Estimating farmers' risk attitudes and risk premiums for the adoption of conservation practices under different contractual arrangements: A stated choice experiment

Elizabeth Canales[1], Jason S. Bergtold[2], Jeffery Williams[3] and Jeffrey Peterson[4]

[1] Graduate Research Assistant, Department of Agricultural Economics, Kansas State University, Manhattan, KS, decm@ksu.edu
[2] Associate Professor, Department of Agricultural Economics, Kansas State University, Manhattan, KS, bergtold@ksu.edu
[3] Professor, Department of Agricultural Economics, Kansas State University, Manhattan, KS, jwilliam@ksu.edu
[4] Professor, Department of Agricultural Economics, Kansas State University, Manhattan, KS, jpeters@ksu.edu

Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

Estimating farmers' risk attitudes and risk premiums for the adoption of conservation practices under different contractual arrangements: A stated choice experiment

1. Introduction

In the last few decades, much attention has been given to environmental degradation and to the ways in which sustainable production can be achieved in agricultural systems. Environmental degradation is defined as any disturbance to the environment that can deteriorate soil, water, and/or air resources (Johnson et al., 1997). Some agricultural activities such as soil mechanization and the application of agrochemicals can result in soil erosion, pollution of water bodies, and greenhouse gas emissions (Aneja, Schlesinger, & Erisman, 2009; Carpenter et al., 1998; Galloway et al., 2008; Kim & Dale, 2008; Lal, 1993).

The ecosystem services produced when conservation practices are in place have a value in society, and by creating a market for these services, farmers could receive an incentive to adopt these practices (Ribaudo, Greene, Hansen, & Hellerstein, 2010; Whitten & Coggan, 2013). While it has been argued that market-based instruments may be more efficient to encourage conservation (Freeman & Kolstad, 2006), to date, the U.S. government has primarily relied on cash payments through voluntary contractual programs for the adoption of conservation practices (Claassen, Cattaneo, & Johansson, 2008).

Currently, the level of adoption (including the level of voluntary adoption under conservation contracts) is relatively low for some conservation practices (e.g. cover crops). The National Crop Residue Management Survey showed that 21% of corn acreage, 39.3% of soybeans, 19.6% of sorghum, and 14-16% of small grains were managed under no-till (NT) by 2008 (CTIC, 2013). This survey also found that conventional tillage (CT) and reduced tillage (RT) still accounted for approximately 58% of the cultivated land (CTIC, 2013). A survey looking at the adoption of cover crops in the Corn Belt found that only 18% of the farmers had planted cover crops. They also found that adopters had used cover crops on only about 6% of their land (Singer, Nusser, & Alf, 2007). Evidence found in the Agricultural Resource Management Survey also suggests that variable rate technologies have been adopted at a low rate of 8 to 14% between 2005 and 2009 (Schimmelpfennig & Ebel, 2011).

The lack of knowledge about the benefits from conservation practices, lack of infrastructure, lack of support, practice incompatibility, and financial support are some of the potential constraints for the adoption of conservation practices (Rodriguez, Molnar, Fazio, Sydnor, & Lowe, 2009). Additionally, subsidy programs for certain agricultural commodities may have discouraged sustainable practices, causing slower rates of adoption (Derpsch, Friedrich, Kassam, & Li, 2010). For example, subsidies to agricultural inputs and subsidies to corn-ethanol production, which have also resulted in higher commodity prices, may have indirectly resulted in the intensification of agricultural production and the removal of land from conservation retirement programs (Comito, Wolseth, & Morton, 2013; Gill-Austern, 2011). There is also evidence suggesting that higher commodity prices have encouraged some producers to have less diversified rotations on their farms (Fargione et al., 2009; Tyner & Taheripour, 2008).

Risk is an important component of agricultural production, and it plays an important role in farmers' production decisions, particularly decisions concerning the adoption of new conservation practices. In some cases, risk can have a larger effect than cost factors (Sattler & Nagel, 2010). The introduction and intensification of conservation on the farm introduces potential risks into the farm operation due to introduction of new practices and their impacts on the dynamics of cropping systems, contract or practice limitations, and changes in production costs. These changes can result in shifts in net returns (due to changes in crop yields and/or costs) that may not be anticipated a priori. When outcomes are uncertain, given their stochastic nature or their dependence on stochastic events (i.e. weather), farmers may be more hesitant to adopt a practice, requiring additional compensation to induce adoption (Kurkalova et al., 2006). Thus, risk is an important aspect that needs consideration when studying farmers' adoption decisions. However, the risk associated with stochastic variables affecting conservation adoption has not been researched in much detail, particularly when using stated choice applications. In many cases, outcomes are simply assumed to happen with certainty, while in reality, farmers bear a risk of unknown changes in yields, costs and returns, as a result of adopting a particular practice or a bundle of practices, especially under contract.

The purpose of this study is to examine farmers' willingness to adopt and intensify in-field conservation practices under risk, using a stated preference approach. Farmers' decision making for conservation practices adoption and intensification under risk was elicited using a stated choice experiment. Following Hensher, Greene, & Li (2011), a framework that accounts for the stochastic nature of net returns under a conservation contract was used. Information on probabilities of changes in net returns were included as an attribute in the choice experiment and were used to estimate an attribute-specific expected utility term within the random utility model, allowing for the estimation of a parameter for risk attitudes towards net returns in addition to the net return attribute parameter. Specifically, this study examined farmers' willingness to adopt in-field conservation practices under different contractual arrangements with varying levels of conservation intensity, external environmental benefits, level of incentive payment, and incentive payment mechanism. Willingness to accept was estimated for each conservation practice, incentive program mechanism, and off-farm environmental benefits. To study the effect of the risk associated with stochastic net returns on farmers' willingness to adopt and intensify conservation practices, farmers' risk attitude towards changes in net returns and the risk premium for the adoption and intensification of conservation under a conservation contract were estimated.

2. Conservation Practice Background Information

Many conservation practices employed in agriculture provide benefits to the ecosystem, commonly referred to as ecosystem services. Some common ecosystem services derived from the use of in-field conservation practices are carbon sequestration, climate regulation, soil and nutrient cycling, water quality, erosion control, soil quality and productivity, groundwater recharge, pollination by wild species, biodiversity and bio-control (Robbins, 2005).

Some in-field conservation practices that provide numerous benefits to the environment and will be examined in this study are continuous no-till, conservation crop rotations, cover crops, and VRA of inputs. These practices were selected because they are in-field practices commonly known and adopted at different degrees in the region of study. These practices provide benefits to the environment in terms of soil carbon sequestration, erosion reduction, runoff mitigation, as well as providing potential yield increases and reductions in production costs.

Continuous No-till: The Soil Science Society of America (SSSA, 2012) defines conservation tillage as a sequence of tillage operations that leaves at least 30% of crop cover on the surface and whose objective is to diminish the loss of soil and water. Conservation tillage practices such as no-till, strip tillage (ST) and other tillage systems leaving at least 30% of surface cover have proven to be beneficial for the soil. In no-till systems, soil disturbance is limited to nutrient injection. Plant residue is left on the soil surface and only partial removal is allowed. No-till practices leave the greatest level of crop residue on the soil surface. Different from rotational no-till, in continuous no-till, all the crops in the rotation are planted using a no-till drill/planter and no-till equipment is used year round. Some of the benefits associated with conservation tillage systems are an increase in soil organic carbon, soil microbial biomass, reduction of wind and water soil erosion, and enhancement of nutrient cycling (Blanco-Canqui et al., 2009; Campbell, Selles, Lafond, & Zentner, 2001; Kladivko, 2001; Kushwaha, Tripathi, & Singh, 2001; Lal, 1999; Paustian, Six, Elliott, & Hunt, 2000; Wang et al., 2011; Zibilske, Bradford, & Smart, 2002). Another advantage associated with no-till is the preservation of soil moisture (Blevins, Smith, Thomas, & Frye, 1983; Daniel, Abaye, Alley, Adcock, & Maitland, 1999), which may allow farmers to increase production intensity in dryer areas.

Conservation Crop Rotation: Crop rotation consists of rotating different unrelated crops within the same field in a predetermined sequence. A conservation crop rotation would include green manures, perennial grasses, heavy residue cash crops and reduction of fallow periods (NRCS, 2015b). Some benefits associated with crop rotation are the mitigation of diseases, pests, and weeds that accumulate from continuous cropping of the same taxonomic crop families. Other benefits are the carryover of residual herbicide and reduction of allelopathic or phytotoxic effects (Lodhi, Bilal, & Malik, 1987; Pierce & Rice, 1988; Roth, 1996).

Fertility of the soil can be improved by avoiding depletion of common nutrients required by particular crops, using nitrogen fixing crops such as legumes (Zotarelli et al., 2012) or other crops that can introduce necessary elements back into the soil. The use of high residue crops (i.e. wheat, sorghum) and legumes in the rotation have the potential to increase carbon and nitrogen concentration in the soil over the long-term (Kelley et al., 2003; Miglierina et al., 2012). Additionally, improvements in soil structure arise when deep and shallow rooted crops are used in the crop rotation. The increase in soil aggregate stability and improvements in water utilization are further results from the use of crop rotations (Chan & Heenan, 1996; Raimbault & Vyn, 1991)

Cover crops: Use of cover crops as a conservation practice consists of growing seasonal crop varieties between annual cash crops. The objective of the cover crop is to provide protection of the soil surface from soil and water erosion. Cover crops may be a cost-efficient alternative for improving crop nutrient management, while also providing additional conservational benefits. Some additional benefits associated with the use of cover crops are the reduction of wind, water and soil erosion; weed suppression; conservation of soil moisture; improvement in soil structure and the levels of organic matter; and the provision of habitats for beneficial organisms (Snapp et al., 2005).

VRA of Inputs: Variable-rate application (VRA) of inputs consists of spatially varying input rates based on field requirements with the aid of computer-controlled devices. The objective of the VRA of inputs is to maximize the efficiency of input application. For example, fertilizer applications can be managed to increase fertilization in zones with high soil productivity and reduce fertilization in areas with low productivity**.**

VRA of fertilizer technology increases the efficiency of input application, reducing runoff and leaching of nutrients (Khanna and Zilberman, 1997), improving surface and ground water quality. This technology may increase output quantity and quality and reduce input cost, leading to an increase in profitability (Vellidis et al., 2013). The use of positioning systems also reduces the repetition of machinery passes over the same area, reducing labor costs (Adrian, Norwood, & Mask, 2005).

3. Literature Review

Various sources of risk affect agriculture (Beal, 1996). Studies in the literature have provided evidence of the importance of risk in agricultural decisions (Marra & Carlson, 1990) and it has been long argued that risk represents an obstacle in the adoption of new agricultural practices (Aimin, 2010). In some instances, risk factors may me more important than other production factors (Sattler & Nagel, 2010). While risk is central to the study of farmers' decision to adopt agricultural technologies, studies addressing risk in context of adoption have been limited (Marra, Pannell, & Abadi Ghadim, 2003).

Marra, Pannell, & Abadi Ghadim (2003) identified distinctive elements of risk that affect the adoption of new agricultural technologies, namely, perception of the probabilities of the distribution of net returns, the variance of net returns, and the strength and direction of risk attitudes (i.e. risk aversion). Measuring risk aversion without adequate data can be difficult. Researchers have used different strategies to measure the impact of risk on the adoption decision.

Some studies examining adoption in the literature (both, with revealed and stated preference data) have included risk aversion as a dummy variable indicating whether the farm operator is perceived to be risk-averse (Kim, Gillespie, & Paudel, 2005; Shapiro, Wade Brorsen, & Doster, 1992). Shapiro, Wade Brorsen, & Doster (1992) evaluated both, the effect of risk attitude and farmers' subjective perception of risk from the adoption of double crop soybeans. However, while they estimated farmers' Pratt-Arrow measure of risk aversion, in their empirical model they used dummy variables indicating if farmers were risk averse (they used the midpoint of the range of risk aversion as the dividing point). Kim, Gillespie, & Paudel (2005) examined the adoption of BMP in beef cattle production using probit models. In their study, they included farmers' self-identified risk preference as a dummy variable indicating if the farmer was risk averse. Both studies found that risk aversion was an important factor affecting adoption.

Other studies have included a risk aversion coefficient (i.e. Pratt-Arrow measure of risk aversion) when modeling adoption. Ghadim, Pannell, & Burton (2005) examined adoption of chickpeas in Australia using a probit and tobit model. They examined the effect of farmers' risk preferences (Pratt-Arrow risk aversion coefficient); the perception of riskiness of chickpeas production; an interactions between the risk aversion coefficient and area (hectares); relative riskiness of chickpea production; and perceived variance of the net revenue from chickpea production. They found that both, risk aversion and riskiness of the practice, reduced adoption of chickpeas and underweighted the benefits from farm diversification from undertaking this crop enterprise on the farm.

In studies examining stated adoption of conservation systems under conservation incentive programs, the incentive payment always plays an important role on farmers' willingness to adopt. Since introducing new practices on the farm may result in changes in net returns, famers may demand a higher incentive payment to offset that risk. For example, risk-averse operators may require a risk premium to induce their adoption of new practices, even if they obtain higher income as a result of their decision to adopt (Kurkalova et al., 2006). The existence of this risk premium may result in higher WTA estimates. A study by Cooper & Signorello (2008) expanded on previous literature on conservation adoption by proposing a theoretical model that included a risk premium component, as a function of the variance of profits from adopting a new practice, within a random utility framework. To estimate their model empirically, the proposed risk component was estimated as the difference between the mean WTA and the difference in profits from the base state and the adoption state. While additional information on changes in profits is required to estimate the risk premium, farmers were not provided with this information during the decision process. Thus, there may be asymmetry of profit information across farmers.

Several of the studies examining the effect of risk (e.g. risk preference) in adoption models have done so under a deterministic framework. Few have considered the stochastic nature of the adoption process (i.e. Ghadim, Pannell, & Burton, 2005). While the distinctive elements of risk identified by Marra, Pannell, & Ghadim (2003), have been partially or separately addressed in some studies, they have not been extensively studied, particularly in stated choice frameworks.

Uncertainty and risk attitudes in stated preference methods

In many cases, individuals are subject to decisions for which outcomes are not known with certainty, they are stochastic in nature. However, when studying decisions using stated choice frameworks, in most cases individuals are asked to choose between alternative options in a deterministic environment. Recent studies have attempted to study decisions under risk by introducing stochastic attributes in stated choice studies. In these studies, the probability distribution of potential attribute outcomes is provided explicitly in the stated choice tasks.

One approach to model risk is to introduce the probability of occurrence of the attribute in an additive form. That is, the outcome attribute and the risk (i.e. the probability of the attribute outcome) are treated as two separate attributes and a utility parameter is estimated for each one of them individually. A study by Glenk & Colombo (2011) followed such an approach. In their study of public preferences for a climate change mitigation program, they assessed the introduction of risk associated with the program’s potential to achieve emission reductions. In their study, individuals were first presented with a set of choices with no risk. If they chose the program at least once, then they were presented with a second set of choices which provided information on both, the percentage of annual emission reductions from a soil carbon sequestration program and the probability that the program fails to achieve that level of emissions reduction. They estimated three models: (1) no-risk, (2) risk (probability) was modeled as being continuous, and (3) risk (probability) was modeled as being discrete. They found that while risk did not affect the WTP estimates for the non-stochastic attributes, it did affect respondents' preference for the program. They also found a larger WTP for a higher risk of program failure.

In a study of the WTP for a program to reduce the risk of wastewater floods in Switzerland, Veronesi et al. (2014) examined the effect of risk by including an attribute with the frequency of flooding events and a forecast confidence attribute consisting of probabilities that the forecast was correct. They found that uncertainty (probability) of forecast was not a statistical significant factor and was found to be the least important factor in individuals' preference for the abatement program. The authors attributed this result to the respondents' using heuristics to evaluate the probability of forecast occurrence.

Another approach used by some researchers consisted of estimating the effect of the stochastic attribute, and the effect of an interaction term between the attribute and its probability of occurrence (this mirrors the expected value or the use of a linear utility function for the expected utility model). Burghart, Cameron, & Gerdes (2007) studied peoples' preference for a program to invest in energy saving air-conditioning technologies funded with tax credits. They examined the risk that the technology would be successful and the risk that the private sector will develop the technology on its own. They modeled risk by including a discounted expected random utility (the function for the utility was linear).

In a study of preferences for water quality in lakes, Roberts, Boyer, & Lusk (2008) included the risk associated with two attributes, an algae bloom and changes in water level. They presented risk as the probability of occurrence of the algae bloom and the probability to observe a given water level. They introduced aspects of prospect theory by using probability weights. Respondents were asked to complete stated choice tasks with either certain outcomes or risky outcomes. They modeled risk in a multiplicative fashion, by multiplying the probability of occurrence by the attribute outcome (expected value), and estimated a model coefficient for the expected value of the attribute (algae bloom, and each of the water levels). They found higher WTP estimates in the presence of risk. They also found that a model using probability weights, instead of linear weights provided a better statistical fit. Akter, Bennett, & Ward (2012) studied public support for a climate change mitigation plan. The choice experiment presented choice alternatives varying in the cost (higher household cost from higher electricity bills, fuel, etc.), expected rise in temperature and its probability of occurrence. They estimated a parameter for the probability of temperature rise occurrence, and another parameter for the interaction of temperature rise and its probability of occurrence (expected increase in temperature). They found greater support for the plan with greater probability of temperature rises. A study by Rolfe & Windle (2013) analyzed different management programs for coral reefs. They introduced risk in their study by providing decision makers with the percentage of coral reef protected in good condition under each management mechanism conditional on the probability that this level of protection will be obtained. They modeled the choices using a mixed logit model where the condition of the reef, and an interaction term between reef condition and probability of protection were included in the model.

While using the expected value of the stochastic attribute to model choices under risk allows a modeler to capture how respondents' preferences are affected when faced with uncertain outcomes, it assumes risk neutrality (preferences for the risky attribute are assumed to be linear). In order to allow for risk aversion/risk seeking behavior in decision making under risk, some stated choice studies (mainly in the transportation literature) have incorporated risk and uncertainty into choice decisions by introducing aspects of expected utility theory and prospect theory into the random utility decision framework. This approach allows for the estimation of a decision-maker's risk attitude toward the stochastic attribute in addition to the marginal utility (parameter) for the stochastic attribute (Hensher, Greene, & Li, 2011).

Hensher, Greene, & Li (2011) and Li et al. (2012) studied the risk associated with time variability in a scheduling model for car commuters using a choice experiment. Commuters were presented with potential times and their probability of occurrence. The time attribute was incorporated in the random utility function using a general power specification, which exhibits constant relative risk aversion. Probabilities were transformed using separable probability weighting functions. That is, the probability transformation is independent of the outcomes (dependent only on the original probabilities). Other deterministic attributes were included in the random utility in a linear form. They found that the risk-based model predicted optimal departure times better than a purely linear functional form where decision-makers are assumed risk neutral. They also found evidence suggesting that commuters exhibited, in general, risk-taking attitudes.

Other studies have modeled risk within the random utility using a non-expected utility approach which transforms probabilities of occurrence of an event using weighting functions.

Van Houtven et al. (2011) studied disease treatment preference in the presence of mortality risks. They estimated three model specifications with varying treatments for risk: (1) a categorical model for risk (dummy variables for the probabilities of each risk were used), (2) independent weighing functions, and (3) rank dependent utility where probability weights depend of both the original probability and the outcome. They found evidence that supports the use of probability weights and rank dependent utility models. A study by Wibbenmeyer et al. (2013) examined wildfire managers' preferences for fire suppression strategies under two sources of risk: probability that the fire reaches homes or the watershed in the absence of a suppression strategy, and the probability of success of the suppression strategy. They found larger responses to risk for lower probabilities in proportion to the response observed with greater probabilities. They also found that the risk of houses burning had a greater effect among managers than the risk of watersheds burning.

Using data from a stated choice experiment examining people's preferences for a soil carbon sequestration program, Glenk & Colombo (2013) tested different model specifications for the treatment of risk within the random utility model using combinations of: linear expected utility functions of emission reductions (expected value); non-linear expected utility functions, linear probability weights (probability to achieve the emission reductions); non-linear probability weights; and inclusion of a separate disutility parameter for risk (i.e. probability of failure to achieve reduction levels) (Glenk & Colombo, 2011). Their results suggest that significant differences in WTP estimates can be obtained when using different model specifications, as each model revealed different behavioral assumptions. They recommend using models with a non-linear specification for the expected utility component.

Research has consistently pointed to the importance of risk in decision making.

However, studies on the subject of conservation adoption have been mostly restricted to the effect of risk attitudes in the adoption of conservation, and few studies have addressed the adoption decision in a stochastic context. This study expands on previous research by examining conservation program attributes that have not been widely evaluated in the conservation adoption literature to-date, such as farmers' risk attitudes and adoption decisions under risk, and preferences for conservation payment mechanisms (government programs versus market-based mechanisms). This study also examines if the environmental benefits obtained off the farm is an important factor in farmers' decision to adopt conservation practices. Results from this study will provide an understanding of farmers' decision process when adopting conservation practices and conservation program participation. The identification of motivations, as well as obstacles in the adoption of conservation practices is a fundamental necessity for constructing optimal conservation policies and programs.

3. Methods

Random utility framework

Individuals' choice decisions in stated preference models are constructed on the basis that individuals derive utility from product attributes - Lancaster's theory (Lancaster, 1966). In this study, farmer *i* derives utility from choosing conservation contract *j* with a given set of attributes X_j. Let π_{iq} be farmer *i*'s expected net return in the *status quo* and π_j be net returns (excluding any incentive payment) under a conservation contract. Since there is uncertainty concerning the value of net returns, particularly under the conservation contract, π_{iq} and π_{ij} are stochastic in nature with associated variances given by $\sigma^2_{\pi_q}$ and $\sigma^2_{\pi_j}$, respectively. Now let the i^{th} farmer's utility (U_{ij}) from the enrollment in a conservation contract be a function of the contract attributes (X_{ij}), and the stochastic net returns $\pi_{ij}(\sigma^2_{\pi_j})$. That is, farmers receive utility from contract *j*: $U_{ij} = V_{ij}[X_{ij}, F(\pi_{ij}(\sigma^2_{\pi_j}))] + \varepsilon_{i1}$, where V_{ij} represents the systematic component of utility explained by contract attributes and a function of net returns; $F(\cdot)$ is a function describing farmers' valuation of stochastic returns under the contract, allowing for the possibility of a nonlinear relationship, and ε_{ij} is the random component of utility accounting for unobserved factors unknown to the researcher.

Based on random utility theory, farmers choose to enter into a conservation contract if the contract provides them with the highest utility, i.e. $U_i = \max(U_{ij}, U_{iq})$ where U_{iq} is the utility obtained by the farmer if they choose to remain with the *status quo* or what they are currently doing on their operation. Following Hensher, Rose, & Greene (2005), the probability of entering into the conservation contract can be written as $\mathbf{P}(V_{ij} + \varepsilon_{ij} \geq V_{iq} + \varepsilon_{iq}) = \mathbf{P}(-\Delta\varepsilon_i \leq \Delta V_i)$. While V_{ij} and V_{iq} are not separably identifiable, the difference between the two utilities (ΔV_i) is. The difference in utilities can be expressed as $\Delta V_i = f[F(\Delta\pi_i(\sigma^2_\pi)), X; \boldsymbol{\beta}]$, where $\boldsymbol{\beta}$ is the vector of parameters of the utility function (e.g. marginal utilities).

Choice under uncertainty and risk preferences

Decisions under risk and risk preferences have long been evaluated using both, expected utility theory and prospect theory. Expected utility theory initially introduced by Bernoulli and later refined by von-Neumann & Morgenstern (1945) postulates that individuals act as if they maximize expected utility. Under expected utility theory, individuals make decisions between gambles by evaluating the function $EU = \sum p_m U_m$; where E is an expectation operator, and U_m

is the utility associated with a monetary outcome x_m with probability of occurrence p_m.

Assuming constant relative risk aversion (CRRA), the utility expression can be specified using a general power specification (Pratt, 1964). Individual utility for monetary outcomes can be specified as follows:

$$(1) \qquad U(\pi) = \begin{cases} \dfrac{x^{1-\alpha}}{1-\alpha} & if\ \alpha \neq 1 \\ \ln x & if\ \alpha = 1 \end{cases}$$

where α represents the risk aversion coefficient. If $\alpha = 0$, the utility function converges to a linear utility function (expected value) indicating risk neutrality. If $\alpha > 0$, the utility function over net returns is concave indicating risk aversion. On the other hand, values of $\alpha < 0$ indicate risk seeking attitudes. CRRA utility specifications are widely used in the literature as they are simple to implement making them tractable in empirical applications (Meyer, 2010). For a review of other functional forms see Meyer (2010).

While expected utility has been widely used in modeling decisions under risk, it has received some criticism due to its failure to represent individuals' behavior in some empirical applications (e.g. Allais paradox -Allais, 1953). In a seminal paper, Kahneman & Tversky (1979) proposed prospect theory as an alternative to expected utility theory to model decisions under risk. In prospect theory, probabilities are replaced by decision weights that represent the impact of the outcome from the appeal of the prospects evaluated (Kahneman & Tversky, 1979).

In prospect theory, individuals evaluate the function $\sum w(p_m)v(x_m)$ when faced with a gamble (prospect); where v_m is a value function (utility) and $w(p)$ is a probability weighting function with $w(0) = 0$ and $w(1) = 1$ (Kahneman & Tversky, 1979). Under this assumption, risk attitudes are determined by both, the utility from monetary outcomes (v) and the probability weighting function $w(p)$. Here, the value function v can take different specifications. In this study, the utility specified in Equation (1) will be adopted. Different probability weights have been proposed in the literature of which the most commonly used functions are (Stott, 2006):

i. TK-PWF: The Tversky & Kahneman (1992) probability weighting function is a one-parameter function. When $\gamma = 1$ the weighting function is reduced to the linear form: $w(p) = p$. The function is specified as follows:

$$(2) \qquad w(p_m) = \frac{p_m^{\gamma}}{\left(\sum_m p_m^{\gamma}\right)^{\frac{1}{\gamma}}}, \qquad \gamma > 0$$

ii. GE-PWF: The Goldstein and Einhorn (1987) probability weighting function is a two-parameter function. This function is reduced to the TK-PWF when $\tau = 1$. This function takes the following specification:

$$(3) \qquad w(p_m) = \frac{\tau p_m^{\gamma}}{\tau p_m^{\gamma} + \sum_{k \neq m} p_k^{\gamma}}, \qquad \gamma, \tau > 0$$

iii. P1-PWF: This function is a one-parameter probability weighting function proposed by Prelec (1998), and is specified as follows:

$$(4) \qquad w(p_m) = e^{-(-\ln p_m)^{\gamma}}, \qquad \gamma > 0$$

iv. P2-PWF: This function is a two-parameter probability weighting function proposed by Prelec (1998). P1-PWF is an especial case of P2-PWF when $\tau = 1$. The function is specified as:

(5) $$w(p_m) = e^{-\tau(-\ln p_m)^{\gamma}}, \qquad \gamma, \tau > 0$$

In these probability weighting functions, γ is the parameter that controls the curvature (shape) of the functions, allowing for both concave and convex regions of the function. If $\gamma < 1$, the function is characterized by an inversed S-shape with overweighting ($w(p) > p$) of low probabilities and underweighting ($w(p) < p$) of high probabilities. Conversely, if $\gamma > 1$, the function is characterized by a S-shape with underweighting of low probabilities and overweighting of high probabilities. For the two-parameter weighting function (i.e. GE-PWF and P-PWF), the additional parameter τ controls the elevation of the inflection point where the function goes from concave to convex (or convex to concave). If individuals weigh probabilities equally (assign the same weight to low and high probabilities), then a linear probability weighting function results, where $w(p_m) = p_m$.

A rich specification following Hensher, Greene, & Li (2011) combines the elements of expected utility and prospect theory into the random utility model. Using expected utility theory to model risk allows for the estimation of individuals' risk preferences based on the curvature of their utility over the stochastic attribute. This approach also draws from prospect theory the introduction of probability weights (Equations 2 to 5) to allow for individuals to subjectively assign decision weights to the original probabilities. This approach results in a non-linear utility specification within the random utility model. In addition, this approach is more flexible in that it allows for the estimation of a utility parameter for net returns in addition to farmers' risk attitudes. By embedding the extended utility term into the random utility model, the systematic component of indirect utility can be written as follows:

(6) $$V = \beta_0 + \beta_r \left[\sum_m w(p_m) \frac{x_m^{1-\alpha}}{1-\alpha} \right] + \sum_k \beta_k X_k$$

where β_r is the parameter associated with the risky attribute x; $w(p_m)$ is a non-linear probability weighting function; α is an attribute-specific risk aversion coefficient, representing individuals' attitude towards the risk associated with the stochastic attribute; X_k is a set of deterministic attributes (attributes for which the outcome is known with certainty); and β_k is a vector of parameters associated with the deterministic attributes. Hensher, Greene, & Li (2011) refer to the term $\beta_r \left[\sum_m w(p_m) \frac{x_m^{1-\alpha}}{1-\alpha} \right]$ as the attribute specific expected utility.

4. Survey Data

Conservation workshops

This study examined the adoption of conservation practices by farmers in Kansas. A stated choice survey was administered during a series of workshops held across 10 locations spanning the state of Kansas from December 2013 to March 2014. Workshop locations were selected based on different weather, landscape and farm demographic characteristics. The cities where the workshops were held are: Salina, Great Bend, Colby, Dodge City, Wellington, Pratt, Hiawatha, Topeka, Manhattan, and Parsons. Prior to administering the stated choice experiment during the workshops, the stated choice survey was field tested with farmers during two focus groups held in Salina and Wellington.

A sample of farms was obtained from the Kansas Farm Management Association (KFMA), which has around 2,300 farms across Kansas that produce crops in their database. Of these farms, approximately 76% are identified as primarily crop producers and 16% are identified as crop/livestock producers. Working with members of KFMA allowed for respondent data to be connected to historical financial data collected by KFMA for the participating farms. A total of 1,513 farmers from the KFMA were mailed letters to attend face-to-face workshops. Of the farmers contacted, 40 were no longer farming, were deceased or could not be located; and 432 responded to the letter. Response to the letters resulted in about 250 of the farmers attending the workshops. The rest of the farmers who responded were interested in participating, but could not attend the workshops on the dates these were held. This resulted in an adjusted response rate of approximately 30%, and an attendance rate of 17%. Workshop attendees were compensated for their time and travel expenses with a stipend of $125 paid in cash.

The workshops consisted of an introductory presentation covering the basic aspects of the conservation practices under study, a time for farmers to answer a survey questionnaire and the stated choice experiment, and a focus group to discuss farmers' views on conservation. Prior to administering the stated choice experiment, farmers were asked to complete a survey with questions covering their farming history, farm operation, and conservation on their farm. Subsequently, farmers were provided with guidelines on how to answer the stated choice experiment. After farmers completed the stated choice exercise, a focus group was conducted where farmers discussed their views on conservation, their experience using conservation practices, benefits and disadvantages from using conservation practices on their farm, and their experience participating in conservation programs.

Survey data

Data from farmers with incomplete responses for needed variates were not considered, leaving 234 farmers' data for analyses. Table 1 presents farmers demographics reported in the survey and compares them to the 2012 U.S. Census of Agriculture (NASS-USDA, 2014) and the demographics of KFMA members in 2013 (KFMA, 2014). All of the farmers in the study were aged between 20 and 84, with a sample average of 56 years which could be considered representative, in terms of age, of the average Kansas farmer (58 years – as reported in the U.S. Census of Agriculture). However, the average size (including CRP land) of the farm operation in the sample (2,508 acres and sales value of $400,000 to $599,999) is larger than the average farm size of 747 acres and sales value of $298,845 in Kansas, as reported in the 2012 Census of Agriculture. It should be noted that, small size farms, hobby/residential farms or farms operated by retired operators (sales < $250,000) represent a significant share of the total U.S. farm population (Lambert, Sullivan, Claassen, & Foreman, 2007). In the U.S. Census of Agriculture, farmers with sales lower than $99,999 represent roughly 74% of the total farms (NASS-USDA, 2014). This study focuses on medium to large farms, excluding small hobby farmers, retired farmers, and very large operations. Medium and large farmers were chosen as the study group because farm size plays an important role for conservation practice adoption, particularly for practices that are management intensive as they require operators to be devoted to farming because of the additional learning, time and financial investment needed (Lambert et al., 2007).

Table 1 Average farm characteristics

Variable	N	Mean	SD	Min.	Max.	2012 Census of Agriculture	2013 KFMA
Age (yrs.)	234	56	13	20	84	58	----
Acres	234	2,508	1,981	110	14,875	747	2,196
Sales	234	6.20[b]	2.04	1	9	$ 298,845	$618,416

[a] Source: National Agricultural Statistics Service, USDA (2014)

[b] Mean sales of 6.20 corresponds to the sales category of $400,000 to $599,999

When comparing the farm demographics of the farmers who participated in the survey to those of all KFMA members, the sample is representative of the KFMA group. KFMA members are a good sample of farmers to study as they generally operate medium to large size farming operations, which is the main target of this study. Hence, results in this study should be interpreted as representing conservation practices adoption decisions by medium to large farm operators in Kansas.

Figure 1 Percentage of farmers who currently used the selected conservation practices.

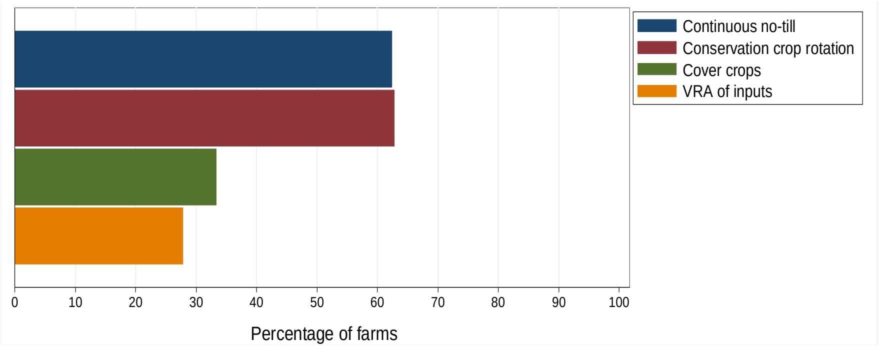


Figure 1 shows the percentage of farms whose operators reported using the selected conservation practices. A higher percentage of farmers reported the use of continuous no-till (62.4%) and conservation crop rotation (62.8%). While 86% of the farmers had periodically used no-till practices on a particular crop (rotational tillage), only 62.4% of them had practiced continuous no-till on some part of their farm operation. Consistent with findings by (Grandy et al., 2006), only a fraction of no-till producers have adopted continuous no-till. A fewer number of farmers indicated that they had used cover crops (33.3%) and VRA of inputs (27.8%). Several of the farmers who indicated using these practices have not fully adopted them; some of them have only experimented, whereby the minimum percentage of cropping land under each selected practice ranges from 1-3%. The adoption rates of these practices was high in the study group, this is due to the nature of the survey which focuses on intensification of conservation. Thus, the survey group sample targeted and made be more favorable for farmers that had already adopted some sort of conservation on their farm

Descriptive statistics of the data, including contract attributes, demographics, and farm characteristics used in estimating the models are presented in Table 3. Observations from 234 farmers were deemed appropriate for estimation, resulting in 2,808 usable observations.

Table 3 Data summary statistics

	Complete Sample (N=2,808)			
Variable	Mean	SD	Min	Max
Dependent variable: (adopt=1, status quo=0)	0.462	0.499	0	1
Contract attributes:				
Incentive payment ($/acre-year)	37.121	25.613	0	75
Incentive program (1= carbon market, 0= federal program)	0.504	0.500	0	1
Conservation practices				
Continuous no-till	0.516	0.500	0	1
Conservation crop rotation	0.507	0.500	0	1
Cover crops	0.517	0.500	0	1
Variable rate application of inputs	0.523	0.500	0	1
Percentage change in net returns				
Percentage of loss in net returns	12.46%	5.60%	5%	20%
Percentage of gains in net returns	12.46%	5.60%	5%	20%
Probability of changes in net returns				
Probability of loss in net returns	19.99%	12.75%	5%	35%
Probability of no change in net returns	59.95%	14.14%	40%	80%
Probability of gains in net returns	20.06%	12.75%	5%	35%
Offsite environmental benefits				
Low	0.337	0.473	0	1
Moderate	0.325	0.468	0	1
High	0.338	0.473	0	1
Farm/farmers' characteristics:				
Adopted continuous no-till	0.624	0.484	0	1
Adopted conservation crop rotation	0.628	0.483	0	1
Adopted cover crops	0.333	0.471	0	1
Adopted variable rate application of inputs	0.278	0.448	0	1
Western	0.218	0.413	0	1
Central	0.419	0.493	0	1
Total acres (hundreds of acres)	25.088	19.814	1.1	148.75

Stated choice design

In order to assess farmers' willingness to adopt and intensify conservation on their farms, farmers were asked to complete a stated choice exercise. The attributes in the contract were selected in a way to mimic current conservation programs. Under current government conservation program, farmers receive an incentive payment for a conservation plan consisting of various conservation practices. In order to address environmental concerns, through monetary incentives, programs like the CSP encourage farmers to maintain existing conservation practices and to intensify conservation on their working lands by adopting new conservation practices (NRCS, 2015a). Farmers who adopt new practices are faced with potential changes in their bottom line as yields and input costs change due to the implementation of new agricultural practices.

Respondents were presented with twelve hypothetical contract choice scenarios with two alternatives, a conservation contract and a status quo option. The contract features evaluated were:

i. *Conservation practices to adopt under the contract*: the conservation practices evaluated were continuous no-till, conservation crop rotations, cover crops and VRA of inputs. The conservation practices were treated as dichotomous attributes in the experimental design to determine if the practice was required under the contract. The practices present in each set were presented in the contract as a bundle to represent different levels of conservation intensification. This attribute was included not only to account for adoption but also for conservation intensification. Some practices are currently widely adopted; however, conservation programs strive for additionality by encouraging farmers to undertake more conservation efforts while also providing incentives to maintain and manage existing conservation practices.

ii. *Incentive payment*: the annual per acre incentive payments evaluated were $0, $15, $30, $45, $60, and $75. These payments, while hypothetical, are in accordance with base payments reported under CPS and EQIP in Kansas[1].

iii. *Incentive program*: this study evaluated two incentive programs, a federal program (EQIP/CSP-like program) and a carbon credit payment through a carbon market. Payments for carbon sequestration can be established though contracts where farmers get paid per ton of carbon sequestered, as an alternative to per-acre payments for the practices implemented (Antle, Capalbo, Mooney, Elliott, & Paustian, 2003). To avoid further complicating the choice task in the experiment, in this study farmers were presented with a payment per acre for the practices adopted.

iv. *Off-farm environmental benefits from adopting conservation practices*: While economic drivers are a main factor in conservation contracts, the decision to adopt conservation practices is also affected by factors other than economic motivations (Chouinard, Paterson, Wandschneider, & Ohler, 2008). It has been argued that famers who are more conservation-minded are more likely to adopt conservation practices (Greiner, Patterson, & Miller, 2009), and that a higher level of benefits from conservation motivates greater adoption (Reimer & Prokopy, 2014). This study examined the extent to which the effectiveness of conservation practices in achieving environmental benefits off-farm

---

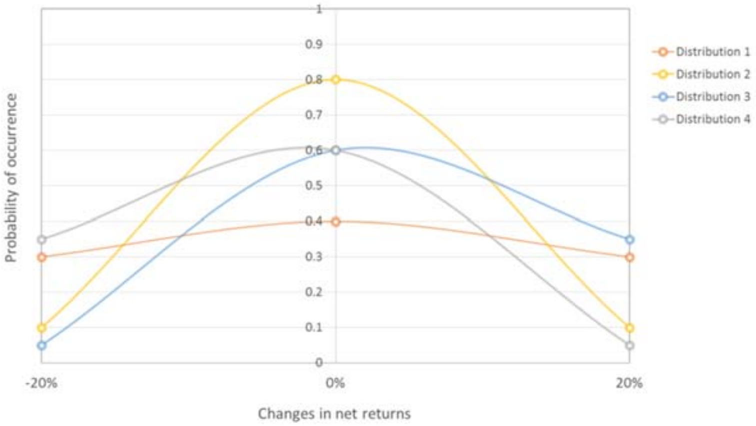
[1] EQIP payment rates for the conservation practices examined in 2012 are: No-till practices=$12.26/acre; Conservation crop rotation=$6.73/acre; VRA of fertilizer=$13.94; and Cover crops=$27.40 for single species and $47.15/acre for multiple species. Kansas Practice Payment Schedule for EQIP - Fiscal Year 2012 available at: http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_031993.pdf

affects farmers' actions on-farm. Three hypothetical levels of off-far environmental benefits were included: Low, Medium and High.

v. *Riskiness of the contract*: While some agricultural practices have proved to be profitable, they have not been fully adopted. This indicates that there are factors other than the profitability of a technology affecting farmers' choices. An important factor farmers consider is the risk associated with a technology. Risk is introduced to the operation as new practices are adopted that could increase the variability of costs, crop yields, and returns. In addition, the restrictions of the contract may introduce inflexibility which may affect a famer's ability to react to external events. For example, if a farmer enrolls in a contract that requires him to plant cover crops for the next five years, planting a cover crop in a dry year may affect the yields of the following cash crop.

In this study, the riskiness of the contract was introduced in the experiment by presenting a distribution of potential changes in average net farm income over the timeframe of the contract with corresponding probabilities of occurrence. The design of the experiment had four distributions for potential changes in net returns for adopting the contract. The distributions of potential changes in net returns were assumed symmetric with equal potential gains and losses, varying only by the level of potential changes: (1) 5% Loss, 0% change, 5% Gain; (2) 10% Loss, 0% change, 10% Gain; (3) 15% Loss, 0% change, 15% Gain; and (4) 20% Loss, 0% change, 20% Gain. The design also consisted of four distributions of probabilities associated with the potential changes in net returns. Two of the probability distributions are symmetric with equal probability of observing losses and gains. The first distribution (P: 30% of loss, P: 40% of no change, P: 30% of gains) is meant to represent a scenario where the outcomes are more uncertain with the probability of occurrence of the three outcomes being almost equal. The second distribution (P: 10% of loss, P: 80% of no change, P: 10% of gains), represents a distribution where there is a high probability that net returns will not change, with a low and equal probability of obtaining a loss or a gain. The third distribution (P: 5% of loss, P: 60% of no change, P: 35% of gains) is more heavily weighted towards observing a gain than to observing a loss, while the forth distribution (P: 35% of loss, P: 60% of no change, P: 5% of gains) is more heavily weighted towards losses than to gains. While farmers were only presented with three probability outcomes (a discrete distribution as opposed to a continuous distribution), for illustration purposes Figure 2 depicts that distributions that are intended to be represented in the design, using the example where the distribution of outcomes is 20% Loss, 0% change, 20% Gain.

Figure 2 Distribution of the probabilities of net returns change in stated choice design



Contract attributes and levels are reported in Table 4. The contract presented to farmers was a standard 5-year contract with verification of compliance by a program professional. A clause included in the contract stated that farmers had to make a full repayment of the incentive payments received plus any administrative costs if they were found in violation of the contract (if they fail to provide the practices stipulated in the contract).

A fractional-factorial experimental design with 288 choice sets was obtained from a $2^5 \times 6 \times 3 \times 4^2$ full factorial design. This design allows for the identification of main effects and two-way interaction effects (Louviere et al., 2000). The set of choice scenarios chosen was the candidate set with the highest D-efficiency score (D-efficiency =93.6). The 288 combinations were blocked into 24 blocks with 12 choice sets. Each farmer was presented with 12 choice scenarios, each containing a conservation contract and a constant *status quo* option. An example of a choice set is presented in Figure 3. The design was generated using PROC OPTEX in SAS® (SAS Institute Inc, 1999)

Figure 3 Example of choice task.

Conservation Practices	Continuous No-till Conservation Crop Rotation Cover Crops Variable Rate Application of Inputs	
Incentive Program	Carbon Credit Payment through a Carbon Market	
Incentive Payment	$45/acre	
Riskiness	Average Change in Net Returns Over 5 Years	Probability of Occurrence
	10% Loss	5% Very unlikely
	No change	60% Likely
	10% Gain	35% Medium likelihood
Off-farm Environmental Benefits	Moderate	

Would you adopt this system or stay with the Status Quo?

☐ **Adopt** ☐ **Status Quo**

Table 4 Contract attributes and attribute's levels

Contract Feature	Description	Levels			
Continuous no-till	Planting crops directly into the crop residue without disturbing the soil in all the crops in rotation in a particular field.	Included, Not included			
Conservation crop rotation	Three or more year rotation with three or more crop types, including a combination of high residue crops, grasses and/or legumes.	Included, Not included			
Cover Crops	Planting a single or multiple cover crop species between regular cash crops for primarily conservation purposes.	Included, Not included			
VRA of inputs	Use of site-specific information for input application rates within a field, including sensor-based and/or map-based methods.	Included, Not included			
Incentive payment	Payment ($/acre) offered annually during the length of the contract.	$0/acre, $15/acre, $30/acre, $45/acre, $60/acre, $75/acre			
Incentive Program	Type of mechanism through which the payment is offered, administered and regulated.	Federal Program or Carbon Credit Payment through a Carbon Market			
Offsite Environmental Impact	Potential off-farm environmental benefits of the practices stated under each scenario (e.g. downstream water and air quality).	Low, Moderate, High			
Riskiness: Impact on Net Returns					
Average Change in Net returns over 5 years[1]	Distribution of income changes over a 5 years period (length of the contract).	-20% 0% +20%	-15% 0% +15%	-10% 0% +10%	-5% 0% +5%
Probability of changes in net returns[2]	Probability distributions for potential net income changes.	5% 60% 35%	30% 40% 30%	35% 60% 5%	10% 80% 10%

[1,2] Each column represents a distribution. The first row in each column represents losses, second column represents no changes in net returns, and the third row represents gains.

5. Empirical Model

An attribute specific extended expected utility model is estimated, which takes into consideration the stochastic nature of farmers' net returns and risk preferences by embedding expected utility and prospect theory within the random utility framework, allowing for the estimation of a parameter for net returns in addition to farmers' risk attitudes.

Following Hensher, Greene, & Li (2011), the attribute specific expected utility term that models the stochastic component of net returns for the situation modeled here is given by the following expression:

$$(7)\qquad EEUT = \beta_{EUT}\left\{ \left[w(p_1)(\pi_0 - \Delta\pi^-)^{1-\alpha} + w(p_2)(\pi_0)^{1-\alpha} + w(p_3)(\pi_0 + \Delta\pi^+)^{1-\alpha} \right] / (1-\alpha) \right\}$$

where expected utility is the probability weighted average utility of the potential three net returns outcomes, and β_{EUT} is utility parameter measuring farmers preference for net returns. This parameter is expected to be positive under the assumption that farmers are utility maximizers. Risk perception is an important factor in individual's choices (Weber & Milliman, 1997), especially in the agricultural sector where outcomes are stochastic in nature (Beal, 1996). A higher risk associated with the conservation contract is expected to result in a lower willingness to enroll in the contract. Under this model specification, α is the risk attitude towards net returns and is expected to be positive a priori, indicating risk aversion. Since risk attitude can vary across individuals, the risk attitude parameter was modeled as a function of regional characteristics and farm size measured by total acreage such that, $\alpha = \alpha_0 + \alpha_1 Western + \alpha_2 Central + \alpha_3 FarmSize$.

The model where the attribute specific expected utility term is embedded into the random utility framework to model decisions under risk is estimated using the following functional form for the systematic component of the indirect utility function:

$$
\begin{aligned}
V_{ij} &= \beta_0 + EEUT_{ij} + \beta_{pay}Payment_j + \beta_{prg}Program_j + \beta_{nt}NT_j + \beta_{nt\_sq}NT_j \times NT_{SQ} \\
&+ \beta_{rot}Rot_j + \beta_{rot\_sq}Rot_j \times Rot_{SQ} + \beta_{ccrop}Cover_j + \beta_{ccrop\_sq}Cover_j \times Cover_{SQ} \\
&+ \beta_{VRA}VRA_j + \beta_{VRA\_sq}VRA \times VRA_{SQ} + \beta_{LE}LowEnv + \beta_{ME}MidEnv
\end{aligned} \tag{8}
$$

Four different models were estimated using the probability weighting specifications outlined in Equations (2) to (5) and an additional model was estimated where the probability weighing function was assumed to be linear ($w(p) = p$). Separable decision weights were used, that is, probability weights depend on the original probabilities only, and not on the outcomes. Since farmers form their own expectations of potential net returns based on their own (or their peers') experiences, the probability weighing function's parameters are expected to be statistically significant and are expected to result in an overweighting of low probabilities and underweighting of large probabilities as findings in previous empirical applications suggest (Kahneman & Tversky, 1979; Lattimore, Baker, & Witte, 1992; Prelec, 1998; Tversky & Kahneman, 1992). Since probability weights can also reveal risk, risk attitude is expected to be larger in the linear probability specification where no weighting functions are applied to the original probabilities.

The models were estimated using an error component framework to capture heterogeneity across farmers. Let the utility of farmer i (i=1,…,235) associated with contract j (j= 1,2) in each choice scenario t (t=1,…,12) be:

$$
U_{ijt} = V(\boldsymbol{\beta}, \mathbf{x}_{ijt}) + \theta_j E_{ij} + \varepsilon_{ij} \tag{9}
$$

where $V(\cdot)$ is the systematic component of the utility using the non-linear specification as described in Equation (8); E_{ij} is the error component or alternative specific random individual effects, included to control for unobserved heterogeneity not accounted for in the model specification; and θ_j is the standard deviation of the error component and assumed to be equal to one. The individual random component ε_{ij} is independent and identically distributed (IID) extreme value Type I (Louviere, Hensher & Swait 2000). The structural model that estimates the conditional probability of farmer *i* choosing contract *j* is then given by (Bhat, 1998; Greene, 2012):

$$\text{(10)} \qquad \text{Prob}(y_{it} = 1 \mid E_{ij}) = \frac{\exp\left[V(\boldsymbol{\beta}, \mathbf{x}_{ijt}) + \theta_j E_{ij}\right]}{\sum_J \exp\left[V(\boldsymbol{\beta}, \mathbf{x}_{iqt}) + \theta_j E_{iq}\right]}$$

A restriction was imposed by setting the systematic component of the utility associated with the *status quo* equal to zero ($V_{i0t} = 0$). The model was estimated using the PROC NLMIXED procedure[2] in SAS.

Risk Premium

The risk premium P, is the dollar amount that would make farmers indifferent between adopting a risky contract and a risk-free contract. Farmers are said to be indifferent between the two contracts if the probability of adoption between the two contracts is equal as follows:

(**Error! No text of specified style in document.**1)

$$\Lambda\left(\beta_0 + \tilde{\beta}_r E[U(\pi)] + \sum_k \tilde{\beta}_k X_k\right) = \Lambda\left(\beta_0 + \tilde{\beta}_r U\left(E[\pi] - P\right) + \sum_k \tilde{\beta}_k X_k\right)$$

where $\Lambda(.)$ is the logistic cumulative distribution function. Equation 1.15 shows the probability of a risk-free contract in the right hand side, and the probability of adopting a risky contract in the left-hand side. This expression can be further simplified to:

---

[2] The PROC NLMIXED procedure fit the model by maximizing an integrated likelihood approximation by adaptive Gauss-Hermite quadrature.

(**Error! No text of specified style in document.**2)

$$E[U(\pi)] = U\left(E[\pi] - P\right), \qquad \text{or}$$

(**Error! No text of specified style in document.**3) $\left(E[U(\pi)]\right)^{-1} = E[\pi] - P$

The right hand side of Equation (13) is also known as the certainty equivalent (CE) and represents the sure amount farmers will be willing to accept to avoid a risky contract with a higher return. The risk premium then is estimated as the difference between the expected net returns (mean of net returns) under the contract and the certainty equivalent (Pratt, 1964).

(**Error! No text of specified style in document.**4) $P = E[\pi] - CE$

The risk premium represents the amount farmers would be willing to pay to avoid a risky contract by replacing it for a contract with a sure payoff, that is, a contract where they obtain the mean net returns (expected profits under the contract). The risk premium was estimated using the parameter estimates from Equations (7) and (8).

Model Assessment

Since the different models evaluated in this section have different parameters and specifications for the probability weighing function, a test for non-nested hypothesis is necessary to judge goodness of fit across the different models. A method commonly used to evaluate a model in empirical applications is the likelihood ratio index or Pseudo R-squared (Greene, 2012). Let each model be indexed by $g\ (g = 1, \ldots, G)$ with a set of parameters given by K_g, the likelihood ratio index adjusted for the number of parameters is then given by (M. E. Ben-Akiva & Lerman, 1985):

(**Error! No text of specified style in document.**5) $$(\overline{\rho}_g^2) = 1 - \frac{L_g(\hat{\beta}) - K_g}{L(0)}$$

where $L_g(\hat{\beta})$ is the log-likelihood for the estimated model and $L(0)$ is the log-likelihood for the constant only. The measure of $-2L_g(\hat{\beta}) - 2K_g$ is known as the Akaike Information Criterion (AIC) and is also used to compare models, where a smaller AIC value is better (Greene, 2012). In order to discriminate between two models (model 1 and model 2), on the basis of which performs better, Ben-Akiva & Swait (1986) proposed a test where under the assumption that model 1 is the true specification, and given that the probability that the measure of fitness for model 2 $(\overline{\rho}_2^2)$ is greater than that of model 1 $(\overline{\rho}_1^2)$ by some $Z > 0$, it asymptotically holds that:

(**Error! No text of specified style in document.**6)

$$\text{Prob}\left(\left|\overline{\rho}_2^2 - \overline{\rho}_1^2\right| \geq Z\right) \leq \Phi\left(-\sqrt{-2Z\,L(0) + (K_2 - K_1)}\right)$$

where Φ is the standard normal cumulative distribution function. Equation (1.20) represents the upper bound for the probability of incorrectly selecting the wrong model based on the goodness of fit (Ben-Akiva & Lerman, 1985).

6. Results

Model estimation results

Results of the models estimated using expected utility and probability weights are reported in Table 5. The parameters estimates for incentive payment, incentive program, conservation practices and off-farm environmental benefits are consistent in sign and magnitudes across probability weighting specifications. In terms of goodness of fit, the TK-PWF and GE-PWF models would seem to be preferred based on the adjusted Pseudo R-squared and the Information

Criterion (AIC). Results from the Ben-Akiva and Swait (1986) test (Table 6) suggest that the GE-PWF is the preferred model, followed by TK-PWF and P2-PWF which are preferred to P1-PWF and to the linear probability weighting specification. For an example of how to interpret results, from the Ben-Akiva and Swait (1986) test considerer the results comparing model P1-PWF and TK-PWF in Table 6. The resulting probability of 0.006 indicates that the probability that the goodness of fit of P1-PWF is larger than that of TK-PWF in a sample of 2,808 observations is less than 0.006.

The alternative specific constant was negative in all the models and statistically significant in only two of the models (linear probability weighting specification and GE-PWF). Given that the alternative specific constant is associated with the contract alternative, this result could indicate a preference for the *status quo*. An error component was included in the model to control for unobserved variability across individuals. The error component was highly significant in all the models, indicating significant unobserved heterogeneity across respondents.

Table 5 Model estimate results for the attribute specific extended expected utility models

	Linear probability	**TK-PWF**	**GE-PWF**	**P1-PWF**	**P2-PWF**
Constant	-51.7204***	-42.7103	-60.8061***	-35.7249	-43.4662
	(8.0624)	(54.2032)	(10.1715)	(31.5567)	(64.2332)
Risk attitude parameters (α)					
α_0	0.7528***	0.7085*	0.8135***	0.6440**	0.7113*
	(0.0105)	(0.3718)	(0.0159)	(0.3194)	(0.4298)
Western	0.0485	0.0153	-0.0610	0.0117	0.0156
	(0.0322)	(0.0439)	(0.0414)	(0.0084)	(0.0553)
Central	0.0125	0.0082	-0.0079	0.0065	0.0083
	(0.0087)	(0.0195)	(0.0064)	(0.0052)	(0.0240)
Acres	-0.0004**	-0.0002	0.0002*	-0.0002	-0.0002
	(0.0002)	(0.0005)	(0.0001)	(0.0001)	(0.0006)
Probability weighting parameters					
γ	---	1.1398***	0.9607	0.9916***	0.9924***

		(0.0994)	(0.6510)	(0.0242)	(0.0215)
τ	---	---	0.9804 ***	---	1.0185 ***
			(0.0205)		(0.0296)
Contract parameters					
β_r	4.0307 ***	3.2394	4.7886 ***	2.4154	3.3127
	(0.6469)	(5.5350)	(0.8371)	(3.5555)	(6.5216)
Payment	0.0491 ***	0.0494 ***	0.0492 ***	0.0492 ***	0.0494 ***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Program	-0.2501 **	-0.2462 **	-0.2474 **	-0.2502 **	-0.2462 **
	(0.1025)	(0.1027)	(0.1026)	(0.1026)	(0.1027)
NT	-1.3622 ***	-1.3650 ***	-1.3506 ***	-1.3645 ***	-1.3643 ***
	(0.1695)	(0.1700)	(0.1696)	(0.1696)	(0.1700)
$NT_j \times NT_{SQ}$	1.8234 ***	1.8308 ***	1.8188 ***	1.8285 ***	1.8304 ***
	(0.2031)	(0.2038)	(0.2034)	(0.2033)	(0.2038)
Rot	-0.6514 ***	-0.6554 ***	-0.6491 ***	-0.6610 ***	-0.6561 ***
	(0.1608)	(0.1616)	(0.1611)	(0.1609)	(0.1619)
$Rot_j \times Rot_{SQ}$	0.4026 **	0.4143 **	0.4013 **	0.4133 **	0.4147 **
	(0.1938)	(0.1948)	(0.1942)	(0.1940)	(0.1951)
Cover	-0.7479 ***	-0.7626 ***	-0.749 ***	-0.7530 ***	-0.7639 ***
	(0.1265)	(0.1271)	(0.1268)	(0.1266)	(0.1272)
$Cover_j \times Cover_{SQ}$	0.4950 **	0.5140 **	0.4926 **	0.5081 **	0.5166 **
	(0.1989)	(0.2001)	(0.1994)	(0.1991)	(0.2006)
VRA	-0.7953 ***	-0.8038 ***	-0.8053 ***	-0.7962 ***	-0.8041 ***
	(0.1206)	(0.1211)	(0.1208)	(0.1207)	(0.1211)
$VRA \times VRA_{SQ}$	0.7676 ***	0.7735 ***	0.7798 ***	0.7652 ***	0.7737 ***
	(0.2061)	(0.2068)	(0.2063)	(0.2063)	(0.2068)
LowEnv	-0.3646 ***	-0.3675 ***	-0.3755 ***	-0.3653 ***	-0.3671 ***
	(0.1255)	(0.1258)	(0.1257)	(0.1255)	(0.1258)
MidEnv	-0.2401 *	-0.2497 **	-0.2578 **	-0.2410 *	-0.2495 **
	(0.1253)	(0.1257)	(0.1256)	(0.1253)	(0.1257)
σ_{EC}	2.2312 ***	2.2713 ***	2.2413 ***	2.2508 ***	2.2711 ***
	(0.3263)	(0.3313)	(0.3278)	(0.3281)	(0.3316)
			Model fit statistics		
No. of Observations	2808	2808	2808	2808	2808
Log Likelihood	-1415.6	-1412.7	-1411.1	-1415.7	-1412.6
AIC	2869.1	2865.3	2864.1	2871.5	2867.1
Pseudo R-squared	0.273	0.274	0.275	0.273	0.274
Adjusted R-squared	0.263	0.264	0.264	0.262	0.263

*,**,*** statistically significant at the 1%, 5% and 10% level. Standard errors in parenthesis.

[1] Carbon Credit Payment through a Carbon Market was used as the base scenario.

Table 6 Ben-Akiva and Swait test results

Model 1	Model 2	Probability[1]
GE-PWF	Linear probability	0.0041
GE-PWF	TK-PWF	0.0694
GE-PWF	P1-PWF	0.0019
GE-PWF	P2-PWF	0.0414
TK-PWF	Linear probability	0.0143
TK-PWF	P1-PWF	0.0066
TK-PWF	P2-PWF	0.1830
P2-PWF	Linear probability	0.0231
P2-PWF	P1-PWF	0.0105
Linear probability	P1-PWF	0.1221

[1] Probability of incorrectly choosing model 2 given that model is the true model.

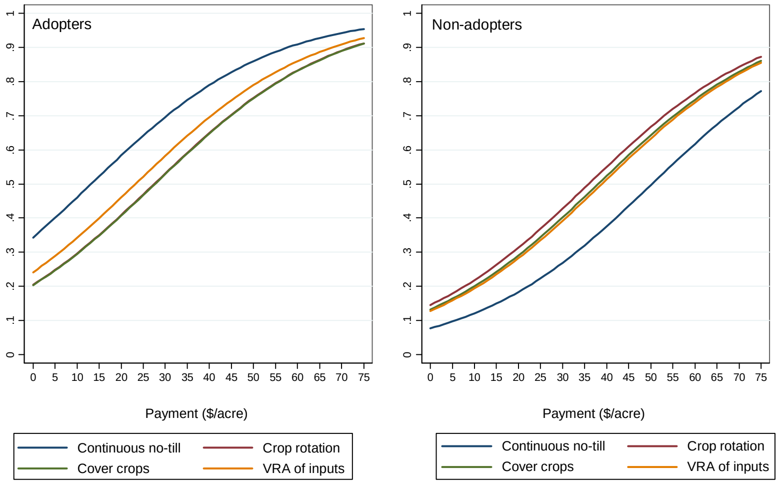
The payment coefficient was positive and statistically significant in all the model versions (Table 5). Incentive payment has consistently been identified in the literature as an important factor in the decision to adopt conservation practices (Cooper, 2003; Dupont, 2010; Kurkalova et al., 2006; Lichtenberg, 2004; Ma, Swinton, Lupi, & Jolejole□Foreman, 2012). While to some farmers the incentive payment may not be the primary motivation for adoption, monetary incentives can ease their transition into a new production system (Reimer & Prokopy, 2014). Incentive payments can cover the cost of the practice, allowing farmers to experiment with conservation practices to determine if these are suitable for their operations. Results from a study of farmers' participation in a cost-sharing program for the adoption of BMP found that a one percent increase in the incentive payment increased participation by 0.23-0.25% (Dupont, 2010). It has been also suggested that the lack of benefits from conservation programs, in many cases is, a barrier for participation by adopters and non-adopters alike (Reimer & Prokopy, 2014).

The program coefficient was negative and statistically significant in all models. These results provide evidence indicating a lower likelihood of adoption for the same level of incentive payment if the mechanism through which the incentive payment is offered is a carbon credit program. This result suggests a preference for federal programs over market-based programs. In a study of farmers’ willingness to participate in conservation programs, Ma, Swinton, Lupi, & Jolejole-Foreman (2012) found no statistical difference between a conservation incentive program provided through the government and a non-governmental organization. However, the type of program run by the non-governmental organization was not specified in the choice experiment.

A lower willingness to participate in a conservation program that offers incentive through a carbon market could be related to famers’ unfamiliarity with this type of program. Only 14.3% of the farmers in this study had participated or knew someone who had participated in any carbon credit trading program (specifically, the Chicago Climate Exchange). Of these farmers, about one third rated their experience as poor, specifically due to the lack of payment. Similarly, about 30% of the farmers agreed that the payments offered were fairly low. A negative experience with a previously established and failed carbon market could create unfavorable views towards market-based approaches to incentivize conservation adoption. In addition, uncertainty about the development of a GHG federal policy that would create demand for carbon offsets that could lead to the establishment of a robust carbon market may be another important factor affecting farmers’ perceptions and willingness to enroll in a carbon credit program. Zeuli and Skees (2000) argued that the risk of non-binding policies being developed is a factor that could affect the development of a carbon market, mainly due to the uncertainty about trading volumes and the price of carbon credits. Being locked into a contract to supply carbon credits in a market without legal binding for potential buyers may be a deterrent to farmers' willingness to participate. In addition, the past history of carbon markets, such as the Chicago Climate Exchange could have colored farmers views about this potential payment mechanism.

The parameters associated with the four conservation practices were negative and statistically significant in all the models. In agreement with prior expectations, the magnitude of the utility parameters indicates a lower likelihood of adoption for farmers who have not previously adopted these practices. For farmers who have adopted these practices, the likelihood of enrolling in a conservation program increases. Figure 4 depicts the differences in the likelihood of adoption for each of the conservation practices for adopters and non-adopters. As shown in the graphs, farmers are more likely to enter into a five year contract if they have previously adopted the practice. This difference is more significant for continuous no-till, where for each level of incentive payment, non-adopters are less likely to adopt continuous no-till than any other practice, but for the same level of incentive, adopters of no-till are more likely than adopters of the other practices to enter into the contract.

Figure 4 Probability of adoption for each practice under varying incentive payments



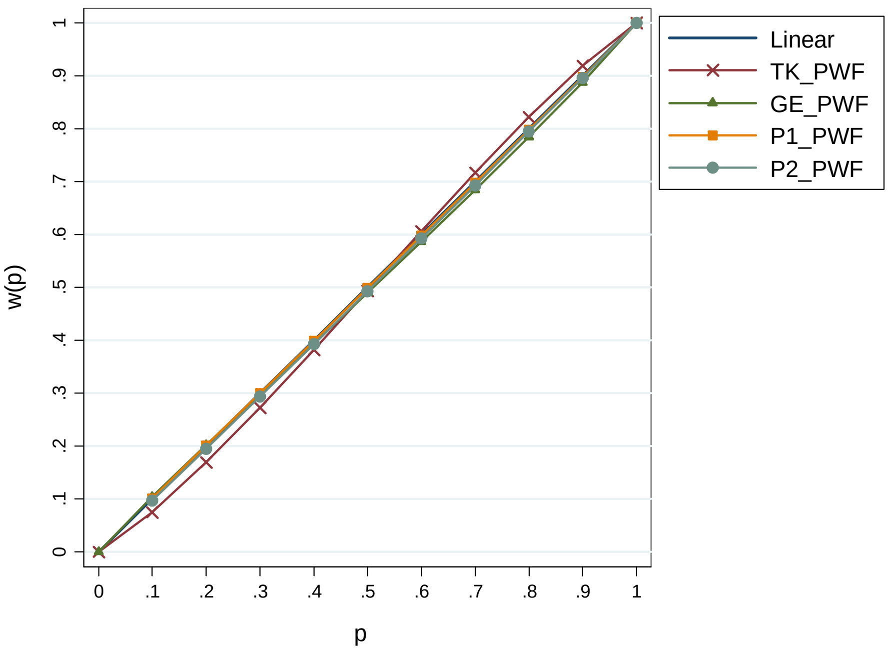
Note: Probabilities estimated assuming high off-farm benefits, mean values for changes in net returns, and a federal program.

The parameters for low and medium off-farm environmental benefits were negative and statistically significant, indicating that farmers were less likely to adopt contracts with lower off-farm environmental benefits. Consistent with previous research, this finding suggests that farmers care for the environmental impacts of their practices, not only at the farm level, but also off the farm. In a study of famers' participation in U.S. Farm Bill Conservation Programs, Reimer and Prokopy (2014) found that off-farm environmental benefit was one of the main drivers of program participation. They also found that awareness of external environmental benefits was an attitude that characterized the highest adopters (adopters of numerous conservation practices). In addition, their results indicated that on-farm environmental benefits and financial benefits were likewise important to those farmers who cared about external environmental impacts. A study by Ma, Swinton, Lupi, & Jolejole-Foreman (2012) found that a higher environmental performance increased farmers' likelihood to consider entering into a conservation program, however, farmers were less likely to enroll land in these programs potentially due to the higher cost associated with higher conservation intensity. An application that stems from this result is the importance of stressing the benefits from conservation not only on-farm but also off-farm to encourage higher levels of conservation adoption. Based on the results of a study of carbon offset program for the adoption of no-till and permanent covers, it has been suggested that incentive payments coupled with farmers' better understanding of the benefits from adopting these practices could encourage greater adoption levels (Morand & Thomassin, 2005).

Probability weights, risk attitude, and risk premium

Results corresponding to the probability weights showed minimal transformation of probabilities into decision weights. While the probability weighing function parameters were statistically significant, the results suggest little use of subjective judgments of original probabilities when assessing risk. This reveals limited use of heuristics, that is, the use of previous experience and/or current knowledge about the likelihood of net returns outcomes. Probability weighting responses are illustrated in Figure 5. The direction of the GE-PWF and P1-PWF models showed a behavior consistent with overweighing of low probabilities and underweighting of large probabilities, while TK-PWF suggests underweighting of low probabilities and overweighting of large probabilities. Both, overweighing (Kahneman & Tversky, 1979; Lattimore et al., 1992; Prelec, 1998; Tversky & Kahneman, 1992), and underweighting of low probabilities have been found in empirical applications (Humphrey & Verschoor, 2004; D. C. Roberts, Boyer, & Lusk, 2008). However, as discussed above, there is minimal transformation of original probabilities in this study. The lines are nearly flat and virtually undistinguishable from the linear specification, as shown in Figure 5.

Figure 5 Probability weighing functions

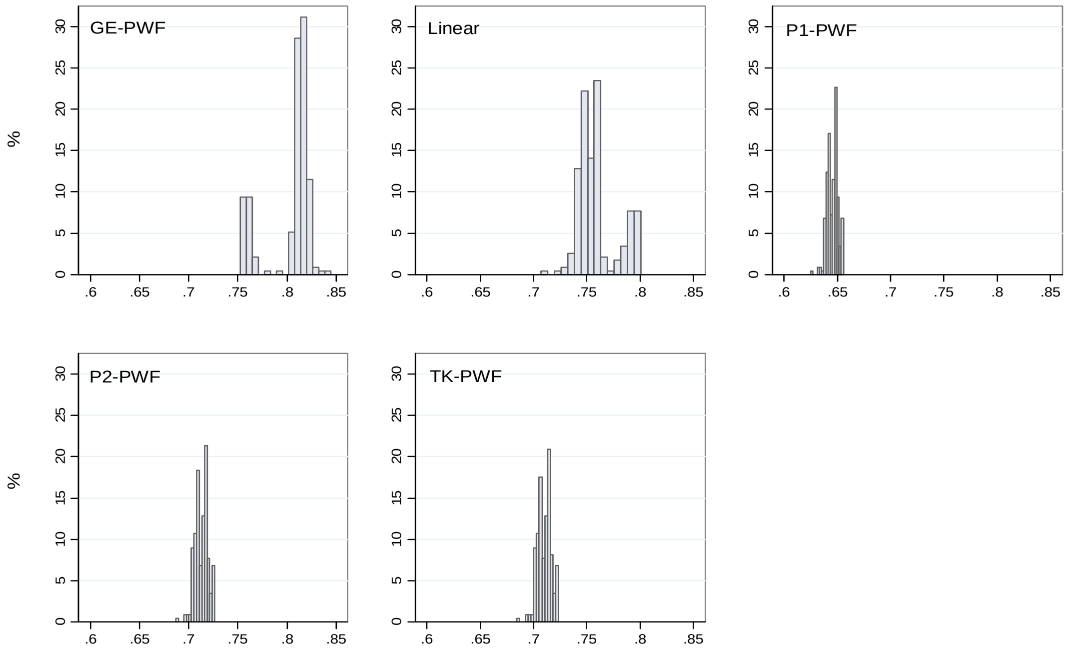


Subjective probabilities could reflect people's perception of uncertainty (Anderson & Dillon, 1992) and aversion to risk as certain outcomes are underweighted, revealing some level of pessimism (Lattimore, Baker, and Witte, 1992). For example, consider the probability associated with no changes in net returns. While it was the most certain outcome in each choice set (with a probability of occurrence ranging from 50-80%), it was slightly underweighted. In addition, no strong evidence of prospect pessimism was found as the sum of the probabilities was close to one in all the models (when the sum of the weights is less than one, this is referred to as prospect pessimism (Lattimore et al., 1992)). However, it is important to note that, as evidence in the psychological literature suggest, the context and format in which the probabilities are presented during the experiments affects respondents' transformation of probabilities and assessment of risk (Visschers, Meertens, Passchier, & De Vries, 2009).

The parameters associated with the expected utility of net returns (β_r) was positive in all models but only statistically significant in the linear probability weighting specification and GE-PWF models. A positive parameter indicates that farmers are more likely to enter into a conservation contract as the value they place on net returns increases. However, the insignificance of the parameter may indicate that the risk associated with the contract and farmers' assessment of uncertainty through probability weights could have a greater effect on farmers' likelihood of entering into the contract than the value they place on the actual outcome.

The constant parameter of risk attitude towards net returns was positive and statistically significant across all models. Risk attitude parameters corresponding to $\alpha > 0$ indicate risk aversion. In this study, regional variables were not found to significantly affect farmers' level of risk aversion. Farm size as measured by acres was found to be positive and statistically significant in the GE-PWF model, indicating that farmers with larger farms are more likely to exhibit higher risk aversion. This could be associated with the fact that more acres under the contract could represent a larger potential change in and impact on total net returns. The distributions of the predicted risk attitude parameter for each model specification are depicted in Figure 6. It can be seen from this graph that the risk parameters have little dispersion; this is due to the small effect of regional and farm size characteristics. It can also be noted that the predicted level of risk aversion varies across model specifications, with the linear probability specification and the GE-PWF models having more dispersion and revealed risk attitude. It is expected that risk attitudes would fluctuate according to the model used, as these have different underlying behavioral assumptions. It is important thus, to identify the model that best suits the data. Risk aversion parameters found in agriculture-related literature differ depending on the model used and the context of the study. However, most studies agree that, in general, farmers exhibit risk aversion. For some risk aversion estimates in previous studies see (Kumbhakar, 2002; Pennings & Garcia, 2001; Saha, Shumway, & Talpaz, 1994).

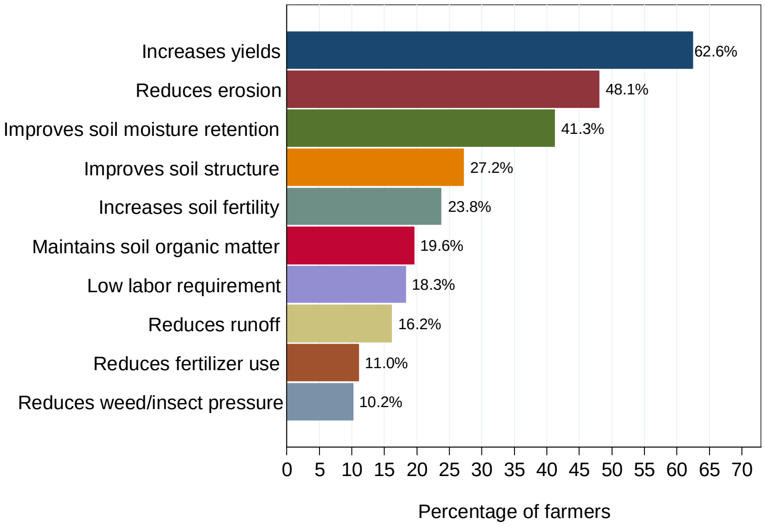
Figure 6 Distribution of predicted risk attitude parameters



The risk attitude parameter estimated in this study was relatively small, indicating modest risk aversion. However, risk attitude is context specific (MacCrimmon & Wehrung, 1990). In numerous studies, individuals' risk attitude is elicited using money lotteries. When assessing risk using lottery ticket experiments, responses may represent risk attitudes for extreme events. Nonetheless, issues in agricultural production (e.g. yields, prices) are mainly associated with non-extreme probabilities (Just, 2003). In this study, farmers where presented with a situation where deviations from their expected returns could occur as a result of their decision to enter into a conservation contract. In this scenario, farmers may behave as to prevent losses, especially if adopting these practices is not considered a production priority.

It has also been suggested that risk may be related to outcome expectations, whereby expectations of a better outcome could also influence people's perception of risk (March & Shapira, 1987; Sitkin & Pablo, 1992). Commonly, farmers adopt practices if they receive a private benefit (e.g. profit improvements through increasing yield or cost reductions). If farmers expect to improve their income streams when adopting conservation practices, then an outcome with lower or unchanged net returns may be perceived as an undesirable outcome. For example, 62% of the farmers in this study reported that that they would not adopt conservation practices if these failed to improve net farm income. In addition, further analysis of the data reported by these farmers (see Figure 7) revealed that increases in yields is the factor most desired in a conservation practice (ranked as the top three benefits by 62.2% of the farmers), above both soil erosion reduction (48.1%) and soil moisture retention (41.3%). Thus, it is plausible that famers have higher expectations for net returns under conservation.

Figure 7 Benefits from conservation practices most important to farmers



Another factor affecting risk perception is contract restrictiveness. Contract restrictiveness seems to be a major factor in farmers' decision to not enter into a conservation contract. Contract restrictiveness was listed by 34.8% of the farmers as one of the top three reasons for opting out in the stated choice experiment. Contracts could potentially limit farmers' ability to respond and adjust their cropping systems to varying weather and market conditions. As De Pinto, Magalhaes, Ringler (2010) suggest, being locked into a contract with certain practices increases a farmer's vulnerability "to shocks and economic fluctuations". Ma, Swinton, Lupi, & Jolejole-Foreman (2012) found that the type of conservation program and the restrictions of the program affect farmers' experience with these programs, influencing their willingness to adopt conservation contracts. Risk from restrictions imposed by a conservation contract could have a larger effect if farmers perceive that under a five year contract, their decision could have consequences that extend into the long-term. As Just (2003) pointed out, long-term changes pose a greater risk to farmers. Zeuli and Skees (2000) also note that the risk that stems from this type of contract, specifically carbon contracts, is the irreversibility of the decision. Some farmers may be less willing to commit to the contract if they have to bear risk for an extended period of time.

As previously discussed, there are different factors affecting farmer's attitude towards risk and in some cases gains in net returns are not sufficient to induce farmers' adoption of certain agricultural practices. In a study of the adoption cost of conservation tillage, Kurkalova, Kling, and Zhao (2006) found that the incentive to induce adoption was higher than the gains in net returns from the adoption of conservation tillage. The premium for the adoption of conservation practices could be the result of aversion to risk and sunk costs (Kurkalova, Kling, and Zhao, 2006). However if not accounted for directly, the effect of sunk costs could be revealed in farmers' risk attitudes (Ridier, Chaib, and Roussy, 2012). Some of these sunk costs could include the cost of machinery ownership. In this study, results also indicated that equipment cost was an important consideration affecting farmers' choices in the experiment.

Results from estimating the risk premium for the adoption of the conservation contract as well as estimates of certainty equivalent estimated using the regression results are reported in

Table 7 for the different attribute specific extended expected utility models. There are differences in the resulting measures of risk premium across the different probability weighting specifications. From the results, it is also apparent that the use of probability decision weights increases the estimated level of risk, taking into account farmers' subjective interpretation of the presented probability distributions and preferences. As shown in Table 7, the premium obtained with the linear probability weighting specification is lower compared to the estimates obtained with the nonlinear weights. The risk premium obtained when using probability weights ranges from 3.6% to 4.4% of net returns per acre for the preferred models (GE-PWF, TK-PWF, and P2-PWF).

Table 7 Risk premium estimates

	Linear probability	TK-PWF	GE-PWF	P1-PWF	P2-PWF
Expected net returns	100.03%	98.63%	99.00%	100.06%	98.51%
Expected utility	12.62	12.92	12.52	14.43	12.86
Certain equivalent	99.78%	95.07%	94.64%	99.92%	94.61%
Risk premium	0.25%	3.56%	4.36%	0.15%	3.90%

Percentage levels are relative to the level of net returns. For example, the risk premium for the TK-PWF is 3.56% of the farmers' net return.

The risk premium is the cost from risk bearing and in this application is found to be moderate. Including subjective probability introduces farmers' personal judgment/beliefs of how likely net returns outcomes are to occur, which could also reflect how optimistic or pessimistic farmers' expectations are. In this study, subjective probabilities did not reveal strong pessimism in terms of the expectation of outcome occurrences. When perceptions about the probabilities of outcomes are largely pessimistic, this can result in a higher revealed level of risk. Nonetheless, while transformation of probabilities were not large, the effect from using probability weights was significant, as differences in risk premium estimates when compared to using a linear probability suggest. Since the models with probability weighting specifications were preferred over the model with original probabilities, this suggests that it is important to evaluate respondents' subjective probabilities; otherwise, estimates of risk perceptions could be underestimated.

Marginal Willingness to Accept

Estimates of marginal willingness to accept (mWTA) per acre for the contract attributes are reported in Table 8. Estimates of mWTA were estimated as the ratio of the marginal utility of the contract attributes to the marginal utility of incentive payment, i.e. $\beta_{attribute} / \beta_{pay}$. Estimates of willingness to accept for farmers, who have already adopted conservation practices, were adjusted using the estimates associated with previous adoption. Asymptotic standard errors were estimated using the Delta method (Greene, 2012). As can be observed in Table 8, mWTA estimates are very consistent across the different model specifications.

Table 8 Farmers' marginal willingness to accept ($/acre)

Attributes	**Linear probability**	**TK-PWF**	**GE-PWF**	**P1-PWF**	**P2-PWF**
Estimates for non-adopters					
Continuous No-till	27.73***	27.65***	27.45***	27.74***	27.64***
	(3.50)	(3.49)	(3.49)	(3.50)	(3.49)
Crop Rotation	13.26***	13.28***	13.19***	13.44***	13.29***
	(3.29)	(3.29)	(3.28)	(3.29)	(3.29)
Cover Crops	15.22***	15.45***	15.22***	15.31***	15.47***
	(2.59)	(2.59)	(2.59)	(2.59)	(2.59)
VRA of inputs	16.19***	16.28***	16.36***	16.19***	16.29***
	(2.46)	(2.46)	(2.46)	(2.46)	(2.46)
Estimates for adopters					
Continuous No-till	-9.39***	-9.44***	-9.51***	-9.43***	-9.44***
	(2.54)	(2.53)	(2.54)	(2.54)	(2.53)
Crop Rotation	5.06**	4.88*	5.04**	5.04**	4.89*
	(2.53)	(2.53)	(2.53)	(2.53)	(2.53)
Cover Crops	5.15	5.04	5.21	4.98	5.01

	(3.35)	(3.35)	(3.36)	(3.35)	(3.36)
VRA of inputs	0.57	0.61	0.52	0.63	0.62
	(3.63)	(3.62)	(3.62)	(3.62)	(3.62)
Estimates for other attributes					
Incentive Program[1]	5.09**	4.99**	5.02**	5.09**	4.99**
	(2.09)	(2.09)	(2.09)	(2.09)	(2.09)
Low off-farm Env. Benefits	7.42***	7.44***	7.63***	7.43***	7.44***
	(2.56)	(2.55)	(2.56)	(2.56)	(2.55)
Medium off-farm Env. Benefits	4.89*	5.06**	5.24**	4.90*	5.05 **
	(2.55)	(2.55)	(2.56)	(2.55)	(2.55)

*,**,*** statistically significant at the 1%, 5% and 10% level. Standard errors in parenthesis.
Standard errors were estimated using the Delta method.

[1] Carbon Credit Payment through a Carbon Market was used as the base scenario.

The mWTA estimates for the conservation practices (no-till, cover crops, conservation crop rotation and VRA of inputs) represent the payment amount farmers require in order to adopt these practices. The mWTA for the conservation practices was estimated separately for adopters and non-adopters. Some of the factors that could affect the WTA estimates for the conservation practices are opportunity cost of adopting these practices in comparison with alternative production methods and sunk costs that could include investment in human capital and/or equipment ownership (Kurkalova et al., 2006). The cost of the practice is also an important factor in the adoption of conservation practices (Lichtenberg, 2004). Some studies have estimated the level of incentive necessary to encourage adoption for different conservation practices under different arrangements (Cooper, 1997; Cooper & Signorello, 2008; Peterson, Smith, Leatherman, Hendricks, & Fox, 2012).

The mWTA for farmers who have not adopted continuous no-till was estimated at $27.45 - $27.74 per acre across models with different probability weighting specifications. In a study conducted in Iowa, Kurkalova, Kling, and Zhao (2006) found that the incentive level to encourage the adoption of conservation tillage in corn was $4.10/acre and $6.00/acre in soybeans. Peterson et al. (2012) found a mean estimate of $9.68 for continuous no-till and $4.78

for rotational no-till. Kurkalova, Kling, and Zhao (2006) found that farmers' premium for the adoption of conservation tillage in corn or soybeans represented ~13% of farmers' expected returns under conventional tillage and for other crops it represented ~62%. Large willingness to accept estimates in the present study could be the result of the requirement that no-till would be continued over the five years of the contract, without room for soil disturbance if needed (as seen by the farmer). It was been suggested that some no-till farmers may till the ground in response to economic or seasonal drivers (Llewellyn, D'Emden, & Kuehne, 2012).

For adopters of continuous no-till, the results in this study suggest that they would be willing to pay around $9.39 - $9.51 to keep using continuous no-till. This result may be related to sunk costs and irreversibility, particularly equipment ownership and human capital investment. These farmers may have already incurred the required investment to establish the practice on their farms. In addition, famers may be willing to pay as a result of the private benefits obtained (e.g. yield benefits, soil quality, etc.). A similar conclusion was reached by Cooper (1997) regarding conservation tillage in Iowa. Chouinard et al. (2008) also found evidence suggesting that farmers are willing to pay for stewardship. Specifically, they estimated that farmers were willing to pay $4.52/acre (estimated as forgone income). This result may also shed some light on the additionality to enrollment in conservation practices. It is apparent from this result than some farmers would adopt these practices in the absence of incentive payments. However, with low incentive payments, new adopters are less likely to be added. In a study of additionally from enrollment in federal programs in Ohio, Mezzatesta, Newburn, and Woodward (2013) found low levels of additionality for conservation tillage (19%), while additionality for cover crops was around 90%.

The mWTA for non-adopters of conservation crop rotation ranged from $13.19 to $13.44 across probability weighting specification. The estimate for adopters was around $5 per acre, but the estimate was not statistically significant. The mWTA estimated for cover crops ranged from $15.22 to $15.47/acre across all models. This estimate is lower than expected, considering the costs of plating cover crops and farmers' lack of experience with this practice. Singer, Nusser, and Alf (2007) estimated that on average farmers in the U.S. Corn Belt required about $23 per acre to induce the use of cover crops. The estimated mWTA for VRA of inputs ranged from $16.19 to $16.36 across the models with embedded expected utility. Farmers may be reluctant to adopt VRA technologies and may require a higher payment if they perceive these technologies as not being suitable for their operation and if they perceive they have relatively homogenous land (Hudson & Hite, 2003). In addition, given the complexity of this practice, the lack of knowledge may deter adoption, especially for farmers who are not first-time adopters (Batte, 2000; Lamb, Frazier, & Adams, 2008).

The mWTA estimates for the incentive program ranged from $4.99 to 5.09/acre. This result indicates that farmers require an additional payment if the channel through which the conservation program provides and administers the incentive payment is a carbon market. The lack of farmers' awareness of this type of program, the lack of policies for the creation of a binding carbon market, in addition to negative experiences with previous carbon markets may all explain this result. From the sample of farmers who previously participated in a carbon trading scheme, it seems likely that the low payments offered attracted mainly farmers who had already adopted conservation tillage, in the absence of any incentive payment. Thus, low incentive payments may result in low levels of additionality, a major component of program effectiveness (Mezzatesta, Newburn, and Woodward, 2013).

Findings in this study also suggest that conservation bundles with lower off-farm environmental benefits require a larger incentive payment when compared to bundles with higher benefits. Farmers require an additional payment of \$4.89 to \$7.63/acre if the bundle of practices they are required to adopt under the conservation contract does not deliver high environmental benefits. This result has important implications for the development of conservation programs. It is important to work towards improving farmers' awareness of the external benefits (social benefits) of their production decisions. With higher benefits from conservation, adoption in the absence of monetary incentives could increase (Mezzatesta, Newburn, and Woodward, 2013). As the results in this study suggest, if farmers recognize the public (social) environmental benefits from the use of conservation on their farms, they may be more willing to enroll in conservation programs, and it may reduce the level of incentive payment required to encourage enrollment and adoption of bundles of conservation practices.

7. Conclusions

This study was designed to determine the factors affecting the adoption and intensification of conservation practices under a contract. Various factors involved in a conservation contract were analyzed, the risk of net returns, bundle of practices to adopt, the type of conservation program, and the off-site benefits from the program. The results in this study suggest that the incentive payment required for farmers who have adopted conservation practices is significantly lower than the necessary payment for non-adopters. It is possible that if incentive payments are too low, programs may be more attractive to farmers who have already adopted these practices, reducing the potential additionality and associated benefits from these programs.

In the case of continuous no-till, given that farmers have already incurred significant investment, and given the private benefits, adopters may be willing to pay to continue using this practice.

The results in this study also suggest that farmers prefer federally-run programs over market based carbon programs. Given that a limited number of farmers are aware of the mechanism under which carbon offset programs work and that some of the farmers who previously participated in a carbon trading program had negative experiences, it is important to consider these factors if efforts for the establishment of a carbon market are to take place in the future. Farmers may require a premium if incentives are offered through a carbon market, and if incentives payments are low, mainly famers who have already adopted the practices may be attracted, resulting in low additionality to enrollment in such programs. More importantly, policies are to be in place if a carbon market is to be established. If a binding market exists and public trust in the programs increases, farmers' willingness to participate could be higher. In addition, findings in this study suggest that views regarding the off-farm benefits from agricultural conservation may have an important effect in farmers' willingness to participate in conservation programs and the incentive required under adoption. Hence, education about the societal benefits of on-farm conservation may be an important element to increase the effectiveness of conservation programs.

This study assessed the effect of risk on the adoption and intensification of conservation on the farm by evaluating the effect of the nonlinearity of expected utility for net returns and by including farmers' subjective assessment of probabilities. This method allowed for the estimation of the marginal utility from stochastic net returns and a parameter that measures farmers' risk attitude towards variability in net returns. In this study, farmers were found to exhibit risk aversion and to moderately use subjective probabilities when evaluating risk of net returns under a conservation contract. Together, these results showed that risk exposure has a significant effect on the adoption and intensification of conservation practices. Net returns are stochastic, and the distribution of potential outcomes affects farmers' willingness to embark in conservation programs that may result in changes in their expected returns. These results offer some insight into the importance of considering uncertainty in outcomes when designing incentive programs and extension programs to encourage the adoption of conservation systems (Isik and Yang, 2004).

These results also provide important information for extension applications. As some studies have previously suggested, it is important to provide farmers with the range of potential outcomes when promoting new technologies (Ghadim, Pannell, & Burton, 2005). As farmers are informed about the impact of these technologies in the first years of adoption, efforts can focus on providing farmers with tools to improve their probability of obtaining favorable outcomes to reduce their perception of uncertainty and the effect of perceived risk on the decision to implement and intensify conservation on their farms.

While this study did not directly measure the effect of contract length, further analysis of farmers' responses indicated its negative effect. Farmers reported that the inflexibility of the contract was the main reason for opting out of the contract. Longer contracts can increase the risk for farmers. Given the dynamics in commodity markets and the development of new technologies, it becomes difficult for farmers to anticipate what will happen in five years (Cattaneo, 2003). Shorter and more flexible contracts may increase farmers' participation in conservation contracts and may reduce the risk of defaulting or withdrawing from the contract (Cattaneo, 2003). Knowing the potential risk and what incentives farmers may require to reduce potential risks introduced to the farm would ensure that practices, once adopted, are not discontinued.

Previous research findings have indicated that withdrawals from conservation contracts were more likely to occur during the first years of implementation (Cattaneo, 2003). This indicates that there is gap between farmers' expectations and the reality when adopting conservation practices. When expectations are not met, then conservation practices may be unadopted. Thus, conservation education may be the most important factor when promoting conservation programs. It is important that farmers have realistic expectations about the benefits of the practices and how to manage them to obtain better results. A better understanding about the practices and how to manage them to reduce risk, the program mechanism, and the on-farm and off-farm benefits from using conservation may reduce the incentive needed to encourage adoption and may increase the effectiveness of conservation programs.

There are some limitations to this study that need to be acknowledged. This study does not make distinction among the crops for which the practices in the contract had to be implemented, and as findings in previous research suggest, the adoption premium may be vary across different crops (Kurkalova, Kling, and Zhao, 2006). Thus, the incentive payment estimated may be interpreted as a general estimate of the incentive required for the main crops grown in the studied region. In addition, the scope of this study was limited in terms of the sample of farmers studied. The sample of farmers surveyed was medium to large farmers in Kansas who were part of the same farm management association. Thus, the extrapolation of results to the farmers in the Great Plains of the U.S. and beyond needs to be done with that in mind.

Notwithstanding its limitations, this study offer some important insights into the adoption of conservation practices and how some factors affect farmers' decisions to enroll in conservation contracts. Further work needs to be done to establish how gains and losses affect the risk associated with potential net returns. This can be done by estimating a rank-dependent expected utility model or by adopting cumulative prospect theory in which a different utility is estimated for gains and losses. In addition, to improve the analysis, more net returns outcomes could be included to better trace the curvature of the utility of net returns and the risk attitude parameter. Further research may also explore heterogeneity across individual responses by adopting a random parameters logit model. However, as additional levels of complexities and nonlinearities are included, a larger sample size would be needed.

References

Adrian, A. M., Norwood, S. H., & Mask, P. L. (2005). Producers' perceptions and attitudes toward precision agriculture technologies. *Computers and Electronics in Agriculture, 48*(3), 256-271.

Aimin, H. (2010). Uncertainty, risk aversion and risk management in agriculture. *Agriculture and Agricultural Science Procedia, 1,* 152-156.

Akter, S., Bennett, J., & Ward, M. B. (2012). Climate change skepticism and public support for mitigation: Evidence from an Australian choice experiment. *Global Environmental Change, 22*(3), 736-745.

Anderson, J. R., & Dillon, J. L. (1992). *Risk analysis in dryland farming systems* Food & Agriculture Org.

Aneja, V. P., Schlesinger, W. H., & Erisman, J. W. (2009). Effects of agriculture upon the air quality and climate: Research, policy, and regulations. *Environmental Science & Technology, 43*(12), 4234-4240.

Antle, J., Capalbo, S., Mooney, S., Elliott, E., & Paustian, K. (2003). Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture. *Journal of Environmental Economics and Management, 46*(2), 231-250.

Batte, M. T. (2000). Factors influencing the profitability of precision farming systems. *Journal of Soil and Water Conservation, 55*(1), 12-18.

Beal, D. J. (1996). Emerging issues in risk management in farm firms. *Review of Marketing and Agricultural Economics, 64*(03)

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand* MIT press.

Ben-Akiva, M., & Swait, J. (1986). The Akaike likelihood ratio index. *Transportation Science, 20*(2), 133-136.

Bhat, C. R. (1998). Accommodating flexible substitution patterns in multi-dimensional choice modeling: Formulation and application to travel mode and departure time choice. *Transportation Research Part B: Methodological, 32*(7), 455-466.

Blanco-Canqui, H., Stone, L., Schlegel, A. J., Lyon, D., Vigil, M., Mikha, M., Rice, C. (2009). No-till induced increase in organic carbon reduces maximum bulk density of soils. *Soil Science Society of America Journal, 73*(6), 1871-1879.

Blevins, R., Smith, M., Thomas, G., & Frye, W. (1983). Influence of conservation tillage on soil properties. *Journal of Soil and Water Conservation, 38*(3), 301-305.

Burghart, D. R., Cameron, T. A., & Gerdes, G. R. (2007). Valuing publicly sponsored research projects: Risks, scenario adjustments, and inattention. *Journal of Risk and Uncertainty, 35*(1), 77-105.

Chan, K., & Heenan, D. (1996). The influence of crop rotation on soil structure and soil physical properties under conventional tillage. *Soil and Tillage Research, 37*(2), 113-125.

Chouinard, H. H., Paterson, T., Wandschneider, P. R., & Ohler, A. M. (2008). Will farmers trade profits for stewardship? Heterogeneous motivations for farm practice selection. *Land Economics, 84*(1), 66-82.

Claassen, R., Cattaneo, A., & Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: US experience in theory and practice. *Ecological Economics, 65*(4), 737-752.

Comito, J., Wolseth, J., & Morton, L. W. (2013). The state's role in water quality: Soil and water conservation district commissioners and the agricultural status quo. *Human Organization, 72*(1), 44-54.

Cooper, J. C. (1997). Combining actual and contingent behavior data to model farmer adoption of water quality protection practices. *Journal of Agricultural and Resource Economics, 22*(1), 30-43.

Cooper, J. C. (2003). A joint framework for analysis of agri-environmental payment programs. *American Journal of Agricultural Economics, 85*(4), 976-987.

Cooper, J. C., & Signorello, G. (2008). Farmer premiums for the voluntary adoption of conservation plans. *Journal of Environmental Planning and Management, 51*(1), 1-14.

Daniel, J., Abaye, A., Alley, M., Adcock, C., & Maitland, J. (1999). Winter annual cover crops in a Virginia no-till cotton production system: II. Cover crop and tillage effects on soil moisture, cotton yield, and cotton quality. *J.Cotton Sci, 3*(3), 84-91.

Derpsch, R., Friedrich, T., Kassam, A., & Li, H. (2010). Current status of adoption of no-till farming in the world and some of its main benefits. *International Journal of Agricultural and Biological Engineering, 3*(1), 1-25.

Dupont, D. P. (2010). Cost-Sharing incentive programs for source water protection: The grand river's rural water quality program. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie, 58*(4), 481-496.

Fargione, J. E., Cooper, T. R., Flaspohler, D. J., Hill, J., Lehman, C., Tilman, D., Oberhauser, K. S. (2009). Bioenergy and wildlife: Threats and opportunities for grassland conservation. *Bioscience, 59*(9), 767-777.

Freeman, J., & Kolstad, C. D. (2006). Prescriptive environmental regulations versus market-based incentives. *Moving to Markets in Environmental Regulation: Lessons from Twenty Years of Experience: Lessons from Twenty Years of Experience:* 1.

Galloway, J. N., Townsend, A. R., Erisman, J. W., Bekunda, M., Cai, Z., Freney, J. R., Sutton, M. A. (2008). Transformation of the nitrogen cycle: Recent trends, questions, and potential solutions. *Science (New York, N.Y.), 320*(5878), 889-892.

Ghadim, A. K. A., Pannell, D. J., & Burton, M. P. (2005). Risk, uncertainty, and learning in adoption of a crop innovation. *Agricultural Economics, 33*(1), 1-9.

Gill-Austern, D. (2011). The impact of rising corn prices on the conservation reserve program: An empirical model. *Undergraduate Economic Review, 7*(1), 22.

Glenk, K., & Colombo, S. (2011). How sure can you be? A framework for considering delivery uncertainty in benefit assessments based on stated preference methods. *Journal of Agricultural Economics, 62*(1), 25-46.

Glenk, K., & Colombo, S. (2013). Modelling outcome-related risk in choice experiments. *Australian Journal of Agricultural and Resource Economics, 57*(4), 559-578.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review, 94*(2), 236.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology, 38*(1), 129-166.

Grandy, A., Robertson, G., & Thelen, K. (2006). Do productivity and environmental trade-offs justify periodically cultivating no-till cropping systems? *Agronomy Journal, 98*(6), 1377-1383.

Greene, W. H. (2012). *Econometric analysis* (7th ed.). Upper Saddle River, New Jersey: Pearson Prentice Hall.

Greiner, R., Patterson, L., & Miller, O. (2009). Motivations, risk perceptions and adoption of conservation practices by farmers. *Agricultural Systems, 99*(2), 86-104.

Hensher, D. A., Greene, W. H., & Li, Z. (2011). Embedding risk attitude and decision weights in non-linear logit to accommodate time variability in the value of expected travel time savings. *Transportation Research Part B: Methodological, 45*(7), 954-972.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: A primer* Cambridge University Press.

Hudson, D., & Hite, D. (2003). Producer willingness to pay for precision application technology: Implications for government and the technology industry. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie, 51*(1), 39-53.

Humphrey, S. J., & Verschoor, A. (2004). The probability weighting function: Experimental evidence from Uganda, India and Ethiopia. *Economics Letters, 84*(3), 419-425.

Isik, M., & Yang, W. (2004). An analysis of the effects of uncertainty and irreversibility on farmer participation in the conservation reserve program. *Journal of Agricultural and Resource Economics, 29*(2), 242-259.

Johnson, D., Ambrose, S., Bassett, T., Bowen, M., Crummey, D., Isaacson, J., Winter-Nelson, A. (1997). Meanings of environmental terms. *Journal of Environmental Quality, 26*(3), 581-589.

Just, R. E. (2003). Risk research in agricultural economics: Opportunities and challenges for the next twenty-five years. *Agricultural Systems, 75*(2), 123-159.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society, 47*(2), 263-291.

Kim, S., Gillespie, J. M., & Paudel, K. P. (2005). The effect of socioeconomic factors on the adoption of best management practices in beef cattle production. *Journal of Soil and Water Conservation, 60*(3), 111-120.

Kim, S., & Dale, B. E. (2008). Effects of nitrogen fertilizer application on greenhouse gas emissions and economics of corn production. *Environmental Science & Technology, 42*(16), 6028-6033.

Kladivko, E. J. (2001). Tillage systems and soil ecology. *Soil and Tillage Research, 61*(1), 61-76.

Kumbhakar, S. C. (2002). Specification and estimation of production risk, risk preferences and technical efficiency. *American Journal of Agricultural Economics, 84*(1), 8-22.

Kurkalova, L., Kling, C., & Zhao, J. (2006). Green subsidies in agriculture: Estimating the adoption costs of conservation tillage from observed behavior. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie, 54*(2), 247-267.

Kushwaha, C., Tripathi, S., & Singh, K. (2001). Soil organic matter and water-stable aggregates under different tillage and residue conditions in a tropical dryland agroecosystem. *Applied Soil Ecology, 16*(3), 229-241.

Lal, R. (1999). Long-term tillage and wheel traffic effects on soil quality for two central Ohio soils. *Journal of Sustainable Agriculture, 14*(4), 67-84.

Lal, R. (1993). Tillage effects on soil degradation, soil resilience, soil quality, and sustainability. *Soil and Tillage Research, 27*(1), 1-8.

Lamb, D. W., Frazier, P., & Adams, P. (2008). Improving pathways to adoption: Putting the right P's in precision agriculture. *Computers and Electronics in Agriculture, 61*(1), 4-9.

Lambert, D. M., Sullivan, P., Claassen, R., & Foreman, L. (2007). Profiles of US farm households adopting conservation-compatible practices. *Land use Policy, 24*(1), 72-88.

Lancaster, K. J. (1966). A new approach to consumer theory. *The Journal of Political Economy, 74*(2), 132-157.

Lattimore, P. K., Baker, J. R., & Witte, A. D. (1992). The influence of probability on risky choice: A parametric examination. *Journal of Economic Behavior & Organization, 17*(3), 377-400.

Li, Z., Hensher, D. A., & Rose, J. M. (2010). Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence. *Transportation Research Part E: Logistics and Transportation Review, 46*(3), 384-403.

Li, Z., Tirachini, A., & Hensher, D. A. (2012). Embedding risk attitudes in a scheduling model: Application to the study of commuting departure time. *Transportation Science, 46*(2), 170-188.

Lichtenberg, E. (2004). Cost-responsiveness of conservation practice adoption: A revealed preference approach. *Journal of Agricultural and Resource Economics, 29*(3), 420-435.

Llewellyn, R. S., D'Emden, F. H., & Kuehne, G. (2012). Extensive use of no-tillage in grain growing regions of Australia. *Field Crops Research, 132*, 204-212.

Lodhi, M., Bilal, R., & Malik, K. (1987). Allelopathy in agroecosystems: Wheat phytotoxicity and its possible roles in crop rotation. *Journal of Chemical Ecology, 13*(8), 1881-1891.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications* Cambridge University Press.

Ma, S., Swinton, S. M., Lupi, F., & Jolejole-Foreman, C. (2012). Farmers' willingness to participate in Payment-for-Environmental-Services programmes. *Journal of Agricultural Economics, 63*(3), 604-626.

MacCrimmon, K. R., & Wehrung, D. A. (1990). Characteristics of risk taking executives. *Management Science, 36*(4), 422-435.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics* Cambridge university press.

March, J. G., & Shapira, Z. (1987). Managerial perspectives on risk and risk taking. *Management Science, 33*(11), 1404-1418.

Marra, M. C., & Carlson, G. A. (1990). The decision to double crop: An application of expected utility theory using stein's theorem. *American Journal of Agricultural Economics, 72*(2), 337-345.

Marra, M., Pannell, D. J., & Abadi Ghadim, A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: Where are we on the learning curve? *Agricultural Systems, 75*(2), 215-234.

Meyer, J. (2010). Representing risk preferences in expected utility based decision models. *Annals of Operations Research, 176*(1), 179-190.

Mezzatesta, M., Newburn, D. A., & Woodward, R. T. (2013). Additionality and the adoption of farm conservation practices. *Land Economics, 89*(4), 722-742.

Morand, H., & Thomassin, P. J. (2005). Changes in Quebec cropping practices in response to a carbon offset market: A simulation. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie, 53*(4), 403-424.

NRCS - Natural Resources Conservation Systems. (2013). NRCS Conservation Programs. Available at: http://www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/

NRCS. (2015a). Conservation Stewardship Program - Payment for Performance. http://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/programs/financial/csp/?cid=nrcs143_008316

NRCS. (2015b). 2015 KS Practice payment cost data. http://efotg.sc.egov.usda.gov/treemenu.aspx

Paustian, K., Six, J., Elliott, E., & Hunt, H. (2000). Management options for reducing CO2 emissions from agricultural soils. *Biogeochemistry, 48*(1), 147-163.

Pennings, J. M., & Garcia, P. (2001). Measuring producers' risk preferences: A global risk-attitude construct. *American Journal of Agricultural Economics, 83*(4), 993-1009.

Peterson, J. M., Smith, C. M., Leatherman, J. C., Hendricks, N. P., & Fox, J. A. (2012). The role of contract attributes in purchasing environmental services from landowners. *Kansas State University, Kansas,*

Pierce, F. J., & Rice, C. W. (1988). Crop rotation and its impact on efficiency of water and nitrogen use. *Cropping Strategies for Efficient use of Water and Nitrogen,* (croppingstrateg), 21-42.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica: Journal of the Econometric Society, 32*(1), 122-136.

Prelec, D. (1998). The probability weighting function. *Econometrica, 66*(3), 497-527.

Raimbault, B., & Vyn, T. (1991). Crop rotation and tillage effects on corn growth and soil structural stability. *Agronomy Journal, 83*(6), 979-985.

Reimer, A. P., & Prokopy, L. S. (2014). Farmer participation in US farm bill conservation programs. *Environmental Management, 53*(2), 318-332.

Ribaudo, M., Greene, C., Hansen, L., & Hellerstein, D. (2010). Ecosystem services from agriculture: Steps for expanding markets. *Ecological Economics, 69*(11), 2085-2092.

Ridier, A., Chaib, K., & Roussy, C. (2012). The adoption of innovative cropping systems under price and production risks: A dynamic model of crop rotation choice. Paper presented at the *EAAE Seminar: Price Volatility and Farm Income Stabilization: Modelling Outcomes and Assessing market and Policy Based Response,* Feb 2012, Dublin, Ireland.

Robbins, A. (2005). Ecosystem services markets.

Roberts, D. C., Boyer, T. A., & Lusk, J. L. (2008). Preferences for environmental quality under uncertainty. *Ecological Economics, 66*(4), 584-593.

Rodriguez, J. M., Molnar, J. J., Fazio, R. A., Sydnor, E., & Lowe, M. J. (2009). Barriers to adoption of sustainable agriculture practices: Change agent perspectives. *Renewable Agriculture and Food Systems, 24*(1), 60-71.

Rolfe, J., & Windle, J. (2013). Including management policy options in discrete choice experiments: A case study of the Great Barrier Reef. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie, 61*(2), 197-215.

Roth, G. W. (1996). *Crop rotations and conservation tillage*

Saha, A., Shumway, C. R., & Talpaz, H. (1994). Joint estimation of risk preference structure and technology using expo-power utility. *American Journal of Agricultural Economics, 76*(2), 173-184.

SAS Institute Inc., SAS/QC® User's Guide, Version 8, Cary, NC: SAS Institute Inc., 1999. 1994pp.

Sattler, C., & Nagel, U. J. (2010). Factors affecting farmers' acceptance of conservation measures - a case study from north-eastern Germany. Land use Policy, 27(1), 70-77.

Schimmelpfennig, D., & Ebel, R. (2011). On the doorstep of the information age: Recent adoption of precision agriculture US Department of Agriculture, Economic Research Service.

Shapiro, B. I., Wade Brorsen, B., & Doster, D. H. (1992). Adoption of double-cropping soybeans and wheat. *Southern Journal of Agricultural Economics, 24*, 33-33.

Singer, J., Nusser, S., & Alf, C. (2007). Are cover crops being used in the US Corn Belt? *Journal of Soil and Water Conservation, 62*(5), 353-358.

Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the determinants of risk behavior. *Academy of Management Review, 17*(1), 9-38.

Snapp, S., Swinton, S., Labarta, R., Mutch, D., Black, J., Leep, R., O'Neil, K. (2005). Evaluating cover crops for benefits, costs and performance within cropping system niches. *Agronomy Journal, 97*(1), 322-332.

Soil Science Society of America. (2012). Glossary of Soil Science Terms. Available at: https://www.soils.org/publications/soils-glossary#

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty, 32*(2), 101-130.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*(4), 297-323.

Tyner, W., & Taheripour, F. (2008). Biofuels, policy options, and their implications: Analyses using partial and general equilibrium approaches. *Journal of Agricultural & Food Industrial Organization, 6*(2)

Van Houtven, G., Johnson, F. R., Kilambi, V., & Hauber, A. B. (2011). Eliciting benefit-risk preferences and probability-weighted utility using choice-format conjoint analysis. *Medical Decision Making: An International Journal of the Society for Medical Decision Making, 31*(3), 469-480.

Vellidis, G., Ortiz, B., Beasley, J., Hill, R., Henry, H., & Brannen, H. (2013). Using RTK-based GPS guidance for planting and inverting peanuts. *Precision agriculture, 13* (pp. 357-364) Springer.

Veronesi, M., Chawla, F., Maurer, M., & Lienert, J. (2014). Climate change and the willingness to pay to reduce ecological and health risks from wastewater flooding in urban centers and the environment. *Ecological Economics, 98*, 1-10.

Visschers, V. H., Meertens, R. M., Passchier, W. W., & De Vries, N. N. (2009). Probability information in risk communication: A review of the research literature. *Risk Analysis, 29*(2), 267-287.

Von Neumann, J., & Morgenstern, O. (1945). Theory of games and economic behavior. *The Bulleting of the American Mathematical Society, 51*(7), 498-504.

Wang, Y., Tu, C., Cheng, L., Li, C., Gentry, L. F., Hoyt, G. D., Hu, S. (2011). Long-term impact of farming practices on soil organic carbon and nitrogen pools and microbial biomass and activity. *Soil and Tillage Research, 117*, 8-16.

Weber, E. U., & Milliman, R. A. (1997). Perceived risk attitudes: Relating risk perception to risky choice. *Management Science, 43*(2), 123-144.

West, T. O., & Post, W. M. (2002). Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal, 66*(6), 1930-1946.

Whitten, S. M., & Coggan, A. (2013). Market-based instruments and ecosystem services. *Ecosystem Services in Agricultural and Urban Landscapes*, 178-193.

Zeuli, K. A., & Skees, J. R. (2000). Will southern agriculture play a role in a carbon market? *Journal of Agricultural and Applied Economics, 32*(2), 235-248.

Zibilske, L., Bradford, J., & Smart, J. (2002). Conservation tillage induced changes in organic carbon, total nitrogen and available phosphorus in a semi-arid alkaline subtropical soil. *Soil and Tillage Research, 66*(2), 153-163.