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Abstract

A growing number of studies in finance and economics seek to explain insurance choices using the assumptions advanced by behavioral economics. One recent example in agricultural economics is the use of cumulative prospect theory (CPT) to explain farmer choices regarding crop insurance coverage levels (Babcock, 2015). We build upon this framework by deriving willingness to pay (WTP) for insurance programs under alternative assumptions, thus extending the model to incorporate farmer decisions regarding whether or not to purchase insurance. Our contribution is twofold. First, we study the sensitivity of farmer WTP for crop insurance to the inclusion of CPT parameters. We find that loss aversion and probability distortion increase WTP for insurance while risk aversion decreases it. Probability distortion in losses plays a particularly important role. Second, we study the impact of yield distribution skewness on farmer WTP assuming CPT preferences. We find that WTP decreases when the distribution of yields moves from negatively- to positively-skewed and that the combined effect of probability weighting in losses and skewness has a large negative impact on farmer WTP for crop insurance.

Keywords: Crop Insurance; Cumulative Prospect Theory; Premium subsidy; Skewness;

JEL classification: D81, Q10, Q12, Q18

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1. Introduction

A growing literature in finance and economics attempts to explain insurance choices using behavioral economic assumptions. Barberis (2013b) provides a comprehensive review of advances in the application of cumulative prospect theory (CPT). CPT preferences are characterized by four parameters (Tversky and Kahneman, 1992). *Reference dependence* refers to the fact that people derive utility from gains and losses relative to some reference point rather than from absolute levels of wealth. For *loss averse* individuals, losses loom larger than gains. *Preference reversal* implies that individuals are risk averse in gains and risk seeking in losses. *Decision weighting* implies overweighting of small probabilities and underweighting of large probabilities. In the field of insurance, CPT helps to explain phenomena such as the purchase of low deductible insurance plans (Sydnor, 2010), of home and automobile insurance plans (Barseghyan *et al.*, 2013) and the unattractiveness of annuities (Hu and Scott, 2007). In agricultural economics, while the vast majority of previous work has used the standard expected utility theory (EUT) framework (see for instance Du *et al.* (2017) for one of the latest research in this realm), one recent example uses CPT to explain observed choices regarding crop insurance coverage levels among U.S. farmers, conditional on the purchase of insurance (Babcock, 2015). We aim to study CPT preferences as determinants of farmer decisions to insure, especially under alternative assumptions about the distribution of crop yields. Although several recent studies have experimentally elicited CPT preferences (Bocquého *et al.*, 2014; Bougherara *et al.*, 2017), eliciting these preferences among farmers remains a challenge. We therefore employ simulation, which is particularly useful when estimating the impact of unobservable determinants such as risk preferences.

We use a framework similar to that used by Babcock, which we extend in order to model the choice regarding whether or not to insure. Our objective is twofold. First, we aim to study the impact of CPT parameters, in particular loss aversion and probability weighting, on the decision to insure. To do so, we compute farmer willingness to pay (WTP) for insurance and extend the preference scenarios investigated by Babcock by undertaking a systematic sensitivity analysis. We find that loss aversion and probability distortion both increase the incentive to insure, while risk aversion decreases this incentive. In particular, we find evidence that probability distortion in losses plays a significant role in determining WTP. Second, we aim to determine the impact of skewness in the distribution of yields on farmer WTP for insurance as a function of CPT parameters. Indeed, since the 90s, agricultural economists have recognized the impact of crop yield distributional assumptions on the calculation of insurance premiums (Nelson, 1990; Coble *et al.*, 1996). However, these analyses model preferences using the assumptions of EUT. We argue that distributional assumptions matter all the more in a CPT framework. In finance, for example, some studies have considered the impact of asset skewness on pricing in a CPT framework (Barberis and Huang, 2008; Ågren, 2006). To the best of our knowledge, the impact of such distributional assumptions in a CPT framework has not yet been considered in the realm of agricultural economics. Our results indicate that WTP decreases when the yield distribution moves from negatively- to positively-skewed and that the combined effect of probability weighting in losses and skewness has a large negative impact on the decision to insure.

Our paper is organized as follows. Section 2 introduces our modeling and simulation framework. In section 3, we study farmer insurance decisions when they are assumed to have EUT preferences vs. CPT preferences and carry out a sensitivity analysis on these results. In section 4, we examine the impact of yield skewness on the insurance choices of farmers with CPT preferences. Section 5 concludes.

2. Modeling the farmer's decision to insure

In this section, we introduce our model (section 2.1) and the parametrization we use in our simulations (section 2.2).

2.1. The model

In this paper, we use Babcock's insurance modeling framework and, for the sake of clarity and brevity, focus solely on corn[1]. Considering a representative corn farm that is assumed to purchase revenue insurance, let y and P, respectively, denote the stochastic farm yield and harvest-period futures price distributed according to the joint distribution function $F(y, P)$, with $0 < y < b$ and $0 < P < \infty$. The initial per-acre revenue guarantee is expressed as a fraction, α, of the product of expected yield and expected price: $R_g = \alpha.E(P).E(y)$ where expectations are taken at the time the insurance contract is signed. Farmer and insurance company expectations are assumed to be identical. Each level of coverage α is associated with a corresponding proportionate premium subsidy rate $s(\alpha)$.

The per-acre premium subsidy therefore depends on both the coverage level and the premium level: $S(\alpha) = s(\alpha)\rho(\alpha)$ where ρ is the unsubsidized premium, which is assumed through-

[1]Babcock analyses three different crops (corn, wheat and cotton) in three different US counties.

out to be set at actuarially fair levels. The producer premium or subsidized premium equals $\rho_p(\alpha) = \rho(\alpha).(1 - s(\alpha))$. Therefore the expected per-acre subsidy for buying insurance simply equals the premium subsidy $S(\alpha)$. The type of revenue insurance purchased by almost all farmers increases the level of the revenue guarantee if the actual price at harvest is greater than the expected price. The indemnity function is thus $I = max[\alpha.E(y).max(E(P), P) - Py, 0]$, and $\rho(\alpha) = \int_0^b \int_0^\infty I \, \mathrm{d}F(y, P)$ where $\mathrm{d}F(y, P)$ is the joint distribution function of price and yield.

Farmers are assumed to have preferences as described by CPT (Tversky and Kahneman, 1992). Each farmer values a risky prospect that can take on $m + n$ discrete values, x_i, each with an associated probability, p_i. The total value of the risky prospect is then the weighted average value of the x_i's, which writes:

$$V = \sum_{i=m}^{n} v(x_i)\pi(p_i) \tag{1}$$

where $\pi(p_i)$ translates a probability to a decision weight and $v(0) = 0$.

Functional forms for the value function $v(.)$ and the decision weighting functions $\pi(.)$ are given by:

$$v(x) = \begin{cases} x^a & \text{if} \quad x \geq 0 \\ -\lambda.(-x)^a & \text{if} \quad x < 0 \end{cases} \tag{2}$$

$$\begin{cases} w^+(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{1/\gamma}} \\ w^-(p) = \frac{p^\delta}{[p^\delta + (1-p)^\delta]^{1/\delta}} \end{cases} \tag{3}$$

where a is the concavity of the value function and λ is a loss aversion parameter. γ and δ are parameters of the probability weighting functions.

The x_i values in Eq. 1 are sorted from smallest to largest where m values are negative losses and n values are positive gains. These values do not represent absolute levels of income or wealth, but rather changes in income or wealth from an initial reference point. Thus no change means that $x_i = 0$.

We depart from Babcock by considering the reference point R' defined in Eq. 4 and the associated gain or loss for the *ith* realization of price, yield and indemnity, where the crop revenue is defined as $R = P_i.y_i$:

$$R' = E(R) \text{ with } x_i = P_i.y_i + I_i - \rho(\alpha)(1 - s(\alpha)) - R' \tag{4}$$

R' is equivalent to Babcock's first reference point $R_1 = E(R)+\rho(\alpha)(1-s(\alpha))$ with $x_i = P_i.y_i+I_i-R_1$. It is also equivalent to Babcock's second reference point $R_2 = E(R)$ with $x_i = P_i.y_i + I_i - R_2$, assuming the subsidized premium is not a sunk cost.

Assuming that farmers do buy insurance, Babcock seeks to determine the optimal level of crop insurance coverage α under cumulative prospect theory, i.e. the level that maximizes the expected value of crop revenue under CPT assumptions (Eq. 1). He considers three representative farms (producing corn, wheat and cotton) in three US counties (York, NE, Sumner, KS, and Lubbock, TX, respectively) and uses observed data to calibrate the model (see Babcock, 2015: Table 2). Premium rates are then simulated by drawing yields and prices from calibrated distributions. In turn, these rates are then used to compute values of the value function (Eq. 1) in order to find the maximum. Like Babcock, we compute certainty equivalent returns expressed in \$/ac rather than presenting results in the value function space. From here, however, our modeling approach differs from Babcock in that we extend the model to incorporate the farmer's decision whether or not to insure.

Miranda (1991), Smith *et al.* (1994) and Skees *et al.* (1997) assumed that farmers seek insurance coverage in order to minimize the variance of their net yield or, equivalently, to maximize their yield risk reduction, as measured by the difference between the variance of the yield and the variance of the net yield. In contrast, Mahul (1999) and Bourgeon and Chambers (2003) assumed that farmers seek insurance in order to maximize the expected utility stemming from their net yield. We adopt a third approach, which is also based on (expected) utility maximization, but assumes that the maximization process consists of a lottery choice. In this framework, each farmer faces the following two lotteries:

- *'Insurance lottery'*: if the farmer purchases insurance, he[2] pays a premium and expects to receive a non-zero indemnity whenever he suffers an insured loss. The outcome he expects is $x_i^{insured} = P_i.y_i + I_i - \rho_p(\alpha) - E(R)$
- *'Non-insurance lottery'*: if the farmer does not purchase the insurance, the outcome he

[2] As is common practice in the principal/agent literature, throughout the paper, we will refer to the insurer as "she" and to the farmer as "he".

expects is $x_i^{noninsured} = P_i.y_i - E(R)$

Following Eq. 1, the expected values of the above lotteries are given by $V^{insured}$ and $V^{noninsured}$. In this framework, farmer i will decide to purchase insurance as long as the 'insurance lottery' provides him with an expected value greater than or at least equal to the 'non-insurance lottery'. Eq. 5 gives the farmer decision rule, where the dummy variable d_i equals one if farmer i decides to buy insurance:

$$d_i = 1 \quad \Leftrightarrow \quad \mathrm{E}\big(V^{insured}(\rho_p)\big) \geq \mathrm{E}\big(V^{noninsured}(\rho_p)\big) \tag{5}$$

which may be rewritten as:

$$d_i \times \big(\mathrm{E}\big(V^{insured}(\rho_p)\big) - \mathrm{E}\big(V^{noninsured}(\rho_p)\big)\big) \geq 0 \tag{6}$$

For each farmer, we can then find the threshold subsidized premium ρ^* that leaves him indifferent between both lotteries ($i.e.$, $V^{insured}(\rho^*) = V^{noninsured}(\rho^*)$). The threshold subsidized premium can be understood as the highest premium that ensures that Eq. 6 holds when $d_i = 1$, or alternatively, as his willingness to pay (WTP) for transferring the risk to the insurer.

We aim to explain farmer WTP for insurance as a function of CPT parameters. As developed by Babcock (pp.1373-1374), the convexity of the value function in losses creates a disincentive for farmers to insure. This convexity in losses must be offset either by loss aversion (avoiding a loss is valued more than obtaining a corresponding gain) or probability distortion (overweighting of low probability events) in order for farmers to be willing to insure. This is why we expect WTP to increase with loss aversion (for $\lambda > 1$) and with probability distortion (for $\gamma < 1$ and $\delta < 1$). As for risk aversion (a), two opposing effects are at play. WTP is expected to increase with risk aversion in gains, but decrease with risk seeking in losses, making it impossible to predict the net impact of these effects beforehand.

2.2. Data and parametrization

We use the same data as Babcock, focusing exclusively on corn (see Babcock: second column of Table 1, p.1375): the expected yield is 190 bu/ac and the expected price is \$4.40/bu; there is no price-yield correlation; yields are assumed to follow a Beta distribution (min=0, max=250, shape1=9.340, shape2=2.949) and price is assumed to follow a log-normal distribution with parameters $\mu = 1.417$ and $\sigma = 0.358$.[3] The coverage level α takes on discrete values ranging from 0.5 to 0.85 in 0.05 increments. Each level of α is associated with a corresponding proportionate premium subsidy rate s as follows: $[\alpha = 0.5; s = 0.67]$; $[\alpha = 0.55, 0.60; s = 0.64]$; $[\alpha = 0.65, 0.70; s = 0.59]$; $[\alpha = 0.75; s = 0.55]$; $[\alpha = 0.8; s = 0.48]$; and $[\alpha = 0.85; s = 0.38]$.

Like Babcock, the analyses reported in section 3 are obtained by drawing 5,000 Beta yields and log-normal prices to simulate the distribution of possible revenues and deriving the variables required to implement the modeling strategy described in the previous subsection.[4]

In section 4 we turn to an analysis of the impact of the yield distribution skewness on farmer decisions to insure, and thus proceed in a slightly different way. With respect to yields, we fix prices to their expected value, namely \$4.40/bu; thus, only yields are random. Second, the 5,000 yield draws are no longer obtained from Babcock's Beta distribution, but rather from a skew-normal distribution, chosen for its desirable properties as regards skewness parameterization.[5] A random variable Z is said to be skew-normal distributed with parameters ξ, ω and η if $Z \sim SN(\xi, \omega^2, \eta)$, where $SN(\xi, \omega^2, \eta) = 2\phi(\frac{Z-\xi}{\omega})\Phi(\eta\frac{Z-\xi}{\omega})$ with $\phi(.)$, and $\Phi(.)$ denoting the $N(0,1)$ density and cumulative distribution function, respectively (Azzalini, 2005, 2011).[6] In the definition of the skew-normal distribution, ξ is a location parameter, ω is a scale parameter and η is a shape parameter. The advantage of the skew-normal distribution over the Beta distribution for our analysis is that, as can be shown from Azzalini (2011), the SN-distribution skewness measure κ is fully determined by the shape parameter η since $\kappa = \frac{4-\pi}{2}\big(\frac{\eta\sqrt{2/\pi}}{\sqrt{1+\eta^2}}\big)^3\big(1 - \frac{2}{\pi}(\frac{\eta}{\sqrt{1+\eta^2}})^2\big)^{-3/2}$. Figure 1 shows that a skew-normal distribution can satisfactorily be adjusted to Babcock's Beta distribution as well as to the 5,000 empirical Beta-distributed draws used in section 3. Table 1 accordingly shows that the first three moments closely match for the three distributions we consider. In section 4, we therefore use skew-normal as the reference distribution from which yields are drawn and, in order to study the impact of skewness, we vary the shape parameter η while holding the location and scale parameters fixed at their estimated values, namely $\xi = 226$ and $\omega = 47.247$.

[3] These values are derived from Babcock's expected price (\$4.40/bu) and price volatility (37%) parameters.

[4] Although the purpose of this paper differs from that of Babcock, for control purposes, we replicate the results of Babcock's Table 3 and find similar results (see Table 6 in appendix). This exercise confirms that the specific draw for the empirical crop revenue distribution that we generate does not significantly differ from Babcock's.

[5] The skew-normal distribution has already been used in several strands of the economics literature (Ball and Mankiw, 1995; Chen *et al.*, 2014; Kim *et al.*, 2014; Peat *et al.*, 2014; Jochmans, 2017), notably to study insurance (Vernic, 2006; Bernardi *et al.*, 2012; Eling, 2012) and agricultural (Robbins and White, 2011) issues.

[6] Azzalini and Capitanio (1999, 2003) outline a method for generating skew-normal distributed random variates.

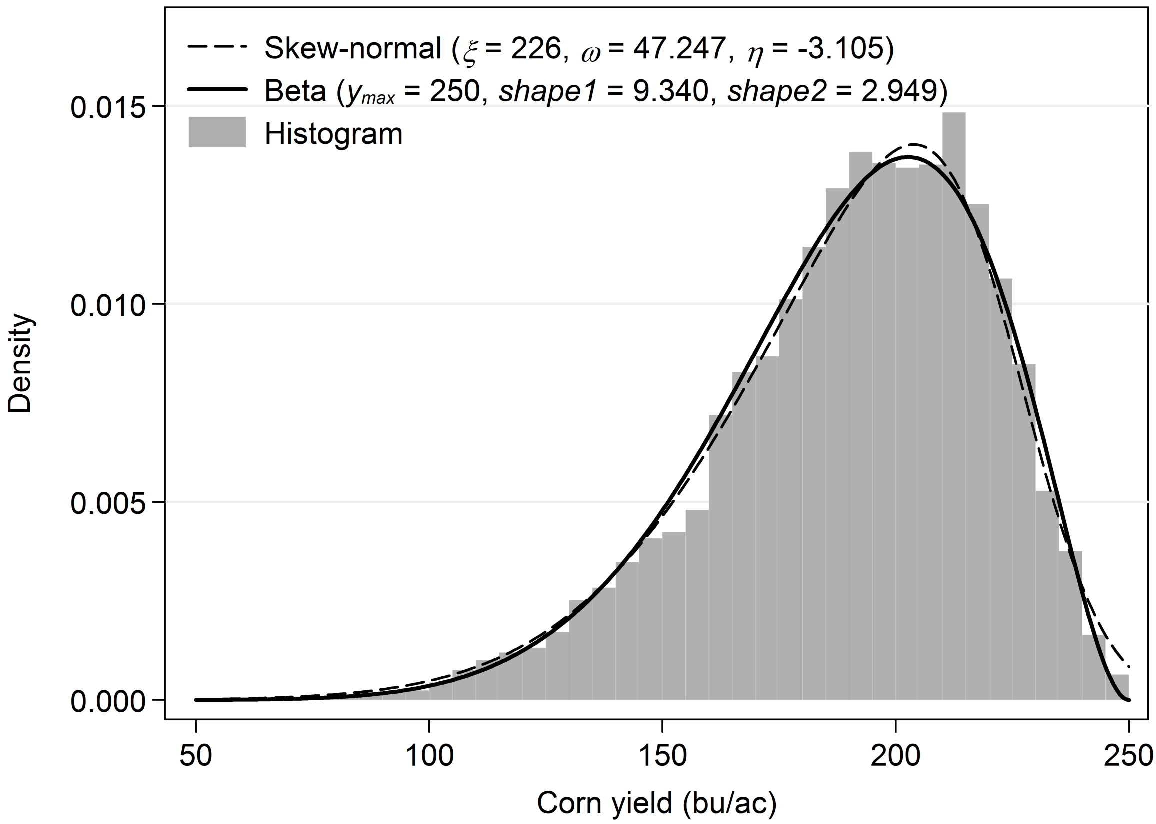

Figure 1. Superimposition of Babcock's Beta distribution, the histogram of the empirical 5,000 Beta-distributed yields used in section 3 and the adjusted skew-normal distribution used in section 4

Table 1. First Three Moments for Babcock's Beta Distribution, the Empirical 5,000 Beta-distributed Yields Used in Section 3 and the Adjusted Skew-normal Distribution used in Section 4

Distribution	Mean	St. dev.	Skewness
Babcock's Beta distribution (a)	190.01	29.29	-0.621
Section 3 empirical Beta-distributed draws	190.68	29.14	-0.686
Section 4 adjusted skew-normal distribution	190.04	30.74	-0.683

(a) The Beta distribution is defined by the parameters reported in Babcock: "Yield Parameters" section, second column of Table 1, p.1375.

3. Farmer Insurance choice with CPT vs. EUT preferences

Two issues are addressed in the following subsections. First, in section 3.1, we analyze the impact of computing farmer WTP for insurance using CPT preferences as compared with EUT preferences, assuming that the CPT preference parameter values are those presented in Tversky and Kahneman. Second, in section 3.2, we study the degree to which the decision to insure is sensitive to the chosen preference parameter values. Recall that, in section 3, Babcock's Beta distribution was used to randomly draw yields such that the theoretical yield distribution skewness is -0.621 and the empirical yield distribution skewness is -0.686 (see Table 1).

3.1. Comparing farmer WTP for insurance: EUT vs CPT using Tversky and Kahneman's parameter values

In this section, we aim to examine farmer decisions to buy crop insurance as a function of farmer preferences. Considering representative farmers and using the CPT framework to model their risk preferences, Babcock sought to explain observed choices for crop insurance coverage conditional on farmers actually buying insurance. We depart from this objective in that we model the decision whether or not to buy insurance by computing the farmer's WTP to insure.

We will now consider the farmer's decision to insure for each coverage level. Using the functional forms described by Tversky and Kahneman, we compute farmer willingness to purchase insurance under the alternative assumptions of CPT and EUT preferences. Results are presented in Table 2 as a function of coverage level α and the associated subsidy level s.

Table 2. Farmer Decisions to Insure Under Reference Point R' Defined in Eq. 4

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cov.	Subsidy	Premiums ($/ac)		CPT (a)			EUT (b)		
level	s	Unsubsidized	Subsidized	CER	WTP	Optimal	CER	WTP	Optimal
α		premium	premium	(c)		subsidy (d)	(c)		subsidy (d)
		ρ	ρ_p	($/ac)	($/ac)	s^*	($/ac)	($/ac)	s^*
0.85	0.38	84.01	52.08	-4.99	124.43	-0.48	6.49	69.83	0.17
0.80	0.48	63.36	32.95	-7.33	101,46	-0.60	7.49	52.17	0.18
0.75	0.55	46.23	20.80	-11.88	80.92	-0.75	5.80	37.68	0.19
0.70	0.59	32.41	13.29	-17.58	62.87	-0.94	3.13	26.15	0.19
0.65	0.59	21.68	8.89	-23.66	47.27	-1.18	0.54	17.30	0.20
0.60	0.64	13.83	4.98	-28.64	34.30	-1.48	-0.58	10.92	0.21
0.55	0.64	8.30	2.99	-33.32	23.78	-1.86	-1.93	6.49	0.22
0.50	0.67	4.60	1.52	-37.06	15.52	-2.37	-2.81	3.57	0.23

(a) Cumulative Prospect Theory with $\lambda = 2.25$, $a = 0.88$, $\gamma = 0.61$, $\delta = 0.69$; (b) Expected Utility Theory with $\lambda = 1$, $a = 0.88$, $\gamma = 1$, $\delta = 1$; (c) CER stands for Certainty Equivalent Return; (d) The optimal subsidy is defined as $1 - WTP/\rho$, that is, the subsidy rate required in order for WTP to equal the unsubsidized premium.

First, we replicate Babcock's results for the chosen parameters by computing the unsubsidized premiums (see column (1)), the subsidized premiums (see column (2)), and the corresponding certainty equivalent returns (see column (3)) under CPT preferences. We find similar levels of certainty equivalent return (see Babcock: p. 1379, Table 3, Column 1). Then, using the decision rule described in Eq. 6, we compute the farmer willingness to pay for insurance under each coverage level using Tversky and Kahneman's CPT preference parameter values. Results are presented in column (4) of Table 2. WTPs range from around $16/ac for a coverage level of 0.50 to around $124/ac for a coverage level of 0.85. These values are higher than the subsidized premium and even the unsubsidized premium for all coverage levels, indicating that farmers with CPT preferences choose to insure whatever the coverage level. We next compute the optimal subsidy (see column (5)), i.e. the subsidy rate necessary in order for WTP to equal the unsubsidized premium. Assuming Tversky and Kahneman's CPT preferences, we find negative optimal subsidies, indicating that farmers do not in fact require subsidies in order to buy insurance.

Result 1 *Using Tversky and Kahneman's CPT preference parameter values (*$\lambda = 2.25$*,* $a = 0.88$*,* $\gamma = 0.61$*,* $\delta = 0.69$*), farmers always purchase insurance whatever the coverage level. Under this assumption, therefore, farmers do not require subsidies in order to buy insurance.*

In the remaining columns of Table 2, we compute certainty equivalent returns (column (6)), willingness to pay for insurance (column (7)) and optimal subsidy rates (column (8)) assuming farmers have EUT preferences. We find that WTP values under the assumption of EUT preferences are much lower than those found under the assumption of CPT preferences, ranging between \$4/ac and \$70/ac. With EUT preferences, farmers are unwilling to purchase unsubsidized insurance, as also evidenced by the fact that the optimal subsidy rates are all positive. These rates are, however, small in absolute value compared to both the optimal CPT subsidy rate (column (5)) and the implemented subsidy rates s.

Finally, we compute the 'optimal' risk aversion a^* (see Table 3, column 3), that is, the values a required in order to justify the subsidy rates offered under the assumption of EUT preferences ($\lambda = 1$, a^*, $\gamma = 1$, $\delta = 1$). Table 3 shows that for the offered subsidy rates, farmer risk aversion should be in the 0.37-0.50 range rather than the 0.88 value that has been assumed so far, suggesting that farmers must actually be more risk averse in order to justify the subsidy rates that are currently being offered.

Table 3. Optimal Risk Aversion with Reference Point R' Under EUT Preferences ($\lambda = 1$, a^*, $\gamma = 1$, $\delta = 1$)

Coverage level α	Subsidy s	Optimal risk aversion a^* (a)	CER (\$/ac) (b)	WTP (\$/ac) (c)
0.85	0.38	0.50	-2.00	52.08
0.80	0.48	0.40	-0.83	32.95
0.75	0.55	0.36	-0.51	20.80
0.70	0.59	0.34	-0.41	13.29
0.65	0.59	0.38	-0.72	8.89
0.60	0.64	0.36	-0.50	4.98
0.55	0.64	0.38	-0.70	2.99
0.50	0.67	0.37	-0.58	1.52

(a) The optimal level of risk aversion is defined as the level of parameter a required in order for WTP for insurance to equal the subsidized premium ρ_p under EUT; (b) CER stands for Certainty Equivalent Return; (c) This column serves as a cross-check: by the definition of a^*, the corresponding computed WTP should be, and actually is, found to be equal to the subsidized premium ρ_p reported in Table 2, column 2.

Result 2 *Under the assumption of EUT preferences and Tversky and Kahneman's risk aversion parameter values ($\lambda = 1$, $a = 0.88$, $\gamma = 1$, $\delta = 1$), farmers never purchase unsubsidized insurance, whatever the coverage level. In this case, a subsidy is required in order for farmers to buy insurance, but the subsidy rates required to incite farmers to purchase insurance are smaller than those that are actually offered, implying that, conditional on the chosen preference parameters, farmers are over-subsidized. A greater degree of risk aversion than that described by Tversky and*

Kahneman is therefore necessary in order to justify the subsidy rates that are currently being offered (specifically, parameter a should be in the 0.37-0.50 range).

3.2. Sensitivity to changes in CPT parameters

To simulate the impact of preference parameters on WTP for insurance, we allow the risk aversion parameter a to vary within the $[0.5, 1]$ range by increments of 0.1, the loss aversion parameter λ to vary within the $[1, 3.5]$ range by increments of 0.5, and the probability distortion parameters δ and γ to vary within the $[0.5, 1]$ range by increments of 0.1. To conduct this sensitivity analysis, we additionally consider Tversky and Kahneman's parameter values, namely $a = 0.88$, $\lambda = 2.25$, $\delta = 0.69$, and $\delta = 0.61$. For the sake of brevity and clarity, we restrict the insurance coverage level to 85%.

Next we recompute farmer WTP for insurance considering all possible parameter combinations, that is, $7^4 = 2,401$ unique combinations. This is equivalent to simulating the choices of $2,401$ farmers, each having preferences that are characterized by a different set of parameter values. Among these farmers, we are able to identify those who would have bought insurance (whose WTP is above the offered premium) and those who would not have bought insurance (whose WTP is below the offered premium).

To illustrate the results of this analysis, we plot farmer WTP as a function of risk aversion (a), loss aversion (λ), and probability distortion in losses (δ), holding the probability distortion in gains γ at Tversky and Kahneman's value of 0.61 (Figure 2). On the same graph, we also plot the unsubsidized (fair) premium ρ and the subsidized premium ρ_p ($s = 0.38$).

Figure 2 shows that WTP decreases with risk aversion, increases with loss aversion, and increases with probability distortion in losses. Using the parameter combinations we consider, farmers always purchase insurance under the subsidized premium, suggesting that farmers are over-subsidized if we are to assume that they have CPT preferences. However, the left panel of Figure 2 also shows that small enough levels of risk aversion and high enough levels of loss aversion are necessary in order for farmers to purchase unsubsidized insurance. When farmers overweight small probabilities in losses ($\delta = 0.5$; right panel), however, they always purchase insurance, even without subsidy.

To explore these results further, we regress simulated farmer WTP values on their preference parameters as specified in Eq. 7. The model was specified such that the constant β_{EUT_RN} can be interpreted as farmer WTP assuming EUT preferences ($\lambda = 1$, $\gamma = 1$ and $\delta = 1$) and risk

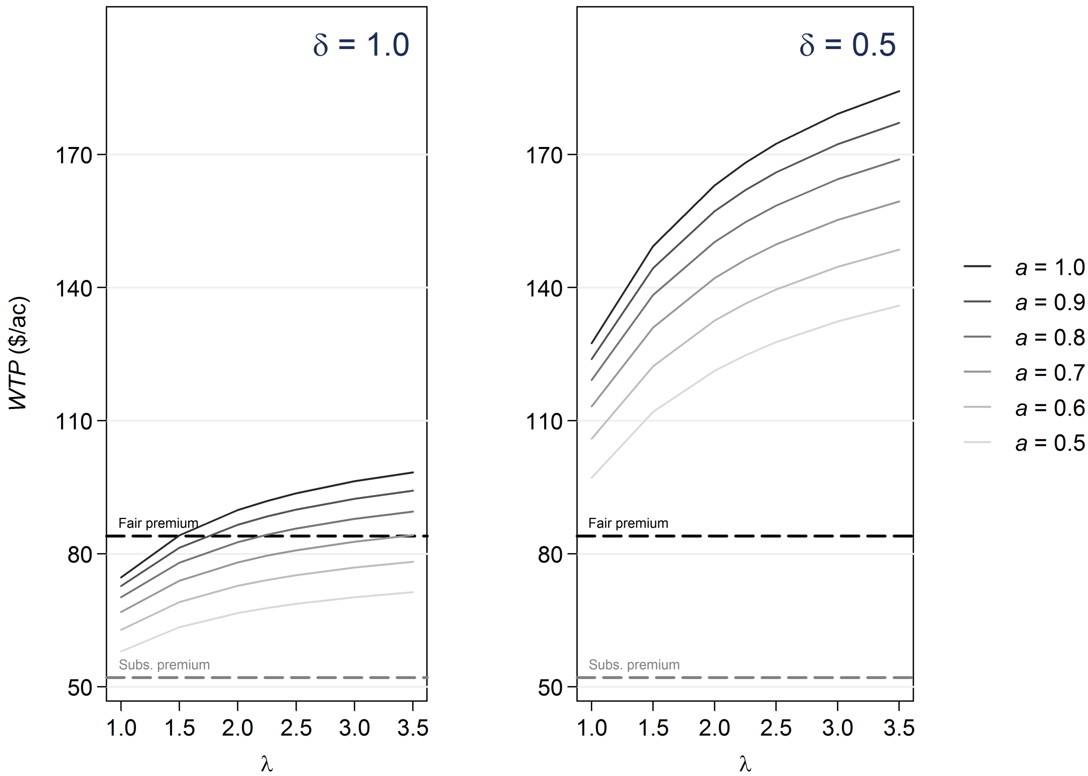

Figure 2. Impact of Risk Aversion (a), Loss Aversion (λ), and Probability Distortion in Losses (δ) on Farmer Willingness to Pay for Insurance Assuming a Probability Distortion in Gains $\gamma = 0.61$ and an 85% Coverage Level

neutrality ($a = 1$).

$$WTP = \beta_{EUT\_RN} + \beta_a(1-a) + \beta_\lambda(\lambda - 1) + \beta_\gamma(1-\gamma) + \beta_\delta(1-\delta) + \epsilon \tag{7}$$

According to the hypotheses developed in section 2.1 and consistent with the graphical analysis, we expect WTP to increase with loss aversion ($\lambda > 1$). That is, we expect $\beta_\lambda > 0$. We also expect WTP to increase with probability distortion ($\gamma < 1$ and $\delta < 1$), expecting $\beta_\gamma > 0$ and $\beta_\delta > 0$. As for risk aversion (a), two opposite effects are at play. WTP is expected to increase with risk aversion in gains but to decrease with risk seeking in losses such that we are not able to make an ex-ante prediction regarding the sign of parameter β_a.

While WTP is indeed a variable of interest, we are more interested in the rule determining whether or not farmers decide to purchase insurance. We therefore modify Eq. 7, using as our dependent variable the surplus defined by $WTP - \rho$, i.e. the difference between WTP and the unsubsidized premium. We therefore estimate the empirical model specified in Eq. 8 with $\beta_0 = \beta_{EUT\_RN} - \rho$. When $WTP - \rho$ is positive (resp. negative), farmers insure (resp. do not insure).

$$Surplus = \beta_0 + \beta_a(1-a) + \beta_\lambda(\lambda - 1) + \beta_\gamma(1-\gamma) + \beta_\delta(1-\delta) + \epsilon \tag{8}$$

Table 4 reports the estimated parameters for Eq. 8, considering both the entire sample of simulated farmers (model (1)) as well as two subsamples: those who actually insure (model (2)) and those who do not (model (3)).

Table 4. OLS Regression of Surplus (\$/ac) for an 85% Coverage Level (Eq. 8)

Dependent variable	(1) Whole sample $WTP - \rho$		(2) Insured farmers $WTP - \rho>0$		(3) Uninsured farmers $WTP - \rho<0$	
	Parameter estimate	Marginal effect	Parameter estimate	Marginal effect	Parameter estimate	Marginal effect
β_0	-11.71***		-16.87***		-7.56***	
	(0.41)		(0.46)		(0.39)	
β_a	-67.03***	0.59***	-74.56***	0.66***	-43.87***	0.39***
	(0.76)	(0.007)	(0.82)	(0.007)	(1.10)	(0.010)
β_λ	11.93***	0.27***	13.11***	0.30***	7.57***	0.17***
	(0.16)	(0.004)	(0.17)	(0.004)	(0.21)	(0.005)
β_γ	14.43***	-0.09***	15.27***	-0.09***	11.79***	-0.07***
	(0.75)	(0.005)	(0.75)	(0.005)	(0.82)	(0.005)
β_δ	128.34***	-0.89***	142.46***	-0.98***	64.11***	-0.44***
	(0.78)	(0.005)	(0.91)	(0.006)	(1.67)	(0.011)
#Obs	2,401		1,980		421	
R squared	0.9448		0.9394		0.8417	

Notes: Standard errors are in parentheses. Marginal effects are computed as the change in surplus in response to a 1% change in parameter value at the values elicited by Tversky and Kahneman: 0.88 for risk aversion a, 0.61 for probability distortion in gains γ, 0.69 for probability distortion in losses δ, and 2.25 for loss aversion λ); *** denotes statistical significance at the 1% level.

We find a negative constant, $\beta_0 < 0$, meaning $\beta_{EUT\_RN} < \rho$, which indicates that risk-neutral-EUT farmers have no incentive to insure. As expected, we also find that loss aversion and probability distortion increase the incentive to insure ($\beta_\lambda > 0$, $\beta_\gamma > 0$, $\beta_\delta > 0$). While the impact of risk aversion was theoretically uncertain, we find that it decreases the incentive to insure ($\beta_a < 0$): the positive impact of risk aversion in gains is overcome by the negative impact of risk seeking in losses. Marginal effects were computed as semi-elasticities, depicting the WTP variation in \$/ac for a 1% increase in the respective parameter value. Considering model (1) in Table 4, we find that farmer surplus is most impacted by changes in probability distortion in losses, for which a 1% increase in distortion (*i.e.*, a 1% decrease in the δ parameter) leads to a \$0.89/ac increase in surplus. This is one and a half times the effect of risk aversion and more than three times the effect of loss aversion in absolute value, and almost ten times the effect of probability distortion in gains. The dominant impact of probability distortion in losses may thus explain to a large extent Result 1 in section 3.1, according to which a farmer with Tversky and Kahneman' CPT preferences would always purchase insurance, whereas an EUT farmer would only purchase insurance if subsidized. Next we consider models (2) and (3). For insured farmers (model (2)), the impact of probability distortion in losses is higher than for the sample as a whole, such that WTP is large enough to lead farmers to insure. In contrast, for uninsured farmers (model (3)), the impact of probability distortion in losses is small: a 1%

increase in probability distortion in losses leads to only a \$0.44/ac increase in farmer surplus. Together with a lower impact of loss aversion, this yields a large enough decrease in WTP to lead farmers to refuse insurance.

We can now conclude with the following general result.

Result 3 *Loss aversion and probability distortion increase the incentive to insure, while risk aversion decreases the incentive to insure (risk aversion in gains is overcome by risk seeking in losses). Probability distortion in losses has the greatest impact on farmer surplus.*

4. Analyzing the impact of skewness on CPT farmer insurance choice

Since the 90s, agricultural economists have recognized the implications that assumptions about crop yield distributions can have for the calculation of insurance premiums (Nelson, 1990; Coble *et al.*, 1996). More recently, the question of how crop yields are distributed has been debated in the literature (Just and Weninger, 1999; Atwood *et al.*, 2003; Ramirez *et al.*, 2003; Sherrick *et al.*, 2004; Harri *et al.*, 2009; Claassen and Just, 2011). Importantly, all of these papers model preferences under EUT assumptions. We argue that distributional assumptions matter to an even greater extent in a CPT framework. In finance, Barberis (2013a,b) reviews papers demonstrating that probability weighting and loss aversion can explain some economic puzzles. CPT helps to explain phenomena such as the purchase of low deductible insurance (Sydnor, 2010) and home and automobile insurance (Barseghyan *et al.*, 2013), as well as the unattractiveness of annuities (Hu and Scott, 2007). We know of two theoretical papers that deal with the impact of CPT preferences when risk is skewed. Barberis and Huang (2008) theoretically show that a positively-skewed asset is overpriced as compared to EUT predictions when investors put more weight on the tails. Ågren (2006) finds similar results using a different modeling framework. To the best of our knowledge the impact of distributional assumptions regarding yields has not yet been investigated under CPT assumptions in the field of agricultural economics. We expect that parameters such as loss aversion and probability weighting will impact insurance decisions differently depending on crop yield skewness. In particular, given previous findings in finance, a CPT farmer should place a greater value on more positively-skewed yield distributions and would therefore be less willing to insure under these conditions.

In this section, we study the impact of yield skewness on surplus, $WTP - \rho$ as defined in section 3, when farmers are assumed to have CPT preferences. Recall that, in this section, price is non-random and we use a skew-normal distribution because we can easily parametrize skewness (see section 2.2). For the simulation, we vary the skew-normal distribution shape parameter η such that the yield distribution skewness measure κ takes on values in the $[-1, 1]$ range in increments of 0.25.[7] CPT preference parameters are chosen using the same ranges as in section 3.2 and for brevity and clarity, we again restrict the coverage level to 85%. Each of our 2,401 simulated farmers was thus faced with 9 yield distributions, resulting in 21,609 simulations.

First we review the intuition behind these results by presenting them graphically. Figure 3 reports the impact of yield skewness κ on farmer surplus ($WTP - \rho$) according to loss aversion λ and probability distortion in losses δ, assuming Tversky and Kahneman's parameter values for risk aversion ($a = 0.88$) and probability distortion in gains ($\gamma = 0.61$). Several conclusions can be derived from these plots.

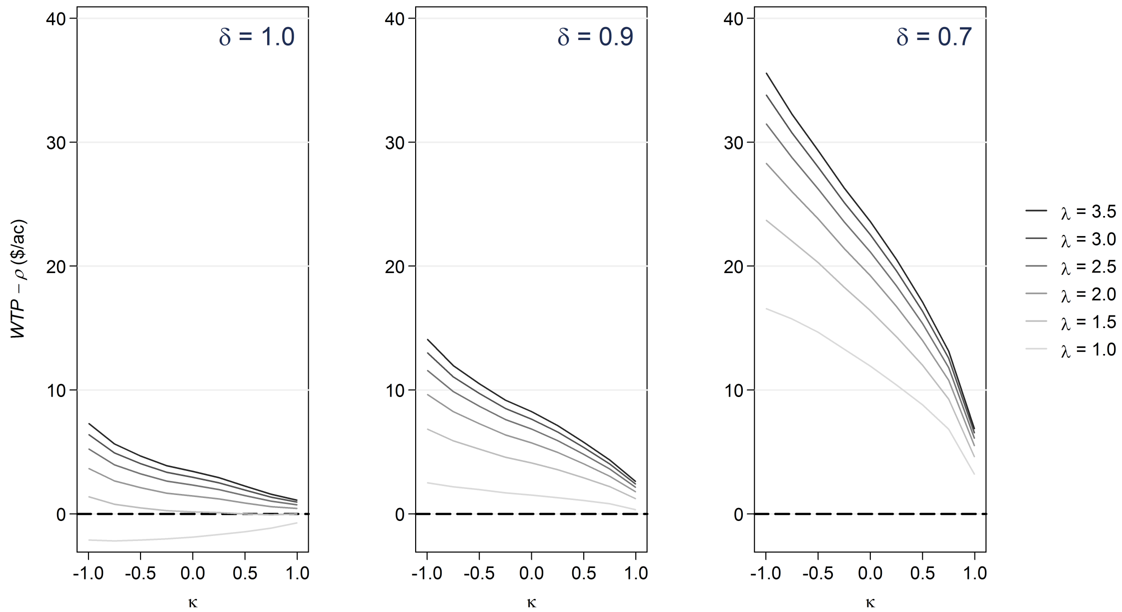

Figure 3. Impact of skewness (κ) on farmer surplus depending on loss aversion (λ) and probability distortion in losses (δ), assuming risk aversion $a = 0.88$, probability distortion in gains $\gamma = 0.61$, and an 85% coverage level

First we consider the left panel of Figure 3, in which there is no probability distortion in losses ($\delta = 1$), and more specifically the case without loss aversion ($\lambda = 1$, lighter gray line). We find that whatever the skewness level, the farmer will never insure because the surplus is always negative. On the one hand, the more negatively skewed the yield, the more negative the surplus. In this case, large losses occur, but with a small probability. On the other hand, the

[7]The definition of κ from η for the skew-normal distribution (see section 2.2) implies that the extreme values for κ cannot be exactly ± 1 but rather $\pm\frac{4-\pi}{2}\left(\frac{2}{-2+\pi}\right)^{3/2} \sim \pm 0.995$. Nevertheless, other values considered for κ are ± 0.75, ± 0.50, ± 0.25, and zero, consistent with the 0.25 increment we use.

more positively skewed the yield, the less negative the surplus. Under these conditions, small losses occur with a high probability. All in all, in the absence of loss aversion and probability distortion in losses, WTP is not high enough to incite the farmer to insure.

Next we consider the case where farmers distort probabilities in losses ($\delta < 1$), but are not averse to losses ($\lambda = 1$), as evidenced by comparing the lighter gray lines in the middle and right panels of Figure 3. Even a small distortion in losses (middle panel) leads the farmer to insure, whatever the level of skewness. Moreover, the slope of the line becomes steeper when the probability distortion in losses increases (moving from the middle panel to the right panel), revealing that probability distortion in losses plays an important role in determining the decision to insure. Additionally, the more negatively skewed the yield, the higher the surplus: the farmer incurs large losses with small probabilities, as in the left panel, but he overweights these small probabilities such that his willingness to insure increases above the offered premium, making surplus positive. Symmetrically, the more positively skewed the yield, the lower the surplus: as before, the farmer incurs small losses with high probabilities, but he underweights these high probabilities such that his willingness to insure decreases; however, WTP nevertheless remains large enough to generate a positive surplus, which leads the farmer to insure.

Finally, we consider the impact of loss aversion. In all of the panels in Figure 3, the darker the line, the greater the degree of loss aversion. Overall, we find that the greater the loss aversion parameter, the greater the surplus from insurance. First, the more negatively skewed the yield, the greater the surplus: the farmer incurs large losses with small probabilities and, due to loss aversion, these losses loom larger than gains such that he is more willing to insure. On the contrary, the more positively skewed the yield, the lower the surplus: although the farmer incurs losses with high probabilities, as these losses become smaller they loom less and less large relative to gains, such that he is less and less willing to insure.

As in the previous section, we further analyze these findings by regressing simulated farmer surplus ($WTP - \rho$) on preference parameters, this time incorporating yield skewness. We specify two empirical models, one without interaction terms between yield skewness and CPT preference parameters (Eq. 9) and one with these interaction terms (Eq. 10).

$$Surplus = \beta_0 + \beta_a(1-a) + \beta_\lambda(\lambda - 1) + \beta_\gamma(1-\gamma) + \beta_\delta(1-\delta) + \beta_\kappa \kappa + \epsilon \tag{9}$$

$$Surplus = \beta_0 + \beta_a(1-a) + \beta_\lambda(\lambda-1) + \beta_\gamma(1-\gamma) + \beta_\delta(1-\delta) + \beta_\kappa\kappa \qquad (10)$$
$$+\beta_{\kappa,a}\kappa(1-a) + \beta_{\kappa,\lambda}\kappa(\lambda-1) + \beta_{\kappa,\gamma}\kappa(1-\gamma) + \beta_{\kappa,\delta}\kappa(1-\delta) + \epsilon$$

Marginal (semi-elasticity) effects for yield skewness are computed at $\kappa = -0.683$ which is the value found for the skew-normal distribution that fits Babcock (2015)'s Beta distribution (see section 2.2, Table 1); CPT preference parameter values are those described by Tversky and Kahneman in the previous section. OLS estimation results for Eq. 9 and Eq. 10 are presented in Table 5.

Table 5. OLS regression of surplus (\$/ac) for an 85% coverage level (Eq. 9 and Eq. 10)

	(1) Without interaction		(2) With interaction	
	Parameter estimate	Marginal effect	Parameter estimate	Marginal effect
β_0	-4.11***		-4.11***	
	(0.15)		(0.10)	
β_a	-31.06***	0.27***	-31.06***	0.40***
	(0.27)	(0.002)	(0.19)	(0.002)
β_λ	4.16***	0.09***	4.16***	0.13***
	(0.06)	(0.001)	(0.04)	(0.001)
β_γ	6.69***	-0.04***	6.69***	-0.06***
	(0.27)	(0.002)	(0.19)	(0.002)
β_δ	69.29***	-0.48***	69.29***	-0.66***
	(0.28)	(0.002)	(0.19)	(0.002)
β_κ	-7.76***	0.05***	1.82***	0.09***
	(0.07)	(0.000)	(0.16)	(0.000)
$\beta_{\kappa,a}$			20.60***	
			(0.29)	
$\beta_{\kappa,\lambda}$			-2.60***	
			(0.06)	
$\beta_{\kappa,\gamma}$			-4.45***	
			(0.29)	
$\beta_{\kappa,\delta}$			-38.29***	
			(0.30)	
#Obs	21,609		21,609	
R squared	0.8116		0.9088	
Adj R squared	0.8116		0.9088	

Notes: Standard errors are in parentheses. Marginal effects are computed as the change in surplus for a proportional 1% change in parameter value at the values elicited by Tversky and Kahneman (0.88 for risk aversion a, 2.25 for loss aversion λ, 0.61 for probability distortion in gains γ and 0.69 for probability distortion in losses δ) and at skewness value $\kappa = -0.683$ (the skewness of the skew-normal distribution that fits Babcock's Beta distribution); *** denotes statistical significance at the 1% level.

First we consider model (1) in Table 5 (no interaction). All parameters are highly significant. Estimated parameters for the CPT independent variables have similar signs to those found in section 3.2 (see Table 4). However, this similarity must be viewed with some caution given that the yield distribution was different and price was random in the previous estimation. As in the first regression, this indicates that loss aversion and probability distortion increase the incentive to insure, while risk aversion decreases it. The interesting result in this section concerns the estimated parameter for skewness (β_κ). As expected, this parameter is negative and highly significant, suggesting that the incentive to insure decreases when the skewness parameter κ increases from negative values to positive values. When κ increases, the farmer incurs lower and lower losses with higher and higher probabilities, and greater and greater gains with lower and lower probabilities. As depicted in the graphical analysis, the negative estimated parameter indicates that the expected utility of gains offsets the expected utility of losses such that the incentive to insure decreases. The marginal effect computed at $\kappa = -0.683$ indicates that a 1% more negatively-skewed distribution leads to a \$0.05/ac increase in surplus. This effect is small compared to the marginal effect of probability distortion (with an absolute value of \$0.48/ac). Of all the preference parameters, probability distortion in losses has the greatest marginal effect on surplus. The finding that yield skewness has a negative impact on the decision to insure may be considered as similar to the results of Coble *et al.* (1996) who study the impact of the variance of return to insurance on participation in a Multiple Peril Crop Insurance program using an EUT framework. These authors indeed find a negative impact of return variance, indicating that farmers who expect to receive smaller but more frequent indemnities (small variance) are more likely to purchase insurance than producers for whom indemnities are rare but potentially large (large variance). Since they compute the variance of return to insurance only on the left tail of the yield distribution (*i.e.*, below the guaranteed yield), *ceteris paribus*, the increase in the variance of return to insurance reflects an increase in negative skewness.

In this study, we are interested in the channel through which yield skewness impacts insurance decisions, and especially in the role of CPT preferences. To this end, we also estimate a model that includes interaction terms between skewness and CPT parameters (see model (2) in Table 5). The signs and the associated significance levels of the estimated parameters considered in model (1) are unchanged except for the skewness parameter, which becomes positive with the inclusion of these interaction terms. The estimated parameters associated with the variables interacted with κ are also highly significant. Model (2) shows that skewness has a direct positive impact on surplus and both positive and negative indirect impacts through the CPT preference parameters. All marginal effects have the same sign and significance as in model (1), yet they are higher in absolute value. The parameter of greatest magnitude is again probability distortion in losses. Next, we consider interaction effects. When κ increases, the farmer incurs lower and lower losses with higher and higher probabilities and incurs greater and greater gains with lower and lower probabilities. First, the incentive to insure increases with risk aversion when κ increases: as the distribution becomes more skewed to the right, risk aversion in gains offsets risk seeking in losses such that the incentive to insure increases. Second, the incentive to insure decreases with loss aversion when κ increases: when loss aversion increases, losses loom larger and larger but when κ increases at the same time, losses are smaller and smaller, causing the overall interaction effect to be negative. Third, the interaction coefficients between probability distortions and skewness are both negative: when κ increases, large gains are less and less likely and small losses are more and more likely, such that on the one hand, overweighting of low probability gains decreases the incentive to insure and, on the other hand, underweighting of high probability losses also decreases the incentive to insure. Among the four interaction effects, the largest in absolute value is that associated with probability distortion in losses.

We can now proceed with the following conclusion.

Result 4 *Overall, the incentive to insure decreases when the yield distribution moves from negative skewness to positive skewness. When interaction effects are accounted for, probability distortion in losses has the largest impact on surplus, such that skewness has two competing effects on the incentive to insure: (i) a direct positive effect, through which smaller losses with higher probabilities offset greater gains with lower probabilities; (ii) an indirect negative effect, through which high (low) probabilities are under(over)-weighted, such that smaller losses with higher probabilities no longer offset greater gains with lower probabilities. Taken together, the indirect negative effect of skewness overrides the direct positive effect, and the combined effect of skewness and probability distortion in losses is particularly important in shaping farmer insurance decisions.*

5. Conclusion

In this paper, we aim to explain the decisions regarding whether or not to purchase crop insurance within a behavioral economic framework. To accomplish this, we model this decision as a lottery choice and compute farmer willingness to pay as a function of the preference parameters identified by cumulative prospect theory (CPT). Simulating a broad set of possible parameter combinations, we find that CPT preferences can contribute to explaining insurance decisions. In particular, our results indicate that probability distortion in losses plays a large role in determining WTP, serving to increase the incentive to insure relative to the EUT assumption of no probability distortion. Hypothesizing that insurance decisions are shaped by CPT preferences especially when yields are skewed, we indeed find that distributional assumptions shape farmer insurance choices both directly and indirectly through the interaction of the yield skewness parameter with CPT preference parameters, and in particular with probability distortion in losses.

The effects we find are far from negligible. First, when considering revenue insurance and a coverage level of 85% (section 3.2), the estimated parameters for Eq. 8 (see Table 4, whole sample) indicate that moving from an assumption of no probability distortion in losses ($\delta = 1$) to Tversky and Kahneman's finding ($\delta = 0.69$), i.e. a 31% increase in distortion, translates to a \$39.79/ac increase in farmer surplus generated by insurance. This represents some 47% of the unsubsidized premium (\$84.01/ac, see Table 2, column (3)), and as much as 76% of the subsidized premium (\$52.08/ac, see Table 2, column (4)) given the subsidy rate (38%) currently offered. Similarly, when considering crop yield insurance, a coverage level of 85%, and interaction effects with skewness (section 4), moving from no probability distortion in losses to Tversky and Kahneman's degree of probability distortion in losses raises farmer surplus by \$29.59/ac, which amounts to 83% of the subsidized premium that was offered for the Actual Production History (APH) insurance contract in York county (NE) in 2009 (\$35.47/ac).[8]

Thus, our results raise the important question regarding the actual nature of farmer preferences, and, assuming they are CPT-like, of the particular parameter values that best characterize them. If these parameters are assumed to be equal to those found by Tversky and Kahneman, we find that Babcock is right to assume that farmers do buy insurance. Our sensitivity analysis reveals, however, that other parameter combinations can lead to the simulated farmer deciding not to purchase insurance. While applications of CPT in the literature often assume that preference parameter values are equal to those elicited by Tversky and Kahneman, we find that the values at which these parameters are set, especially with respect to probability distortion in losses, can have a significant impact on farmer insurance choices. Since it is unlikely that all farmers share the same preferences, this result may contribute, along with more standard adverse selection and moral hazard considerations, to explaining why subsidizing insurance appears to be necessary in order to incentivize farmers to purchase insurance.

Given that risk parameters are unobservable, attempts to elicit them have met with challenges (Just *et al.*, 2010). Tversky and Kahneman experimentally estimated the risk preferences

[8]See Risk Management Agency (RMA)'s 2009 'Summary Of Business' dataset for corn, available at https://prodwebnlb.rma.usda.gov/apps/SummaryofBusiness/

of a sample of students under particular specifications for the utility function (using the same parameter for risk attitudes in gains and losses) and the probability weighting function, which generated an estimated parameter value of 0.69 for the probability distortion in losses. When this parameter has been elicited for farmers, however, it has differed from this cardinal value due to differences between the samples and the empirical specification and estimation methods used. Following a specification similar to Tversky and Kahneman, Bougherara *et al.* estimate a value for probability distortion in losses of 0.84 among a sample of French farmers. Using a Prelec probability weighting function and the same parameter for probability distortion in gains and losses, Bocquého *et al.* find a value of 0.66 among another sample of French farmers. Using the same specifications without the use of ML estimation, Liu finds a value of around 0.69 among a sample of Chinese cotton farmers, while Nguyen and Leung find a value of 0.75 among a sample of Vietnamese fishermen, and Tanaka *et al.* find a value of 0.74 among a sample of Vietnamese villagers. Finally, in contrast to these results, Humphrey and Verschoor find an S-shaped distortion function ($\delta = 1.38$) among a sample of Ugandan farmers.

This short review reveals the challenge of eliciting preference parameters that are intended to have a general scope: all of the above-mentioned figures are contingent on the specific samples used and technical assumptions made in order to estimate them. The challenge is even more substantial considering that these figures only represent mean sample estimates, whereas individual heterogeneity is likely to exist (Harrison and Rutström, 2009) and this heterogeneity is mostly unobserved. In identifying directions for future research in production economics and farm management, Chavas *et al.* (2010) point to the role of risk/uncertainty and heterogeneous managerial abilities as the top two most important priorities. Research that elicits heterogeneous risk preferences addresses both of these priorities, and attempts to do so have already been made (Hey and Orme, 1994; Harrison and Rutström, 2009). At the very least, knowing the distribution of individual risk preferences would enable practitioners to fine tune insurance programs in order to set subsidy rates at efficient levels and avoid the unnecessary waste of public funds, a long-debated issue especially in the U.S. (Goodwin and Smith, 2013). For this reason, we contend that studies such as Babcock's and ours provide valuable insights regarding the determinants of farmer insurance choices and the key preference parameters that should guide the design of insurance programs.

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A. Certainty Equivalent Returns from Crop Insurance with Cumulative Prospect Theory Using Three Alternative Reference Points for Corn

Table 6 presents certainty equivalent returns for the base case of parameters for corn and the three reference points (R1, R2, and R3) as in Babcock (2015: Table 3) and provides the results of our own replication. Overall, our replication yields similar results. The optimal coverage level is 0.85 for reference points R_1 and R_2. There is a wider range of coverage levels in our replication for R_3. We find the highest certainty equivalent returns for coverage levels 0.75 and 0.70, whereas Babcock finds the highest certainty equivalent return is for a coverage level of 0.75 only.

Table 6. Certainty Equivalent Returns from Crop Insurance with Cumulative Prospect Theory Using Three Alternative Reference Points for Corn: Babcock's results vs. our replication

	Reference point R_1		Reference point R_2		Reference point R_3	
Coverage level α	Babcock's Table 3 Column 1	Our replication	Babcock's Table 3 Column 2	Our replication	Babcock's Table 3 Column 3	Our replication
0.85	-2.1	-5.0	46.9	46.2	10.3	2.8
0.80	-5,3	-7.3	15.5	15.1	17.7	12.1
0.75	-10.5	-11.9	-2.3	-2.5	20.1	16.1
0.70	-16.5	-17.6	-10.9	-11.0	18.8	16.1
0.65	-22.7	-23.7	-18.7	-19.1	15.3	13.3
0.60	-27.8	-28.6	-25.5	-26.0	13.3	12.1
0.55	-32.6	-33.3	-31.1	-31.7	10.0	9.2
0.50	-36.4	-37.1	-35.7	-36.2	7.4	6.9

Note: Reference points are defined in Babcock (2015: p.1374) as follows; $R_1 = E(R) + \rho(\alpha)(1 - s(\alpha))$ with $x_i = P_i.y_i + I_i - R_1$, $R_2 = E(R)$ with $x_i = P_i.y_i + I_i - R_2$, $R_3 = \rho(\alpha).(1s(\alpha))$ with $x_i = I_i - R_3$.

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