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Measuring the effect of risk attitude on marketing behavior

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Abstract

Despite extensive study, researchers continue to search for consistent and reliable measures of risk preferences to explain market behavior. We find that a measure, combining experiments rooted in expected utility theory and measures derived from surveys, explains spot and contractual sales, but does not exhibit substantially greater explanatory power than its underlying components. Survey-based measures are generally more significant indicators of marketing choices, but experimental measures reveal how risk attitudes vary over a range of probable outcomes, which is important in light of increased commodity price volatility. Given recently identified limitations on the applicability of expected utility theory, we suggest that researchers include survey methods to obtain low-cost supplemental measures.

JEL classifications: D03, D81, M31, Q13

Keywords: Risk attitude; Risk behavior; Marketing

1. Introduction

The notion that risk attitude influences behavior is intuitively appealing, but difficult to measure. While measurement of risk attitudes has traditionally been conducted in an expected utility framework, consensus on its appropriateness appears to be waning (Just, 2011; Just and Peterson, 2010; Just et al., 2010). Further, empirical evidence on the consistency of risk preferences and their relationship to behavior varies by conceptual model used and related measurement issues (Anderson and Mellor, 2009; Dohmen et al., 2011; Fausti and Gillespie, 2006; Fellner and Maciejovsky, 2007; Pennings and Smidts, 2000). In this situation, it may be prudent to focus on a framework that combines different measures of risk attitudes and provides statistical tests of their adequacy when evaluating the effect of risk attitudes on behavior.

Two fundamental approaches exist to quantify risk preferences—measures derived from experiments conducted under the expected utility framework and measures derived from survey respondents' answers to multi-item scales (Antle, 1987; Chavas and Holt, 1990; Goodwin and Schroeder, 1994; Pennings and Smidts, 2000; Smidts, 1997). Despite the popularity of the experimental approach in the early 1980s (e.g., Binswanger, 1981), few applications appear in agricultural economics following an acrimonious exchange on the usefulness of the procedure (Grisley and Kellogg, 1983, 1985). As an exception, Pennings and Garcia (2001) utilize both methods to develop a higher order or global risk attitude construct (GRAC). Using statistical tests to assess the relative importance of different measures, they identify a link between risk preferences and producers' intent to use futures markets. Notwithstanding these findings, "simple questions and Likert multi-item scales are often preferred by applied researchers because of their ease of inclusion in mail surveys and/or their relative low cost ..." (Hudson et al., 2005, p. 41).[1] Recently recognized concerns about empirical implementation of expected utility theory (EUT) add to the uncertainty of how to effectively measure risk preferences and their impact on behavior (e.g., Just, 2011; Just and Peterson, 2010; Just et al., 2010). Clearly, these

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[1] Papers citing Pennings and Garcia (2001) typically acknowledge the comprehensive approach combining scale and experimental measures of risk attitude and proceed to use one or the other measure individually in their own work (e.g., Franken et al., 2012; Hudson et al., 2005; Lusk and Coble, 2005) or reference the use of factor analysis to combine measures (e.g., Pope et al., 2011; Tonsor et al., 2009).

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limitations do not preclude use of EUT, but they do raise questions about its relative ability to predict behavior as well as its use to describe or prescribe behavior. In light of these recent developments and researchers' reliance on simpler risk attitude measures, reconsideration of the usefulness of Pennings and Garcia's (2001) framework seems warranted.

In this study, following Pennings and Garcia (2001), we develop a GRAC from measures derived from certainty equivalents obtained through computerized lottery experiments (i.e., EUT) and from multi-item scales obtained through a personally administered survey. Following Pennings and Smidts (2003), negative exponential functions (EXP) and inverse power transformation (IPT) functions are fit to certainty equivalents to determine whether utility functions are globally concave (risk averse) or convex (risk seeking) consistent with the Pratt (1964) and Arrow (1971) framework or whether an inflection point exists consistent with prospect theory (Kahneman and Tversky, 1979). Risk attitude measures are tested for convergent validity using factor analytic methods (Bollen, 1989; Hair et al., 1995; Thompson, 2004), and nomological validity using a hurdle model relating risk attitudes to marketing behavior (Cragg, 1971; Katchova and Miranda, 2004).[2]

The analysis is performed for a sample of Midwest corn and hog producers for whom accounting data are available. In contrast to prior studies that investigate the influence of risk attitudes on the use of an individual marketing tool, we examine the effect of risk attitudes on the adoption and proportional use of several marketing alternatives (i.e., spot transactions and various contracts). We extend Pennings and Garcia's (2001) framework by relating risk preferences to actual marketing choices and by accounting for other factors identified in the literature as influencing marketing decisions. The analysis, which is framed in a GRAC structure, sheds light on whether simpler measures adequately reflect the role of risk preferences in producer decision making, and identifies the benefits of using alternate risk measures and procedures in explaining behavior.

2. Literature review

Several studies have examined the consistency of risk attitude measures and/or their ability to predict behavior in a variety of settings. Fellner and Maciejovsky (2007) and Anderson and Mellor (2009) provide thorough summaries of this extensive literature. Here, we review recent studies that focus on issues most directly related to our research with emphasis on the agricultural economics literature. First, we highlight the lack of consensus in the literature on the relative ability of risk attitude measures derived from experiments and surveys to explain behavior. Then, we review recent research calling into question theory and procedures underlying most experiment-based approaches for eliciting risk preferences.

A concise review of the literature illustrates a lack of consensus on the relative explanatory power of experiment (i.e., lottery) and survey (i.e., scale item) based measures of risk attitude. Among the first to make such comparisons, Pennings and Smidts (2000) detect some convergence between measures, but find that scale items correspond more closely with intentions to reduce risk, while lotteries predict reported market behavior better. Building on this work, Pennings and Garcia (2001) show that a procedure that identifies common variation among measures can provide a superior representation of risk preferences. They utilize common variance among scale and lottery measures to reflect unobservable risk attitudes as a GRAC, and demonstrate that the measure is related to farmers' intent to use futures markets. Though the lottery is the statistically dominant component of the GRAC, scales also explain producers' intentions. Subsequent research confirms that the measures are related (Anderson and Mellor, 2009), but a recent large study by Dohmen et al. (2011) strongly contradicts findings that lotteries have superior predictive power. They find scale items, not lotteries, explain behavior in many settings, and the best predictor in any particular situation is a context-specific survey item. Similarly, based on the analysis of survey items, Fausti and Gillespie (2006) recommend simpler procedures framed in the context of interest.

Recent studies call into question the applicability of theory and procedures commonly underlying experimental elicitation of risk preferences. For instance, Just and Peterson (2010) and Just (2011) employ a method to assess the empirical adequacy of EUT by calibrating a utility function to revealed behavior. Empirically, both studies find limited applicability of EUT. Just and Peterson (2010, p. 16) identify, "EUT is ... applicable only when expected payoffs of gambles are similar or when more than half of wealth is at risk," which would make measuring preferences of most nondeveloping world agricultural producers extremely costly. Similarly, Just (2011) concludes that large wealth transfers are necessary to justify large changes in risk aversion under EUT and suggests that prospect theory also seems inappropriate given his results. Just and Lybbert (2012, p. 1) investigate aversion to marginal changes in risk as opposed to standard measures of (average) risk aversion and suggest, "While a high degree of correspondence can be found between these experimental results and real-world response to risk (e.g., Pennings and Garcia, 2001), framing risk as static gambles in isolation may be too restrictive a frame." Other efforts to make experiments more consistent with the real world include distinguishing between risk (i.e., outcomes with known probabilities) and ambiguity (uncertainty about probabilities) and accounting for background risk in addition to the focal risk studied (Barham et al., 2012; Herberich and List, 2012).

On balance, the literature suggests that measurement of risk preferences should be framed in a situation that reflects the relevant decision-making context. Nevertheless, it is also clear that risk measurement is complex, and alternative measures can yield different conclusions as to individuals' risk preferences. In this context, when attempting to measure impacts of inherently

[2] Convergent validity (i.e., positive correlation) refers to whether variables reflect the same construct, and nomological validity reflects meaningful relation to other constructs, e.g., measures of behavior (Churchill, 1995).

unobservable risk attitudes on behavior, it seems sensible to consider a framework that incorporates various aspects of risk attitude—a notion that is only highlighted by the discord in the literature about how to conceptualize it. We investigate the value of combining risk attitude measures, each of which may not be entirely consistent, to explain market behavior using the GRAC measure.

3. Research measures and methods

3.1. Risk context

MacCrimmon and Wehrung (1990) and Shapira (1997) have demonstrated that risk attitude is context- or situation-specific, and that attitudes are more consistent when their measures are framed in a relevant context. We examine Illinois agricultural producers' attitudes toward price risk for hogs and corn. Price risk is substantial in production agriculture, and producers have numerous marketing tools available to help them manage this risk. Hence, we elicit risk attitudes in the context of commodity price fluctuations and relate these measures to producers' actual use of cash transactions, forward contracts, futures and options contracts, and marketing contracts.[3]

A unique dataset was assembled by interviewing agricultural producers in 2006, for which annual accounting and production records are kept for these producers through the Farm Business Farm Management (FBFM) program at the University of Illinois. This approach eliminates the need for producers to consult records to provide accurate estimates of such data during interviews (Pennings et al., 2002). FBFM is a cooperative educational service available to all agricultural producers in Illinois for a fee (Lattz et al., 2005). Presently, about one out of five Illinois commercial farms with over 500 acres or over $100,000 total farm sales participate. Interviewed FBFM producers are generally representative of larger commercial producers, as shown by comparisons of 2006 FBFM records with United States Department of Agriculture (2007) census data (Table 1). The program assists producers with management decisions by providing business analysis through computerized processing of records for income tax management. Secondary production and accounting data are collected annually by 58 full-time field staff specialists serving nine FBFM associations or regions. The resulting dataset provides extensive information on the cost and debt structure of the farm operations, as well as the source of revenues (i.e., grain or livestock production).

Four rounds of pre-tests—two with FBFM personnel on campus and 2 with 10 producers at their residences—were performed. Using a personal interview process in pre-tests is more likely to yield improvements to the questionnaire than impersonal administration (Reynolds and Diamantopoulos, 1998). In each case, survey items were modified, eliminated, and added based on comments regarding any ambiguity or other difficulty experienced with responding to the questionnaire. When possible, items that require ratings or checking boxes were employed in place of open-ended questions, based on reports from the survey literature that respondents prefer the former over the latter (Pennings et al., 2002). Consequently, pre-test participants sometimes noted omission of potentially relevant response alternatives, one of the most common errors detected via survey pre-testing (Hunt et al., 1982).

One hundred fifty producers were contacted and as encouragement for their participation in interviews were offered a chance at one of ten $100 lottery prizes. Balakrishnan et al. (1992) found that using a lottery prize giveaway significantly increases willingness to respond to surveys. Personal interviews, averaging just over an hour, limited the sample size but enhanced the reliability of survey responses and enabled collection of risk attitude measures via computerized lottery experiments. In total, 50 hog producers and 49 corn producers were interviewed. Interviews were conducted over a six-month period at the producers' farms or privately at Illinois Extension offices. This lengthy interview period reflects the time-intensive nature of driving to visit with individual producers and the greater availability of crop producers during certain times of the year (Pennings et al., 2002).

3.2. Certainty equivalence technique

Producers were asked to "put themselves in the situation of selling their commodity" when completing a computerized experiment where they faced two alternatives—one with a 50%/50% lottery (representing spot price risk) in which initial upper and lower bounds were set by researchers based on historical price ranges and one with a fixed price randomly generated by the computer within the initial price range. Prices for corn were in dollars per bushel and for hogs were in dollars per hundredweight, and spanned both gain and loss domains (i.e., ranged above and below average production costs). Hog producer experiments were available on either a live hog or lean hog (carcass) price basis, whichever producers were more familiar with. Based on producers' choices, the computer updates the fixed price and lottery price options, and does so for five iterations for each of seven utility points and three consistency checks, entailing a total of 50 decisions (five iterations per utility point for 10 total utility points). On average, the experiment took 11 minutes to complete or about 13 seconds per decision. Earlier studies report a longer elicitation process ranging from 20 to 35 minutes, which, in part, may be due to slower computer processing when data were collected for these studies (Pennings and Garcia, 2001; Pennings and Smidts, 2000, 2003).

To allow for flexibility in measuring preferences (Pennings and Smidts, 2003), the resulting certainty equivalents are fit to negative exponential (EXP) and IPT functions to determine the

[3] While specialty crop (e.g., seed, nongenetically modified, or identity preservation) contracts could be distinguished as production contracts, since producers may not take ownership of the seed or crop in some cases, they are categorized here as specialty marketing contracts following Katchova and Miranda (2004).

Table 1
Comparison of size distribution for sample and industry

Distribution of hog producers by size				Distribution of crop producers by size		
	FBFM surveyed producers (2006)	IL (2007)	US (2007)		FBFM surveyed producers (2006)	US harvested cropland (2007)
>5,000 head	33.33%	17.70%	10.68%	>2,000 acres	8.33%	4.98%
2,000–4,999 head	37.50%	12.47%	6.78%	1,000 to 1,999 acres	35.42%	5.94%
1,000–1,999 head	12.50%	10.81%	4.66%	500 to 999 acres	35.42%	9.12%
500–999 head	6.25%	8.33%	4.49%	<499 acres	20.83%	79.96%
200–499 head	10.42%	9.76%	5.69%			
<200 head	0.00%	40.94%	67.70%			

Note: 2007 Census of Agriculture, available at http://www.agcensus.usda.gov/Publications/2007/Full_Report/usv1.pdf.

shape of producers' utility functions $u(x)$. The EXP function implies constant absolute risk attitude and increasing proportional risk attitude and is expressed as

$$u(x_i) = \frac{1 - e^{-c(x_i - x_L)}}{1 - e^{-c(x_H - x_L)}}, \tag{1}$$

where x_L and x_H are lower and upper bounds of the outcome range of the 50%/50% lottery, x_i is the assessed certainty equivalent, and c is the risk attitude coefficient. A risk attitude coefficient $c > 0$ implies concavity (risk aversion), $c < 0$ implies convexity (risk seeking), and $c = 0$ implies linearity (risk neutral). The IPT function is given by

$$u(x_i) = \frac{1}{1 - e^{\left[-\alpha - \beta(1/\gamma)\log(1+\gamma X_i)\right]}}, \tag{2}$$

where x_i is again the certainty equivalent and α, β, and γ are coefficients characterizing the shape of $u(x)$. Here, S-shaped utility functions (concave, i.e., risk averse in gains, and convex, i.e., risk seeking in losses) described in Kahneman and Tversky's (1979) prospect theory may be observed, where the inflection point may be given by $u(x) = 1/2 \times (1 - \gamma/\beta)$. Since certainty equivalents, and not utility points, are elicited with error by experiments, the inverses of EXP and IPT functions are estimated. The inverse of the EXP function is

$$x_i = \frac{\ln\left(0.5\left(e^{-cx_l} + e^{-cx_h}\right)\right)}{-c} + e_i, \tag{3}$$

where x_l and x_h, respectively, represent the low and high outcomes of the 50%/50% lottery, and e_i is a residual error term. The inverse of the IPT function is given by

$$x_i = \frac{1}{\gamma} e^{-\frac{\gamma}{\beta}\left(\log\left(\frac{1}{u(x_i)} - 1\right) + \alpha\right)} - 1 + \varepsilon_i, \tag{4}$$

where ε_i is a residual error term.

3.3. Risk attitude scales

We follow the iterative procedure proposed by Churchill (1995) to obtain reliable and valid scales.[4] First, a pool of survey items (i.e., potential indicators) was accumulated. Specifically, we start with items previously validated in agricultural marketing contexts (e.g., Pennings and Garcia, 2001). The clarity and appropriateness of the items were evaluated through pre-tests with producers of hogs and corn. Producers completed the questionnaire and indicated any ambiguity or difficulty experienced in responding to items. Their feedback suggested the need to only modify a few items in the interest of clarity, which is not surprising given the use of these items in previous research. The survey items used to measure risk attitude are listed in Table 2.

3.4. Control variables

Based on the literature, we identify variables that have been used to explain contract choice in agricultural markets. Prior research commonly controls for the effects of age or experience and education of the producer, size of the operation, and degree of leverage (i.e., debt) on marketing decisions. Studies find that age is negatively related to the percentage of crops forward priced (Musser et al., 1996) and to contract production of hogs (Key and McBride, 2003), and experience is negatively related to the proportion of crop sales made with futures and options contracts (Sartwelle et al., 2000; Shapiro and Brorsen, 1988). Older producers may rely on experience to profitably time cash sales and may be reluctant to diverge from the status quo in markets where contracting is historically uncommon. Hence, we expect producer's AGE in years to be positively related to cash sales and negatively related to contract use.

College education is expected to lead to greater use of more sophisticated and flexible forward pricing tools such as futures and options contracts, but the evidence is mixed (Goodwin and Schroeder, 1994; Musser et al., 1996; Shapiro and Brorsen, 1988), and education appears to be negatively related to contract production of hogs (Key and McBride, 2003).

[4] Reliability pertains to whether variables are consistent with the concept they are intended to measure, and validity pertains to the extent that a set of measures correctly represents the concept.

Table 2
Scale items representing farmers' risk attitude and results of factor analysis

	Hog and corn data	
Risk attitude item	Factor 1	Factor 2
1. I usually like "playing it safe" (for instance, "locking in a price") instead of taking risks for market prices for my commodity.	***0.916***	0.209
2. When selling/marketing my commodity, I prefer financial certainty to financial uncertainty.	***0.745***	0.202
3. When selling/marketing my commodity, I am willing to take higher financial risks in order to realize higher average returns.	0.032	***0.573***
4. I like taking financial risks with my commodity farm business.	0.450	***0.609***
5. I accept more risk in my commodity farm than other commodity farmers.	0.188	***0.562***
6. With respect to the conduct of business, I dislike risk.	0.304	***0.512***
Reliability:		
Cronbach's alpha	0.839	0.700
Cronbach's alpha based on standardized items	0.841	0.700

Note: Scaling was from −4 for strongly risk seeking to 4 for strongly risk averse. For hog farmers, *hogs* was used in place of *commodity*. For grain farmers, *grain* was used in place of *commodity*. Strong factor loadings are bolded and italicized.

Substitutability may exist among these marketing tools, as each type may limit price risk exposure to some degree (Franken et al., 2012). A college education or even college training in futures and options may then reduce reliance on other types of contracts. Reluctance to sign longer term contracts may also reflect an awareness and desire to maintain flexibility in the face of changing market conditions. Thus, we anticipate that COLLEGE, which equals one if the producer has a college education and zero otherwise, is positively related to forward pricing tools (i.e., forward contracts and futures and options) and negatively related to use of marketing contracts. Forward pricing is also significantly associated with larger acreage crop farms (Goodwin and Schroeder, 1994; Sartwelle et al., 2000; Shapiro and Brorsen, 1988), and contract hog production is generally greater among operations raising larger numbers of hogs. Hence, we expect positive relationships between use of these contracts and size as approximated by SALES (in \$1,000).

Typically, contract use is expected to be greater among producers bearing more debt, as lenders may extend additional loans to operations with stable cash flows. While the DEBT/ASSET ratio is expected to reflect this effect, we note that existing evidence using this measure is quite mixed (Davis and Gillespie, 2007; Goodwin and Schroeder, 1994; Katchova and Miranda, 2004; Key and McBride, 2003; Musser et al., 1996; Shapiro and Brorsen, 1988). Finally, we include HOGS, which equals one for hog producers and zero otherwise (i.e., crop producers), to control for industry effects with no *a priori* expectations as to the direction of these effects.

3.5. Modeling marketing behavior

Several studies investigating determinants of the proportion of a crop contracted have employed Tobit procedures (e.g., Goodwin and Schroeder, 1994; Musser et al., 1996; Shapiro and Brorsen, 1988). Following Katchova and Miranda (2004), we employ Cragg's (1971) hurdle or two-step model, which allows independent variables to have differential effects on decisions to use contracts and how much of production to contract. The model is the sum of the log-likelihood of a probit regression (first two terms) and the log-likelihood of a truncated regression (second two terms) and is given by

$$\ln L = \sum_{c_i=0} \ln \Phi\left(-\gamma' z_i\right) + \sum_{\alpha_i>0} \left\{ \ln \Phi\left(\gamma' z_i\right) + \ln\left[\frac{1}{\sigma}\varphi\left(\frac{\alpha_i - \beta_\alpha' x_i}{\sigma}\right)\right] - \ln \Phi\left(\frac{\beta_\alpha' x_i}{\sigma}\right)\right\}, \quad (5)$$

where $\Phi(\bullet)$ is the standard normal probability density function, $\boldsymbol{x}_i$ and $\boldsymbol{z}_i$ are vectors of independent variables, $\boldsymbol{\beta}_\alpha$ and $\boldsymbol{\gamma}$ are vectors of coefficients, σ is the standard deviation, and α_i denotes the proportion contracted.

4. Results of risk attitude measurements

4.1. Expected utility framework

Ten certainty equivalents were assessed for seven utility levels between $u(x) = 0$ and $u(x) = 1$ with two certainty equivalents measured at $u(x) = 0.25$, $u(x) = 0.50$, and $u(x) = 0.75$ as checks of internal consistency.[5] If producers respond in accordance with EUT, certainty equivalents for a given utility level should differ only by random response error. Pairwise t-tests indicate no statistically significant difference between assessed certainty equivalents for each of the consistency checks ($P >$ 0.23). This result implies that producers' decisions are consistent and substantiates the experiment design's resemblance to the real business context, thereby limiting response mode effects (Payne, 1997; Shapira, 1997).

Certainty equivalents are fit to inverses of EXP and IPT functions to determine the global shape of producers' utility functions. A producer is assigned to the EXP group if EXP estimation fits the data as well as or better than IPT estimation. However, if the mean squared error from IPT estimation

[5] Except for the first lottery, in which based on historical prices outcomes were set at lower and upper bounds of \$27.00 and \$61.50 per hundredweight (cwt) for hogs and \$1.35 and \$3.50 per bushel (bu) for corn, outcomes depend on producers' prior choices between lotteries and certain prices. Thus, outcome ranges and expected values of lotteries vary across producers. In the interest of space, readers are directed to Pennings and Smidts (2003) for full details regarding EXP and IPT estimation and to Pennings and Garcia (2001) for full details about construction of the GRAC, which we follow closely.

Table 3
Comparing average fit of EXP and IPT functions for EXP and IPT groups

	EXP ($N = 74$)			IPT ($N = 25$)				
	Adj R^2	RMSE	c	Adj R^2	RMSE	Gamma	Beta	Alpha
Median	0.9990	0.2485	0.0000	0.9992	0.1212	13.6667	126.0721	−72.9669
Mean								
EXP	0.9981	0.8698	−0.1891	0.9931	1.963	63.6363	758.0779	−89.0266
	(0.0003)	(0.1130)		(0.0010)	(0.3962)			
IPT	0.9846	0.9791		0.999	0.6951			
	(0.0135)	(0.1505)		(0.0002)	(0.1559)			
Difference	0.0135	−0.1093		−0.0059***	1.2680***			
	(0.0135)	(0.1312)		(0.0010)	(0.3269)			

Table 4
Shape of utility functions elicited from lottery task

	All producers	Hogs producers	Corn producers
N	99	50	49
Risk averse	14%	12%	16%
Risk neutral	28%	28%	29%
Risk seeking	32%	34%	31%
S-shaped	25%	26%	24%
	100%	100%	100%

Table 5
Results from regressions of inflection points on average production costs

	Coefficient	Adj R^2	Joint H_0: $\beta_1 = 1$ and $\beta_0 = 0$
Average production cost (β_1)	0.9934***	0.9605	$F(2, 23) = 0.8400$
	(0.0411)		Prob> $F = 0.4425$
Constant (β_0)	1.2127		
	(1.2382)		

Note: $N = 25$. Triple asterisk (***) denotes statistical significance at the 1% level.

Table 6
Pairwise t-test of mean differences between inflection points and average production costs

	Mean		Mean
Producer type	Inflection point	Average production cost	Difference
All producers	23.5000	22.4344	1.0656
	(4.1535)	(4.1009)	(0.8090)
Hog producers	42.7669	41.5192	1.2477
	(1.3781)	(1.1984)	(1.5774)
Grain producers	2.6275	1.7592	0.8683***
	(0.0818)	(0.1190)	(0.1665)

Note: $N = 13$ for hog producers, 12 for grain producers, and 25 for all producers. Triple asterisk (***) denotes statistical significance at the 1% level.

is significantly lower than that from EXP estimation, based on pairwise t-tests, then the producer is assigned to the IPT group. Thus, on average, IPT estimation yields statistically higher R-squares and lower root mean squared errors (RMSEs) for the IPT group, but there is no statistical difference between the two estimation techniques for the EXP group (Table 3). Of the 99 producers examined, 74 exhibit EXP utility functions and 25 exhibit IPT functions. For the EXP group, the risk attitude coefficient c indicates that the median producer is risk-neutral and the mean producer is risk-seeking. For the IPT group, producers, on average, have an S-shaped (convex, concave) function (i.e., $\beta > \gamma$). No IPT producers have reverse S-shaped functions sometimes identified in other studies (e.g., Pennings and Smidts, 2003).

Table 4 summarizes the classifications of utility function shape for the whole sample and by hog and corn producers. Across samples, a smaller proportion of the producers are risk-averse than risk-neutral and risk-seeking, and nearly a quarter possess S-shaped utilities. The finding of fewer risk-averse producers compared to risk-neutral and risk-seeking is consistent with prior research (e.g., Pennings and Garcia, 2001; Pennings and Smidts, 2000), and Pennings and Smidts (2003) find that about 30% of producers in their sample have S-shaped utilities.

Estimates of the IPT function also allow derivation of inflection points for IPT group utility functions, which closely correspond to 2006 production costs. The slope coefficient from an OLS regression of inflection points on average costs of production is not statistically different from one (Table 5). Simpler pairwise t-tests of mean differences corroborate this finding for the full sample but also reveal how closely infection points correspond to average production costs for hog and corn producer subgroups (Table 6). For hog producers, the difference is not statistically significant, but for grain producers, the average inflection overestimates average production costs. This is consistent with hog producers thinking about both costs and revenues (i.e., prices) on a per hog basis. Crop producers, due to yield variation, typically think of average production costs per acre instead of dollars per bushel as crop prices are quoted. Since yield variation makes it difficult to accurately convert production costs from a per acre to a per bushel basis, crop producers may tend to overestimate production costs to arrive at a conservative break-even price as a reference point when thinking in terms of gains and losses in lottery experiments.

Table 7
Classification of respondents based on average sum scores of risk attitude scales

	All producers		Hog producers		Corn producers	
	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2
Risk averse	69%	51%	58%	52%	80%	49%
Risk neutral	11%	5%	12%	10%	10%	0%
Risk seeking	20%	44%	30%	38%	10%	51%

Note: $N = 99$.

4.2. Scaling framework

Exploratory factor analysis of items in Table 2 for the hogs and corn group yielded eigenvalues for the first two factors of 2.87 and 1.11, supporting a two factor model of risk aversion where the first and second factors, respectively, explained 47.90% and 18.50% of the variation in the data. The first two items in Table 2 comprise scale 1 and the last four comprise scale 2. All of the factor loadings of the items exceeded 0.50, and Cronbach's (1951) alphas between 0.70 and 0.90 indicate high reliability for the construct measurement (Streiner and Norman, 1995).

Based on average sum scores for these risk attitude factors or scales, producers are classified as risk averse (positive scores), risk neutral (zero scores), or risk seeking (negative scores) in Table 7. Note that some of the scale's items required recoding so that negative scores imply risk seeking and positive scores imply risk aversion. By these measures, the proportion of risk-averse producers is notably higher than indicated by measures rooted in the expected utility approach (i.e., comparing classifications in Tables 4 and 7). It may be that Table 4 statistics underestimate the percentage of risk-averse producers, as producers with S-shaped utility functions may exhibit risk aversion for prices ranging in the domain of gains, and IPT estimates do not provide a risk attitude coefficient as is provided by EXP estimates.[6] It is worth noting that average sum scores of risk attitude scales 1 and 2 indicate greater proportions of risk averse producers in the IPT (S-shaped) utility function group (84% and 56%, respectively) than among those in the EXP group (64% and 49%, respectively), and also that a large percentage of the IPT group uses contracts that may limit their exposure to price risk (Table 8). This result is not surprising, as S-shaped utility functions are risk-averse in gains and risk-seeking in losses, and commodity prices were fairly profitable at the time of the survey.

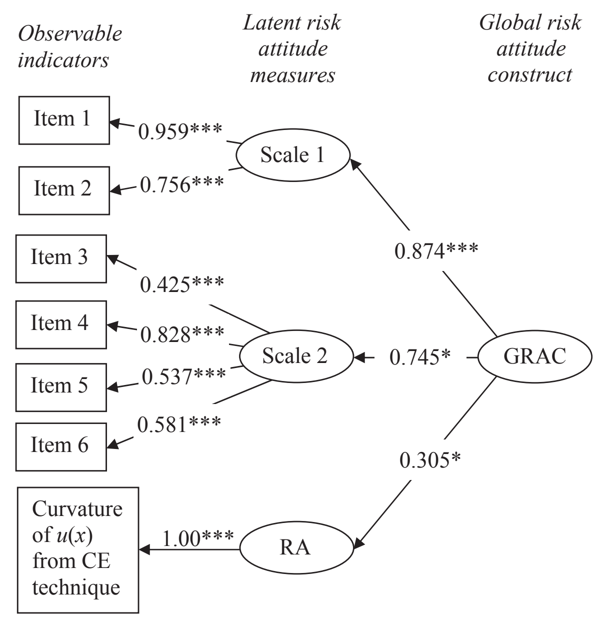
4.3. GRAC

Figure 1 shows the results of confirmatory factor analysis to investigate the presence of a higher order measure of risk attitude or a GRAC, which is composed of risk aversion coefficients computed from the certainty equivalent measure given by Eq. (1) and the two scale measures.[7] The analysis was conducted on the subsample of 74 producers for which certainty equivalents fit the EXP function better than the IPT function, as risk attitude coefficient may be ascertained from EXP estimates but not IPT estimates (see footnote 7). The analysis differs from exploratory factor analysis in that items 3–6, for instance, are permitted to influence only scale 2. This second-order model quantifies the presence of a common, higher order,

Table 8
Contract use and risk attitude scales for producers with EXP and IPT (S-shaped) utility functions

	EXP		IPT	
	Factor 1	Factor 2	Factor 1	Factor 2
Risk preference				
Risk averse	64%	49%	84%	56%
Risk neutral	14%	3%	4%	12%
Risk seeking	23%	49%	12%	32%
Contract use				
Futures and options	40%		35%	
Forward contracts	66%		74%	
Marketing contracts	25%		39%	

Note: $N = 25$.



Note: Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

Fig. 1. Second-order confirmatory factor model.

[6] While Pennings and Smidts (2003) were able to distinguish risk preferences in both gain and loss domains by applying the EXP method to a total of seven certainty equivalents, the number of certainty equivalents above inflection points in our data appears to be insufficient to consistently detect statistically positive risk attitude coefficients (i.e., risk aversion) over just the gains domain.

[7] Estimated relationships can be expressed as $y = \Lambda_y \eta + \varepsilon$ between observed variables y and first-order factors η and $\eta = \Gamma\xi + \zeta$ between first-order factors and second-order factors ξ, where Λ_y and Γ are matrices of partial regression coefficients commonly referred to as factor loadings and ε and ζ are residual errors. See Pennings and Garcia (2001) for a more detailed account of the measurement model for the second-order factor.

latent factor based on correlations across the three latent risk attitude measures. Each of the three latent risk attitude measures is significantly related to the GRAC at the 10% level or better. The model exhibits good coherence to the data with χ^2/df of 1.22 ($P = 0.262$), RMSE of 0.047, and Tucker Lewis index (TLI) of 0.962 supporting the presence of a GRAC.[8] Asterisks in Figure 1 reflect the significance of GRAC components. Interestingly, in contrast to Pennings and Garcia (2001), where the GRAC was driven by experimentally derived measures, here scales have a relatively greater influence on the GRAC composition. This point is also reflected in the relative ability of individual components of the GRAC to explain behavior, as discussed in the next section.

5. Relation between risk attitude and marketing behavior

Marginal effects from regressions for adoption (i.e., binary probit) and proportional use (i.e., truncated least squares) of various marketing alternatives are presented in Table 9 for hog and corn sales.[9] In particular, we examine producers' usage of marketing contracts, forward contracts, futures and options, and spot sales.

Results for several producer characteristics are consistent with prior findings. For instance, age is positively related to spot market use and negatively related to contract use, which may reflect older producers capitalizing on experience to profitably time cash sales or their reluctance to diverge from the status quo in markets where contracting is not the norm historically. Unit requirements (i.e., bushels and hundredweight) of standardized futures and options contracts may limit smaller producers' ability to utilize them. Producers with larger operations, as indicated by sales, as well as those with college education are more likely to use futures and options. Of the producers using futures and options, those with college education use these marketing tools proportionally less. Thus, college-educated producers may feel more comfortable using futures, but do so more sparingly. Such interesting subtleties are observable due to the hurdle model approach used here (Cragg, 1971; Katchova and Miranda, 2004) and may be masked in prior studies using Tobit regressions. Producers with higher DEBT/ASSET ratios use spot markets less and forward contracts more. The intuition here is that more leveraged producers may require more stable cash flows to repay debt, regardless of their inherent preferences for risk. Relative to crop producers, there is lower use of forward contracts and futures and options by hog producers, but greater use of marketing contracts.

Notably, risk aversion (GRAC) decreases proportional use of spot markets and increases proportional use of forward contracts but not futures and options. Clearly, finding that producers with relatively greater aversion to risk make greater use of forward contracts to limit their exposure to cash price variation is an intuitive result. The finding for futures and options is unexpected, however, and may reflect that futures and options are also used for reasons other than risk abatement. During interviews, some producers noted that they at times utilize futures markets in a more speculative manner, and the fact that futures and options usage was not distinguished by motives (i.e., hedging vs. speculation) in data collection may contribute to confounding effects.

Another unexpected result is that risk aversion significantly decreases proportional use of marketing contracts for hog and corn sales. However, this finding is particularly sensitive to model specification. Replacing the debt-to-asset ratio by an alternative measure (i.e., capital replacement and term debt repayment margin) or using soybean sales in place of corn sales yields differing results. Under these specifications, the probability of using marketing contracts increases with risk aversion (respective P-values of 0.104 and 0.016), but risk aversion has no significant effect on proportional usage. Similarly, using the full sample and a binary dummy variable for the IPT group suggests greater probability of marketing contract usage by producers with S-shaped utility functions (P-value $= 0.082$), in probit regressions using the alternative debt measure but not the debt-to-asset ratio.[10] This finding may reflect loss-averse producers' willingness to sign contracts offering price floors or premiums over cash prices that help to ensure profitability.

Table 10 compares R^2 values from alternative regressions using each of the measures of risk attitude to assess their relative explanatory contribution. The GRAC is the best predictor in only two of these regressions, but is a close second in many of the others. In light of the relative importance of the scale measures in the GRAC formulation, it is not be too surprising that these measures provide somewhat similar or even modestly better explanatory power than the more sophisticated construct. Examination of the importance of the individual risk coefficients (not shown) also is supportive of the scale measures. For the regressions, the measures derived from scales typically are at least as significant as the GRAC and more significant than the measure derived from experiments alone. Only for the binary probit models of forward contract adoption did the experimentally derived measure provide a significant and a more intuitively positive relationship than the scale measures. This effect is not significant for the GRAC measure either, which is heavily influenced by the scale survey items.

These findings differ from Pennings and Garcia's (2001) results in which the GRAC is more heavily influenced by experimental measures than by scales, and is superior to the underlying components as a predictor of producers' intended behavior. In addition, Pennings and Garcia's (2001) GRAC has

[8] For RMSE, a value below 0.08 indicates a close fit (Browne and Cudeck, 1986). For TLI, a value greater than 0.90 is recommended (Hair et al., 1995).

[9] To examine the sensitivity of our results, the analysis was conducted using the capital replacement and term debt repayment margin in place of the debt-to-asset ratio or using soybean sales in place of corn sales. Except as otherwise noted, the results are largely similar to those presented here.

[10] Such findings of sensitivity to specification can emerge when the correlation between different measures of the financial situation and risk attitudes are nonzero.

Table 9
Marginal effects for hog and corn sales regressions

	Spot sales		Marketing contract		Futures & options		Forward contract	
	Binary probit	Truncated OLS	Binary probit	Truncated OLS	Binary probit	Truncated OLS	Binary probit	Truncated OLS
Age	0.0079**	0.0108***	−0.0124**	0.0172***	−0.0248***	−0.0143	−0.0053	−0.0008
	(0.0040)	(0.0041)	(0.0050)	(0.0037)	(0.0091)	(0.0101)	(0.0051)	(0.0062)
College	0.0240	−0.0357	−0.0122	−0.4058***	0.2675*	−0.4622**	0.0496	0.1334
(1 = Yes, 0 = No)	(0.0724)	(0.0652)	(0.0700)	(0.1007)	(0.1449)	(0.2140)	(0.0898)	(0.1051)
Sales	−0.0005	−0.0006	0.0004	−0.0065**	0.0105***	0.0008	−0.0006	0.0041
($100,000)	(0.0016)	(0.0013)	(0.0014)	(0.0029)	(0.0037)	(0.0039)	(0.0017)	(0.0043)
HOG	−0.0577	0.3989***	0.1694*	0.6874***	−0.4475***	−0.4251	−0.5449***	−0.5932***
(1 = Yes, 0 = No)	(0.0867)	(0.0795)	(0.0917)	(0.1618)	(0.1497)	(0.2787)	(0.1056)	(0.2218)
Debt/asset	−0.0007	−0.0047***	0.0019	0.0008	0.0024	0.0055	0.0029	0.0051**
	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0031)	(0.0047)	(0.0023)	(0.0025)
GRAC	−0.0081	−0.0147**	0.0087	−0.0344*	0.0157	−0.0211	0.0115	0.0188*
	(0.0078)	(0.0068)	(0.0073)	(0.0198)	(0.0146)	(0.0181)	(0.0102)	(0.0109)
Sigma	–	0.2269***	–	0.1023***	–	0.2584***	–	0.2641***
		(0.0242)		(0.0209)		(0.0622)		(0.0428)
Observations	71	62	71	12	71	29	71	51
Censored	–	9 truncated	–	59 truncated	–	42 truncated	–	20 truncated
Log likelihood	−23.1162	11.2832	−21.7598	10.3281	−36.3233	15.5511	−25.4614	15.1886
Pseudo R^2	0.1436	0.3645	0.3254	0.0071	0.2435	0.1305	0.3968	0.3984

Note: Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

Table 10
R^2 for models of marketing methods for hog producers and corn producers using alternative measures of risk attitude

	Spot		Marketing contract		Futures & options		Forward contracts	
	Probit	Truncated	Probit	Truncated	Probit	Truncated	Probit	Truncated
Scale 1	0.1299	**0.3725**	**0.3343**	0.0090	**0.2522**	0.0989	0.3924	0.3960
Scale 2	0.1338	0.3134	0.3051	0.0251	0.2315	0.1619	0.3899	0.3652
$u(x)$	0.1245	0.3148	0.3333	**0.0475**	0.2459	**0.1862**	**0.4099**	0.3554
GRAC	**0.1436**	0.3645	0.3254	0.0071	0.2435	0.1305	0.3968	**0.3984**

Note: Best R^2 is bolded.

a significantly positive influence on producers' *intended* futures market usage, while we find no such relationship between actual futures market usage and any of the risk attitude measures. Notably, Pennings and Garcia's (2001) structural equation model accounts for measurement and modeling error but does not distinguish between adoption and proportional use of marketing methods and does not control for other producer characteristics as we do here.

6. Conclusions

In light of concerns about conceptual models used to derive risk preferences and differences in their ability to explain behavior, we reevaluate the usefulness of an approach proposed by Pennings and Garcia (2001) that combines alternate risk measures to more completely reflect preferences. We develop a GRAC composed of multi-item scales and EUT-based measures, and examine its relation to several distinct marketing choices for hog producers and corn producers. The importance to decision makers of understanding these relationships is highlighted by recent changes in volatility in most commodity markets and the likelihood that this uncertainty will continue due to changes in climate conditions and in the world economy.

The findings highlight the usefulness of Likert scales in explaining behavior. Regression analyses reveal that increasing risk aversion is statistically associated with avoidance of spot market transactions and greater reliance on forward contracts. Here, using the GRAC offers similar or better explanatory power than its underlying measures. However, in other cases, the scale measures provide modestly better explanatory power and significant findings—a result consistent with their relative importance in the GRAC formulation. Despite the conceptual attractiveness of combining various risk attitude measures, the overall findings suggest that this practice may yield little relative gain in explaining behavior.

While the findings show the usefulness of the Likert scales, they do not support their complete superiority over lottery measures as identified by Dohmen et al. (2011). Similarly, they differ with Anderson and Mellor (2009) who find little consistency across survey and experimental risk measures, and Pennings and Smidts (2000) who find that lottery measures explain market behavior better than scales. Our findings are somewhat similar to Pennings and Garcia (2001) who demonstrate that a GRAC utilizing common variance among scale- and lottery-based measures is statistically related to producers' intended use of futures markets. However, the superiority of their GRAC measure relative to its underlying components, and the relatively greater contribution of the EUT measure to its formulation, is not observed in our results. A possible explanation for these differences is our focus on multiple aspects of actual marketing behavior, rather than solely on intentions (Pennings and Garcia, 2001) or usage of a single marketing option (Pennings and Smidts, 2000). Alternatively, the finding may reflect the issues raised about EUT measures and the adequacy of risk attitude measures derived from experiments based on EUT (e.g., Barham et al., 2012; Herberich and List, 2012; Just, 2011; Just and Peterson, 2010; Just et al., 2010).

Several aspects of our results provide insights into research practices and point to areas for further work. First, researchers should seriously consider using survey-based measures of risk attitude; our results highlight their effectiveness. Not only do they offer a low-cost option that reflects behavior well, but they can supplement experiments, allowing for checks of consistency and accuracy of EUT measures and permitting comparative analysis of risk-related behavior.

Second, while we find that scale measures work well, EUT measures have performed better in other studies. Future work to identify under what circumstances simpler rather than combined risk attitude measures are more useful would be beneficial to researchers. In a related vein, our findings may be consistent with concerns for the realism of experiments, reinforcing the need to improve this approach. This is particularly important because the use of scale procedures alone does not permit measurement of risk aversion coefficients nor allow inferences to be drawn about whether agents possess globally concave (risk averse), convex (risk seeking), or S-shaped utility functions. Indeed, a full 25% of our sample exhibit risk aversion over the gain domain and risk-seeking preferences over the loss domain, corresponding to prospect theory. Failure to incorporate these preferences could lead decision makers to poorly anticipate the consequences of heightened volatility as producers respond "unexpectedly" to increasing and decreasing changes in market prices. Of course, this notion also raises the challenge of incorporating loss aversion into the GRAC construct.

Finally, the results presented here indicate that much of the unexplained variance in marketing behavior reflects factors other than error in measuring risk attitude. Proper specification of the surrounding economic environment can only lead to more accurate measurement of the effect of risk on behavior.

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