) x IPE_i$ for the participating producers is only 61.2% of the sum of their AFP, which means that 38.8% of the total indemnity payments would have to be externally subsidized. This percentage external subsidy is denoted by PES in Table 3.

Also note that, because of the relatively high subsidy level, all participating producers now pay 90% or less than what is actuarially fair. However, while nearly 15% are charged 45% or less, another 13% or so pay 80% or more of the AFP. That is, just by chance, two producers with identical yield risk profiles would often end up paying very different crop insurance premiums and thus receiving vastly disproportionate shares of the intended government subsidy. While this simplistic scenario seems to approach the high levels of subsidy (PES) that have been needed in practice in order to achieve substantial (90% or more) rates of voluntary producer participation, it is important to ascertain if analogous results are observed under more plausible scenarios.

A perhaps more realistic scenario (S2) assumes a 20% risk protection premium (RPP) on the farmer side, a 20% positive premium estimation bias on the insurer side (IB), and a PMAD of 35% on both the producer and the insurer estimates. Note that these IB and PMAD magnitudes are consistent with what was found in the previous section and, in fact, this scenario calibrated to also require a 40% level of external subsidy (PES) in order to achieve a 90% PPR (Table 3). As in S1, if the insurer's premium estimates are not subsidized (PS=0), 50% participation is still observed because RPP=IB, but the 20% RPP reduces the necessary PES to just 1.6%. However, the distribution of the premiums paid becomes even more disperse, with 15% of the farmers paying 65% or less and 80% paying 30% or more than what they should. At PS=48% (PES=39.8% and PPR=90.3%), while nearly 20% of the participating producers are charged 40% or less, another 20% pay 80% or more of the AFP. Again, just by chance, a producer would quite often end up paying twice as much as another one who has an identical yield risk profile.

The third scenario (S3) is the same as S2 but assumes a 50% correlation (CC=0.50) between the producer and the insurer premium estimates. A certain degree of correlation would be expected in practice since the RMA considers the farm's recent yield history on its rating protocol and the farmer could give some weight to the insurer's quote when determining what he/she thinks the actuarially fair premium is. Note that, as expected, such correlation noticeably reduces the amount of subsidies required to achieve high levels of participation. Specifically, a PES of just 26.6% (versus 39.8% under S2) is now sufficient to motivate 90% of the producers to purchase insurance. However, it does not seem to affect the dispersion of the premiums to be paid by farmers whose underlying AFP is the same

(Table 3). Note that at this PPR of 90%, 14.4% of the farmers end up paying 45% or less while 17% would purchase insurance paying the full AFP or more.

The fourth scenario (S4) incorporates the likely unrealistic assumption sometimes found in the literature that the produced knows that the AFP is but the RMA does not. Thus, the RMAD for the producer and insurer premium estimates are set at zero and 2.0 respectively. In addition, it is assumed that the insurer estimate is unbiased and the producers are willing to pay a 20% RPP. While this scenario also reduces the amount of external subsidies required to achieve high levels of participation, the dispersion of the premiums to be paid by farmers remains high. For example, at the PPR of 90%, 16% of the farmers end up paying 65% or less while 15% would purchase insurance paying 10% or more than the AFP.

Numerous other scenarios are presented in Table 3 involving various combinations of producer and insurer PMADs, PB, IB, RPP and CC. From these scenarios it is concluded that while some such combinations result in a high percentage of producers participating at relatively low levels of external subsidy (PS and PES), as long as a non-negligible PMAD (≥2.0) is assumed to be associated with the insurer's estimate for the AFP, the dispersion of the premiums to be paid by "identical" farmers remains high. It can thus be argued that this is an unavoidable disadvantage of crop insurance. While, through substantial external subsidies, it is possible to avoid a situation where too many farmers end up paying more than the AFP, it appears that the distribution of those subsidies across participating farmers will always be highly and randomly uneven. Just by chance, some producers will receive a large share of the subsidy while others get none or very little.

While, in order to facilitate comparisons, the previous analysis focus on the case of a group producers with identical risk profiles, a logical extrapolation of the above results is that an individual with a low-risk operation (i.e. whose AFP is relatively low) could very well end up paying a similar or even larger premium than another high-risk farmer. An alternative, of course, would be for the insurer to charge the same "average" premium to all producers whose operations appear to face about the same yield risk. The problem with this is that, because of the previously illustrated difficulties with accurately assessing farm-level risk (i.e. estimating the AFP), producers with substantially different risk exposure (i.e. AFP) could end up paying the same "average" premium.

Concluding Remarks

Due to the nature of the analyses, the results presented in this paper have to be based on simulated rather than actual yields. However, the mean and variances of the distributions from which the yields are being simulated are clearly in line with what has been documented in previous literature (**references**) and observed in practice. While the simplifying assumption of yield normality might not hold in practice (**references**), there is no reason to expect that the results would be much different if yields were assumed to be non-normally distributed. Finally, the underlying producer behavior assumptions are very reasonable likely to resemble their actual decision-making process.

Thus, it would appear that the allocation of the subsidies to the crop insurance program across participating producers could be highly uneven. Clearly since neither the producer nor the insurer are certain about what the actuarially fair premium is, due to the substantial random errors that are expected on what they perceive or estimate it to be, some will receive much more generous subsidies than others. That is, just by chance, it is not unlikely that a producer will receive less than half as much premium payment support from the government as another "identical" operator. Since both face the same yield and revenue risk, this is clearly not an optimal safety net scheme.

References

Ramirez, O.A., C.E. Carpio, and R.M. Rejesus (2011). "Can Crop Insurance Premiums be Reliably Estimated?" *Agricultural and Resource Economics Review* 40(1): 81-94.

Ramirez, O.A., S.K. Misra, and J.E. Field (2003). Crop yield distributions revisited. *American Journal of Agricultural Economics* 85(1)(February 2003):108-120.

Table 1: Actuarially Fair Premium (AFP), Average of Premium Estimates (APE), Mean Absolute Deviation of the Premium Estimates from the AFP (MAD), Percentage Bias (PBIAS) and Percentage MAD (PMAD) for two alternative underlying corn yield distributions with 5 different standard deviations (STD).

	Normal Distribution - Mean = 180					Non-Normal Distribution - Mean = 180				
STD	**AFP**	**APE**	**MAD**	**PBIAS**	**PMAD**	**AFP**	**APE**	**MAD**	**PBIAS**	**PMAD**
30.00	0.97	1.38	0.96	41.58	98.46	7.14	8.73	5.57	22.36	78.07
35.00	2.50	3.12	1.89	24.96	75.70	10.20	11.67	6.82	14.38	66.86
40.00	4.93	5.71	3.08	15.80	62.39	13.70	14.70	8.02	7.27	58.55
45.00	8.26	9.26	4.47	12.18	54.13	17.29	17.84	9.20	3.19	53.22
50.00	12.37	13.52	5.95	9.30	48.06	21.17	21.20	9.92	0.17	46.87

Table 2: Distribution of the premiums paid by participating producers under various combinations of insurer premium bias (IPB), producer risk protection premiums (RPP), insurer and producer PMADs (IPMAD and PPMAD), and correlations between the insurer and the producer premium estimates (CORR).

IPB	0.00		0.00		0.00		0.00		0.00		-15%		15%	
RPP	0.00		0.00		0.00		10%		15%		15%		15%	
IPMAD	30%		40%		40%		50%		50%		50%		50%	
PPMAD	30%		40%		40%		50%		50%		50%		50%	
CORR	0.00		0.00		0.60		0.60		0.60		0.60		0.60	
Scenario	**S1a**	**S1b**	**S2a**	**S2b**	**S3a**	**S3b**	**S4a**	**S4b**	**S5a**	**S5b**	**S6a**	**S6b**	**S7a**	**S7b**
GSR	0.000	0.520	0.000	0.650	0.000	0.520	0.000	0.570	0.000	0.520	0.000	0.440	0.000	0.590
PPR	0.500	0.902	0.499	0.897	0.500	0.901	0.560	0.898	0.589	0.900	0.679	0.902	0.499	0.901
PPG	0.200	0.538	0.266	0.665	0.100	0.502	0.129	0.551	0.123	0.503	0.257	0.515	0.005	0.509
PAFP														
20%	1.000	0.985	1.000	0.742	1.000	0.881	0.866	0.792	0.866	0.809	0.779	0.756	0.964	0.852
25%	1.000	0.889	0.938	0.644	0.957	0.823	0.834	0.737	0.834	0.760	0.749	0.712	0.929	0.795
30%	1.000	0.793	0.878	0.550	0.915	0.763	0.802	0.682	0.803	0.710	0.719	0.669	0.894	0.739
35%	1.000	0.696	0.821	0.457	0.874	0.701	0.770	0.625	0.772	0.659	0.690	0.624	0.860	0.681
40%	1.000	0.601	0.765	0.369	0.833	0.638	0.739	0.569	0.741	0.609	0.661	0.580	0.827	0.622
45%	0.919	0.507	0.712	0.283	0.794	0.575	0.708	0.511	0.711	0.558	0.633	0.535	0.795	0.562
50%	0.840	0.416	0.660	0.200	0.756	0.510	0.677	0.451	0.681	0.507	0.605	0.491	0.762	0.501
55%	0.765	0.329	0.611	0.120	0.717	0.443	0.648	0.391	0.651	0.454	0.577	0.446	0.730	0.439
60%	0.694	0.248	0.563	0.045	0.680	0.375	0.619	0.330	0.623	0.400	0.549	0.401	0.699	0.375
65%	0.626	0.168	0.518	0.000	0.642	0.305	0.590	0.269	0.594	0.347	0.522	0.356	0.668	0.311
70%	0.562	0.095	0.473	0.000	0.607	0.234	0.562	0.207	0.566	0.292	0.496	0.311	0.638	0.245
75%	0.501	0.025	0.432	0.000	0.571	0.163	0.534	0.143	0.538	0.237	0.470	0.266	0.608	0.178
80%	0.444	0.000	0.391	0.000	0.537	0.092	0.507	0.078	0.511	0.182	0.444	0.220	0.580	0.110
85%	0.391	0.000	0.354	0.000	0.503	0.021	0.480	0.013	0.485	0.126	0.419	0.174	0.551	0.042
90%	0.341	0.000	0.317	0.000	0.471	0.000	0.455	0.000	0.460	0.069	0.394	0.127	0.523	0.000
95%	0.295	0.000	0.283	0.000	0.439	0.000	0.429	0.000	0.434	0.012	0.370	0.080	0.496	0.000
100%	0.252	0.000	0.251	0.000	0.407	0.000	0.403	0.000	0.409	0.000	0.346	0.033	0.470	0.000
105%	0.211	0.000	0.220	0.000	0.375	0.000	0.379	0.000	0.384	0.000	0.322	0.000	0.443	0.000
110%	0.173	0.000	0.192	0.000	0.345	0.000	0.354	0.000	0.359	0.000	0.299	0.000	0.417	0.000
115%	0.140	0.000	0.166	0.000	0.315	0.000	0.329	0.000	0.335	0.000	0.276	0.000	0.391	0.000
120%	0.111	0.000	0.141	0.000	0.287	0.000	0.306	0.000	0.311	0.000	0.254	0.000	0.367	0.000
125%	0.085	0.000	0.119	0.000	0.259	0.000	0.283	0.000	0.288	0.000	0.233	0.000	0.343	0.000
130%	0.062	0.000	0.098	0.000	0.231	0.000	0.262	0.000	0.266	0.000	0.212	0.000	0.319	0.000

Notes: GSR, PPR, PPG, stand for the Government Subsidy Rate to each individually estimated premium, the Producer Participation Rate in the program, and the Percentage (of the total program indemnities) Paid by the Government. The percentages on the first column under PAFP are the percentages of the AFP. The numbers in the columns next to them are to be interpreted as follows: on the second column, for example, there is a 100% probability that the producer will end up paying more than 40% of the AFP, a 91.9% probability that he/she will pay more than 45% of the AFP, an 84.0% probability that he/she will pay more than 50% of the AFP, and so on.