Farmers' valuation of changes in crop insurance coverage:
A test of third generation prospect theory

Mary Doidge
Department of Agricultural, Food, and Resource Economics
Michigan State University
doidgema@msu.edu

Hongli Feng
Department of Agricultural, Food, and Resource Economics
Michigan State University
hennes65@msu.edu

David Hennessy
Department of Agricultural, Food, and Resource Economics
Michigan State University
hennes64@msu.edu

Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

Abstract

Recent work has shown that expected utility theory does not accurately characterize farmers' crop insurance purchases. Prospect theory has been proposed as a more suitable framework, allowing for loss as well as risk aversion. This work examines farmers' valuation of changes to crop insurance policies through the lens of third generation prospect theory. Rather than measure gains and losses from a static reference point, third generation prospect theory allows for uncertainty in both the reference and prospect choices, determining gains and losses on a state-by-state basis. Data were obtained from surveys of corn and soybean producers in Michigan and Iowa. Participants were asked to suppose they had a plot of land in corn with a hypothetical revenue distribution and a baseline revenue insurance policy. They were asked how much they would be willing to pay or accept for insurance policies with higher or lower coverage levels. To assess the suitability of third generation prospect theory, value and probability weighting function parameters were estimated by nonlinear least squares. Parameters estimates indicate that third generation prospect theory better fits our data than prospect theory with a constant reference point. The analysis was extended to examine farmers' crop insurance responses to proposed cuts in federal crop insurance policies. This work is important for understanding how farmers value crop insurance policies and how they may respond to changes in crop insurance premiums.

Introduction

Crop insurance is an important tool that allows farmers to manage some of the risk inherent in agricultural production. In the United States, crop insurance is heavily subsidized by the federal government. Federal crop insurance subsidies were introduced in 1980 in an effort to encourage uptake and reduce disaster payments to farms by the federal government. The introduction of and increases in premium subsidies has achieved the government's goal of increasing insurance rates among farmers. The proportion of insured acres reached its peak in 2015, with 88% of all planted acres (over 210 million acres) falling slightly to 86% in 2017 (Zulauf et al., 2018). As discussed by O'Donoghue (2014) and Zulauf et al. (2018), a strong relationship exists between acres covered by federal crop insurance and the rate of subsidisation, with higher subsidisation rates encouraging adoption of higher coverage level policies.

Several crop insurance products are available to American farmers. Once they decide to insure their crop, they must choose how they want to insure their acres (basic, optional, or enterprise units) and between yield and revenue insurance. Yield insurance protects farmers from a decrease in yields only, and is paid out at the harvest price. Revenue insurance protects a farmer from a drop in revenue below his insured level, allowing for decreases in crop yield or in the price of that crop set by the Risk Management Agency (the agency that operates the Federal Crop Insurance Corporation, which manages the federal crop insurance program) (Shields, 2013). For both, farmers must choose the level of coverage to purchase which ranges from 50% to 85% of the expected value, based on their farm's past production history.

Insurance premium subsidies vary with the level of coverage that a farmer purchases. Premiums for catastrophic coverage (covering yield losses of 50% at 55% of the prevailing price) are fully subsidised by the federal government (although farmers must pay an administration fee for these insurance policies). The subsidy level for crop insurance premiums decreases with coverage level, such that those purchasing crop insurance with a higher coverage level have a smaller proportion of their insurance premiums subsidised by the government, but the actual subsidy is in fact larger than for lower levels of insurance (Shields, 2013; Du, Feng, and Hennessy, 2016).

Crop insurance subsidies come at significant cost to the federal government, which subsidises an average of 62% of the premium costs of these policies (Shields, 2013). The federal government also reimburses private insurance companies for administrative costs, which totals over $1 billion annually (CBO, 2016). In 2009, approximately $5.4 billion was paid in insurance premium subsidies with over $2 billion distributed to farmers through these subsidies for corn alone (Shields, 2013). The total cost of the program in 2011 were estimated at over $11 billion, with $7.5 billion of that paid as premium subsidies (Glauber, 2013). Total costs under the current program are expected to be $88 billion between 2017 and 2026 (CBO, 2016).

Because of the significant cost of crop insurance subsidies, there have been calls for these subsidies to be reduced or eliminated. With a new federal administration in 2017 and a new Farm Bill expected in 2018, crop insurance subsidies and other supports to farmers may be reduced. The proposed 2019 Fiscal Year budget includes significant changes to crop insurance policy, limiting subsidized crop insurance eligibility to farmers with less than $500,000 adjusted gross income and reducing the mean subsidy rate from 62% to 48% (OMB, 2017). For 2017 rates, a reduction of this magnitude would save the government approximately $1 billion, although this number does not account for potential increases in disaster payments to compensated uninsured producers (Zulauf et al., 2018). How farmers respond to changes in subsidies and, consequent changes in their insurance premiums, is an important subject of study. Previous studies have investigated the relationship between premium price and insurance demand, finding that farmers’ demand for insurance is elastic, such that farmers would likely respond to increases in premiums by reducing their coverage levels (O'Donoghue, 2014). If reductions in subsidies cause farmers to make changes to their coverage levels or insurance decisions, an increase in disaster payments may be observed in the event of significant decreases in yield or revenue. Farmers may also change their production plans if their insurance premiums increase.

Agents' insurance purchasing behaviour is typically modelled with the expected utility theory framework. In the face of risky outcomes, agents are assumed to be expected utility maximizers. For insurance choices, including those for crop insurance, expected utility theory predicts that farmers will choose the policy that maximizes their expected utility of profits from crop production. Expected utility theory generally posits that agents have a concave utility function to incorporate risk aversion. If insurance is available at an actuarially fair premium (such that the insurance premium is equal to the expected indemnity), risk averse agents should fully insure their losses under this theoretical framework.

Despite the popularity of these models, however, recent research has shown that crop insurance purchase decisions are not always guided by the expected utility framework. Using data from crop insurance policies purchased in 2009 by American corn and soybean producers, Du, Feng, and Hennessy (2016) demonstrated that farmers' crop insurance choices are inconsistent with expected utility maximization. They showed that the coverage level elected by farmers was, on average, lower than the coverage level expected if farmers behaved as expected utility maximizers. Nor did farmers choose the policy level that maximized their subsidy. Contrary to subsidy maximisation, the coverage level chosen by farmers decreased with an increase in out-of-pocket prices of insurance policies (prices net of any government subsidies), despite the fact that the dollar value of subsidies increased with coverage level.

In many instances of expected utility failing to explain observed insurance behaviour, prospect theory has been suggested as an alternative, whether over- or under-insurance is observed (e.g. Du et al., 2016; Sydnor, 2010). Developed by Kahneman and Tversky (1979), prospect theory differs from expected utility theory in that it determines gains and losses with respect to a particular reference point; these gains and losses are treated differently by agents. In prospect theory the disutility of losing a certain amount relative to the reference point is greater in magnitude than the utility experienced from gaining the same amount relative to that reference point. Agents are therefore said to be loss averse. Rather than an expected utility function concave over its entire support, prospect theory posits a value function concave over gains and convex over losses leading to risk aversion in the gain domain, but risk seeking behaviour in the loss domain. (Kahneman and Tversky, 1979). Prospect theory also introduces nonlinearity in probabilities with a probability weighting function, which over-weighs low probability events and under-weights high probability events (Kahneman and Tversky, 1979).

Prospect theory has been applied to insurance purchases as an alternative to expected utility theory in several different contexts (Barberis, 2013). Examining a large number of home insurance contracts, Sydnor (2010) found that the high deductible chosen in many actual home insurance policies implied an unreasonably high level of risk aversion under expected utility theory. The probability weighting function, which overweighs low probability events, was able to explain the chosen deductibles not explained by risk aversion alone. In the context of home insurance, this implies an overweighting of low probably but potentially catastrophic events, leading homeowners to over insure from an expected utility standpoint (Sydnor, 2010). Barseghyan et al. (2013) also found evidence of loss aversion in home and auto insurance contract choice. Observing that people chose a deductible larger than that which would be predicted by expected utility theory, they found evidence of loss aversion resulting primarily from overweighing low probability events.

In a purely theoretical model, Schmidt (2015) demonstrates that, in a two-state world (the agent either experiences a loss or no loss) prospect theory prediction that agents should either purchase no insurance or fully insure (i.e. there is no interior solution). These results hold when the uninsured status quo and wealth with insurance are used as reference points. However, the specification of prospect theory employed by Schmidt induced loss aversion from the value function alone rather than the value function and probability weights.

In the context of agricultural production, prospect theory has been used in a limited amount to explain farmers' behaviour. Bocquého et al. (2014) conducted experiments with farmers in France to determine whether expected utility or cumulative prospect theory (Tversky and Kahneman, 1992) better explained farmers' decisions. Estimating prospect theory parameters of French farmers through multiple price list games developed by Tanaka et al. (2010) (similar to those developed by Holt and Laury, 2002). They found evidence of loss aversion and probability weighting, supporting the use of cumulative prospect theory models rather than those based on the expected utility framework as a model of farmer behaviour.

Liu (2013) examined adoption of a particular technology, Bt cotton, among Chinese farmers, looking at the factors that may influence adoption of the genetically modified crop. Despite the potential for higher profits by cultivating Bt cotton, some farmers were reluctant to adopt. Liu (2013) posits that this may be due to the higher cost and uncertain yield of the genetically modified cotton seed, causing farmers to experience a loss of revenue if adoption does not result in more revenue. She predicts that risk averse and loss averse farmers may therefore delay adoption. Experiments similar to those in Tanaka et al. (2010) were used to estimate prospect theory parameters, which were then used as independent variables in regressions to determine the probability of adoption. Farmers who exhibited loss aversion were likely to delay adoption of the new technology, while those whose behaviour was consistent with probability weighting (over-weighting rare events) were found to adopt earlier.

Prospect theory provides a natural theoretical lens for crop insurance choices that cannot be explained by expected utility theory. As pointed out by Du et al. (2016), it is likely that farmers have a reference outcome to which they compare yearly yield and revenue outcomes. They may be averse to revenue outcomes below this reference point. Observations of under-insurance, from an expected utility standpoint, may be due to risk-loving behaviour observed when faced with losses, due to convexity of the prospect theory value function in the loss domain. Babcock (2015) applied the prospect theory model to crop insurance choices, examining crop insurance purchases among US farmers in 2009. Using simulated crop yield and price data and accepted prospect theory parameter values, he found that the prospect theory model was better able to explain observed choices than expected utility theory. However, this finding was sensitive to the reference point used in the analysis. When insurance policies were treated as investment tools (i.e. when per-acre revenue and per-acre revenue plus out of pocket premium were used as reference points), prospect theory was not able to explain observed choices. Under prospect theory, the optimal coverage level choices were consistent with those observed in farmers' actual insurance purchases when insurance policies were treated as a standalone investment (i.e. when the reference point was defined as farmers' out of pocket premium) (Babcock, 2015).

While prospect theory has advantages over expected utility theory in explaining certain observed behaviours, in its original form uncertain outcomes are compared to a particular fixed reference point. The analysis in Babcock (2015) points to a weakness in this theoretical framework: results often depend on the choice of reference point. Under traditional specifications of prospect theory, gains and losses are typically measured with respect to an outcome observed with certainty. The results in Barseghyan et al., 2013 and Sydnor (2010) in support of prospect theory rely on using the household's expected outcome as a reference point from which gains and losses are determined. In stylized economic experiments used to measure prospect theory parameters, lotteries are most often valued with respect to a certain outcome (REFERENCES). Some conceptualizations of prospect theory allow for stochastic reference points. For example, Kőszegi and Rabin (2006) develop a model that determines the expected utility of each outcome and uses this as the baseline against which gains and losses are determined. However, while this model does allow for uncertainty in the reference point, it still assumes the same reference point in each possible state of the world.

When considering economic and agricultural events, it is unlikely to be the case that a risky prospect is compared to a certain outcome. It is possible that, since a baseline outcome may itself be risky, the way in which a farmer determines gains and losses from a particular reference point may also vary depending on the state that occurs. When deciding whether or not to purchase crop insurance, or deciding among coverage level options, farmers must compare two uncertain outcomes. This uncertainty cannot be adequately addressed in prospect theory models that assume a fixed reference point. To deal with uncertainty in the reference choice, Schmidt, Starmer, and Sugden (2008) have extended the prospect theory model. Their so-called third-generation prospect (PT^3) theory follows Sugden's (2003) rank dependent subjective expected utility framework and defines a value function using the outcome of a reference choice in the same state of the world against which gains and losses are measured. PT^3 has been shown to be consistent with WTA/WTP discrepancies in the face of uncertainty (Schmidt et al., 2008).

In this paper, we apply PT^3 to farmers' crop insurance choices. We assess the ability of PT^3 to explain farmers' valuation of changes to their crop insurance choices. Using data from surveys conducted with farmers in Michigan and Iowa, we use their reported willingness to pay (WTP) and willingness to accept (WTA) for increases and decreases in coverage level to estimate PT^3 value function parameters. We find support for PT^3 in our parameter estimations, with the parameters estimated suggesting risk and loss aversion among agricultural producers, as well as a moderate degree of probability weighting. Our estimated parameters are consistent with those estimated in other studies of agricultural producers (Bocquého et al., 2013). We also find that PT^3 parameter estimates are closer to values published in past work than those estimated with prospect theories that assume a constant reference point, providing further support for the PT^3 framework. This work furthers our understanding of how farmers chose among the crop insurance products available to them, and how they perceive production risk.

Conceptual Framework

We begin by supposing that a farmer is faced with the choice of purchasing a revenue insurance policy for a unit of land on his farm for the coming growing season[1]. Let r represent his per-acre revenue, unknown when this decision is made, $\bar{r}$ his average revenue[2] (APH x price), and c his chosen coverage level. The policy will pay an indemnity if the farmer's revenue

---

[1] This assumes farmers make coverage decision on a year-by-year basis, thinking only of the coming growing season.

[2] APH denotes actual production history, typically a ten-year average of historical yields used to determine premium rates.

falls below his insured revenue; if his revenue is above this amount, he will receive no payment. The indemnity that a farmer will be paid is shown in (1). The fair premium (the expected value of the indemnity), is as shown in (2).

$$\textit{indemnity} = \max\left\{c\bar{r} - r, 0\right\} \tag{1}$$

$$\text{fair premium} = \int_0^{c\bar{r}} \left(c\bar{r} - r\right) dF\left(r\right) \tag{2}$$

The premium paid by the farmer for the policy, p, is the value of the fair premium less the subsidy he receives. The subsidy amount $s\left(c\right)$ is determined by the coverage level, and so the subsidised premium paid by farmers for the insurance policy with coverage level ϕ is denoted by (3).

$$p\left(c\right) = (1 - s(c)) \int_0^{c\bar{r}} \left(c\bar{r} - r\right) dF\left(r\right) \tag{3}$$

The farmer's per-acre revenue, w, is as shown in (4). It is determined by the revenue received for his crop, any indemnity payment he receives, and the premium he must pay for his insurance policy.

$$w\left(r, c, p\right) = \max\left[c\bar{r}, r\right] - p\left(c\right) \tag{4}$$

Expected Utility

In the expected utility framework, farmers should choose the coverage level that maximizes their expected utility of income[3], so that $c^* = \arg\max_c E\left[u\left(\max\left[c\bar{r}, r\right] - p\left(c\right)\right)\right]$, where $u\left(\bullet\right)$ is a concave utility function. An increase in coverage level increases the revenue

---

[3] For simplicity, we assume zero costs of production and no income from non-farm sources.

guarantee and the probability that the farmer will receive an indemnity payment, increasing his utility, but will cost more than his original policy. For a farmer to choose a higher coverage level $c' > c^*$, his expected utility must be at least as high as his original utility.

The maximum amount that the farmer is willing to pay (WTP) for an increase in coverage level should be the amount above $p^* = p\left(c^*\right)$ that keeps his expected utility constant. That is,

$$E\left[u\left(w\left(r, c^*, p^*\right)\right)\right] = E\left[u\left(w\left(r, c', p^* + WTP_{c^* \to c'}\right)\right)\right] \tag{5}$$

Similarly, for $\phi'' < \phi^*$, the minimum amount that he should be willing to accept (his WTA) should be the amount that his expected utility is unchanged such that

$$E\left[u\left(w\left(r, c'', p''\right)\right)\right] = E\left[u\left(w\left(r, c^*, p^* - WTA_{c^* \to c''}\right)\right)\right] \tag{6}$$

For goods with close substitutes, any difference in agents' WTA and WTP will be caused only by the income effect. For increments in coverage level, this should be small, so that a farmer's WTP and WTA for changes in coverage level should not differ by much. Despite this theoretical result, previous research has consistently found that WTA exceeds WTP, often by a significant margin (Brown and Gregory, 1999; Horowitz and McConnell, 2002; Tunçel and Hammitt, 2014). This has been found with studies of physical objects, environmental quality, and health, among others, and holds a variety of elicitation methods (e.g. economic experiments or hypothetical statements of WTP and WTA).

Prospect Theory

Loss aversion is one of the proposed explanations for the observed willingness to pay/willingness to accept disparity, suggesting that people experience more disutility from a loss than utility from a gain of the same magnitude. This may explain why people are willing to pay less to obtain an item than they are willing to accept to give up that same item, as has been found in many economic experiments. Prospect theory accounts for loss aversion in a way that is not explained by expected utility theory, treating losses and gains from a particular reference point differently (Kahneman and Tversky, 1979).

For outcomes with discrete distribution functions, the expected utility framework is linear in probabilities such that the expected utility of an uncertain outcome is defined as $U(x)=\sum_{i=1}^{n}u(x_i)\theta_i$, where θ_i is the probability that state i will occur. The utility function for outcome i, $u(x_i)$, is an increasing function, concave over outcomes. In prospect theory, utility of the outcome is determined similarly, but with some key differences. The agent's value function, $V(x)$, is defined as

$$V(x)=\sum_{i=-m}^{n}v(x_i)\pi(\theta_i) \tag{7}$$

in which $v(x_i)$ is the value of x_i and $\pi(\theta_i)$ is the weighted probability of outcome i. Outcomes are defined with respect to some reference point, from which gains ($x_i > 0$) and losses ($x_i < 0$) are measured.

One of the main features of prospect theory is the way in which gains and losses are treated by agents. Gains and losses are determined with respect to the agent's particular reference point. Rather than a utility function that is concave over its entire domain (gains and losses), prospect theory posits a value function that is concave over gains but convex over losses. The magnitude of the value function may also be different for gains and losses to incorporate loss aversion observed in many scenarios, such that losses are felt more keenly than gains. The value function proposed by Kahneman and Tversky (1979) that accounts for this is shown in equation (8)

$$v(x) = \begin{cases} x^{\alpha_{gain}} & \text{if } x \geq 0 \\ -\lambda(-x)^{\alpha_{loss}} & \text{if } x < 0 \end{cases} \tag{8}$$

where $0 < \alpha_{gain}, \alpha_{loss} < 1$ (and often $\alpha_{gain} = \alpha_{loss}$ is assumed). The curvatures of the value function in the two domains are determined by α_{gain} and α_{loss}, while $\lambda > 1$ implies loss aversion.

Decision weights of probability, $\pi(\theta_i)$ in equation (7), is another way in which prospect theory differs from expected utility. Decision weights are commonly modelled such that low probability events are over weighted and high probability events are under weighted. Several weighting functions have been proposed, but the one most commonly employed is as in Kahneman and Tversky (1979). Their proposed weighing function is of the form

$\pi(\theta) = \frac{\theta^{\beta}}{\left(\theta^{\beta} + (1-\theta)^{\beta}\right)^{\frac{1}{\beta}}}$, where β is the probability weighting parameter. This function causes the value function $V(x)$ to be non-linear in probabilities, and also contributes to observed loss aversion.

Cumulative Prospect Theory

Cumulative prospect theory, developed by Kahneman and Tversky (1992), retains the value function and decision weights of prospect theory developed earlier by the same authors (equation (8), above) (Kahneman and Tversky, 1979). However, cumulative prospect theory introduces a cumulative probability weighting function that determines decision weights for gains and losses differently, such that a prospect with n potential gains assigns any gain i , with outcomes ranked $x_i \leq \ldots \leq x_n$ the decision weight

$$\pi_i^+ = w^+\left(\theta_i + \ldots + \theta_n\right) - w^+\left(\theta_{i+1} + \ldots + \theta_n\right) = w^+\left(\theta_i\right) \tag{9}$$

such that $w^+\left(\theta_i + \ldots + \theta_n\right)$ is the probability of receiving at least outcome i and $w^+\left(\theta_{i+1} + \ldots + \theta_n\right)$ is the weighted probability of receiving an outcome strictly greater than i. A loss i of m total potential losses $x_m \leq \ldots \leq x_i$ is similarly assigned the probability weight

$$\pi^- = w^-\left(\theta_m + \ldots + \theta_i\right) - w^-\left(\theta_m + \ldots + \theta_{i-1}\right) = w^-\left(\theta_m\right) \tag{10}$$

These probability weighting functions weigh cumulative probabilities, such that

While cumulative prospect theory adds features to prospect theory, it still assumes a constant reference point, which may not be suitable for all decision-making contexts.

Third Generation Prospect Theory

Prospect theory and cumulative prospect theory propose important alternatives to expected utility theory that may more accurately describe how agents choose among risky prospects. However, both compare risky outcomes to a certain reference point. This may not always be a reasonable assumption, especially when applying prospect theory to the context of agricultural production. Third generation prospect theory (PT^3), developed by Schmidt et al. (2008) builds on the previous versions of prospect theory, including a value function concave over gains and convex over losses as well as weighted probabilities that overweigh low probability events and underweight high probability events. However, PT^3 does not suppose a fixed reference point, and instead compares risky prospects to a reference choice that also depends on the state of nature.

The value function used in PT^3 follows the function proposed by Kahneman and Tversky (1979), and is of the form

$$v(z) = \begin{cases} z^{\alpha} & \text{if } z \geq 0 \\ -\lambda(-z)^{\alpha} & \text{if } z < 0 \end{cases} \tag{11}$$

with $0 < \alpha < 1$ indicating a function concave over gains and convex over losses, and $\lambda > 1$ indicating loss aversion. An agent's objective function is defined as

$$V(f,h) = \sum_i v(z_i)\pi(\theta_i) \tag{12}$$

where, as above, $\pi(\theta_i)$ is the weighted probability of state i occurring.

The key difference between prospect theory as proposed by Kahneman and Tversky (1979, 1992), and PT^3 is that z_i is the difference between the outcomes in state i of choice f and the reference choice h, against which gains and losses are measured, rather than a fixed reference point. The value function $v(z_i)$ is accordingly called the relative value function. In this framework, gains and losses for alternative f with respect to the reference choice h are compared for each potential state of the world are separately, such that the difference between the two outcomes in in state s_i is determined by

$$z_i = f(s_i) - h(s_i) \tag{13}$$

When $h(s_i)$ is a certain outcome, this function is equivalent to the previous conceptions of prospect theory.

In the context of crop insurance choices, we define a farmer's revenue in state i without insurance as his reference choice, h_i, and the revenue that he would receive in state i if he chose the policy with coverage level c as f_{ic}, his value of the insurance policy can be valued according to PT^3. In each potential state of the world, the potential revenue outcomes without and with crop insurance are compared to determine whether the insurance policy results in a gain or a loss relative to his revenue without insurance. The differences in each possible state i, $z_i = f_{ic} - h_i$, are valued according to (11), and the value of the insurance policy with coverage level c, f_c, relative to revenue without insurance, the reference choice h, is determined by (12).

A farmer should choose the insurance policy with coverage level that maximizes his value function such that

$$c^* = \arg\max_c V\left(f_c, h\right) \tag{14}$$

yielding the maximized value function $V\left(f_{c*}, h\right)$.

We can also use this framework to determine how much a farmer would be willing to pay or accept for changes in his coverage level from a baseline insurance policy. The maximum amount that the farmer would be willing to pay to increase his coverage level is the amount that leaves his valuation unchanged at the maximum, such that $WTP_{c*\to c'}$ satisfies

$$V\left(f_{c*}, h\right) = V\left(f_{c'}, h, WTP_{c*\to c'}\right) \tag{15}$$

Similarly, the minimum amount that he would be willing to accept for a decrease in coverage level should be the amount such that

$$V\left(f_{c*}, h\right) = V\left(f_{c''}, h, WTP_{c*\to c''}\right) \tag{16}$$

In each state of the world, we define $z_{ic'} = f_{ic*} - h_i - WTP_{c*\to c'}$ and $z_{ic''} = f_{ic*} - h_i + WTA_{c*\to c''}$.

Data

Data were collected from surveys of corn and soybean farmers in Michigan and Iowa in late 2016 and early 2017. These two states were chosen to represent typical farms in the U.S. corn belt (Iowa) and states in which mixed farming is more prevalent (Michigan). Farmers who grew at least 100 acres of corn or soybeans in 2016 in either of the two states were eligible to participate. Surveys were administered to farmers through mail (77% of respondents), online (18%), and in person at farmer meetings (5%). The survey was tested in the summer of 2016. Researchers travelled to various farmer meetings in Michigan and invited attendees to complete the survey. Farmers were compensated at these meetings for their time. In late 2016 and early 2017, the researchers travelled to other meetings in Michigan and Iowa sponsored by Michigan State University and Iowa State University, respectively, at which farmers were invited to complete the survey.

The majority of surveys were completed by farmers online and through the mail in the winter and spring of 2017. Surveys were administered by the Centre for Survey Statistics & Methodology (CSSM) of Iowa State University. A sample of addresses for 2,000 farmers (1,000 in each state) was purchased from Farm Market iD and provided to CSSM staff. This sample included email addressed for approximately two thirds of these farmers. Farmers for whom email addresses were provided were initially sent letters to let them know they would receive an email with a link to the online survey. Emails were sent to 1,278 farmers (677 in Michigan and 601 in Iowa), of which 50 initially completed the online version of the survey. An additional sample file of 598 farmers, 299 in each state, was later obtained from Farm Market iD. CSSM staff prepared and mailed paper invitation letters to those respondents informing them that they would be receiving an email invitation to complete the online survey. From these additional addresses, 40 respondents completed the survey. For both samples, reminder emails were sent roughly a week after the initial electronic invitation. Respondents who completed the survey online were compensated between $19 and $28 depending on the outcome of an economic experiment not discussed in this work.

Surveys were mailed to 1,925 farmers, including those who had not completed the initial online survey and those for whom no email address was provided. Mailings included a postage paid return envelope and an incentive of $2. One week after the initial mailing, a reminder postcard was sent. An additional survey was sent to 1,531 farmers roughly three weeks after the initial mailing. A total of 470 completed surveys were returned to the CSSM. The surveys captured information about farmers' demographics, their farm operations, and past insurance choices and payments. Farmers were asked about their insurance purchase decisions and any insurance payments they received in the preceding five years (from 2011 to 2015). They were asked about other activities they employ, besides crop insurance, to mitigate risk (e.g., using futures markets, purchasing named-peril insurance policies, etc.). The survey also asked participants about the importance of non-financial factors in their insurance decisions.

To investigate how farmers value changes in coverage level from a baseline policy, they were shown a per-acre revenue distribution for corn. The hypothetical distribution was designed such that the actuarially fair insurance premium was typical for corn production in mid-Michigan. The discrete distribution indicated number of years in twenty they could expect to receive that particular revenue (see Figure 1). Farmers were asked to suppose that they had a revenue insurance policy with 75% coverage, with the fair premium and revenue guarantee for this policy shown. They were asked to report the maximum amount that they would be willing to pay to increase their coverage to 80% and 85%, and the minimum amount they would be willing to accept to decrease their coverage to 70% and 65%. For each insurance policy, farmers were given the average revenue and the revenue guarantee of the policy. Changes in coverage level, revenue guarantee, and the probability of making a claim from this baseline policy are given in Table 1. Farmers were asked to choose their WTP and WTA from given ranges. For this analysis, the mid point of each response was chosen as a farmer's WTP or WTA to evaluate the ability of third generation prospect theory to explain observed valuations. We use the data to estimate the PT^3 parameters and assess the ability of PT^3 to explain farmers' valuation of changes to the crop insurance coverage.

Empirical Framework

We first examine farmers' stated WTP responses to motivate the use of prospect theory in their valuation of crop insurance policies. As discussed in the conceptual framework section of this paper, farmers should be willing to fully insure if they behave as expected utility maximizers. Accordingly, their WTP for changes in coverage level should be the same as the change in fair premium under the same conceptual framework. We also expect that farmers are equally sensitive to gains and losses when determining their WTP and WTA for changes in coverage level. If, however, farmers behave according to prospect theory, we should observe loss aversion in that they are more responsive to losses than to gains. As a first pass analysis, we determine the impact of expected losses and expected gains on their stated WTP. Gains and losses are defined with respect to the baseline 75% coverage policy in each state i. Expected loss is defined as the product of a loss in state i and the probability of sate i occurring, such that $E\left[loss_{nc}\right]=\sum_i loss_{nci}*\theta_i$, where θ_i is the probability of state i occurring. Expected gains are defined similarly, with $E\left[gain_{nc}\right]=\sum_i gain_{nci}*\theta_i$. We regress participant n's WTP on expected gains and losses, estimating

$$WTP_{nc}=\eta_0+\eta_1\mathrm{E}\left[loss_{nc}\right]+\eta_2\mathrm{E}\left[gain_{nc}\right]+\varepsilon_{nc} \tag{17}$$

where WTP_{nc} is farmer n's additional willingness to pay for the insurance policy with coverage level c, $c \in \{65\%, 70\%, 80\%, 85\%\}$. If farmers do not exhibit behaviour consistent with prospect theory, we expect $\eta_1 = \eta_2$ indicating that they are equally sensitive to gains and losses when determining their willingness to pay for the alternative coverage level. However, if farmers are loss averse, we expect $\eta_1 > \eta_2$, such that they are more sensitive to losses than to gains and suggesting that prospect theory may more accurately describe their behaviour.

After the above initial analysis, we use third generation prospect theory to examine farmers' valuation of changes to crop insurance policies, estimating the parameters of the value and probability weighting functions to assess the theoretical framework's ability to explain observed choices. The majority of studies that estimate prospect theory parameters ask participants to make binary choices between risky prospects, from which the model's parameters are estimated. The values estimated in the experiments conducted by Kahneman and Tversky (1979) are often used as a benchmark from which other parameter estimates are evaluated.[4] Rather than asking farmers to choose between to policies, we asked them to report how much they would be willing to pay or accept for policies with higher or lower coverage levels.

From a baseline of an uninsured state, let h_{ni} be the revenue that farmer n receives from his plot of land in random state i without an insurance policy. When determining the value of a policy with coverage level c under PT^3, the farmer will compare the monetary outcome of the policy in each random state to the value he would receive if no insurance policy was purchased.

---

[4] This paper reported the median parameter values, and this method remains popular in the literature, although it has been met with some criticism. See Harrison and Swarthout (2016) for a discussion of this issue.

We let f_{nci} represent the monetary value received by farmer n in state i with a policy that offers coverage level c, defined as

$$f_{nci} \equiv rev_{nci} - prem_c \tag{18}$$

where rev_{nci} is the revenue farmer n receives with coverage level c in state i, and $prem_c$ is the premium of that particular policy.

The monetary difference between the uninsured state and baseline without insurance in state i is defined as

$$z_{nci} \equiv f_{nci} - h_{ni} \tag{19}$$

Farmer n's valuation of a policy with coverage level c in state i is determined by

$$v(z_{nci}) = \begin{cases} {z_{nci}}^{\alpha} & z_{nci} \geq 0 \\ -\lambda \left| z_{nci} \right|^{\alpha} & z_{nci} < 0 \end{cases} \tag{20}$$

where α determines the curvature of the value function and λ determines the magnitude of loss aversion. His value of the policy with coverage level c, compared to the reference point of no insurance is determined by

$$V_{nc} = \sum\nolimits_i v(z_{nci}) \pi(\theta_i) \tag{21}$$

where $\pi(\theta_i)$ is the weighted probability of being in state i. We use the same probability weighting function as in Schmidt et al (2008), defined as $\pi(\theta) = \frac{\theta^{\beta}}{\left(\theta^{\beta} + (1-\theta)^{\beta}\right)^{\frac{1}{\beta}}}$ [5]. The

---

[5] This is the probability weighting function proposed by Kahneman and Tversky (1979). Others have been proposed that retain the same qualitative properties of overweighing low probability events. See Prelec (1998), for an example.

parameter $\beta \in (0,1)$ determines the degree of probability weighting, such $\beta = 1$ indicates no probability weighting and the probabilities are taken at face value.

Whether a farmer would choose to be insured, based on the above framework, is determined by equation (21). If $V_{nc} > 0$, the farmer would experience a higher utility with insurance, and would therefore opt for coverage; if $V_{nc} \leq 0$, he would choose to remain uninsured.

We can also this theoretical framework to determine a farmer's valuation of crop insurance policies from a baseline coverage level to estimate value function parameters. Babcock (2015) determines the individually optimal crop insurance coverage levels by estimating their prospect theory certainty equivalent (CE) value. The CE is the amount that agents would accept rather than an uncertain prospect or gamble; an agent is indifferent between this certain amount, valued according to her utility function, and the uncertain prospect. We take this approach to estimate PT[3] value and probability weighting function parameters, treating farmers' WTP as their certainty equivalent for a change in coverage level.

We use h_{n75i} to denote he revenue farmer n would receive with the 75% insurance policy in each possible state of nature i. This serves as the farmers' reference point in state i. The monetary value received in state i under the alternative policies is represented by f_{nci}, with $c \in \{65\%, 70\%, 80\%, 85\%\}$ denoting the alternative coverage levels. The monetary difference between the baseline and alternative policies in state i is defined as

$$z_{nci} \equiv f_{nci} - h_{n75i} \tag{22}$$

Farmer n's valuation of revenue received in state i of a policy with coverage level c, compared to the baseline with 75% coverage is determined by

$$v(z_{nci}) = \begin{cases} z_{nci}{}^{\alpha} & z_{nci} \geq 0 \\ -\lambda |z_{nci}|^{\alpha} & z_{nci} < 0 \end{cases} \tag{23}$$

Farmer n's value of a policy with coverage level c is

$$V_{nc} = \sum_i v(z_{nci})\pi(\theta_i) \tag{24}$$

using the same probability weighting function as above.

A farmers' maximum willingness to pay for a higher coverage level and his minimum willingness to accept for a lower coverage level is the amount that he would pay or accept with certainty for an uncertain gain or loss in revenue. We therefore treat this amount as his certainty equivalent (CE), valued according to his utility function.[6] Letting $WTP_{nc} > 0$ denote farmer n's maximum willingness to pay to increase his coverage level to $c \in \{80\%, 85\%\}$, and $WTP_{nc} < 0$ his minimum willingness to accept for $c \in \{65\%, 70\%\}$, WTP_{nc} should be such that

$$U(WTP_{nc}) = V_{nc} = \sum_i v(z_{nci})\pi(\theta_i) \tag{25}$$

Supposing a constant relative risk aversion utility function, with $U(WTP_{nc}) = WTP_{nc}{}^{\alpha}$, the parameters α and λ in the value function, and the probability weighting function parameter β should be the values that satisfy (25).

We can estimate the PT^3 parameters with nonlinear least squares estimation, minimizing the sum of squared differences between the value of the change in coverage level and the CE of

---

[6] We value the agent's certainty equivalent according to his utility function rather than his value function. Experiments conducted by Novemsky and Kahneman (2005) suggest that loss aversion is not exhibited when the loss is intended, such as making a payment, rather than when a loss results from a risky choice. We thus do not value his CE with the value function that incorporates loss aversion.

reported WTP (the sum of squared errors). Assuming $U\left(WTP_{nc}\right)=V_{nc}+\varepsilon_{nc}$, we estimate the parameters $\widehat{\alpha},\widehat{\beta}$ and $\widehat{\lambda}$ that minimize

$$\sum_{nc}\varepsilon_{nc}{}^{2}=\sum_{nc}\left[U\left(WTP_{nc}\right)-V\left(z_{nci}\right)\right]^{2} \tag{26}$$

We also explore other model specifications, omitting the probability weighting function $\pi\left(\theta_i\right)$ (that is, assuming $\beta=1$) to estimate α and λ only. We then set $\lambda=1$ and estimate α and β. We also allow for different curvature parameters in the gain and loss domains, estimating α_{loss} and α_{gain} along with β and λ.

To compare PT^3 and prospect theory specifications with a constant reference point, we estimated value function parameters using farmers' stated WTP and the revenue guarantee of the baseline insurance policy as a constant reference point. Parameters were similarly estimated by nonlinear least squares methods, as in equation (26), but defining

$$z_{nci}\equiv f_{nci}-h_{n75}$$

where h_{n75} is the revenue guarantee of the 75% coverage policy (the same value in all possible states of nature). We estimated parameters with the same model specifications used to test PT^3 (estimating α,β, and λ, then omitting the probability weighting function, setting $\lambda=1$, allowing α to differ in the gain and loss domains).

Results

Summary statistics

A total of 612 surveys were completed, with 43% of respondents operating farms in Michigan and 57% in Iowa. Summary statistics for survey respondents are presented in Table 2 below. Participants had been farming for over 34 years, on average. The mean farm size was just under 960 acres, with the majority of participants growing corn and soy in the past year. Over 80% of respondents had purchased insurance in the past five years, and almost 70% had made an insurance claim in the same time period. In addition to MPCI, farmers used a variety of other risk management tools in their farm operations, as reported in Table 3. The most popular of these, employed by over 78% of respondents, was agriculture risk and price loss coverage (ARC and PLC, respectively), followed by forward and minimum price contracts (used by over 69%). Named peril insurance (e.g. hail insurance), was the third most popular of these other strategies, with approximately 60% of farmers reporting use. The others, in order of frequency, were the use of risk-mitigating technologies, such as drainage tile and other physical investments, futures and options markets, and supplemental coverage option (SCO).

Valuation of changes in coverage level

Average WTA and WTP for alternative coverage level policies, compared to the baseline policy with 75% revenue coverage, are plotted against changes in fair premium in Figure 2. The 45° line indicates the change in fair premium, which should be the amount that farmers are willing to pay/accept for an increase/decrease in coverage level if they are risk-averse expected utility maximizers. As the figure shows, farmers' mean WTA for decreases in coverage level are closer to the change in fair premium than their mean WTP for increases, suggesting that the farmers value gains less than corresponding losses in coverage level. Table 4 shows the mean WTA and WTP responses for the different coverage level policies.

Farmers' sensitivity to decreases in coverage level is more formally demonstrated with a regression of their WTA and WTP responses on expected losses and expected gains of the alternative insurance policies. As shown in Table 5, the larger coefficient on expected losses indicates that expected losses have more impact on farmers' stated WTA than expected gains have on their WTP. This behaviour is consistent with prospect theory, providing motivation for exploring valuation of changes to crop insurance coverage level through this theoretical framework.

Prospect theory parameter estimation

Results for PT^3 parameters estimates are presented in Table 6. The parameter estimates provide support for third generation prospect theory, with estimated parameter values consistent with risk aversion and loss aversion. Our statistically significant estimates of α , β , and λ (0.166, 0.444, and 1.646, respectively) denote significant risk aversion and probability weighting, and moderate loss aversion through the loss aversion parameter. Figure 3 shows the probability weighting function with a value of β set equal to 0.444. As shown in this figure, this value of β denotes considerable weighting of probabilities, with events with probabilities of approximately 0.25 and less given more weight than the actual probability that they would occur, and those with probabilities over 0.25 underweighted.

These values differ from the parameters estimated by Kahneman and Tversky (1979), which are often used as benchmark values in discussions of prospect theory. Their seminal paper estimated α of 0.88, β of 0.69, and λ of 2.25. These values denote moderate risk aversion, probability weighting, and loss aversion, respectively. The prospect theory parameters estimated by Liu (2013), ($\alpha = 0.48$, $\beta = 0.69$ and $\lambda = 3.47$) and Bocquého et al. (2013) ($\alpha = 0.51$, $\beta = 0.65$ and $\lambda = 3.76$) are similar to those in Kahneman and Tversky (1979). The studies by Liu (2013) and Bocquého et al. (2013) estimated prospect theory parameters among agricultural producers in China and France, respectively. Our estimated parameters are consistent with the qualitative conclusions of other estimates (risk aversion, probability weighting, and loss aversion) but our parameter estimates differ from those in previous work, suggesting a higher degree of risk aversion and probability weighting, and lower loss aversion from the loss aversion parameter.

We also estimated the PT^3 parameters with alternative model specifications, as outlined above. When β was set to one (no probability weighting), the estimates for α and λ are inconsistent with prospect theory. The estimated value of α of 0 suggests extreme risk aversion, such that agents would not be willing to taking on any risk. Additionally, the estimated value of λ of over 9 implies extreme loss aversion not observed in other prospect theory studies. This model specification therefore does not seem to be a good fit for our data.

The third column of Table 6 present the parameters estimated when λ was set to 1 (so that any loss aversion is a result solely of the probability weighting parameter β). The estimates of α and β are much closer to those estimated in previous prospect theory studies. The values of these parameter estimates suggest significant risk aversion and probability weighting, with an estimated value of α of 0.198 and an estimated β of 0.444, both significantly different from zero.

The fourth specification of the model estimated β and λ as before, but allowed for different values of α in the gain and loss domains of the value function. This estimation resulted in similar parameter values for α in the gain domain and β as in other models, but the estimates of α in the loss domain and λ were not statistically significant. The final model specification estimated α in the gain and loss domains as well as β, with λ set equal to one. The estimated values of α were 0.164 in the gain domain and 0.300 in the loss domain (both statistically significant), suggesting more risk aversion in the gain domain than risk seeking in the loss domain (a steeper curve over gains than losses). The estimated value of β is similar to that in the previous specifications.

Parameter estimates for prospect theory with the revenue guarantee of the 75% coverage policy (a constant reference point) are presented in Table 7. When the three value function parameters were estimated, the estimated value of α was not statistically significant from zero. The value of β, 0.312, was similar to the PT^3 parameter estimates and statistically significant. The estimated value of λ, however, denoted a higher level of loss aversion than PT^3, with a value of over 4. When we estimated different values of α in the gain and loss domains, we obtained similar results, with α not statistically different from zero in either domain. In this model specification, the value of β was no longer statistically significant, and the estimate of λ was consistent with the previous specification. When we set $\lambda = 1$ and estimated different values of α in the gain and loss domains as well as β, the parameter estimates were similar to those of PT^3, with estimated values of α_{gain} of 0.167, α_{loss} of 0.274, and β of 0.444, all statistically different from zero.

A comparison of the parameters estimated using the PT^3 and prospect theory model specifications suggest that PT^3 is more suitable than the model that compares uncertain prospects to a certain reference point. With the exception of the last model specification that estimated $\alpha_{gain}, \alpha_{loss}$ and β (i.e. when λ was set to 1), the estimates of α were not different from zero when a constant reference point was used (see Table 7). The estimated values of β are statistically significantly different from zero in some model specifications, but not all. The estimated values of λ are statistically significant and do denote a considerable degree of loss aversion. In contrast, the estimates for α and β are statistically significant in all model specifications and consistent across the different PT^3 models tested (see Table 6). The PT^3 parameter estimates are consistent with risk and loss aversion and are consistent with parameter values estimated in other studies (see Bocquého et al., 2014). We therefore suggest that PT^3 is a suitable framework through which to analyse farmers' valuation of crop insurance coverage levels.

Potential Policy Implications

Our parameter estimates suggest that third generation prospect theory can be used as a theoretical framework through which to examine farmers' crop insurance choices. In this section, we use the parameters estimated in the previous section to explore what this theoretical framework predicts about farmers' crop insurance purchases and the implications of proposed changes to policy premiums. Federal budget proposals include significant cuts to crop insurance subsidies, decreasing the average subsidy rate from 62% to 48%. This would result in increases in farmers' out of pocket premiums. It is not known to what extent these premium increases will change farmers' crop insurance choices.

To explore the potential ramifications of cuts to premium subsidies, we use the same hypothetical revenue distribution used in our WTP scenarios. We use parameters estimated from farmers' WTP and WTA responses (α =0.166, β 0.444, and λ =1.646), and calculate policy values according to (21). We first examine the scenario with no insurance as a baseline, determining the optimal coverage level (i.e., the one that maximizes the farmer's value function) as if he was making an initial insurance purchase under the current subsidy regime. We then use a baseline policy with 75% revenue coverage to explore whether an alternate coverage level would be valued more highly from this baseline insurance policy, again using current subsidy levels. Finally, we examine how proposed subsidy cuts might affect farmers' insurance purchasing behaviour under third generation prospect theory.

While the average crop insurance subsidy rate is 62%, policies that offer different coverage levels are subsidised at different rates. Policies that cover catastrophic losses (referred to CAT insurance policies, covering 50% of yield losses at 55% of the prevailing commodity price) are completely subsidised by the federal government. The rate of subsidisation decreases as the coverage level increases, with optional and basic unit policies offering 85% coverage subsidised at 38% (Du et al., 2016). We base our analysis on the current subsidy rates of optional and basic units, as the mean subsidy rate for these policies is 62%. (This differs from the mean subsidy rate for enterprise unit policies, which is currently 75% (Du et al., 2016)).

The valuation of crop insurance policies under PT^3 with uninsured revenue as the reference point are presented in the first column of Table 8. Although all the policy values are negative, indicating that remaining uninsured is the individually optimal choice under PT^3, the policy that has the highest valuation provides 75% revenue coverage. When we examine values of policies with varying coverage levels, using the 75% coverage as a baseline, we see that retaining the 75% coverage policy is still the policy with the highest value, as the value of policies with higher and lower coverage levels are all negative. This indicates that with this revenue distribution and current policy subsidy rates, farmers with a revenue insurance policy with 75% coverage should not make any changes to their coverage level under PT^3.

The proposed cuts to federal crop insurance subsidies does not specify whether the subsidies of all policies will be cut by the same proportion, only that average subsidies would be cut to 48% from 62%. To explore the changes in insurance policy values under PT^3, we reduced each subsidy level by 14%. Using these subsidy levels, we calculated the value of alternative coverage levels using a 75% policy subsidised at 55% (the current subsidy rate) as the reference point. As shown in the third column of the Table 8, in this scenario the 75% policy has the lowest value. The policy with the highest valuation is the 50% coverage level policy, indicating that farmers would optimize their value function by switching from 75% coverage to 50% coverage under PT^3.

Although these calculated valuations are for a stylized revenue distribution, they can offer some insight into how farmers might choose among the policies available to them. If they value policies according to PT^3, farmers would consider their revenue in many states of nature rather than using a fixed reference point. Under third generation prospect theory, remaining uninsured is personally optimal, as all insurance policies have a negative valuation. This is at odds with the American farming population, as the overwhelming majority of farmers elect at least some level of coverage. However, we observe that the policy with the highest value offers 75% coverage. This is closer to farmers' actual insurance purchase behaviour than is predicted by expected utility theory, which predicts that farmers should choose the policy with the highest coverage level (Du et al., 2016).

When we suppose that farmers are valuing alternative coverage levels from a baseline 75% policy and current average premium subsidies, we observe that all alternative coverage levels have negative values. Using the proposed premium subsidy cuts, from the current average of 62% to 48%, we observe that keeping the 75% coverage policy results in the lowest valuation. Under PT^3 and the distribution used, farmers would be better off by switching to any alternative coverage level than keeping their baseline policy. A change to any alternative coverage level would result in a higher value than remaining at 75% coverage, but policies with lower coverage levels are more highly valued than those with coverage above 75%. While this issue and this particular framework should be studied in more detail, our analysis suggests that farmers would be better off reducing their coverage level when faced with the proposed premium increases.

Further discussion and conclusions

Recent work has shown that expected utility theory to be inconsistent with farmers' crop insurance purchases (Du et al., 2016). Prospect theory is often posed as an alternative framework with which to examine agents' risky decisions. This framework has been applied in a limited extent to agricultural production and in the context of crop insurance purchases specifically. Previous work has found support for prospect theory among agricultural producers, with prospect theory found to perform better than expected utility theory in experimental settings (Bocquého et al., 2014; Liu, 2013). Prospect theory has also been found to out-perform expected utility theory in explaining farmers' observed crop insurance choices (Babcock, 2015). However, previous explorations of farmers' behaviour through the lens of prospect theory have used model specifications with a constant reference point from which gains and losses are determined. As discussed in the introduction, this may not a realistic assumption in agricultural production.

In this paper, we examined the ability of third generation prospect theory to explain farmers' reported valuation of increases and decreases in crop insurance coverage levels. We chose PT^3 to more accurately model risk in the reference choice. Rather than defining gains and losses from a constant reference point, PT^3 determines gains and losses from a risky baseline on a state-by-state basis. Using WTA and WTP data from hypothetical crop insurance parameters, we estimated parameters of PT^3 value functions, exploring various model specifications. The parameter estimates are different from those typically used in the economic literature (those estimated in Kahneman and Tversky, 1979), but they do suggest risk and loss aversion, as well as a moderate degree of probability weighting. The parameter estimates of PT^3 were more consistent with other estimates of prospect theory parameters than those estimated using a constant reference point (the revenue guarantee of the 75% coverage insurance policy), suggesting that third generation prospect theory more accurately describes farmers' behaviour.

Our findings on prospect theory suggest that farmers are both risk and loss averse. They also suggest that farmers apply non-identity decision weights rather than evaluating probabilities as given. Both of these results are consistent with traditional conceptualizations of prospect theory. However, our findings in support of PT^3 also suggest that farmers do not determine a loss from a single reference point as posited by prospect theory and cumulative prospect theory, and that considering losses on a state-by-state basis may be more suitable. While farmers may not consider eight potential states in their on-farm decision making as in our stylized crop insurance scenarios, they may consider more than one state (e.g., significant losses, outcomes that are approximately average, and above average yields) when comparing their current crop insurance contracts to alternatives available to them.

When looking at policy valuations under PT^3, we find that among the different coverage levels, the policy offering a 75% revenue guarantee is valued most highly. From the baseline 75% insurance policy, farmers' optimal policy choice remains unchanged, such that the value of every other coverage level is negative. Exploring the impact of proposed subsidy cuts, we find that the 75% coverage policy has the lowest valuation, indicating that farmers would be better off switching to any alternative coverage level, but that reducing coverage would be personally optimal.

Examining how farmers value crop insurance policies is important in understanding how they may respond to changes in crop insurance policies. Changes to federal agricultural funding have recently been proposed; these changes include significant reductions in crop insurance subsidy rates. These changes would cause potentially significant increases in the out-of-pocket premiums faced by farmers. It is important to study how farmers will respond to potential changes in their insurance premiums. Because of the current extent of crop insurance uptake (i.e.

the majority of corn and soybean farmers already insure their acres with federally-subsidised crop insurance policies) it is important to consider farmers' valuation of changes to their policies from a baseline insurance policy, as with prospect theory.

Increases in crop insurance premiums are likely to impact farmers' decisions to insure their planted acres, and the coverage levels they choose. These choices may have downstream impacts on agricultural production in the United States which should be considered. Previous analyses on crop insurance subsidies have found that lower insurance premiums (through high subsidies) influence farmers' production practices and acreage decisions (Goodwin and Smith, 2013). While not all effects of crop insurance subsidies are positive (for example, farmers may convert marginal land for crop production, with negative environmental consequences (Miao et al. (2016)), how farmers will react to higher premiums, and the resulting impacts on domestic agricultural production should certainly be considered.

Consequences of crop insurance subsidy cuts may include farmers no longer electing to insure their acres or purchasing policies with lower coverage levels. Crop insurance subsidies were initially introduced in an effort to promote uptake and reduce government disaster payments. These goals were generally achieved. How producers react to proposed decreases in insurance uptake and coverage levels should be considered in terms of their impacts on government outlays to compensate farmers in the event of catastrophic losses, especially since subsidy reductions are largely framed as decreasing federal spending on agricultural programs.

In our crop insurance scenarios in this analysis, we chose a revenue insurance policy with 75% coverage as a baseline policy, and eight possible states of nature. Further explorations into PT^3 could examine how farmers respond to different distributions and different baseline reference points, and the framing of the possible states of nature. These analyses could provide a more comprehensive picture of how farmers value crop insurance policies, and how they may react to future changes in the crop insurance products available to them.

Tables and figures

Table 1. Changes in revenue guarantee and probability of payment from baseline crop insurance policy (75% coverage).

Variable			Baseline		
Coverage level	65%	70%	75%	80%	85%
Revenue guarantee	$393	$424	$454	$484	$514
Change in revenue guarantee from baseline policy (per acre)	-$61	-$30	-	+$30	+$30
Change in expected revenue from baseline policy (with no change in policy premium, per acre)	-$8.93	-$5.90	-	+$6.05	+$13.52
Probability of making a claim	0.10	0.10	0.20	0.20	0.30

Table 2. Summary statistics of survey respondents.

Variable	Mean	Median	SD	N
Number of years farming	34.2	36	12.7	603
Acres farmed	959	689.5	910.0	606
Corn acres	451.6	300.0	497.6	572
Soy acres	364.8	250	349.1	561
Purchased MPCI 2011-2015	80.2%	-	-	606
Received indemnity payment 2011-2015	69.3%	-	-	475

Table 3. Proportion of farmers reporting use of other risk management strategies, by risk management tool.

Risk management tool	Proportion Using
ACR/PLC	78.3%
Forward and minimum price contracts	69.4%
Named peril insurance	60.5%
Technologies	56.4%
Futures and option markets	36.6%
Other	7.8%
SCO	6.3%

Table 4. Mean hypothetical WTA and WTP for changes in coverage level from baseline 75% coverage.

	-10% (-$8.89)	-5% (-$5.90)	+5% (+$6.05)	+10% (+$13.53)
Mean response	-9.31	-8.39	4.69	7.04

Table 5. Impacts expected loss and expected gain on WTA and WTP (linear RE and FE regression)

	WTA/WTP	
	RE	FE
E[loss]	1.165 ***	1.166***
E[gain]	0.558***	0.556 ***
Constant	0.108	0.117

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. PT^3 parameter estimates for various model specifications.

	1	2	3	4	5
α				0.168***	0.164***
(gain domain)	0.166***	0	0.198***	(0.010)	(0.010)
α				0.056	0.300***
(loss domain)	(0.010)		(0.010)	(0.066)	(0.007)
β	0.444***	1 (by construction)	0.440***	0.443***	0.444***
	(0.011)		(0.006)	(0.011)	(0.011)
λ	1.646***	9.182	1 (by construction)	2.470	1 (by construction)
	0.036			(0.594)	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Prospect theory parameter estimates, revenue guarantee of the 75% coverage policy used as the reference point

	1	2	3	4	5
α				0.000	0.167***
(gain domain)	0.000		0.000	(0.020)	(0.010)
α				0.000	0.274***
(loss domain)	(0.019)			(0.081)	(0.006)
β	0.312***	1 (by construction)	0.000	0.312	0.444***
	(0.014)			(1.359)	(0.011)
λ	4.130***		1 (by construction)	4.130***	1 (by construction)
	(0.067)			(0.081	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Crop insurance policy valuations under PT^3, with various reference points, using estimated parameter values ($\alpha = 0.166, \lambda = 1.646, \beta = 0.444$).

	Reference point		
	No insurance	75% coverage	
		Current average subsidy level	Proposed average subsidy level
85%	-6.09	-0.97	-1.67
80%	-5.91	-1.39	-1.63
75%	-5.40	0	-3.05
70%	-8.40	-0.16	-0.32
65%	-8.00	-0.20	-0.28
60%	-7.32	-0.20	-0.23
55%	-9.64	-0.21	-0.22
50%	-8.38	-0.21	-0.21

Figure 1. Hypothetical revenue distribution shown to farmers.

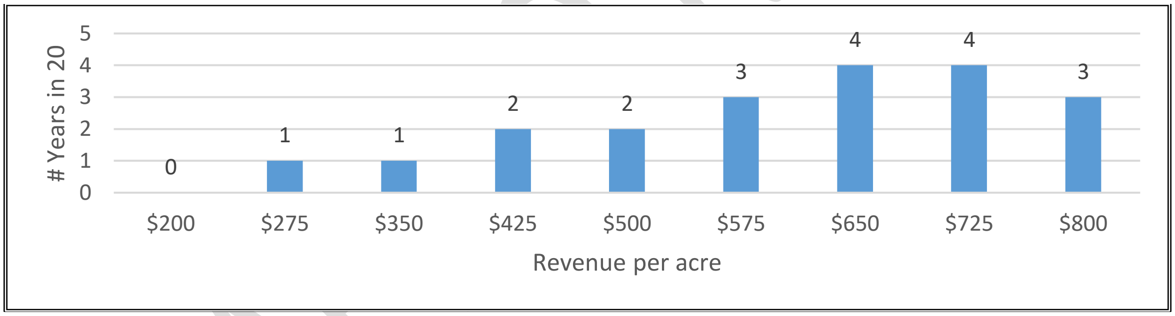


Figure 2. Plot of mean responses (WTA and WTP) and change in fair premium.

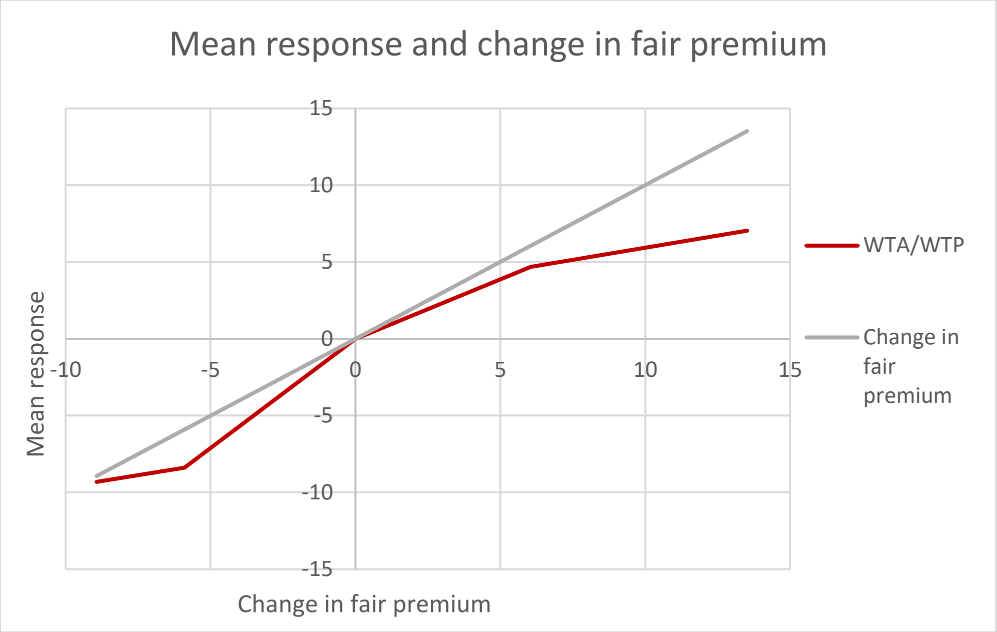
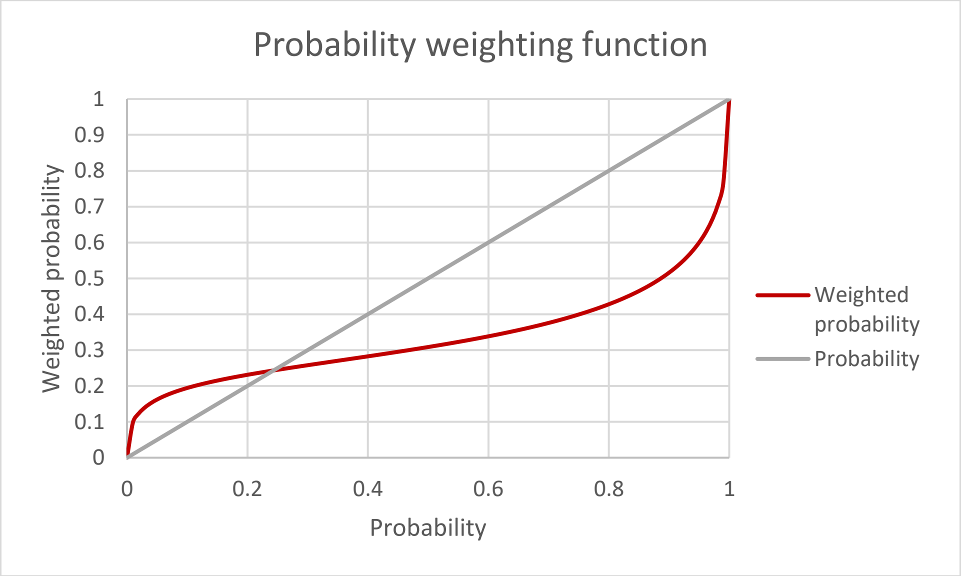


Figure 3. Probability weighting function with $\beta = 0.444$



References

Babcock, B.A. 2015. Using cumulative prospect theory to explain anomalous crop insurance coverage choice. *American Journal of Agricultural Economics* 97(5): 1371-1384.

Barberis, N.C., 2013. Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives* 27(1): 173-96.

Barseghyan, L., Molinari, F., O'Donoghue, T. and Teitelbaum, J.C., 2013. The nature of risk preferences: Evidence from insurance choices. *American Economic Review* 103(6): 2499-2529.

Bocquého, G., Jacquet, F. and Reynaud, A. 2014. Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field experiment data. *European Review of Agricultural Economics* 41(1): 135-172.

Brown, T.C., and Gregory, R. 1999. Why the WTP-WTA disparity matters. *Ecological Economics* 28(3): 323-332.

Congressional Budget Office (CBO). 2016. Options for Reducing the Deficit: 2017 to 2026 Reduce Subsidies in the Crop Insurance Program. Retrieved from https://www.cbo.gov/budget-options/2016/52167.

Du, X., Feng, H. and Hennessy, D. A. 2016. Rationality of choices in subsidized crop insurance markets. *American Journal of Agricultural Economics* 99(3): 732-756.

Glauber, J. W. 2013. The growth of the federal crop insurance program, 1990-2011. *American Journal of Agricultural Economics* 95 (2): 482–88.

Goodwin, B. K., and Smith, V.H. 2013. What harm is done by subsidizing crop insurance? *American Journal of Agricultural Economics* 95 (2): 489–97.

Harrison, G.W. and Rutström, E.E., 2009. Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics* 12(2): 133-158.

Harrison, G.W. and Swarthout, J.T., 2016. Cumulative prospect theory in the laboratory: A reconsideration. *Center for the Economic Analysis of Risk, Working Paper, 2.*

Holt, C. A., and Laury, S.K. 2002. Risk aversion and incentive effects. *American Economic Review* 92(5): 1644-1655.

Horowitz, J.K., and McConnell, K.E. 2003. A review of WTA/WTP studies. *Journal of Environmental Economics and Management* 44(3): 426-447.

Kahneman, D., and Tversky, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47(2): 263-292.

Kőszegi, B. and Rabin, M., 2006. A model of reference-dependent preferences. *The Quarterly Journal of Economics* 121(4): 1133-1165.

Liu, E.M. 2013. Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics* 95(4):1386-1403.

Miao, R., Hennessy, D.A., and Feng, H. 2016. The Effects of Crop Insurance Subsidies and Sodsaver on Land-Use Change. *Journal of Agricultural and Resource Economics*, 41(2): 247-65.

Novemsky, N. and Kahneman, D. 2005. The boundaries of loss aversion. *Journal of Marketing Research* 42(2): 119-128.

O'Donoghue, E.J. 2014. The Effects of Premium Subsidies on Demand for Crop Insurance. ERR-169, U.S. Department of Agriculture, Economic Research Service.

Office of Management and Budget, 2017. A New Foundation for American Greatness, Budget of the US Government Fiscal Year 2018. Accessed from https://www.whitehouse.gov/omb/budget

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

Risk Management Agency. 2017. "The Risk Management Safety Net: Market Penetration and Market Potential." September 2017.

Schmidt, U., Starmer, C., and Sugden, R. 2008. Third-generation prospect theory. *Journal of Risk and Uncertainty* 36(3): 203-223.

Schmidt, U. 2016. Insurance demand under prospect theory: a graphical analysis. *Journal of Risk and Uncertainty* 83(1): 77-89.

Shields, D.A. 2013. Federal crop insurance: Background. R40532. Congressional Research Service.

Sugden, R. 2003. Reference dependent subjective expected utility. *Journal of Economic Theory* 111(2): 172-191.

Sydnor, J. 2010. (Over)insuring Modest Risks. *American Economic Journal: Applied Economics* 2(4): 177-199.

Tanaka, T., Camerer, C.F. and Nguyen, Q., 2010. Risk and time preferences: linking experimental and household survey data from Vietnam. *American Economic Review* 100(1): 557-71.

Tunçel, T. and Hammitt, J.K. 2014. A new meta-analysis on the WTP/WTA disparity. *Journal of Environmental Economics and Management* 68(1): 175-187.

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

Zulauf, C., Schnitkey, G., Coppess, J., and Paulson, N. 2018. Premium subsidy and insured U.S. acres. *farmdoc daily* (8):46, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, March 15, 2018. Retrieved from http://farmdocdaily.illinois.edu/2018/03/premium-subsidy-and-insured-us-acres.html