# Challenging Belief in the Law of Small Numbers

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**Introduction**

The context of row crop risk management continues to grow more complex. While the magnitude of price and yield risk changes over time, the development of sophisticated risk management tools and complex government policies may improve growers' ability to manage risk -- if these instruments are used correctly. Conversely, these instruments may actually increase risk exposure if used incorrectly. Gone are the days when growers had access only to individual yield insurance and national triggered price programs. In 1996, revenue insurance became available for many crop growers. For most major crops, the acreage covered by revenue insurance now far exceeds that covered by yield insurance. The 2008 farm bill created the complex risk policies of ACRE and SURE (Ubilava et al.). Mitchell et al. argue that ACRE, which subsumed multiple revenue risks and integrated with other risk instruments, was difficult for growers to understand and difficult for county USDA officials to implement. Current farm bill proposals are now focused on various shallow loss programs such as Agricultural Risk Coverage (ARC), Stacked Income Protection Plan (STAX) and Supplemental Coverage Option (SCO) which layer risk protection on top of crop insurance. Thus, producers are likely to continue to be confronted with complex risk management tools which may overlap or leave gaps in risk protection. Further, the decision becomes even more complex when one considers the possibility of also using futures or forward contracts.

**Implications for risk management education**

The additional complexity of the risk management context also challenges those who educate and advise crop producers on risk management decisions. Simply interpreting the mechanics of SCO is not easy because of the complex design. Furthermore analyzing the potential implications and choices a producer may make with such a product also involves

stochastic analysis. In this paper we make the argument that while tremendous advances in the ability to model agricultural risk have been made, we are still constrained by a widespread lack of farm-level data.  This is particularly challenging given the nature of crop revenue risk. We argue this has significant implications for extension and educational programs.

Frequently, those involved in working with crop producers are asked to advise producers regarding risk policy and risk management decisions.  The more complex the problem the more likely we will be asked for guidance.  Thus, it appears we are truly in a teachable moment.  Having said that, what approach should one take when asked for risk management recommendations?  Over the course of our careers the authors have seen a gamut of approaches that we describe as ranging from one extreme which essentially emulates the admonition from Hippocrates " to first do no harm" to the opposite extreme that we characterize as "If they want it bad they will get it bad."  Our premise in this paper is that we can improve producer risk management if the right approaches are taken, but caution is merited or we will mislead clientele with faulty analysis.

Ultimately, our analysis follows the vein of literature taken by Peterson and Tomek where they evaluate marketing strategies given a 40-year lifetime for a producer.  They conclude there is little chance to discriminate between such strategies. In effect, large-sample inferior strategies may frequently appear superior in small samples.  We follow the flavor of their work, but use crop insurance and farm programs as the context rather than pricing strategies.

**Progress in modeling risk**

Risk research has moved dramatically forward in developing analytical tools but also in understanding risk behavior and perceptions. We now have spreadsheet software capable of

computational techniques that required main frame computers 25 years ago.  This includes

optimization packages and easy-to-use simulation packages that allow one to simulate

multivariate mixed non-normal distribution which had previously been computationally

difficult.  Progress on data has also been made.  Convenient databases providing NASS area-

level production and acreage estimates and prices can be downloaded quickly.  Long time

series of weather data are available from NOAA, and futures prices are widely available from

private sources.  All of these advances make it more practical to provide sound risk

management analysis.

What, has largely remained unchanged is that weather and other risks still drive crop

yield risk and farm-level time-series yield data tend to be scarce and relatively short.  Given

that farm level yield risk is central to assessing crop insurance participation, product options,

unit structure, and coverage levels, this is a significant problem.  Further area products do not

require farm yields, but assessing the efficacy of area products does.  In our analysis we focus

on the implication of these short series on risk analysis

**The Law of Small Numbers**

At a conference addressing the modeling of agricultural risk decisions related to farm

policy, it seems quite appropriate to remind ourselves of the truly seminal work of Tversky

and Kahneman (TK) regarding cognitive errors individuals make when confronted with

randomness.  This body of work was a significant reason why Kahneman was eventually

awarded a Nobel Prize.  Further, this foundational work contributed to the explosion of

economic research we now call behavioral economics.

Tversky and Kahneman summarized this work as follows:

"Thus far, we have attempted to describe two related intuitions about chance. We proposed a representation hypothesis according to which people believe samples to be very similar to one another and to the population from which they are drawn. We also suggested that people believe sampling to be a self-correcting process. The two beliefs lead to the same consequences. Both generate expectations about characteristics of samples, and the variability of these expectations is less than the true variability, at least for small samples.

The law of large numbers guarantees that very large samples will indeed be highly representative of the population from which they are drawn. If, in addition, a self-corrective tendency is at work, then small samples should also be highly representative and similar to one another. People's intuitions about random sampling appear to satisfy the law of small numbers, which asserts that the law of large numbers applies to small numbers as well."

Thus, TK assert two tendencies among individuals which may lead to errors in assessing risk. First, individuals tend to overestimate the degree to which a small sample represents the population and secondly they often believe that random processes are self-correcting when in fact they are not. Rabin also investigated this phenomenon and illustrates its potential economic implications. The applicability to agricultural risk management seems quite clear. We deal with random prices, yields, and weather that are drawn from distributions of various shapes and families. In the case of yield and revenue associated with crop agriculture we get essentially one observation per year. At that rate of stochastic revelation, small samples grow quite slowly into large samples. While, it seems that the TK results would seem broadly applicable to those working with agricultural risk decision making, our search of the SCOPUS abstracting database finds that their paper is cited 445 times in refereed literature, but not once by an agricultural economics journal.

Assuming for a moment that Tversky and Kahneman's conclusions are applicable to row crop producers then what might we observe? Several possible

manifestations exist, but we would suggest a few likely scenarios.  First, farmers

would put too much weight on an evaluation based on very small samples.  For

example when it comes to farm policy, they might ask for analysis that "shows what

the policy would have done if in place for the last five years."  Or they may discount

weather events that are known to have occurred with some frequency but that have not

been experienced in recent times.  TK assertion of individuals perceiving self-

correction in random draws leads to the idea that 'bad weather and good weather must

average each other out. "

Systemic biases and heuristics being used in in statistically small samples has

the potential to affect farm policy evaluations. Coble and Barnett have questioned

whether errors in subjective probability assessment affects the demand for crop

insurance and underlies the longstanding question regarding why subsidies have

appeared necessary to attract participation in crop insurance.  While little has been

done to investigate this issue in the context of crop insurance, a body of researches on

cognitive bias in other lines of insurance purchase does exist. (Galarza and Carter;

Shapira and Venezia; Johnson et al.)

The final interesting point about TK's paper was not so much addressing errors

made by laymen.  Rather TK pointedly described errors made by scientists in doing

their research!  The fundamental error was misjudging the sample size necessary to

make a statistically valid inference.  This is a problem that has persistently plagued

agricultural policy and insurance research.  However, we will note that TK focused on

the fact that an insufficient sample size may lead to failure to reject the null hypothesis

when in fact a larger sample would reject the null.  Thus, a strong motive exists to

correct sample size if possible. However, in much of the risk management literature optimization and simulation techniques are used and hypothesis tests omitted. Without these tests, there may be a lack of restraint on conclusions drawn from sample samples.

**Empirical Analysis**

In our analysis we investigate the implications of sample size on the evaluation of two simple crop insurance purchase decisions – individual coverage revenue insurance and area revenue triggered SCO. To do so we appeal to a technique common in statistical literature – we evaluate how well a particular estimation or statistical procedure performs given hypothetical, but known distributions. While we do not argue that we do know the true distribution of crop revenue for any particular crop/location, we generate data from a known distribution to investigate the implications of sample size on the modeling.

For this analysis we use futures price from the Commodity Research Bureau (CRB) database and National Agricultural Statistical Service county yield data from 1975 through 2011 for corn and soybeans produced in McLean County, Illinois, cotton produced in Bolivar County, Mississippi, and wheat produced in Wichita County, Kansas. Futures price changes from the RMA preseason price period and the harvest time pricing period are used to measure price risk in a manner consistent with RMA pricing procedures. Technological change has been repeatedly shown to strongly influence crop yield distributions thus county yields are detrended with a linear trend and relative residuals are used to model county yield risk.

Farm yields, which are derived from detrended county yields, follow the formulation of Miranda (1991) as follows:

$$(1) \quad FY_t = \mu_{FY} + \beta(CY_t - \mu_{CY}) + \varepsilon_{FY,t}$$

where:

- $FY_t, CY_t$ are farm yield and county yield at period $t$

- $\mu_{FY}, \mu_{CY}$ are respectively the mean value of farm yield and county yield

- $\beta$ is a coefficient measuring the responsiveness of farm yield to the systematic factors affecting county yield.

- $\varepsilon_{FY,t}$ is idiosyncratic farm yield deviation.

$\varepsilon_{FY,t}$ is assumed to be normally distributed $N(0, \sigma_F^2)$. An acre-weighted average of the sensitivity coefficient $\beta$ across all farms in a county will equal one which is the assumption for this analysis. According to Coble and Barnett (2007), a grid search can be employed to estimate farm yield uncertainty by finding the $\sigma_F$ associated with $\varepsilon_{FY,t}$ that when combined with county yield will produce farm yield variability consistent with 65% coverage level base premium that crop yield insurance purchasers are charged in the county. Base premium rate data is obtained from USDA/RMA databases.

Given the stochastic price, county yields, and idiosyncratic risk, parametric county and farm yield marginal distributions and price distributions are fit using a methods-of-moments estimator. Yields are assumed to conform to the Beta distribution family, while prices are assumed to come from a log-normal distribution. Also, correlations among the three random variables are estimated using the time-series data. We then use the multivariate simulation technique described in Anderson, Harri, and Coble to generate a large sample of 50,000 random draws to reflect the multivariate revenue distribution. Then to

evaluate the implication of small samples on the estimate of insurance rates, samples of 10, 20, and 30 were drawn 50,000 times from the population of 50,000 observations to produce empirical estimates of premium rates.

Two insurance designs were evaluated. The first is that of revenue insurance and the second is a shallow loss design modeled after the supplemental coverage option in the House and Senate farm bill proposals (Chite et al 2013)

Farm-level revenue insurance is modeled at coverage levels of 65 and 75 percent of expected revenue. Indemnities for an individual producer, $i$, per planted acre are calculated as:

$$(2) \quad RevInsIndem_i = \max[0, ((CL_i \times \max(EP, HP) \times APH_i) - (HP \times FY_i))]$$

where $EP$ and $HP$ are the pre-planting expected price and the harvest time price, respectively; $CL_i$ is the coverage level; and $APH_i$ is the farm's actual production history (APH) yield. Crop insurance premiums are subsidized at rates that vary by coverage level. The subsidy rates are 59 percent for 65 percent coverage and 55 percent for 75 percent coverage.

Supplemental Coverage Option (SCO) would provide an indemnity payment when market revenue measured at the county level falls below 90 percent of the expected county revenue as determined from county yield histories and futures prices. The payment size would be determined by the proportion of the range of the loss below 90 percent down to the nominal coverage level of the producer's farm-level crop insurance. The indemnity function for producer $i$ in county $c$ is:

$$(3)\ SCOIndem_i = \left\{ \min \left( \max \left[ 0, \frac{(0.9 - \frac{Rev_c}{ExpRev_c})}{(0.9 - CL_i)} \right], 1 \right) \right\} \times (0.9 - CL_i) \times ExpRev_c$$

where $Rev_c$ is market revenue for the producer's county, $ExpRev_c$ is expected revenue for the

county and $CL_i$ is the producer's coverage level for farm-level revenue insurance. All

producers with the supplemental coverage would receive a payment when the county trigger is

met but the amount of the payment would depend on an individual's crop revenue insurance

coverage level. A producer would pay 30 percent of the actuarially-fair premium (70 percent

subsidy) for this supplemental coverage.

**Results**

Table 1 reports the mean, standard deviation, and coefficient of variation (C.V.) for

each of the crop/county combinations examined. Note that the C.V. of McLean county corn

and soybeans are generally lower than for Bolivar County cotton and Wichita county wheat.

Also county revenue variability is lower than farm revenue in every case as aggregation

generally dampens farm-level risk. This has implications for SCO indemnity relative to RP as

all else equal the county revenue is less risky than the risk level of the average farm in the

county.

Table 2 reports the simulation results for corn and soybeans in Mclean County Illinois.

This location was chosen to reflect the low risk production region in the heart of the Cornbelt.

Two insurance designs are modeled – individual coverage Revenue Protection (RP) and the

Supplemental Coverage Option (SCO). The upper section of the table assumes 75% coverage

RP and a matching 90% to 75% SCO. The lower section of the table assumes 65% coverage

RP and a matching 90% to 65% SCO. This variation is used to illustrate how the range of coverage affects the variability of the rate estimates.

The first row of values report the large-sample mean indemnity per acre for each crop based on 50,000 random draws from the known multivariate distribution. Note the corn premium/acre is generally higher due to a greater per acre crop value. Note also that for both corn and soybeans the SCO expected indemnity exceeds the RP expected indemnity even when SCO covers a range of 15% versus the 75% range covered by RP. These results are more extreme in the lower portion of the table when RP coverage drops to 65% and the SCO range widens. This illustrates the fact that SCO covers a narrow range of liability but it is a range that has much greater probability than the extreme events in the lower tail of the distribution covered by RP.

Below the mean premium per acre we report the standard deviation and coefficient of variation of the estimated indemnity per acre based on 50,000 replications of small samples of 10, 20, and 30. These results are meant to illustrate the effect of small samples on the accuracy of an estimated expected indemnity. We focus on the C.V as it measures variability relative to the mean value. The first result we note is that the RP premium estimate is always more variable than the SCO indemnity because of the RP rate being driven by infrequent but large loss events. The variability increases as the RP coverage is dropped to 65% and the C.V exceeds 1.00 when the sample size is 10.

We also note that increasing sample size from 10 up to 20 and 30 greatly reduces the error of the expected indemnity estimate. The pattern is similar across both crops and coverage levels. Increasing the sample size from 10 to 30 reduces the C.V of expected indemnity by at least 40 percent and by almost half when 65% RP is involved. However we

would note that even a sample size of 30 results in a fairly substantial C.V.  We note this as a sample size of 30 is typically far more years of data than we have at the farm level.  Thus, while being able to obtain 30 years of farm level data would be a relative jackpot of farm level yields; it would still result in substantial error in indemnity estimates for low risk counties.

Table 3 is provided to compare the implications of other riskier regions to the low risk McLean Illinois case.  Here Bolivar county Mississippi cotton and Wichita county Kansas wheat are reported.  In general these results are consistent with that of table 1 except that the C.V. of the rate estimates is generally lower.  This illustrates that in a relative sense riskier regions are easier to rate given a small sample.  Intuitively, it is less likely that small sample will omit the deep loss that drives rates for low coverages and in low risk regions.

In summary the results suggest while variation exists, small samples of 30 or less observations can lead to widely varying and potentially misleading analysis of risks that generally conform to those we examine in agricultural insurance and policy settings.  Note also that we have abstracted away from other complicating factors such as estimating yield trends, structural changes in agricultural markets, and moral hazard that may be induced by policy and cause changes in the probability density.  These issues also add complexity to appropriately modeling agricultural risk.  In the final section of the paper we suggest some possible approaches to address the small sample issue.

**Conclusions**

Given the small sample issues that are likely difficult to fully overcome, we suggest several approaches to conducting analysis of crop revenue risk management decisions.  First, we need to be ever vigilant of falling into the fallacy of the law of small numbers ourselves.

Ultimately, this takes intellectual discipline to stop and consider if our analysis is tainted by this phenomenon. Further, we should hold one another accountable for avoiding these errors when evaluating risk management analysis. It is our perception that given the paucity of citations to TK's work in our literature that we are not attuned to their early work or Kahneman's more recent discussion of this topic and other potential cognitive errors in assessing risk.

On a related note, we suggest that when using simulation or optimization packages to evaluate insurance and farm programs, we need to clearly acknowledge that often we are positing alternative estimators. For example, if you evaluate the expected indemnity of a 75 percent coverage RP insurance policy and compare the results to the rates offered by USDA/RMA, then your estimate and that of RMA are competing estimators of the same risk. Likewise if you use historical data to estimate price volatility and then compare this to the implied volatility from the Black-Scholes formula, you have two competing estimators. Our econometrics training should tell us how to compare two alternative estimators, but it is not as often implicitly done that we assume one estimator is correct and deviation is error on the part of another estimator.

In terms of our analysis that may be constrained by small samples, we see two primary means to mitigate the issue. Both involve augmenting short time series with longer aggregate series of related data. For example modeling a short time series of farm yields may be improved by using a relationship as specified in equation 1. If a longer series of aggregate data is available then less would be demanded of farm yield data. In equation 1, farm yields are necessary to estimate $\beta$ and $\varepsilon_{FY,t}$ but much of the yield risk is captured by the longer county yield series.

A related approach to addressing the issue of short yield series is reported by Rejesus et al at this conference. In this case a long time series of weather data is used to answer the question, what is the long-term probability of observing weather events like those observed in a particular year. Here one is attempting to put unique weather events in the proper probabilistic context. For example, were the weather events that occurred in Illinois during the 2012 crop year a one-in-thirty, one-in-50, or some other probability. Climate division weather data is generally available back to 1895 for the entire U.S. and other sources may be a shorter series but more disaggregated.

A fascinating additional possibility is to attempt to train producers to be more sophisticated risk assessors and managers. Our tendency in outreach and extension programs is to focus on tools and results not the intellectual process used by the producer. An interesting question whether we can teach producers to avoid certain behavioral errors in judgment. To our knowledge this is a largely untapped area of research or extension in agricultural economics.

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Table 1.  Summary Statistics for per acre crop revenue for the four crop/county combinations examined.

| | Corn Farm Revenue | Corn County Revenue | Soybean Farm Revenue | Soybean County Revenue |
|---|---|---|---|---|
| **Mean** | 783.4 | 783.4 | 577.2 | 607.7 |
| **Standard Deviation** | 195.7 | 136.0 | 116.4 | 64.9 |
| **C.V.** | 0.25 | 0.17 | 0.20 | 0.11 |
| | **Cotton Farm Revenue** | **Cotton County Revenue** | **Wheat Farm Revenue** | **Wheat County Revenue** |
| **Mean** | 589.0 | 544.3 | 96.6 | 95.6 |
| **Standard Deviation** | 334.8 | 145.2 | 54.9 | 34.5 |
| **C.V.** | 0.57 | 0.27 | 0.57 | 0.36 |

Table 2. Effect of Sample Size on Revenue Insurance and SCO Premium estimates from Known Illinois Corn and Soybean Distributions

| | McLean Co Ill. Corn | | McLean Co Ill. Soybeans | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| | **75% coverage CRC** | **SCO 90% to 75%** | **75% coverage CRC** | **SCO 90% to 75%** |
| **Mean Premium/Ac.** | 23.13 | 28.33 | 10.94 | 11.13 |
| | | Sample size 10 | | |
| **Std Dev** | 18.46 | 14.18 | 10.03 | 7.39 |
| **C.V.** | 0.80 | 0.50 | 0.92 | 0.66 |
| | | Sample size 20 | | |
| **Std Dev** | 13.15 | 10.07 | 7.04 | 5.19 |
| **C.V.** | 0.57 | 0.36 | 0.64 | 0.47 |
| | | Sample size 30 | | |
| **Std Dev** | 10.76 | 8.24 | 5.72 | 4.22 |
| **C.V.** | 0.47 | 0.29 | 0.52 | 0.38 |
| | **65% coverage CRC** | **SCO 90% to 65%** | **65% coverage CRC** | **SCO 90% to 65%** |
| **Mean** | 9.96 | 33.56 | 3.60 | 11.46 |
| | | Sample size 10 | | |
| **Std Dev** | 11.16 | 18.21 | 5.06 | 7.83 |
| **C.V.** | 1.12 | 0.54 | 1.41 | 0.68 |
| | | Sample size 20 | | |
| **Std Dev** | 7.93 | 12.96 | 3.53 | 5.50 |
| **C.V.** | 0.80 | 0.39 | 0.98 | 0.48 |
| | | Sample size 30 | | |
| **Std Dev** | 6.48 | 10.60 | 2.84 | 4.48 |
| **C.V.** | 0.65 | 0.32 | 0.79 | 0.39 |

Table 3. Effect of Sample Size on Revenue Insurance and SCO Premium estimates from Known Mississippi Cotton and Wichita Wheat Distributions

| | Bolivar Co MS Cotton | | Wichita Co KS Wheat | |
| --- | --- | --- | --- | --- |
| | 75% coverage CRC cotton | STAX 90% to 75% Cotton | 75% coverage CRC Wheat | STAX 90% to 75% Wheat |
| **Mean Premium/AC** | 60.31 | 33.66 | $11.56 | $5.55 |
| | | Sample size 10 | | |
| **Std Dev** | 30.97 | 12.37 | 4.63 | 1.77 |
| **C.V.** | 0.51 | 0.37 | 0.40 | 0.32 |
| | | Sample size 20 | | |
| **Std Dev** | 21.97 | 8.68 | 4.01 | 1.53 |
| **C.V.** | 0.36 | 0.26 | 0.35 | 0.28 |
| | | Sample size 30 | | |
| **Std Dev** | 17.93 | 7.06 | 3.27 | 1.25 |
| **C.V.** | 0.30 | 0.21 | 0.28 | 0.23 |
| **Sample Size** | **65% coverage CRC cotton** | **STAX 90% to 65% Cotton** | **65% coverage CRC cotton** | **STAX 90% to 65% Cotton** |
| **Mean** | 39.89 | 43.74 | $7.98 | $8.02 |
| | | Sample size 10 | | |
| **Std Dev** | 24.20 | 17.50 | 3.67 | 2.73 |
| **C.V.** | 0.61 | 0.40 | 0.46 | 0.34 |
| | | Sample size 20 | | |
| **Std Dev** | 17.17 | 12.32 | 3.18 | 2.36 |
| **C.V.** | 0.43 | 0.28 | 0.40 | 0.29 |
| | | Sample size 30 | | |
| **Std Dev** | 14.01 | 10.01 | 2.60 | 1.92 |
| **C.V.** | 0.35 | 0.23 | 0.33 | 0.24 |