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Producer preferences for contracts on a risky bioenergy crop

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Producer preferences for contracts on a risky bioenergy crop

Abstract

This study employs a stated choice experiment to identify producer preferences for contracts to produce a risky bioenergy crop. The study develops a theoretical framework that takes into account subjective risk preference and perception information while also accounting for heterogeneous status-quo (i.e., current crop) alternatives. Results from our Random Parameter Logit model indicate that price, biorefinery harvest, and establishment cost-share all had significant positive effects on the probability of a producer accepting a contract, whereas contract length have a negative effect. The study also finds evidence of significant preference heterogeneity in producer preferences for biorefinery harvest, yield insurance, and contract length. Incorporating subjective risk perception and risk preference information, as well as accounting for heterogeneous status-quo alternatives in the decision framework improves overall model performance.

Keywords: choice experiment; contract; mean-variance utility; preference heterogeneity; random parameters logit; risk perceptions; risk preferences; willingness to accept compensation

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1. Introduction

Ethanol production in the U.S. is dominated by the use of corn which has generated a debate about the possibility of increased food prices (Runge and Sanauer 2007). Oil price fluctuations (LeBlanc and Chinn 2004), ensuring energy security, production of clean renewable energies, and protecting consumers are among the major reasons for the supply of alternative energy sources (Energy Independence and Security Act (EISA) 2007). To address these concerns, EISA of 2007 mandates that by the year 2022, 21 billion gallons of ethanol be produced from cellulose annually (EISA 2007).

Cellulosic ethanol is ethanol obtained from sources such as switchgrass, wood residues, and corn stover. There is evidence that cellulosic ethanol is both more abundant and also more environmentally-friendly than grain-based biofuels (Perrin et al. 2008). On the other hand, the use of corn residues above a certain threshold (Sesmero et al. 2014; Petrolia 2008a) would result in increased erosion problems. Cellulosic fuels also result in significant reductions in green gas emissions relative to conventional fuels, although sulfur oxide emissions (e.g. SO_2, SO_3) would increase (Petrolia 2006).

Due to the lack of a market for biomass crops in the U.S., as well as the potential yield loss which could be associated with biomass crops, production of a biomass crop could be considered as a risky enterprise. A potential means to induce producers to grow biomass crops is by offering production contracts. Additionally, potential producers may not only be interested merely in contract availability. Producers will accept contracts to produce biomass crops only when they see the overall value of the contract, accounting for both real and perceived risks of switching crops, to be higher than the expected returns from their current crop (Song et al. 2011). As a result, particular contract attributes are important at the margin.

The literature has shown that contract attributes which may be of interest to producers may include price per ton of harvested biomass crop, contract length, availability of yield insurance, biorefinery harvest (versus self-harvest), and establishment cost–share (Bergtold et al. 2014). Other factors that have been shown to influence an individual's decisions under risk are subjective risk perceptions and risk preferences (Petrolia et al. 2015; Petrolia et al. 2013; Lusk and Coble 2005). However, no research has been conducted that specifically addresses how these latter factors affect producers' decisions for accepting contracts to produce biomass crops. Furthermore, no previous research has provided a theoretically-consistent framework through which to analyze such decisions. This research provides these important contributions to the literature.

Past studies regarding cellulosic feedstock production were focused on the feasibility (both economic and technical) and the potential supply of alternative sources of cellulosic biofuel feedstock (e.g. Bangsund et al. 2008; Bruce et al. 2007; De La Torre Ugarte et al. 2007; Khanna et al. 2008; Perrin et al. 2008; Petrolia 2008b), with other work focusing on consumer preferences for biofuels (e.g. Li and McCluskey 2014; Petrolia et al. 2010; Skahan 2010; Solomon and Johnson 2009; Ulmer et al. 2004). For instance, Perrin et al. (2008) estimated the cost of producing switchgrass in commercial quantities. Bruce et al. (2007) also carried out a study similar to Perrin et al. (2008) by providing estimates of the costs associated with the conversion of land for traditional crop production to the production of switchgrass. Bergtold et al. (2014) employed survey methods to study Kansas farmers' willingness to produce alternative cellulosic biofuel feedstocks under alternative contractual, harvesting, and market arrangements.

Altman et al. (2015) investigated the effect of price variability and producer characteristics on producers' willingness to supply biomass (specifically, straw, corn stover, and hay). Mooney, Barham, and Lian (2015) also used contingent valuation data to analyze the near-term supply response for corn stover and switchgrass.

We propose an econometric specification to model the effect of contract attributes on producer preferences that is consistent with expected utility. The attributes tested are biorefinery harvest, availability of yield insurance, crop establishment cost–share, and contract length. Our specification incorporates individual-specific risk preferences (i.e., a risk aversion coefficient) and risk perceptions (i.e., subjective mean and variance associated with crop yields). Importantly, the specification also controls for differences in status-quo, i.e., for heterogeneity in each producer's specific opportunity cost of accepting a biomass contract. Previous work has implicitly assumed a common status-quo for producers. Our specification is an adaptation of Spiegel's (2013) presentation of Sargent's (1987) original mean-variance utility model. The estimated models can then be used to construct estimates of the overall contract values necessary for adoption, probabilities of contract acceptance, and estimates of the incremental values of contract attributes.

We present an empirical application of the model using data from a survey of producers focused on acceptance of contracts to produce Giant Miscanthus. Giant Miscanthus has been identified as a high-yielding bioenergy crop that could be a more promising alternative than switchgrass (Heaton et al. 2004). The grass is cultivated from rhizomes and can reach a height of eight to twelve feet. It takes two to three years to reach full harvest potential. Once established, stands can remain on the field for an average of fifteen years without re-establishment or re-planting, requiring only fertilizer at harvest to replace nutrient loss (Heaton et al. 2010). Giant Miscanthus can thrive on marginal lands which are not suitable for row crops such as corn, although yields tend to be lower on marginal soils (Heaton et al. 2010).

We find that incorporating risk perception and risk preference information, as well as accounting for heterogeneous status-quo information in the decision framework improve overall model performance. Further, we find that price, biorefinery harvest, cost-share, and contract length are significant predictors of producers' decisions to accept bioenergy crop production contracts. Our results also find evidence of significant preference heterogeneity in producers' preferences for biorefinery harvest, yield insurance, and contract length.

The article is organized as follows. The next section describes the underlining theory behind the study, followed by experimental design and data collected; we then detail our econometric model, followed by the econometric results. The paper then ends with some conclusions and implications.

2. Mean-Variance Utility

Following Spiegel's (2013) presentation of Sargent's (1987) original model, suppose the utility from revenue, *R*, is given by:

$$U(R) = -e^{-\delta R},\ \delta > 0 \tag{1}$$

where δ is the risk aversion coefficient.

Taking the first and second derivatives of (1), we have:

$$U^{/}(R) = \delta e^{-\delta R} > 0, \quad U^{//}(R) = -\delta^2 e^{-\delta R} < 0. \tag{2}$$

Equation (2) implies that utility is increasing and concave in revenue, *R*, where concavity suggests risk aversion. Furthermore we can also note that the Arrow – Pratt absolute risk aversion coefficient is given by:

$$-\frac{U^{//}(R)}{U^{/}(R)}=\delta. \tag{3}$$

This suggests that the larger the value of δ, the more risk averse the producer is. Assuming revenue, *R*, is distributed normally with mean, μ and standard deviation, σ then the density of *R* is represented by:

$$f(R)=\frac{e^{\frac{-(R-\mu)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}}. \tag{4}$$

Hence, expected utility can also be represented by the expression:

$$EU(R)=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}-e^{-\delta R}e^{\frac{-(R-\mu)^2}{2\sigma^2}}dR$$

$$=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}-e^{-\left(\delta R+\frac{(R-\mu)^2}{2\sigma^2}\right)}dR. \tag{5}$$

Rearranging the exponent in (5) so as to group terms that depend on *R* and terms that do not depend on *R*, we have:

$$\delta R+\frac{(R-\mu)^2}{2\sigma^2}=\frac{(R-\mu+\delta\sigma^2)^2}{2\sigma^2}+\delta\left(\mu-\frac{\delta\sigma^2}{2}\right) \tag{6}$$

Substituting (6) into (5) yields;

$$EU(R)=-\frac{e^{-\delta\left(\mu-\frac{\delta\sigma^2}{2}\right)}}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}e^{-\frac{(R-\mu+\delta\sigma^2)^2}{2\sigma^2}}dR. \tag{7}$$

Now, for all μ',

$$\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}e^{-\left(\frac{(R-\mu^{/})^2}{2\sigma^2}\right)}dR=1, \tag{8}$$

because the left hand side of the equation is the area under the density function over the entire support when the mean is μ', and with γ as the standard deviation. For any μ', including $\mu' = \mu - \delta\gamma^2$, it follows that

$$EU(R) = -e^{-\delta\left(\mu - \frac{\delta\sigma^2}{2}\right)}.$$

(9)

To simplify the above expected utility function, we take the log of both sides to linearize it.

$$\ln EU(R) = \delta\left(\mu - \frac{\delta\sigma^2}{2}\right) \tag{10}$$

where μ is the mean revenue and σ^2 is the variance associated with the revenue. We assume that the effective objective function is given by the expression in brackets in (10);

$$\mu - \frac{\delta\sigma^2}{2}. \tag{11}$$

3. Experimental Design and Data

A set of contract attributes were established for the experimental design based on a search of the literature and discussion with experts in this area. We settled on five contract attributes: price per ton of harvested grass, contract length in years, percent cost-share of rhizome establishment, availability of yield insurance, and biorefinery harvest. Price had the following levels: \$50, \$60, \$70, \$80, \$90, and \$100 per ton of harvested Giant Miscanthus. Although no markets for Giant Miscanthus or cellulosic feedstocks exist at present, the choice of these levels were guided by prices suggested by McLaughlin et al. (2002) who proposed \$44 /ton for U.S. biomass crops and Khanna et al. (2008) who reported breakeven farm-gate price of Giant Miscanthus to be in the range of \$41-58.

Contract length had three levels: 5, 9, and 13 years. Our inclusion of this attribute was informed by Bergtold et al. (2014). We specified five years as the minimum contract length because Giant Miscanthus takes two to three years to reach first harvest, allowing the producer to harvest at least two years following first harvest to recover, at least partially, the initial establishment cost.

As pointed out by Khanna et al. (2008) growing Giant Miscanthus requires high initial establishment cost. As a result we believe that potential producers may consider initial establishment cost-share. This form of support is captured in an existing government program known as the Biomass Crop Assistant Program (BCAP). Consistent with BCAP cost-share, we presented three levels for this attribute which were 0 percent, 25 percent and 50 percent.

We specified an insurance attribute that indicated whether federal crop yield insurance, at a 65 percent coverage level, was available for purchase. We chose 65 percent because it is the most common yield protection insurance coverage for most crops in the U.S. This attribute was included to serve as a risk management tool for farmers to be able to enter into production of Giant Miscanthus, bearing in mind that there could be yield loss as a result of unfavourable weather conditions, pests, and disease infestation. The inclusion of yield insurance as an attribute was also motivated by the work of Bergtold et al. (2014).

Harvesting of Giant Miscanthus is something that would be of major concern to potential producers since producers may not currently possess proper harvesting equipment. To account for this, we included a binary attribute that indicated whether the Giant Miscanthus would be harvested and transported by the biorefinery. This attribute has previously been considered by

Table 1: Contract Attributes, Levels, and Units/Descriptions

Attribute	**Levels**	**Units/Description**
Price	\$50, \$60, \$70, \$80, \$90, \$100	per ton (Price per acre reported in parentheses, assuming 12 tons/ac)
Contract length	5, 9, and 13 years	in years
Cost-share	0%, 25%, and 50%	Rhizome / establishment cost-share as % of total cost
Insurance	Yes / No	Yes: 65% coverage federal crop yield insurance available for purchase; No: not available
Biorefinery harvest	Yes / No	Yes: bio-refinery will harvest and transport biomass at their expense; No: farmer responsible for harvest at own cost, but bio-refinery responsible for transporting to plant.

Bergtold et al. (2014). Table 1 presents the summary of the attributes, levels, and descriptions/units used in the choice set design.

We elicited three alternative measures of risk preference. The first two questions were subjective measures which allowed respondents to examine their own tolerance of risk relative to other people. The other measure of risk preference captured some form of certainty equivalent information. With this measure, respondents were asked to state the lowest price they would forward a contract to eliminate all price risk in their current crop productions. The exact questions were worded as follows:

> *1) Relative to other farmers, how would you describe your willingness to accept risk in your farm business?*
>
> > *a. Definitely will not accept risk b. Probably will not accept risk c. Indifferent to risk acceptance d. Probably will accept risk e. Definitely will accept risk*
>
> *2) In general, do you consider yourself as more less a risk-taker than your family members, friends and neighbor?*
>
> > *a. More b. Less c. About same*
>
> *3) Assume you were offered the opportunity to lock in a certain price for your "current crop" in the 2015 crop year. What is the lowest price for which you would forward contract to eliminate all price risk for "current crop".*
>
> > *$……….*

We refer to these three measures of risk preference as the 5-point-scale measure of risk preference, the 3-point-scale measure of risk preference, and the certainty-equivalent-based measure of risk preference, respectively.

Using producers' responses to the certainty equivalent risk preference measure, we constructed a variable by dividing the lowest price respondents were willing to lock in a contract to produce their current crop by their expected price which was also elicited in another question. This was derived by the expression:

$\delta_i^{CE} = \frac{lowest\ price\ to\ lock\ in\ contract}{expected\ price}$. Producers with $\delta_i^{CE} < 1$ were considered as risk averse, $\delta_i^{CE} = 1$ were considered as risk neutral, and those with $\delta_i^{CE} > 1$ were considered as risk seekers.

We elicited respondents' subjective perceptions regarding current crop price and yield expectations, as well as how they perceive the yield risk of Giant Miscanthus relative to their current crop. Figure 1 provides the exact wording of the questions used. Using yield and price information, we calculated total revenue, then, assuming a triangular distribution, we constructed mean revenue, μ and variance, σ^2. The use of the triangular distribution for subjective yield distribution elicitation was proposed by Griffiths, Anderson, and Hamal (1987). The subjective questions are straightforward for the respondent, yet it has the flexibility to reflect yield skewness.

1. *What yield do you consider most likely for your current crop in 2015?*
2. *What do you expect will be your lowest yield in 10 years of growing "current crop?"*
3. *What do you expect will be your highest yield in 10 years of growing your "current crop?"*
4. *What price do you consider to be the most likely harvest time price for your "current crop" in 2015?*
5. *What price do you consider there to be only a 10% chance that the harvest time prices will fall below?*
6. *What price do you consider there to be only a 10% chance that the harvest time prices will rise above?*
7. *Research has shown that the average Miscanthus yield in Southeastern cropland is 12 tons/acre and ranges between 9-15 tons/acre. Would you consider that:*
   The yield risk of growing Miscanthus is _______________ *the risk of growing your alternative crop.*

a. Less than b. *Equal to* *Greater than*

Figure 1. Risk perception questions

Our study involved producers who grow a variety of crops with varying levels of revenue and risk, and as a result were willing to substitute different crops for production of Giant Miscanthus. To account for these differences and determine a common measure for status-quo, we used the difference between the expected total revenue per acre from the production of the current crop they were most likely to replace. To achieve this we utilized information on producers' expectations of yield and prices of their current crop to calculate expected revenue per acre. We then calculated the expected revenue difference by subtracting expected returns per acre for growing Giant Miscanthus under a ten year contract (i.e., $69 per ton x 12 tons per acre x 8 years /10 years) to obtain our revenue difference. We assumed $69 is the expected price per ton of harvested Giant Miscanthus and 12 tons per acre is the expected yield of Giant Miscanthus (this information was made known to the respondents as part of the survey). Because Giant Miscanthus takes two to three years to reach full harvest potential it suggests that producers who agree to produce Giant Miscanthus would have to wait until the end of the third year for a marketable harvest. In effect, for a ten-year contract, producers would actually receive payment in only eight of those years.

There were some challenges in establishing total revenue per acre for producers who chose to convert pasture. For example, some pasture producers reported their yield units in number of head per acre per year, and reported price units in dollars per pound. To derive total revenue per acre for these farmers, we consulted John Michael Riley, an Extension Economist in the Department of Agricultural Economics at Mississippi State University (Personal Communication, April, 2015). Given the units and other extra information they provided, for a pasture grazed by cattle we multiplied the number of head of cattle per year by 550 pounds (average weaning weight) before multiplying it by the expected price per pound they provided in order to obtain revenue per acre. However, there were some units reported which did not appear realistic and/or consistent; consequently, we excluded these observations from our analysis.

We partitioned our survey instrument into three main sections: The first section contained a set of general questions regarding producers farming operations. The second part presented information about Giant Miscanthus, followed by explanations of the contract attributes and the choice sets. Choice sets were designed to minimize D-error using NGENE software (ChoiceMetrics 2014). In all, 12 choice sets (rows) were generated which were put into two blocks, with six choice sets in each block. Each respondent was randomly assigned to a block. Figure 2 shows a typical choice set scenario as presented to the respondent. The third part of the survey contained risk assessment questions (for instance questions eliciting risk preferences and risk perceptions) and demographic characteristics such as age, education level, years of farming experience, etc. of the respondents.

We conducted our survey using Qualtrics survey software (Qualtrics Labs, Inc. 2014). We pretested our instrument on twelve producers from Mississippi in August 2014 and made the necessary corrections before sending the final version out in mid-December 2014, after most farmers finished harvesting their crops. Our target population were crop and/or pasture producers in Mississippi and North Carolina as well as members of the "25 x' 25 Alliance".

Suppose a biorefinery is offering you the contracts below to produce Giant Miscanthus as against producing your current crop, which option would you prefer?

Attribute	*Contract A*	*Contract B*	*No Contract*
Price Paid	*$100/ton ($1200/acre)*	*$90/ton ($1080/acre)*	*I would not grow Miscanthus under the offered contracts and would maintain my current crop mix*
Contract Length	*9 years*	*9 years*	
Biorefinery Harvest	*No*	*Yes*	
Yield Insurance Available	*Yes*	*No*	
Rhizome/Establishment Cost-Share	*25%*	*0%*	

I would choose...

[Check only one]	*Contract A*	*Contract B*	*No Contract*
	○	○	○

Figure 2. Example of choice set scenario

Respondents were contacted via third parties who shared emails containing the link to the survey. To encourage participation, we offered a $25 Walmart electronic gift cards to each respondent. We e-mailed a total of 565 producers and received 56 completed surveys yielding a total of 336 (6*56) observations. Previous mail surveys in Mississippi conducted by Hite, Hudson, and Intarapapong (2002) and Petrolia and Kim (2009) resulted in extremely low response rates. A breakdown of our survey responses is presented in Table 2.

Table 3 reports the crops respondents were producing at the time of the survey. The results suggest that most of the farmers produce corn, soybeans, and pasture. A single producer could produce multiple crops. Respondents were asked to indicate a single crop from their current crop mix for which they were most likely to substitute with Giant Miscanthus. This crop then served as the "status-quo" alternative throughout the choice experiment. The results suggest that most of the producers sampled were willing to substitute soybean and pasture production with Giant Miscanthus production.

Table 2: Breakdown of Respondents

Location	**No. of producers contacted**	**No. of producers who did not complete**	**No. of producers who completed**	**Completion rate (%)**
Mississippi	240	16	28	11.7%
North Carolina	300	75	19	6.3%
25 x' 25 Alliance	25	5	9	36.0%
Total	**565**	**96**	**56**	**9.9%**

Table 3: Respondents' current crop(s) produced and crop chosen as most likely to be substituted with Miscanthus

Crop	**Current Crop Produced (frequency of response)***	**Crop chosen as most likely to be substituted with Giant Miscanthus (frequency of response)**
Soybean	33	17
Corn	30	9
Pasture	27	12
Wheat	16	4
Rice	10	1
Cotton	7	1
Grain Sorghum (Milo)	7	3
Other crops	22	9
Total		**56**

* Out of a total of 56 respondents; does not sum to 56 as some respondents reported multiple crops.

Of the 56 participants who completed the survey, 50 (89%) of the respondents were male and six were female. The average age of the producers sampled was approximately 47 years. Respondents' household size ranged from one to six members with average household size of about three members. The average farm size of our survey respondents was found to be around 1,755 acres. While the farm size of our population is larger than the state averages of 287 acres in Mississippi and 168 acres in North Carolina, this is as a result of our target population who were mostly commercial farmers operating on large farms. The majority of the producers sampled had been in the farming business for more than ten years, suggesting that many respondents have the experience necessary to forecast expected yields and prices of their current crops. Results indicated that, on average, about 61 percent of the producers' income comes from farming. None of the producers surveyed had less than a high-school education, the majority of them completed a 4–year degree (B.S or B.A). Table 4 presents summary statistics of demographic variables. Reported in Table 5 are the frequencies at which producers chose Giant Miscanthus production contracts (alternative A or B) or to maintain current crop production (status-quo, alternative C). Approximately two-thirds of the time, a Giant Miscanthus contract alternative was chosen over the status-quo alternative.

Table 4: Summary statistics of demographic variables (N =56)

Variable	**Mean**	**Std. Dev.**
Age (years)	47.29	10.05
Household size	3.39	1.39
Farm size (acres)	1755	2326
Farming experience (years)	12.88	4.21
Years of formal education	15.93	1.82
Percent of income from farm (%)	61.16	40.78

Table 5: Respondents' choice of Giant Miscanthus contract vs. current crop

Alternative	**Frequency**	**Percentage**
Giant Miscanthus contract (alternative A or B)	218	64.9%
No contract (status-quo, alternative C)	118	35.1%
Total	**336**	**100.0%**

4. Econometric model

To account for the existence of preference heterogeneity in producers' preferences for contract attributes, as well as account for scale difference (i.e. relaxing IIA assumption), we specified a Random Parameter Logit (RPL) model. Following Train (2009) and using equation (11), utility of respondent *i* choosing alternative *j* can be written as:

$$U_{ij} = \alpha_0 + \eta_i + \alpha_\mu \mu_i - \left(\alpha_{RA} RA + \alpha_{RL} RL\right)\frac{\delta_i \sigma_i^2}{2} + \boldsymbol{\beta}'\mathbf{X}_{ij} + \mathbf{v}_i{}'\mathbf{X}_{ij} + \boldsymbol{\gamma}'\mathbf{Q} + \varepsilon_{ij} \tag{12}$$

where α_0 is a fixed coefficient capturing inherent preferences for a bioenergy crop alternative (relative to the status-quo) and η_i is the associated random term; *RA* and *RL* are binary indicators for whether a respondent is categorized as risk-loving or risk-averse, respectively; μ , σ , and δ are as defined earlier, with α_μ, α_{RL} , and α_{RA} associated fixed coefficients to be estimated; $\boldsymbol{X}$ is a vector of alternative-specific contract attributes, which includes contract price; biorefinery harvest; yield insurance contract length; and crop establishment cost-share; $\boldsymbol{\beta}$ are the associated coefficients to be estimated; $\mathbf{v}_i$ are individual-specific random terms that capture preference heterogeneity in the attributes; $\boldsymbol{Q}$ is a vector of binary indicators to control for choice question order (there were six choice questions presented to each respondent), with the associated fixed parameters $\boldsymbol{\gamma}$; and ε_{nj} is distributed iid extreme value. Reported in Table 6 is a summary and description of all the variables used in our econometric models.

Table 6: Summary and description of variables

		Mean	**S.D.**
Contract Attributes			
Price ($)		75.00	17.52
Contract length (years)		9 .00	3.27
Cost share (%)		25.22	20.29
Insurance (yes = 1)		0.50	0.50
Biorefinery harvest (yes = 1)		0.50	0.50
Risk Perception Variables			
Net revenue (scaled by /100) ($)		3.75	19.95
Variance (σ^2) (scaled by /1000)		102.93	389.30
Risk Preference Variables			
δ_i^5 = 5- point-scale risk preference measure	Risk averse	0.25	0.43
	Risk loving	0.57	0.50
δ_i^3 = 3- point-scale risk preference measure	Risk averse	0.13	0.50
	Risk loving	0.45	0.50
δ_i^{CE} = certainty equivalent risk preference measure		1.09	0.18

4.1. *Model Variations*

In the existing literature, studies similar to this article have assumed a homogeneous status-quo alternative, i.e., have assumed that all respondents face the same opportunity costs. However, this is likely not the case, especially when dealing with producers who produce different crops, have different net returns, and face different risks. We improve upon previous work by accounting for heterogeneous status-quo alternatives by augmenting our econometric models with respondent-specific information on net revenue and variance, as well as risk preference information. We then tested these models against the base model (i.e. model with a homogenous status-quo alternative) to determine whether there is significant model improvement.

Four alternative models are specified depending upon whether heterogeneity is allowed for in the status-quo alternative, and how δ_i is specified. The "Base" model does not account for heterogeneity in the status-quo alternatives. The remaining three models introduce μ, σ^2, and δ to account for heterogeneity in the status-quo alternatives. We refer to these models by the specification of δ used in each. Thus, the "δ_i^5" model uses the 5-point-scale measure of risk preference, the "δ_i^3" model uses the 3-point-scale measure of risk preference, and the "δ_i^{CE}" model uses the certainty-equivalent-based measure of risk preference. Because δ_i^{CE} is a continuous variable, not discrete like the other two measures, the associated coefficients α_{RL} and α_{RA} collapse into a single coefficient, α_R.

In all models estimated, we implement Carson and Czajkowski's (2013) reparameterization of the coefficient on (the negative of) price to enforce a theoretically correct positive coefficient. This is accomplished by specifying the coefficient on the negative of price as log-normally distributed but with zero variance. The constant and attribute coefficients are randomized and are assumed to follow a normal distribution. The panel nature of the data set, given that each respondent made six choices, was accommodated by constraining the individual-specific attribute coefficients to be equal across choice observations for a given respondent. All models were estimated using simulated maximum likelihood with 600 Halton draws. After estimating all the models explained above, we carried out log-likelihood ratio tests to test for significant model improvement relative to the "Base" model. Specifically, we test the null hypothesis that the coefficients on μ, σ^2, and δ, namely, α_μ, α_{RL}, and α_{RA} (and in the case of δ_i^{CE}, α_R) are jointly equal to zero.

5. Results

5.1. *Producer Preference for Contract Attributes*

Model results are reported in Tables 7 and 8. Results for individual coefficients are fairly robust across model variations. Results indicate that price, contract length, cost share, and biorefinery harvest are all statistically significant, and with the expected sign. Insurance is not statistically significant in any of the models though it had the expected positive sign. Choice-question-order indicators were generally not significant (with one exception), indicating little or no order-driven status-quo bias. Consistent with the literature, biorefinery harvest and increasing cost-share increases the likelihood of contract acceptance, whereas increasing contract length decreases it.

5.2. *Preference Heterogeneity for Contract Attributes*

In terms of testing for producer preference heterogeneity for contract attributes, we found that the standard deviations for contract length, insurance, and biorefinery harvest were all statistically significant. Our results indicate that 89 percent of the respondents preferred shorter contract lengths with the remaining 11 percent preferring longer contracts. Although the mean preference for yield insurance was positive, 77 percent of the respondents had positive preference parameters while the remaining 23 percent put negative weights on yield insurance. Results indicate no significant preference heterogeneity among establishment cost-share preferences. Also, finally, the significance of the standard deviation for the constant indicates a difference in the scale of the variance across alternatives (i.e., a violation of the IIA assumption). This supports our choice of random parameter logit model to relax this assumption.

Table 7: Random Parameter Logit results for "Base" Model and "δ_i^5" Model

	Base Model		**δ_i^5 Model**	
Coefficient	**Coefficient (Std. error)**	**Std. Dev. (Std. error)**	**Coefficient (Std. error)**	**Std. Dev. (Std. error)**
α_0 , η	-3.667***	2.512***	-3.307***	2.186***
	(1.180)	(0.667)	(1.229)	(0.767)
$\ln \beta$ (-Price)	0.053***		0.053***	
	(0.167)		(0.175)	
α_μ			0. 030	
			(0.124)	
α_{RA}			0.007	
			(0.086)	
α_{RL}			-0.017	
			(0.022)	
β , ν (Contact Length)	-0.163**	0.200***	-0.159**	0.201***
	(0.069)	(0.077)	(0.067)	(0.075)
β , ν (Cost Share)	0.018**	0.015	0.018**	0.015
	(0.008)	(0.012)	(0.007)	(0.013)
β , ν (Insurance)	0.334	0.995**	0.308	0.995**
	(0.320)	(0.389)	(0.323)	(0.459)
β , ν (Harvest)	1.514***	1.231***	1.499***	1.194***
	(0.433)	(0.410)	(0.430)	(0.414)
γ_2	0.657		0.657	
	(0.722)		(0.710)	
γ_3	-0.260		-0.261	
	(0.692)		(0.725)	
γ_4	-0.787		-0.792	
	(0.875)		(0.885)	
γ_5	-0.260		-0.263	
	(0.648)		(0.690)	
γ_6	-1.423*		-1.427	
	(0.856)		(0.871)	
Log likelihood	-259.186		-255.581	
AIC	550.400		549.200	
N =		318 Panel = 53)		
LR Statistic $\left(\chi^2\right)$, $H_0: \alpha_\mu = \alpha_{RA} = \alpha_{RL} = 0$			7.21* (3 d.f.)	

Note: Standard errors are in parenthesis. ***, **,* represents significance at 1%, 5%, and 10% statistical levels of significance respectively.

Table 8: Random Parameter Logit results for "δ_i^3" Model and "δ_i^{CE}" Model

	δ_i^3 **Model**		δ_i^{CE} **Model**	
Variable	**Coefficient (Std. error)**	**Std. Dev. (Std. error)**	**Coefficient (Std. error)**	**Std. Dev. (Std. error)**
α_0 , η	-3.162***	2.292***	-3.156**	2.405***
	(1.213)	(0.790)	(1.298)	(0.740)
ln β (-Price)	0.052***		0.052***	
	(0.173)		(0.170)	
α_μ	0.010		0.032	
	(0.072)		(0.191)	
α_{RA}	0.050			
	(0.160)			
α_{RL}	-0.034			
	(0.041)			
α_R			-0.007	
			(0.020)	
β , ν (Contact Length)	-0.150**	0.182**	-0.150**	0.185**
	(0.068)	(0.073)	(0.064)	(0.076)
β , ν (Cost Share)	0.017**	0.015	0.018**	0.014
	(0.008)	(0.013)	(0.007)	(0.014)
β , ν (Insurance)	0.306	0.941**	0.307	1.002**
	(0.329)	(0.442)	(0.329)	(0.439)
β , ν (Harvest)	1.500***	1.215***	1.495***	1.185***
	(0.427)	(0.412)	(0.415)	(0.398)
γ_2	0.631		0.623	
	(0.727)		(0.720)	
γ_3	-0.296		-0.288	
	(0.736)		(0.693)	
γ_4	-0.851		-0.859	
	(0.946)		(0.882)	
γ_5	-0.304		-0.299	
	(0.694)		(0.660)	
γ_6	-1.445*		-1.445*	
	(0.866)		(0.841)	
Log likelihood	-254.798		-256.487	
AIC	547.600		549.000	
N =	318 (Panel = 53)			
LR Test $\left(\chi^2\right)$, $H_0 : \alpha_\mu = \alpha_{RA} = \alpha_{RL} = \alpha_R = 0$	8.78** (3 d.f.)		5.40* (2 d.f.)	

Note: Standard errors are in parenthesis. ***, **,* represents significance at 1%, 5%, and 10% statistical levels of significance respectively.

5.3. *Status-quo and Risk Information Effects*

All things equal, increased mean net returns on a respondent's current crop is expected to reduce the probability of accepting a Giant Miscanthus contract. Results indicate a positive coefficient on mean net returns, but it is not statistically significant.

As demonstrated by Petrolia et al. (2015); Petrolia et al. (2013); and Lusk and Coble (2005), risk preferences and risk perceptions can affect an individual's decision under risk. As demonstrated in the conceptual section earlier, this effect enters the model via the variance on net returns of the current crop. All else equal, an increase in the variance associated with the current crop is expected to increase the probability of a risk-averse respondent to accept a Giant Miscanthus contract, and to decrease that of a risk-loving respondent (both relative to a risk-neutral respondent.) Although not statistically significant, we find the expected signs on α_{RA} and α_{RL}, and this result is consistent across models. For the case of the certainty-equivalent measure of risk preference, we expect that, as the magnitude of the certainty-equivalent associated with the current crop increases, the degree of risk aversion decreases. In other words, given an increase in the variance associated with the current crop along with an increased in the certainty equivalent of the current crop, we expected the probability of accepting a Giant Miscanthus contract to decrease. Results are consistent with this expectation, although not statistically significant. Although we do not find significance on the individual coefficients, we do find, based on our likelihood ratio tests, significant overall model improvement when we incorporate these status-quo and risk information variables into the producer's decision framework, and this finding is consistent across all three model variants that incorporate this information. The improvement suggests that our findings are consistent with economic theory.

5.4. *Welfare Estimates*

Following Bliemer and Rose (2013), we use the Delta method with 25,000 random draws to calculate the mean and 95% confidence intervals on welfare estimates, both for individual attribute increment values as well as overall contract values. As with the raw model estimates, we find little difference across models. Careful interpretation of the welfare estimates is required, because these values are relative to the value of the status-quo alternative. For individual attributes, the welfare values indicate the amount of value that that attribute increment adds to the overall value of the contract.

Table 9 reports the mean attribute increment value and 95 percent confidence intervals associated with the various attributes. Taking the Base model results as representative, the presence of biorefinery harvest adds $28.98 per ton, on average, to the value of a Giant Miscanthus contract, whereas insurance adds $6.21 per ton. A 10 percent increase in cost-share adds $3.40 per ton, whereas each additional year added to the length of the contract reduces contract value by $2.90 per ton.

Table 9: Mean contract attribute increment values and 95% confidence intervals

Attribute	**Mean Contract Attribute Increment Value per ton (95% Confidence interval)**			
	Base Model	δ_i^5 **Model**	δ_i^3 **Model**	δ_i^{CE} **Model**
Contract length	-\$2.90 (-10, 4.58)	-\$3.00 (-11.17, 5.16)	-\$2.88 (-10.67, 4.90)	-\$2.88 (-10.70, 4.93)
Cost-share	\$0.34 (-0.48, 1.17)	\$0.33 (-0.41, 1.08)	\$0.33 (-0.44, 1.11)	\$0.33 (-0.36, 1.035)
Insurance	\$6.21 (-35.83, 48.24)	\$6.23 (-36.41, 48.87)	\$5.85 (-36.34, 48.04)	\$5.86 (-37.74, 49.47)
Biorefinery harvest	\$28.98 (-20.95, 78.92)	\$28.33 (-20.82, 77.48)	\$28.73 (-22.22, 79.68)	\$28.63 (-20.92, 78.17)

Table 10 reports estimated overall contract value for five representative contract scenarios. These also require careful interpretation. As indicated in the table, all welfare estimates are negative, indicating that, relative to an equally-priced status-quo alternative, a Giant Miscanthus contract is perceived to have a lower associated value. In other words, a producer would require additional compensation to accept a Giant Miscanthus contract that delivered an equal amount of revenue as their current crop. Taking the Base model results as representative, a producer offered a 5-year contract with 50 percent cost-share, insurance, and biorefinery harvest would require an additional $33.47 per ton over and above the value of the current crop to accept a Giant Miscanthus contract. Based on our findings, this example represents the most “attractive” contract terms. At the other end of the spectrum would be a 13-year contract, with no cost-share, no insurance, and no biorefinery harvest. Such a contract has an associated price discount of $109.63 per ton. Table 10 reports 3 additional contract scenarios between these two extremes. Overall, these results can be interpreted to indicate that, for whatever reason, while producers may be willing to accept contracts to produce Giant Miscanthus, they will require additional compensation – the magnitude of which is a function of the terms of the contract.

Table 10: Contract Values relative to status-quo crop for Representative Contract Attribute Scenarios

Scenario				Mean Miscanthus Contract Value Relative to Status-quo Crop (95% Confidence interval)			
Contract Length	**Cost-share**	**Insurance**	**Biorefinery harvest**	**Base Model**	δ_i^5 **Model**	δ_i^3 **Model**	δ_i^{CE} **Model**
5	50%	Yes	Yes	-33.47 (-164.79, 97.85)	-26.95 (-151.13, 97.24)	-24.62 (-151.77, 104.09)	-24.62 (-1935.11, 1885.86)
9	25%	No	Yes	-60.51 (-195.78, 74.76)	-53.33 (-182.38, 75.71)	-50.09 (-179.55, 80.41)	-50.09 (-1087.56, 987.38)
13	25%	No	Yes	-72.88 (-228.22, 82.46)	-65.46 (-216.25, 85.33)	-75.05 (-179.21, 29.04)	-75.05 (-314.08, 163.99)
5	0%	No	No	-84.89 (-194.65, 24.88)	-78.14 (-179.08, 22.81)	-61.76 (-209.74, 87.51)	-61.76 (-1188.80, 1065.27)
13	0%	No	No	-109.63 (-256.11, 36.85)	-102.39 (-243.95, 39.18)	-98.39 (-236.84, 40.48)	-98.39 (-710.16, 513.37)

6. Conclusions and Implications

This research provides a theoretically-consistent conceptual framework for modeling producer decisions to accept contracts under risk. Next the paper provides an empirical application focused on southeast U.S. producers' preferences for contracts to produce a bioenergy crop, Giant Miscanthus. As part of this effort, this research identifies which contract attributes affect potential producers' willingness to accept a contract. The attributes considered in our analysis were price, yield insurance availability, contract length in years, establishment cost-share, and biorefinery harvest. Importantly, also incorporated were status-quo alternatives and risk information, specifically information on current crop mean returns and associated variance, risk perceptions, and risk preferences.

Although the attributes considered in our study had been previously identified as important contract attributes in this context, little was known about preference heterogeneity for these attributes. To address this shortcoming, this research adopted a random-parameter logit model which allowed testing for the existence of preference heterogeneity for contract attributes. Finally, the study provided estimates of incremental values for these contract attributes.

Results indicated that higher contract prices, inclusion of biorefinery harvest, and increased establishment cost-share significantly increased the probability of a producer accepting a Giant Miscanthus contract. Increased contract length had a significant negative effect on the probability of contract acceptance. This finding suggests that producers preferred shorter contracts. We also found evidence of preference heterogeneity in producers' preferences for insurance, contract length, and biorefinery harvest. This suggests that producers had diverse preferences over these attributes. Based on our overall contract welfare estimates, we find that although producers may be willing to accept contracts to produce Giant Miscanthus, they will require additional compensation – the magnitude of which is a function of the terms of the contract.

We found that accounting for heterogeneity in the status-quo (i.e. differences in their current crop mean returns and associated variance) as well as risk information (preferences and perceptions) resulted in significant model improvement. Due to our small sample size we did not find individual coefficients significant, but our likelihood-ratio test results indicated significant overall model improvement when these variables were incorporated in our models. This finding is important as it suggests that a failure to account for these differences could bias results and result in misleading conclusions.

A major limitation of the study was the small sample size. Even with the addition of an incentive – a $25 Walmart gift card, we had limited responses. Some of the producers we contacted perceived Giant Miscanthus to be an invasive species, although we informed them that the variety under consideration is a sterile variety which has been approved by the USDA. This perception may have accounted for the large number of respondents that began – but did not complete – the survey.

Despite the Energy Independence and Security Act of 2007's mandate of producing 9 billion gallons of advanced biofuels annually by the year 2017, 15 billion gallons by 2020, and 21 billion gallons by 2022, there still remains a major technological challenge in the process involved in the conversion of lignocellulose biomass to the final biofuel (Hoekman 2009). This continues to hamper the development of markets to absorb cellulosic feedstocks, thereby hindering EISA's mandate.

The first commercial plant for the conversion of lignocellulosic biomass through thermochemical means was the KiOR oil plant in Columbus, Mississippi (Milbrandt et al.McCormick 2013). KiOR's mandate was to utilize non-food based feedstocks, including biomass such as pulp logs, agricultural residues, and energy crops such as switchgrass and sorghum to produce diesel and gasoline blendstocks (KiOR 2015).

With the recent shutdown of the KiOR plant, however, would-be bioenergy feedstock producers in the region are likely now aware of this major setback in the biofuel industry, and the instability of an outlet to sell their biomass crop should they decide to produce it. Further, the recent drastic drop in oil prices from around $110 per barrel in July 2014 to below $50 per barrel in July 2015 will continue to put downward pressure on demand for alternative fuels (Energy Information Administration 2015). Thus we can expect that the growth and development of the biofuel industry in the U.S. will continue to face major challenges unless and until major technological breakthroughs take place.

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