A Comparison of Stated and Revealed Risk Preferences using Safety-First

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Abstract

In this paper we determine the risk preferences of crop producers using the safety-first method. Our methodology is unique, since it utilizes both price and yield risk in the producer's optimization problem. We then compare the derived preferences with the stated preferences of the producers. The stated preferences are obtained from a lottery-style game designed to elicit producers' risk preferences. The study is conducted with data from producers in Nebraska, Iowa and South Dakota and the results indicate that there is in fact a relationship between the preferences derived from our structural model and the ones stated by the producers in the game. This is an important result from a policy-making perspective, as it validates the use of behavior elicitation surveys about risk preferences. Such surveys are often easier to administer and less expensive than collecting information on revealed preferences.

Examining the influence of risk preferences on a farmer's decision-making process is an important policy concern. We define risk as representing any situation in which the outcome of an action is not known with certainty (Chavas, 2004). Risk preferences are varying attitudes or preferences toward different types of risks. Agricultural risk usually arises from uncertain weather and market outcomes. For example, a producer does not know at the beginning of the season if he will receive sufficient precipitation for full yields or if erratic demand and supply conditions in the commodity market will affect output prices. Understanding how a producer will respond to this risk helps policymakers understand how to design policies such as crop insurance that help a producer manage risk, or predict the impacts of risk on the use of resources such as land, water, and fertilizer. Consequently measuring the level of risk and how individual attitudes to this risk evolve is a key concern. Over the past decades several authors, using pre-event information sets, have proposed risk and risk aversion measures in the agricultural context. The purpose of this study is to exhibit a new methodology that can be used to evaluate risk preferences, and to apply that new methodology to a novel panel dataset of farm-level decisions.

In the current literature, most researchers use expected utility (EU) maximization or the safety-first (SF) mechanism to determine the risk preferences of producers (Just and Pope 1979 and de Janvry 1977). In EU theory an individual's risk preferences are represented by a concave utility function $U(a)$ and he/she makes choices to maximize the expected value of utility ($EU(a)$), given that a has some probability distribution (von-Neumann and Morgenstern 1953). In the context of agricultural production, a typically represents profit. Since the producer is forced to undertake the risk of an uncertain profit level, often he/she is willing to pay a premium such that he/she is indifferent between taking the risk and getting a guaranteed return. In EU there are three categories of risk preferences: risk averse, risk neutral and risk loving. A risk averse producer would be willing to pay in order to take the risk, a risk neutral producer would agree to undertake the risk without any premium and a risk loving producer would pay a premium to undertake the risk.

The EU method is popular, yet the risk aversion measures are difficult to estimate, due to substantial data demands such as accurate outcome probabilities, prior yield and input use data. The choice of the functional form of the utility function also heavily influences the end result. Some authors (Tversky 1969, 1975 and Allais 1953) argue that the underlying assumptions (for example, transitivity and substitutability) of utility theory are frequently violated, thereby rendering the EU method ineffective. These axioms are violated because humans often do no act rationally. In contrast, the SF method is less complex and recognizes that individuals generally care more about downside risk than overall risk for uncertain outcomes. In the SF method, we maximize expected return given a downside risk constraint (Arzac and Bawa 1977). Downside risk can be a threshold level such as a catastrophic event, below which a farmer's survival is threatened. A functional form for the utility is not required, since only the disaster income level is necessary to compute the risk aversion measures as individuals are assumed to be risk neutral above the threshold.

In this paper, we ask if stated risk preference is a viable substitute for revealed risk preference when risk preferences are measured using the SF rule. Stated risk preference is measured by individual choices over a hypothetical gamble. The higher the risk in the gamble of choice, the less risk-averse is the individual. There are several objectives of this paper: First, we develop a function to determine the SF risk preferences of a crop producer. This measure incorporates both price and yield risk and to the best of our knowledge has not been generated in the literature before. We then use a farm-level dataset to compare the SF-derived revealed risk preferences to stated risk preferences obtained from a survey.

Calculating empirically-derived revealed risk preferences is costly in time and money, and often is not feasible with limited data. Thus, research on risk preferences could be enhanced if stated risk aversion measures are representative of actual risk aversion. Future research can then focus on designing games, which can extract risk preferences without using other farm variables. Some work (Dillon and Scandizzo 1978, Donkers et al., 2001 and Ding et al. 2010) has already been done in this area. However, none of the previous work verifies the validity of stated preferences by comparing them to the measures obtained from EU or SF methods. If there is no relation between stated and revealed preferences, it may be necessary to continue using EU and SF methods.

Existing Studies on Risk Preference Elicitation

Existing literature on eliciting risk-preference measures is wide and varied (Baker and Haslem 1974, Moscardi and de Janvry 1977, Dillon and Scandizzo 1978, Binswanger 1980, Bar-Shira et al 1997, Abdulkadri et al. 2003, Miyata 2003, Tadeo and Wall 2011). Of these, the three most closely related to our research are Dillon and Scandizzo (1978), Binswanger (1980) and Moscardi and DeJanvry (1977). All three papers determine the stated risk preference distribution of producers and test whether socio-economic characteristics influence farmers' risk behavior, using methodologies closely resembling ours.

Dillon and Scandizzo (1978) employ the survey approach to determine the risk-preference distributions of farmers (small owners and sharecroppers) in northeastern Brazil. The risk-preference distributions are computed for three different specifications of the utility function: mean-standard deviation, mean-variance, and exponential utility function. Their elicitation approach includes two gambles: In the first gamble the subsistence of the farmer is ensured, yet total income is still at risk and in the second the subsistence is also at risk. Each gamble comprises a sure and risky prospect and the payoffs of the risky prospect are altered till the respondent becomes indifferent between the risky and sure prospect. Their conclusions are in line with expectations as farmers are more risk averse when subsistence is at risk than when it is not. Also in both gambles more land owners are risk averse than sharecroppers. The authors also use regression analysis to test whether risk aversion is related to the socioeconomic characteristics of farmers. Binswanger (1980) uses two approaches to determine the true risk-aversion measures of farmers in India. The results show that the experimental-elicitation method is more reliable. A significant percentage of interviewed farmers display contradictory risk-behavior when compared to the experimental method. Many farmers demonstrate extreme variation in risk-preferences between different gambles, which leads Binswanger to conclude that interview methods are unreliable. Surprisingly, in his results the relation between experimentally derived partial risk-aversion and wealth is negligible.

While both papers utilize a sophisticated survey strategy, there is no way of knowing whether the obtained preferences are an actual indicator of true preferences. For example, without incorporating on-farm behavior of the producer, it is unclear whether stated and true preferences actually converge. Finally, the financial and time cost of conducting exhaustive surveys is perhaps not justified, especially if we cannot verify whether the obtained preferences are in fact the true preferences.

Safety-First Risk Preference

Unlike the EU model, preferences in the SF are discontinuous at a certain threshold, which is generally based on a subsistence or disaster level, implying that a producer focuses on minimizing the loss probability. Studies in the agricultural and finance literature have used the safety-first model to characterize risk (Roy 1952, Telser 1955, Lintner 1965, Masson 1972, Bawa 1978, Koehn and Santomero 1980, Sortino and Van Der Meer 1991, Bigman 1996, Campbell et al. 2001 and Gan et al. 2005). Moscardi and deJanvry (1977) use the "safety-first" criterion to determine farmers' risk-aversion parameters and compare those results to socioeconomic characteristics. They find evidence that the majority of producers are risk averse. They use discriminant analysis and regression techniques to conclude that a willingness to take risks is correlated with off-farm income, amount of land controlled, and membership in a solidarity group. A drawback of their approach is that price and yield risk are not individually considered in their model, implying that the uncertainty in income is driven only by yield risk. However, other work has shown that producers are concerned with yield and price risk (Babcock and Henessey 1996).

The SF criterion can be further divided into three categories: (1) minimizing the probability of disaster, (2) Maximizing expected return subject to a small disaster probability and (3) Maximizing the fractile of the distribution (Pyle and Turnovsky 1970, 1971). In method (1) the producer maximizes the probability that his/her income (denoted by x) is above a disaster level (denoted by z). This also indirectly implies that the producer is content with any wealth above the disaster level and does not desire to maximize his wealth above the disaster level. For example, we can write: $Max\ P(x > z) = Max\ \int_{z}^{\infty} U(x)f(x)dx$, where $U(x) = 1$ and $U(x) = 0$, for $x > z$ and $x \leq z$, respectively. The choice of z determines an individual's risk preference. Note that the slope of U above the discontinuity z is zero, indicating that the producer does not consider his expected return in the maximization problem.

In the second method the producer maximizes expected return subject to a small disaster probability. This method is a constrained maximization problem and improves upon the first method such that the producer's utility function, while discontinuous, is linear and upward sloping. The economic problem can be written as $Max\ U(x) = x$ if $x \geq z$ and $Max\ U(x) = x - \lambda$, if $x \leq z$, where λ is the risk aversion measure. The associated Lagrangian is: $L(x, \lambda) = \int_{-\infty}^{\infty} xf(x)dx - \lambda\left[\int_{-\infty}^{z} xf(x)dx - \alpha\right]$. If $\lambda = 0$, then $U(x)$ is continuous and linear and the producer is risk-neutral. While if $\lambda > 0$, the producer is risk averse. Finally in the third method a producer chooses to maximize income conditional on minimizing exposure to downside risk. The problem is formalized as: $Max\ \{z\text{: } \Pr(x \leq z) \leq \alpha\}$. Using Chebychev's inequality this can be rewritten as $Max\{E(x) - \beta * \left(Var(x)\right)^{\frac{1}{2}}\}$, where β is the risk aversion parameter and $\beta * \left(Var(x)\right)^{\frac{1}{2}}$ is the risk premium. A modification of this method (proposed by Magnusson, 1969) is used by Moscardi and deJanvry (1977) to determine the risk aversion parameters.

The first method is unrealistic in the context of farm production, as practice shows that producers care about their income earned above a disaster level. The second method is desirable yet mathematically intractable, since it is difficult to determine closed-form first-order conditions from the Lagrangian once price and yield risk are introduced. The third method is an extension of the second method and has been used in the literature before (Moscardi and deJanvry 1977) for determining risk aversion measure. We add to the existing literature of the third method by introducing price risk in addition to the yield risk.

Methodology for Determining Revealed Preferences

Following the definition of the SF mechanism described in the third method, we write the mathematical problem as:

$$Max\ \{z\text{: } \Pr(\pi \leq z) \leq \alpha\}$$

Where z is the disaster-income level, π is the random income and α is the accepted probability of disaster. Let the mean (μ_π) and standard deviation (σ_π) of π be known. Using Chebychev's inequality the above maximization problem can be written as:

$$Max\ \left\{z\text{: } \left(\frac{Var(\pi)}{(E(\pi) - z)^2}\right) \leq \alpha\right\}$$

Using the assumption that $E(\pi) = \mu_\pi$ and $V(\pi) = \sigma_\pi$ we get:

$$Max\left\{z\text{: } \frac{\sigma_\pi}{(\mu_\pi - z)} \leq k^{-1}\right\}$$

where k is the SF risk aversion parameter. While we model the parameter k as a constant, we recognize that it will vary across individuals and is a function of farm characteristics of the producer. We assume that $\mu_\pi - z \geq 0$. Solving for z in the above equation we get:

$$= Max\{\mu_\pi - k\sigma_\pi\}, \tag{1}$$

Where, $k\sigma_\pi$ is the risk premium. It follows that $k = \alpha^{-\frac{1}{2}}$, which implies that that the inverse of the square-root of the disaster probability is the SF risk aversion parameter. In theory, if we know the disaster probability that an individual is concerned about, it is straightforward to determine the individual's risk aversion parameter and the associated risk premium. However, since this measure will vary across individuals based on observed and unobserved characteristics, it is difficult to measure it empirically.

We assume that income is random due to price (p) and yield (y) risk. Both follow the normal distribution and are independently distributed.[1] Therefore, μ_π can be defined as:

$$\mu_\pi = E(\pi) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(\pi)f(p)f(y)dpdy \tag{2}$$

Where, $\pi = py - \boldsymbol{wq}$, p is the random output price with density $f(p)$ and y is the random yield with density $f(y)$, and $\boldsymbol{q} = (q_1, q_2, \dots, q_6)$ and $\boldsymbol{w}$ are the input quantity and price vectors. We use subscript i $(i = 1,2, \dots, 6)$ to denote the specific input. The standard deviation of profit is defined as follows:

$$\sigma_\pi = \left[E(\pi^2) - \left(E(\pi)\right)^2\right]^{\frac{1}{2}} \tag{3}$$

Where,

$$E(\pi^2) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(\pi)^2 f(p)f(y)dpdy \tag{4}$$

The producer maximizes the objective function in (5) by choosing input quantities. Therefore, the first-order conditions with respect to q_i can be given by:

[1] We assume independence between p and y under the assumption that an individual producer cannot affect market prices for inputs or outputs through his production choices and yield.

$$\frac{\partial \mu_\pi}{\partial q_i} - k\frac{\partial \sigma_\pi}{\partial q_i} = 0$$

$$\Rightarrow k = \frac{\partial \mu_\pi}{\partial q_i} \Big/ \frac{\partial \sigma_\pi}{\partial q_i} \tag{5}$$

Therefore, k is the marginal rate of substitution between the expected value and the standard deviation of income. More intuitively, the producer would be willing to reduce expected income by $k per acre if the standard deviation of income is reduced by 1. For example, suppose $k = 2$, then the producer is willing to forego $2 in expected income for a unit reduction in the standard deviation of income. We note that $\frac{\partial \mu_\pi}{\partial q_i}$ can be written as:

$$\frac{\partial \mu_\pi}{\partial q_i} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\left\{\left(\left(p\frac{\partial y_i}{\partial q_i} - w_i\right)f(y) + \pi_i\frac{\partial f(y)}{\partial q_i}\right)dy\right\}f(p)dp \tag{6}$$

and $\frac{\partial \sigma_\pi}{\partial x_i}$ can be written as:

$$\frac{\partial \sigma_\pi}{\partial q_i} = \frac{1}{2\sigma_\pi}\int_{\infty}^{\infty}\int_{-\infty}^{\infty}\left\{\left(2\pi\left(p\frac{\partial y_i}{\partial q_i} - w_i\right)f(y) + \pi^2\frac{\partial f(y)}{\partial q_i}\right)dy\right\}f(p)dp - \left(\frac{\partial \mu_\pi}{\partial q_i}\right)^2 \tag{7}$$

Where q_i (i =1,2,…,6) are the inputs. Both (6) and (7) have closed form solutions and we substitute the values obtained from equation (6) and equation (7) into equation (5) to determine k.

Estimation strategy

We use MATHEMATICA's *NIntegrate* function to compute the k values for given parameters and q_i values. We estimate the production parameters using the methodology from Just and Pope (1979). Redefining the functional form as:

$$y_j = g(\boldsymbol{q_j}, \boldsymbol{a}) + h(\boldsymbol{q_j}, \boldsymbol{b})\theta + \boldsymbol{D}'\delta + \boldsymbol{I}'\eta, \tag{8}$$

where $\boldsymbol{q_j}$ is a vector of inputs for producer j, $\boldsymbol{a}$ is vector of mean production elasticities and $\boldsymbol{b}$ is a vector of risk production elasticities. $\boldsymbol{D}$ is a vector of weather variables and $\boldsymbol{I}$ is a vector consisting of crop insurance indemnity payments and other federal returns that the producer receives. The purpose of $\boldsymbol{I}$ is to capture moral-hazard in farm decision-making (Horowitz and Lichtenberg 1993). For example, a producer with crop insurance might not be as careful with his input application as someone who does not have crop insurance. I might not only be influencing his/her input usage but also his risk aversion. We capture this variation through the production elasticities. We rewrite equation (8) as:

$$y_j = g(\boldsymbol{q_j}, \boldsymbol{a}) + \boldsymbol{D}'\delta + \boldsymbol{I}'\eta + \epsilon_j^\star, \tag{9}$$

where $E(\epsilon_j^\star) = 0, E\left(\epsilon_j^\star \epsilon_{j'}^\star\right) = 0$ for $j \neq j'$, $\epsilon_j^\star = h(\boldsymbol{q}, \boldsymbol{b})\theta$ and δ and η are the coefficients of D and I. We know from the properties of the standard normal distribution that $E(\theta_j) = 0$ and $E(\theta_j \theta_{j'}) = 0$, for $j \neq j'$. We use a non-linear least squares regression to determine a consistent and asymptotically efficient estimate of $\boldsymbol{a}$ (Malinvaud 1970). Next we obtain the residuals $\widehat{\epsilon_j^\star} = y_j - g(\boldsymbol{q_j}, \widehat{\boldsymbol{a}}) - \boldsymbol{D}'\hat{\delta} - \boldsymbol{I}'\hat{\eta}$ and run an OLS regression of $ln|\widehat{\epsilon_j^\star}|$ on $\ln(h(\boldsymbol{q_j}, \boldsymbol{b})\theta)$ to determine an estimate of $\boldsymbol{b}$. More formally,

$$ln\left|\widehat{\epsilon_j^\star}\right| = B + \mho'(\boldsymbol{q})b + \boldsymbol{D}'\delta + \boldsymbol{I}'\eta + \theta_j,$$

$$E(\theta_j) = 0 \tag{10}$$

Where $\mho(x) = [\ln(q_1), \ln(q_2), \dots, \ln(q_6)]$ is a vector of log-inputs. To obtain an asymptotically efficient estimate of $\boldsymbol{a}$ we run a nonlinear generalized least squares (NGLS) of $y_j^\star = \frac{y_j}{h(\boldsymbol{q_j}, \widehat{\boldsymbol{b}})}$ on $g_j^\star = \frac{g(\boldsymbol{q_j}, \boldsymbol{a})}{h(\boldsymbol{q_j}, \widehat{\boldsymbol{b}})}$, such that the second-stage model becomes:

$$y_j^\star = g_j^\star(q_j, \boldsymbol{a}) + \boldsymbol{D}'\delta + \boldsymbol{I}'\eta + \widetilde{\epsilon}_j \tag{11}$$

Where $\widetilde{\epsilon_j}$ is the new error term and the exogenous variables remain the same as equations (9) and (10). The values from vectors $\boldsymbol{a}$ and $\boldsymbol{b}$ are used in equations (6) and (7) to determine equation (5).

Relationship between Stated and Revealed Preferences

The stated risk preference measures are determined from a series of 14 hypothetical lottery questions, each with two response choices. The questions were asked in a mail survey of crop producers in Nebraska, Iowa and South Dakota. In each case, the first option is a guaranteed payment and the second is a random return with equal probability of a high and low return. We observe the point where the producer shifts from the guaranteed choice to the riskier alternative. The switch point becomes the risk preference measure. If a producer switches early then he is less risk-averse than a producer switching later. The game, along with the expected value of the random return is presented in table 1 in the appendix. A producer who is risk neutral will choose the guaranteed amount ($10,000) in the first question and the gamble in all the questions thereafter since the expected value of the gamble is always higher than the guaranteed amount after the first question.

The stated risk preference parameter is determined using the following formula:

$$\gamma = \frac{s + 2(14 - s)}{14}$$

Where s is the question on which the producer switches to the riskier choice. For example, suppose a respondent chooses the guaranteed amount in the first 7 questions and then switches to the riskier choice from question 8 and onwards. His/her stated risk aversion parameter will be given by $\gamma = \frac{7+2*7}{14} = 1.5$. To compare the stated and revealed preferences, we use a two-step linear model, where the stated preferences are a function of the revealed preferences, which in turn are functions of the individual farm characteristics and other control variables[2]. More formally,

$$\gamma_i = k_i'\beta + \boldsymbol{C}'\delta + u_i \tag{12}$$

$$k_i' = \boldsymbol{S}_i'\phi + \boldsymbol{C}'\delta + v_i \tag{13}$$

Where, k is the revealed risk preference/risk premium parameter from equation (5), S is a vector of producer characteristics such as age, gender, education, sales, percentage of profit, household income, farm assets, if they have crop insurance and if they use any hedging strategies; C is a vector of other control variables and u_i and v_i are the error terms We expect the sign of β to be negative, implying that if revealed risk aversion increases then the producer would be more likely to switch at a later question in the gamble, which would indicate that he is more risk averse

We employ the Tobit and Ordinary Least Squares (OLS) regression to obtain estimates for β, φ, and δ. The Tobit is used in view of the fact that several observations in our dependent variables (γ_i) are clustered at the lower and upper bounds. For example, some respondents only choose the first option or the second option. However, this does not necessarily imply that they are equally risk averse (in case of the first option) or equally risk neutral (in case of the second option).[3] In other words, their true risk preferences are censored. Hence, the OLS estimates might be inconsistent. From our construction we suspect that k_i is endogenous, therefore we use the two-stage least squares estimator and conduct endogeneity tests to validate if k_i is indeed endogenous.

Data

[2] This construction is made in view of the fact that producers are more likely to project their revealed preferences onto their stated preferences than vice-versa.

[3] Another possibility is that the respondent did not understand the game and chose either a or b randomly. Therefore, a Tobit model might be inappropriate in these cases. We estimate an OLS model without these individuals as a robustness test of our results.

We use data from the United States Department of Agriculture's (USDA) Census of Agriculture to determine the state-level output elasticities and then compute individual risk aversion parameters using our theoretical model presented in equations (5), (6) and (7). In addition to the census data we use information from a farm-level survey we conducted in Nebraska, Iowa, and South Dakota. We received over 1500 responses and each producer is matched with his/her individual census data to obtain the remaining farm characteristics. The lottery game mentioned above was also a part of the survey. Producers with missing values in the survey or without census data available are dropped from the analysis, resulting in a usable sample size of 502 crop producers.

The survey includes producer characteristics such as age, gender and education-level. Other variables are household income, farm income, sales, farm assets, and percent of assets after debt. The survey also asks about acres planted, harvested, and yield for 2012 and 2013 and about insurance decisions (type and coverage level) for 2002, 2007, and 2012. We ask for information about corn, soybean and wheat. [4]

We create a panel dataset for the producers matched in the census data, since each matched producer has data for three years: 2002, 2007 and 2012. The panel is unbalanced and has 3083 observations in total, where Nebraska has 1162, Iowa has 1556 and South Dakota has 367.[5] The key variables of interest for determining output elasticity and risk preference parameters are the expenditure variables for fertilizer, chemicals, seed, fuel, utilities and supplies. These are all in dollar terms. While the value of sales is available for 2007 we do not have data for the same variables for 2002 and 2012. Thus, we construct the sales variable for 2002 and 2012 using harvested acreage, mean county level yield data, and state level output prices. The data on county

[4] Less than 5% of the producers report planting wheat in 2012 or 2013.
[5] Some years are missing for producers.

yields and output prices is from the National Agriculture and Statistics Services (NASS). The output elasticities are then calculated by using the estimation strategy from equations (9) and (10), with revenue as a proxy for yield and expenditure as a proxy for input use.[6] The other expenditures are not included in our model as they are not as likely to influence the variance of production risk. However, they are still incorporated in the profit equation as a fixed cost.

To estimate the risk aversion parameters we still need the quantity of each input used. As stated in footnote 6 we cannot determine individual usage of inputs. Instead we develop three separate fertilizer, chemical and seed-use indices to apply in equation (5) along with the output elasticities. We use fertilizer and chemical prices from the relevant crop budget datasets compiled by the University of Nebraska, Iowa State University and South Dakota State University. Based on the per-acre requirement of all the fertilizers and chemicals we create aggregated price indices, which are then used to determine the input use indices.

Results

The output elasticities are presented in table 2. The first part (mean yield) of the table shows the estimated parameters from equation (11) and the second part (yield risk) shows the results from equation (10). The elasticities for the mean yield and the risk terms are in line with expectations. Iowa is the only state where increasing input use has a statistically significant and positive impact on the marginal variance of revenue and by construction, of yield. The mean yield elasticities for Iowa and Nebraska are similar to each other, while the mean elasticities for South Dakota are very different. South Dakota has high fertilizer and seed elasticity, while chemicals are not statistically significant. The results for standard variable inputs (fertilizer, chemicals, and seed) are more robust

[6] While it is ideal to use the yield and input use directly, we do not have data on the exact quantities of each input. For instance in the census data, expenditure for fertilizers is combined for each type of fertilizer. This is true for all the other inputs. We therefore develop aggregated price indices for each input and use them to determine the applied input quantities.

and consistent with expectations than the inputs tied to long-term investment decisions (e.g., utilities, supplies). This may be due to less clarity about which costs to include in those categories for the producers responding to the census questions, or due to greater variability in annual costs.

Only fertilizer, chemical and seed indices are used to determine the risk aversion and risk premiums, since those inputs are the three most likely inputs to increase or decrease the variation in yield. The summary statistics of the risk aversion and risk premiums for each state are presented in table (3). The variance of the risk aversion measure is lowest in Iowa. This can be explained by the fact that cross-sectional yield distribution is clustered around the mean in Iowa. Consequently, producers have less heterogeneous input choices leading to similar expected profits and variance of those profits. Despite similar measures of risk aversion in Iowa and South Dakota, the risk premium and its variance is lower in South Dakota, reflecting a lower standard deviation of profit.

We test 9 different specifications of equation (12), which evaluates the relationship between the stated and revealed risk preference. With the stated preference as the dependent variable, we separate the equation with either the risk aversion or risk premium measure as the appropriate explanatory variable.[7] When the risk premium is used as the explanatory variable, we scale it by 100 without loss of generality. The results of all specifications are in table (4). The first four specifications include all the observations. The first specification is a Tobit model with censoring from above and below. In the second specification we censor from above only and in the third only from below. Finally, we run an OLS with all the observations. Next we drop all producers who never switch to the other choice (dependent variable equaling 1) from the model and run a Tobit, which is censored from above only and an OLS. We then test the opposite case

[7] The risk aversion and risk premium terms are highly correlated. This is due to the fact that the risk premium is a function of risk aversion. However, since income risk σ_π also plays a role in determining the risk premium, we use both of them as our k_i for completeness in equation (12).

by keeping the producers who never switched and dropping the ones who chose only the gamble (dependent variable equaling 2). A Tobit with censoring from below and OLS are run for this case. Finally we drop all producers at the lower and upper bounds and run an OLS. All observations with conflicting choices such as producers who switch back and forth between options or the ones who left some questions blank in the game are dropped. The results for each specification along with the observations are presented in table (4). The second column describes the specification type, the third column shows all observations, which were uncensored in that specification and the fourth and fifth columns show how many of them were left and right censored, respectively. For an OLS all observations are uncensored in the model. The sixth and the seventh columns show β values when the explanatory term is risk aversion and risk premium, respectively.

The coefficients for risk aversion and risk premium can be interpreted as follows: Results from model 1 show that a one unit increase in the revealed risk preference decreases γ by X.[8] Recall that a lower value of the stated preference measure indicates an increase in risk aversion and vice-versa. For example, suppose, the average respondent's γ is 1.5, which implies that he/she switched to the other option on question 7 in the game. According to our results, if the same respondent's true risk preference increases by 1 unit then he will switch later or at the point, where $\gamma = 1.5 - X = 1.19$. This corresponds to a new value of s equal to 11.29. Therefore he/she now switches later between question 12 or 13.[9]

The coefficient in the sixth column for models 1, 2 and 3 has a negative sign. However, only 2 and 3 significant (5% level). When risk premium is used as the explanatory variable none

[8] X here represents the actual value of the coefficient in column six of table 4. However, our dataset is confidential and the resulting analysis cannot be shared without the permission of USDA-NASS. We are awaiting the completion of their internal review of our work and then the results will be shared.
[9] We cannot obtain the exact question since the stated preferences are discrete, while γ is assumed to be continuous.

of the values are significant. Model 4 is the OLS model with all observations and while we obtain the negative sign of β, it is not significant. Models 5 through 9 have a negative coefficient in the sixth column and are significant at the 5% level except model 7, which is significant at the 10% level. Coefficients for models 5 and 6 in the seventh column are also negative and significant. The other exogenous variables are robust across all specifications. Older farmers are generally more risk averse, as are less educated ones. In some models female farmers are less risk averse than male farmers. We cannot conclude much from this result, since the gender distribution is heavily skewed in favor of men. However, we do not detect a significant difference in stated preferences by wealth, which is somewhat surprising.

Conclusion

In this paper we develop a safety-first methodology to determine the risk preferences of farmers. We test our theoretical model with data from Nebraska, Iowa and South Dakota. Our results suggest that there in fact might be a positive relationship between true risk preferences and stated risk preferences. This is an important result from a policymaking perspective. Our results show that with the right elicitation game, true risk preferences of farmers or individuals in general can be determined. One avenue for further work would be to check the robustness of our findings for different regions, where production practices significantly differ.

We must also be aware of some drawbacks in our analysis. The production elasticities are determined using longitudinal production data, which has 5-year time gaps. Since farming practices have changed considerably over the past decade, the elasticities we obtain might not be representative. Also, while crop insurance induced moral hazard is controlled for in our model, it would be preferable to include a guarantee term in our objective function like the one suggested by Babcock and Henessey (1996). We are not able to do so in the current framework due to the fact that closed-form solutions for equation (6) and (7) do not exist.

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Appendix

Tables

Table 1: Lottery Game from Crop Producer Survey

	Guaranteed Amount	Random Return	Expected Return of the lottery	Risk Neutral Choice
1	a. $10,000	b. 50% chance of $18,000, 50% chance of $100	9050	a
2	a. $10,000	b. 50% chance of $20,000, 50% chance of $100	10050	b
3	a. $10,000	b. 50% chance of $21,000, 50% chance of $100	10550	b
4	a. $10,000	b. 50% chance of $22,000, 50% chance of $100	11050	b
5	a. $10,000	b. 50% chance of $23,000, 50% chance of $100	11550	b
6	a. $10,000	b. 50% chance of $24,000, 50% chance of $100	12050	b
7	a. $10,000	b. 50% chance of $25,000, 50% chance of $100	12550	b
8	a. $10,000	b. 50% chance of $26,000, 50% chance of $100	13050	b
9	a. $10,000	b. 50% chance of $27,000, 50% chance of $100	13550	b
10	a. $10,000	b. 50% chance of $28,000, 50% chance of $100	14050	b
11	a. $10,000	b. 50% chance of $30,000, 50% chance of $100	15050	b
12	a. $10,000	b. 50% chance of $32,000, 50% chance of $100	16050	b
13	a. $10,000	b. 50% chance of $34,000, 50% chance of $100	17050	b
14	a. $10,000	b. 50% chance of $36,000, 50% chance of $100	18050	b

Table 2: Production Elasticities (Dependent Variable: Total Sales)

Factor Index		Nebraska	Iowa	South Dakota
Mean				
	Fertilizers	X[a] ***	X***	X***
		(4.33)	(7.02)	(9.62)
	Chemicals	X***	X***	X
		(5.77)	(2.34)	(0.200)
	Seed	X***	X***	X***
		(6.01)	(6.14)	(4.06)
	Fuel	X***	X***	X***
		(5.66)	(5.05)	(-7.54)
	Utilities	X	X	X**
		(-0.53)	(0.14)	(-2.00)
	Supplies	X**	X	X**
		(-2.34)	(0.366)	(-1.89)
Risk				
	Fertilizer	X	X***	X
		(0.04)	(2.90)	(-0.56)
	Chemicals	X	X	X
		(1.05)	(1.33)	(0.88)
	Seed	X	X***	X
		(1.61)	(2.63)	(-0.84)
	Fuel	X	X***	X
		(1.29)	(2.46)	(0.27)
	Utilities	X	X	X
		(-1.34)	(0.85)	(-0.10)
	Supplies	X	X	X
		(-1.11)	(-1.06)	(-0.28)

a: X here represents the actual value of the elasticities. Our dataset is confidential and the resulting analysis cannot be shared without the permission of USDA-NASS. We are awaiting the completion of their internal review of our work and then the results will be shared.
T-values in brackets. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 3: Summary Statistics: Risk Preference Measures

Risk Preference	Nebraska	Iowa	South Dakota
Aversion	X^a	X	0.380
	(X)	(X)	(0.162)
Premium	X	X	27.67
	(X)	(X)	(9.74)

a: Our dataset is confidential and the resulting analysis cannot be shared without the permission of USDA-NASS. We are awaiting the completion of their internal review of our work and then the results will be shared.
The top number is the mean risk aversion and risk premium for producers in each state while the number in parentheses is the standard deviation of the measure.

Table 4: Estimation Results (Dependent Variable: Stated Risk Preference)

No.	Model Type	Observations			Risk Aversion	Risk Premium
		Uncensored	Below	Above		
1.	Tobit (censored above and below)	355	56	91	X (-1.58)	X (-0.29)
2.	Tobit (censored above)	411	0	91	X (-1.67)	X (-0.39)
3.	Tobit (censored below)	446	56	0	X (-1.74)	X (-0.04)
4.	OLS (all observations)	502	-	-	X (-1.16)	X (0.10)
5.	Tobit (dropped 1's)	355	0	91	X (-2.02)	X (-1.74)
6.	OLS (dropped 1's)	411	-	-	X (-2.31)	X (-2.22)
7.	Tobit (dropped 2's)	355	56	0	X (-1.91)	X (0.16)
8.	OLS (dropped 2's)	200	-	-	X (-2.09)	X (0.190)
9.	OLS (dropped 1 and 2's)	150	-	-	X (-2.01)	X (0.32)

a: X here represents the actual value of the coefficients. Our dataset is confidential and the resulting analysis cannot be shared without the permission of USDA-NASS. We are awaiting the completion of their internal review of our work and then the results will be shared.

T-values in brackets. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.