Agricultural and Resource Economics Review (2021), **50**, 367–393
doi:10.1017/age.2021.8

RESEARCH ARTICLE

Heterogeneity in farmers' willingness to produce bioenergy crops in the Midwest USA

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(Received 27 August 2020; revised 18 March 2021; accepted 18 March 2021)

Abstract
Previous studies indicate that "hesitation" and "skepticism" are important barriers to the development of renewable energy industries in the United States. We examine whether key pecuniary and nonpecuniary characteristics of bioenergy crops underlie the hesitation argument. Based on a stated choice experiment, we find that Midwestern producers appreciate certain crop attributes that are found in switchgrass, but not in conventional crops. We also find that producers would be willing to grow switchgrass-like crops for net margins between $222/acre/year and $247/acre/year in marginal counties. We argue that farmers' hesitation and skepticism toward bioenergy crops can be overcome.

Keywords: bioenergy; choice experiment; renewable energy; switchgrass; willingness to accept

Introduction

Governments have exerted effort to develop renewable energy industries in several countries around the globe. The public stimuli often take shape in mandates as in the European Union (E.U.) and in the United States (U.S.). These mandates are necessary responses to rather concerning assessments from the Intergovernmental Panel on Climate Change (IPCC) about negative anthropogenic effects on global surface temperature, average sea level, and snow cover (IPCC 2007). In the E.U., mandatory national targets consisting of 20 percent share of energy from renewable sources were implemented and are due by 2020. In the U.S., the Renewable Portfolio Standards (RPS) and the Renewable Fuel Standard (RFS)—perhaps the two most important measures taken in the country to promote clean energy—define varying targets and timeframes for the introduction of renewable electricity and fuel, respectively. While the RPS mandate defines state-level goals of renewable electricity in retail supply for 29 states plus Washington DC, the RFS is a national-level policy in place to reduce the use of petroleum-based fuels in transportation and heating.

As policies unfold, research has been conducted to assess their efficiency (Menz 2005; Palmer and Burtraw 2005; Sanya 2009; Yin and Powers 2010; Bird et al. 2011; Akadiri et al. 2019; Zhou and Solomon 2020) and to discuss successful and unsuccessful cases (Goldemberg et al. 2004; Blok 2006; Zoellner, Schweizer-Ries, and Wemheuer 2008; Neves and Conejero 2010). In the U.S., state RPS mandates have had an overall success in increasing the use of renewable electricity in retail distribution, mostly coming from windmills and solar panels. The same cannot be said for the RFS program, however. Government reports show that the 10.5 billion gallons target of cellulosic biofuel for 2020 set forth in the Energy Independence and Security Act of 2007 was far too optimistic when compared with the revised target of 590 million gallons (EPA 2020).

These policy performances alone suggest a few insights. In the renewable electricity arena, windmills and solar-based facilities represent 95 percent of the cumulative generation capacity additions since 2001. Biomass-based generation facilities account for 4 percent of all RPS capacity additions (Barbose 2017). This latter fact associated with the poor performance of cellulosic biofuels under the RFS program indicates that biomass has yet to overcome multiple challenges before becoming a prominent feedstock for clean energy generation in the U.S. This context may be shocking for some authors since biomass has been identified as one of the least expensive renewable feedstocks available (de Vries, van Vuuren, and Hoogkijk 2007).

To the best of our knowledge, few studies have deeply examined the underlying factors preventing biomass production and the concomitant emergence of a thriving bioenergy industry in the country. Epplin et al. (2007) is the first study to examine the feasibility of producing cellulosic ethanol from switchgrass based on current technologies and under two alternative coordination arrangements (vertical integration or long-term production contracts between a biorefinery and individual farmers). The results show that farmers would be willing to lease farmland for the production of switchgrass for amounts between \$202 and \$290 per acre, or long-term contract for estimated returns between \$198 and \$300 per acre, assuming that annual harvests yield 5.5 dry tons/acre of biomass. These values related to feedstock procurement would lead to production costs of cellulosic ethanol between \$1.21 and \$1.42 per gallon, assuming that the expenditure goals set by the U.S. Department of Energy's National Renewable Energy Laboratory (NREL) for other operating costs (i.e., enzymes and conversion) are unchanged (Pacheco 2006). Without economic incentives or subsidies, these costs are higher than current corn ethanol production costs, estimated at \$1.01 per gallon in July 2020 (CARD 2020).

Besides the lack of competitiveness in terms of fuel production technology, other authors have deeply investigated agricultural producers' behavior toward bioenergy crops. Rossi and Hinrichs (2011) are the first to document skepticism among small-to-mid-scale farmers involved in a switchgrass project in Iowa and Kentucky. Interview participants revealed strong skepticism about potential benefits that a bioenergy industry could bring. Interviewees also demonstrated uncertainty toward any commercial arrangement to grow switchgrass that could be offered by more dominant industry players. They mentioned that seeing other aspects of the emerging industry such as concurrent investments in transportation and storage infrastructure, and the construction of new facilities using cost-effective conversion technologies would help them make informed decisions to grow switchgrass commercially.

Using a different research approach, Qualls et al. (2012) find significant effects of hesitation on interest to grow switchgrass and share of farmland conversion. In their model, hesitation was defined as reluctance to adopt new production practices until seeing them working for others. The study examined several factors affecting the willingness to grow (WTG) switchgrass in 12 southeastern states, including key farm characteristics and assets availability.

This study has the primary objective to inform decision and policy makers about agricultural producers' WTG bioenergy crops in six Midwestern states with incentives stemming from both RPS and RFS mandates (i.e., Illinois, Michigan, Minnesota, Missouri, Ohio, and Wisconsin). The key intentions are to pinpoint specific regions across the Midwest where switchgrass is more likely to emerge as a viable alternative crop to conventional cropping systems and to identify subgroups of agricultural producers with greater aptitude and interest to engage in new production systems. To do so, we first categorize agricultural regions and farming operations based on secondary data published by highly credible research institutions. Sequentially, we use mail survey data collected between June and September 2014 from 294 agricultural producers with operations within the region of interest. The survey queried about their WTG alternative cropping systems using a discrete choice experiment approach. Data were examined under two adapted versions of the random utility maximization (RUM) model (McFadden 1974) and the results indicate producers' preference heterogeneity as a function of regional characteristics and types of farming operations. Just as importantly, his study also summarizes a serious effort to investigate whether development barriers associated with skepticism and hesitation toward bioenergy crops can be overcome.

The literature on agricultural producers' willingness to dedicate farmland for the production of dedicated energy crops is rather extensive in the U.S. (Rahmani, Hodges, and Stricker 1996; Jensen et al. 2007; Villamil, Silvis, and Bollero 2008; Bergtold, Fewell, and Williams 2014; Caldas et al. 2014; Timmons 2014; Altman et al. 2015; Khanna, Louviere, and Yang 2017; Jiang et al. 2019). The amount of effort exerted by scholars, however, has not translated into adoption of bioenergy crops, despite the well-documented potential as clean energy feedstock. This study builds on that literature and introduces an innovative approach to demonstrate that a lack of training and quality information available to potential bioenergy crop producers imposes severe barriers for development. References are made throughout the narrative to support our findings.

The following sections explain how regions and types of farming operations were categorized according to switchgrass substitution potential. The research methodology section comes after, followed by empirical results, and implications for bioenergy crops. Finally, the conclusion section summarizes findings, recognizes limitations, and suggests future research efforts in the field.

Identifying regional substitution potential for switchgrass

Agricultural regions are categorized by comparing predictions of net margins from a conventional cropping system to expected net margins from switchgrass at the county level. As this study focuses on agricultural producers' preferences and behavior in a broad geographic scope, this preliminary categorization of counties maintains a reduced level of complexity. Corn–soybean rotation is assumed to be our conventional cropping system. Such assumption is reasonable since corn–soybean rotation is the most common cropping system in the region, corresponding to 51 percent of the total area operated in the states under analysis. The state of Illinois leads the rank with the highest share of farmland covered with corn or soybean (76 percent in 2019), followed by

Minnesota (57 percent), Ohio (52 percent), Michigan and Wisconsin (38 percent), and finally Missouri (30 percent) (NASS/USDA 2020).

Because switchgrass (*Panicum virgatum*) is considered by some scholars the "model biomass feedstock" (McLaughlin and Kszos 2005) but has not gained momentum across Midwestern producers, we base county categorization on estimates obtained in related research. We use public multilevel data from the United States Department of Agriculture (USDA) (i.e., the National Agricultural Statistics Service (NASS) and the Economic Research Service (ERS)) and from the Food and Agricultural Policy Research Institute (FAPRI/MU) to estimate net margins from corn–soybean rotation. Expected net margin (ENM) from switchgrass is based on the results of highly cited research papers (Perrin et al. 2008; Griffith et al. 2012). Table 1 summarizes time granularity, spatial granularity, and sources for all data.

Corn and soybean yields (bushels/acre) are disaggregated at the county level. We assume that farms within a given county obtain production yields similar to those obtained in the past six years. Price forecast ($/bushel) for corn and soybean is at best available for the country.[1] Hence, agricultural producers are assumed to receive the prices forecasted by the FAPRI/MU for the next six years, regardless of the location. Farm revenue from corn–soybean rotation (dollars/acre) is assumed to come from corn sales and soybean sales, weighted by the proportion of these two crops in each state. On the expenses side, operating cost (dollars/acre) is assumed to include expenditures for seed, fertilizer, chemicals, custom operations, fuel, lubricants, electricity, repairs, and interest on operating capital and is available at the level of major production regions.[2] We also assume that operating costs (dollars/acre) reported by the USDA/ERS remain stable for the next six years. Operating costs are assumed to come from corn production and soybean production, weighted by the proportion in each state. Finally, ENM is computed based on the data and assumptions described above, corresponding to farm revenue minus operating cost.

Switchgrass farm revenue is assumed to be the same as the compensation offered to Eastern Tennessee agricultural producers engaged in the University of Tennessee Biofuels Initiative (UTBI). The UTBI contract compensates producers with an annual payment of $450 per acre (Griffith et al. 2012). Operating cost is retrieved from Perrin et al. (2008) and is assumed to be similar for all agricultural producers regardless of the location. The annualized cost per acre includes seed, fertilizer, chemicals, mechanical operations, and rent. Estimates indicate that commercial-scale fields have an annualized cost of $133 per acre. Thus, the ENM from switchgrass becomes $317 per acre for all locations.

With expected county-level net margin values from corn–soybean rotation and the ENM from switchgrass, a comparative preliminary analysis can be undertaken. Counties are divided into four categories: (1) counties that have ENM from corn–soybean rotation 30 percent below state average and lower than ENM from switchgrass; (2) those with ENM from corn and soybeans above the bottom threshold of 30 percent of state average, but lower than ENM from switchgrass; (3) counties with a six-year average ENM from corn–soybean rotation above ENM from switchgrass but with two or

[1]Aggregated commodities' prices should not be a concern. The average of differences between the highest and the lowest state prices (as reported by the USDA/NASS for 2007–2012) is $0.58 per bushel of corn and $0.62 per bushel of soybean. Such difference affects farm revenue in plus or minus $25 per acre.

[2]See US farm resource regions link for more information: http://webarchives.cdlib.org/sw1wp9v27r/http://ers.usda.gov/briefing/arms/resourceregions/resourceregions.htm.

Table 1. Summary of Data

	Time granularity	Spatial granularity	Sources
Corn–soybean rotation			
Yield	Annual: 2007–2012	County level	NASS QuickStats
Price forecast	Annual: 2014–2019	National level	FAPRI/MU
Farm revenue	—	—	—
Operating costs	Annual: 2007–2012	ERS farm resource regions	ERS Costs and Returns
Net margin	—	—	—
Switchgrass			
Farm revenue	—	—	Griffith et al. (2012)
Operating costs	—	—	Perrin et al. (2008)
Net Margin	—	—	—

more annual net margins from corn–soybean rotation below ENM from switchgrass; and (4) counties with at most one annual net margin from corn–soybean rotation below ENM from switchgrass. County category 1 can also be interpreted as marginal counties to the production of traditional grain crops but must not be classified under the concept of marginal lands. Jiang, Jacobson, and Langholtz (2018) offer a comprehensive treatment of the concept in the context of bioenergy crops. Skevas, Swinton, and Hayden (2014) and Jiang et al. (2019) focus on marginal land owners and their willingness to produce (WTP) bioenergy crops. At the other end of the spectrum, county category 4 represents the most adapted regions for the production of conventional grain crops. Table 2 summarizes the frequency of county categories per state and Figure 1 displays their location within states. In this study, our main hypothesis is that agricultural producers' WTG bioenergy crops is positive and decreasing in county categories.

Identifying categories of farming operations

Farming operations are categorized based on agricultural producers' responses to the 2012 Census of agriculture administered by the USDA/NASS. Answers to section 29 (Machinery and Equipment) of the census are used as proxy for farming capabilities. From these responses, agricultural producers are grouped depending on the ownership status over farming machinery and equipment—self-propelled grain combine, self-propelled forage harvester, or a set of three equipment to harvest forage (mower/rake/baler). Agricultural producers were grouped as follows: (A) those who own equipment to harvest grain as well as forage crops; (B) those who own equipment to harvest grain crops only; (C) those who own equipment to harvest forage crops only; (D) those who own neither type of equipment. This categorization was possible only because the questionnaire was administered by the USDA/NASS.

We hypothesize that agricultural producers who own machinery/equipment to grow forage crops are more WTG bioenergy crops, given that important alternatives such as miscanthus and switchgrass can be harvested with typical forage equipment (Thorsell et al. 2004). The goal here is to test whether certain characteristics of farming operations

Table 2. Expected Net Margin from Corn–Soybean Rotation by State and by Category (2014–2019). Frequency of County Categories per State

	Corn–soybean rotation	Categories (frequency)			
	ENM by State	(1)	(2)	(3)	(4)
Illinois	374.33	13	20	5	64
Michigan	295.79	9	35	7	10
Minnesota	353.89	8	22	10	38
Missouri	172.38	16	85	0	0
Ohio	355.02	2	13	43	28
Wisconsin	299.31	7	32	20	6
Sum of counties		55	207	85	146
ENM by category		173.65	241.01	351.53	410.52

such as ownership of machinery have a significant effect on the likelihood of growing bioenergy crops. Table 3 summarizes the null hypotheses.

Research methodology

Choice experiments simulate real-world situations to examine how individuals—in our case, agricultural producers dedicated to grain and/or forage crops—make decisions over available alternatives with varying characteristics. Cropping systems can be interpreted as a set of attributes that express value to decision makers. Previous focus group interviews highlight five multilevel pecuniary and nonpecuniary attributes with a major impact on how agricultural producers make planting decisions. The results from these focus group interviews provided background for the survey development. In the choice experiment, we include the key attributes discussed during the focus groups: the ENM per acre per year, net margin variance, the intensity of production practices (e.g., tillage, fertilization, pest control, and irrigation), coordination arrangement, and whether the crop under analysis requires any acquisition of machinery.

In the choice experiment, ENM takes four levels: \$200/acre/year, \$260/acre/year, \$320/acre/year, or \$400/acre/year. These values cover the most likely range of ENM from conventional cropping systems and switchgrass and encompass estimates for farmers' WTG cellulosic feedstocks found in previous studies (Epplin et al. 2007, Timmons 2014). Revenue variance takes three levels: "±40 percent," "±25 percent," or "±10 percent." The intensity of production practices takes two levels: "high" or "low." Coordination arrangement takes three levels: "cooperative," "production contract," or "spot market". Finally, the requirement of machinery acquisition is included in the choice experiment and takes two levels: "yes" or "no." The values in this latter attribute do not vary randomly, however. They are rather adjusted depending on the respondent's category of farming operation. Table 4 outlines the attributes and levels used in the experiment.

Differently from other studies using choice experiment to examine producers' WTG bioenergy crops, this study takes an unlabeled approach. Without stating the crops' name, agricultural producers are requested to respond in a more abstract fashion,

https://doi.org/10.1017/age.2021.8 Published online by Cambridge University Press

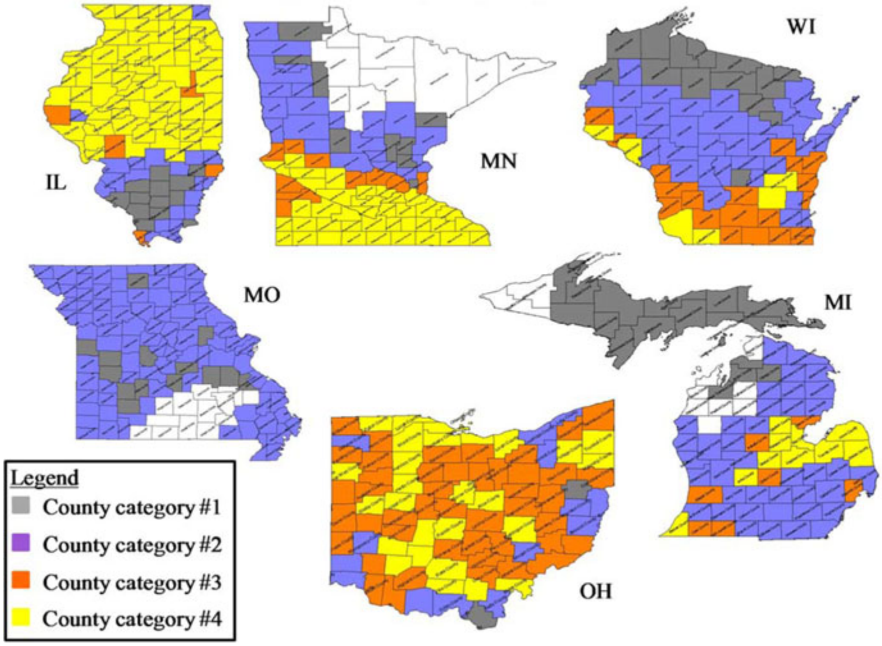

Figure 1. County Categories per State. Source: Designed by the authors.

Table 3. Null Hypotheses: Willingness to Grow (WTG)

H_o:
$WTG_1 > WTG_2 > WTG_3 > WTG_4$
$WTG_{\text{own forage equipment}} > WTG_{\text{do not own forage equipment}}$

leading to skepticism-free estimates. Switchgrass and corn–soybean rotation can be identified from the attribute levels, however. The literature in place points out that switchgrass requires less intensive production practices when compared with corn and soybean crops (Khanna, Dhungana, and Clifton-Brown 2008). FAPRI data corroborate with this fact and indicate that forage crops (e.g., alfalfa) require 31 percent less labor time and effort to reach average yield than corn–soybean rotation. Hence, we use the "intensity of production practices" attribute as an indicator of the cropping systems included in a given choice scenario: a system characterized with "low" intensity of production practices connotes switchgrass, and a system taking the "high" level for this attribute implicitly refers to corn–soybean rotation.

Using this identification and the machinery ownership status of agricultural producers, the surveys are configured to capture realistic preferences. For example, if the questionnaire is to be answered by a producer who falls into category B (i.e., owns equipment to harvest grain only), the crop alternative characterized by "low" intensity of production practices (i.e., representing switchgrass) should always have a "yes" for "requires acquisition of machinery" and a "no" if the intensity of production

Table 4. Attributes and Levels Used in the Choice Experiment

Attributes	Levels
Revenue per acre per year	$200/acre/year
	$260/acre/year
	$320/acre/year
	$400/acre/year
Revenue variance	±40%
	±25%
	±10%
Intensity of production practices	High
	Low
Vertical coordination	Cooperative
	Production Contract
	Spot Market
Requires acquisition of specific machinery	Yes
	No

practices indicates "high." Likewise, if the questionnaire is to be answered by an A producer (i.e., owns equipment to harvest grain as well as forage crops), there should be a "no" for "requires acquisition of machinery" regardless of the alternative crop. It is worth restating that this approach was possible as the survey was administered through the USDA/NASS and we could rely on census data to categorize farming operations based on farmers' machinery/equipment ownership.

The discrete choice experiment uses an efficient fractional factorial design, which accounts for two-way interactions between county category dummies and cropping system attributes. The OPTEX procedure in SAS was used to define 36 choice scenarios and divide them into four blocks.[3] The blocking strategy was defined to decrease the number of scenarios presented to agricultural producers and reduce bias due to fatigue. Hence, each survey respondent was presented with nine different choice scenarios featuring two generic cropping systems (labeled "crop rotation A" and "crop rotation B") and an opt-out alternative (labeled "neither"). By including the opt-out alternative, we remove the market participation assumption and recognize that agricultural producers might choose to farm a different crop if they are restricted to choose from the alternatives presented (Adamowicz et al. 1998). Figure A1 provides an example of choice scenario used in the experiment.

The data used in this study were collected from a mail survey administered through the USDA/NASS. The survey was sent to 4,216 agricultural producers who met the following four participation criteria. First, producers must have responded to the 2012 Census of Agriculture. This criterion implies that the producer is listed in the USDA/NASS data bank. Second, agricultural producers must have reported a farm income of

[3]The experimental design obtained an optimal D-efficiency value of 97.92.

$10,000.00 or more in 2012 to be eligible as survey respondents. This criterion limits the population of producers to professional individuals and excludes those who grow crops for leisure. Although researchers use different techniques to obtain representative responses from professional producers, such criterion is also found in other survey-based studies (Jensen et al. 2007, Paulrud and Laitila 2010). Third, agricultural producers must have reported "value of sales" above $5,000.00 in section 6 (field crops) and/or section 7 (hay and forage crops) of the 2012 census. This criterion seeks to include farmers who produce grains and/or forage crops aiming economic gains, while excluding those focused on other businesses. Finally, the amount of grain and/or forage produced in 2012 and reported in the census must have been produced within the counties of interest. All these criteria were precisely verified prior to the first mailing of the survey.

Eligible producers were randomly selected by the USDA/NASS within each county category rather than randomly selected across the entire region under analysis. The objective here is to obtain a balanced dataset with similar number of observations for each county category, leading to a consistent statistical analysis of agricultural producers' preferences, while controlling for regional specificities. Descriptive statistics of demographic characteristics for the survey sample and population of farmers, who meet the four participation criteria, are presented in Table 5.

In total, each agricultural producer received two letters in the mail and a phone call. The first correspondence contained a cover letter explaining the purpose of the study and a copy of the survey. The second correspondence was sent two weeks after the first aiming to reinforce the importance of the study. It included new copies of the cover letter and survey. Finally, phone calls were made a week after the second mailing to those participants who had not yet returned the surveys. In total, 294 valid surveys were obtained, leading to a 7 percent response rate. The response rate achieved here is comparable to other mail survey-based studies that investigate producers' preferences and behavior. Almost all returned surveys were filled completely, yielding a statistical sample of 2,519 observations (294 surveys each with 9 choice scenarios, approximately).

It is worth noting that the obtained sample is a good representation of the population, controlling participation bias. Table 5 indicates that the summary statistics of experience, age, farm income participation, gender, retirement status, and engagement of producers in renewable energy enterprises are similar for sample and population. There are slight divergences for harvested acres, however. While the sample has an overall mean of 390 acres harvested in 2012, the population of interest harvested 452 acres on average. Except for producers sampled in county category 2, survey respondents appear to have harvested fewer acres than the population in their corresponding counties. The distribution of harvested acres is also more disperse for the population than it is for the sample.

The model

The statistical model used in this article to analyze decision data relies on random utility theory (McFadden 1974, 1981). Agricultural producers are assumed to maximize utility by choosing from a hypothetical set of two cropping systems available to them before the planting season. Following Lancaster (1966), system alternatives are comprised of several attributes that both agricultural producers and analysts can observe. Let S_{it} denote the set of system alternatives (indexed j) available to agricultural producer i in choice scenario t. Let $\boldsymbol{x}_{ijt}$ be the vector of attributes that takes on various levels for

https://doi.org/10.1017/age.2021.8 Published online by Cambridge University Press

Table 5. Demographic Statistics

	Sample	Population		Obs.
Size	294 (persons)	656,917		2,519 (*n*)
County cat. 1	63	56,852		535
County cat. 2	84	278,816		740
County cat. 3	77	134,056		647
County cat. 4	70	187,193		597
Net margin revealed	229.90 (mean)			
County cat. 1	152.69			
County cat. 2	211.60			
County cat. 3	276.12			
County cat. 4	264.73			
Regional rent price	147.93 (mean)			
County cat. 1	83.85			
County cat. 2	135.42			
County cat. 3	175.70			
County cat. 4	197.29			
Acreage	390.2 ± 585.9	451.98 ± 746.37	(mean ± st. dev.)	
County cat. 1	246.53	357.87		
County cat. 2	460.09	450.69		
County cat. 3	385.13	427.70		
County cat. 4	446.90	518.39		
Experience (years)	29.6 ± 15.7	30.3 ± 15.06	(mean ± st. dev.)	
County cat. 1	30.33	30.45		
County cat. 2	29.23	30.14		
County cat. 3	31.94	30.52		
County cat. 4	26.90	30.35		
Age	58.4 ± 13.9	59.79 ± 13.31	(mean ± st. dev.)	
County cat. 1	58.91	60.40		
County cat. 2	60.48	60.14		
County cat. 3	58.06	59.45		
County cat. 4	55.99	59.31		
Farm income %	47 ± 35%	48 ± 36%	(mean ± st. dev.)	
County cat. 1	38%	40%		
County cat. 2	48%	46%		
County cat. 3	53%	49%		

(*Continued*)

Table 5. (*Continued.*)

	Sample	Population	Obs.
County cat. 4	50%	54%	
Gender			
Male	96.6%	96.1%	
Female	3.4%	3.9%	
Retired			
Yes	18%	19.6%	

each system alternative j in choice scenario t. Also, let U_{ijt} be the utility function of agricultural producer i from choosing cropping system $j \in S_{it}$ in choice scenario t.

The utility function is assumed to be of the following form:

$$U_{ijt} = \mathrm{v}_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where v_{ijt} is the deterministic term and ε_{ijt} is the stochastic term. While the latter captures cropping system attributes observed by agricultural producer i but unobserved by the analyst, the former contains attributes observed by both producer and analyst. The stochastic term is assumed to be independent of v_{ijt} and can be argued as agricultural producers' heterogeneity in preferences (Keane 1997) for unobserved characteristics of cropping systems. Regarding the deterministic term, agricultural producer i has preferences for net margins, risk exposure, and other nonpecuniary attributes. Let v_{ijt} be linear in parameters as follows:

$$\mathrm{v}_{ijt} = \beta \boldsymbol{x}_{ijt}, \tag{2}$$

where β is a vector of utility weights measuring N, and $\boldsymbol{x}_{ijt}$ is a vector of equal length N measuring the levels of each attribute for cropping system j. Plugging (2) into (1) we have

$$U_{ijt} = \beta \boldsymbol{x}_{ijt} + \varepsilon_{ijt}. \tag{3}$$

Hence, agricultural producer i chooses from a set of alternative cropping systems to maximize utility. But because the analyst cannot observe ε_{ijt}, an informed assumption regarding its distribution must be made so that estimates resulting from stated decisions can be obtained. A convenient and often made set of assumptions regarding ε_{ijt} is that it is distributed identically and independently across individuals and follows a Gumbel distribution ($\varepsilon_{ijt} \sim$ i.i.d. Gumbel or extreme value type I, in short). The basic multinomial logit (MNL) model (McFadden 1974) for the probability that agricultural producer i chooses cropping alternative c when presented with scenario t can be written as

$$P_{ict} = \Pr\left\{ U_{ict} = \max_{j \in S} U_{ijt} \right\} = \frac{\exp\,(\beta \boldsymbol{x}_{ict})}{\sum_{j \in S} \exp\,(\beta \boldsymbol{x}_{ijt})}. \tag{4}$$

The literature in place has, however, sought to refine McFadden's seminal model in three main fronts: (i) addition of heterogeneity in preferences for observed attributes; (ii) inclusion of preference heterogeneity for unobserved attributes (Keane 1997); and (iii) correlation of observed attributes.[4] The first concern has led scholars to propose and apply the random parameters logit (RPL) model, which is appealing to practitioners due to its ease of use (Fiebig et al. 2010). In this case, utility weights are assumed to be random variables following a predetermined distribution. When applied, the RPL model modifies equation 3 as follows:

$$U_{ijt} = (\beta + \gamma_i)\boldsymbol{x}_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where β is the vector of mean utility weights and γ_i is the vector of individual i-specific deviations from the mean weight. It is worth noting that the utility weight on net margin is commonly kept as a fixed variable rather than random (Goett, Train, and Hudson 2000; Morey and Rossmann 2003). Such restriction has to do with the identification of willingness-to-accept (WTA) estimates, calculated subsequently to model estimation. The second concern serves as a motivation for the scaled multinomial logit (S-MNL) model, which modifies equation 3 as follows:

$$U_{ijt} = \beta\boldsymbol{x}_{ijt} + \frac{\varepsilon_{ijt}}{\sigma_i}, \tag{6}$$

where σ_i varies across agricultural producers and represents an individual-specific scale in the stochastic term. The scale parameter σ is commonly normalized to 1 in order to allow model estimation. The S-MNL model takes the following form:

$$U_{ijt} = (\beta\sigma_i)\boldsymbol{x}_{ijt} + \varepsilon_{ijt}. \tag{7}$$

The third and final concern is whether observed attributes should be correlated (Revelt and Train 1998; Scarpa and Giudice 2004). While most scholars argue that adding this flexibility tends to enhance goodness of fit, others explain that complex models may prevent its implementation due to the rapid increase in the number of parameters (Louviere, Hensher, and Swait 2000; Train 2009). In other words, allowing parameters to correlate freely in complex models forces the number of parameters to increase rather fast, turning estimation unfeasible. Besides these three research fronts, it is worth mentioning that choice behavior specialists have been quite active developing new models and discussing new approaches.

There are strong criticisms against the models presented in equations 5 and 7, however. Authors argue that the utility weight on net margin (or revenue) should be treated as random variables, just as the utility weights related to other attributes are. The underlying reason is that unobserved socioeconomic characteristics are likely to influence individuals to respond differently to revenue (or expense in case of WTP estimation) (Fiebig et al. 2010). Experts have also contended that models with all-random

[4]Other refinements to the MNL model have recently been proposed, such as relaxing the linear utility assumption or estimating preference models in WTP space. Although we recognize the importance of these advances, we call attention to refinements that have been tested in several empirical studies and are widely used in the literature.

coefficients can be empirically unidentified (Train 2009). Yet, it is known that WTA estimates derived from two random coefficients do not converge to identifiable distributions. In the present study, we agree with the latter set of concerns and assume net margin attribute as nonrandom variables.

In this study, two econometric models—RPL and S-MNL—are used to estimate preferences over cropping system attributes. Both models have meaningful advantage over the traditional MNL model because they recognize that subjects are heterogeneous and might have different kinds of appreciation for specific attributes. The modeling question that remains unanswered is how to incorporate agricultural producers' preference heterogeneity for cropping system attributes—through individual-specific deviations from the mean utility weight or through the scale factor. Following the method proposed in Fiebig et al. (2010), we assess model performance by examining the likelihood improvement that is attained by including deviations from mean utility weights or individual scale factors into the seminal MNL model proposed by McFadden (1974).

The RPL model assumes that utility weights are random parameters and follow a predetermined distribution (Train 2009). Based on equation 5, the probability that agricultural producer i chooses cropping alternative c when presented with scenario t becomes

$$P_{ict} = \int \frac{\exp(\beta \boldsymbol{x}_{ict})}{\sum_{j \in S} \exp(\beta \boldsymbol{x}_{ijt})} g(\beta) d\beta, \tag{8}$$

where the distribution of random parameters $g(\cdot)$ is normal and $\beta = \beta + \gamma_i$.

The S-MNL model assumes that utility weights are scaled proportionately across agricultural producers. Based on equation 7, the probability of agricultural producer i choosing cropping system c is

$$P_{ict} = \frac{\exp\ (\beta \boldsymbol{x}_{ict})}{\sum_{j \in S} \exp\ (\beta \boldsymbol{x}_{ijt})}, \tag{9}$$

where $\beta = \beta\sigma_i$, $\sigma_i = \exp\left(\frac{-\tau^2}{2} + \tau\omega_i\right)$, and ω_i takes the standard normal distribution.

Correlation of coefficients was assumed absent due to the complexity of the model. Given the objective of the study (i.e., to examine whether regional characteristics and farming capability influence decision), two-way interaction effects bring the total number of parameters to 52 and 29 (RPL and S-MNL, respectively) as opposed to 13 in the main effects RPL and 8 in the main effects S-MNL. Hence, allowing correlation of coefficients in the model with two-way interactions would add over 200 parameters to be estimated which is computationally unfeasible. The next section analyzes the results derived from these models.

Sequentially, WTA values for cropping system attributes are computed for aggregated counties and for each county category separately by taking the ratio of the estimated coefficient on the observed attribute to the net margin coefficient, times two due to effects coding (Lusk, Roosen, and Fox 2003). Statistical variability in WTA estimates is calculated using the parametric bootstrapping technique as proposed by Krinsky and Robb (1986). For each crop attribute, WTA estimates are compared across county categories using the complete combinatorial method proposed by Poe, Giraud, and Loomis (2005).

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Empirical results

The estimates for two RPL models are reported in Table 6. While column 2 presents estimates for the entire region of interest (the main effects model), column 3 presents county-category-specific estimates (the two-way interactions model). Estimates for the S-MNL models are presented in Table A1. Although RPL and S-MNL estimates are similar in direction and magnitude, deviations from mean utility weights seem to accommodate preference heterogeneity far better than scale factors. Departing from the basic MNL model, simple calculations indicate that the inclusion of individual deviations in the main effects model improves goodness of fit by 18.8 percent, while the inclusion of scale factors improves fit by 4.8 percent. In the two-way interactions version, RPL improves fit by 18.63 percent, while S-MNL improves fit by 4.09 percent. Due to the substantial difference in model performance, we will base the following discussion on results stemming from the RPL model.

The main effects RPL model shows that all attributes included in the experiment influence utility and drive agricultural producers' preferences for crop attributes. As expected, the estimates on net margin, absence of machinery acquisition, and low intensity of production practices are valuable to agricultural producers and increase utility; variance of annual net margins and the use of hybrid governance strategies (i.e., specification contract or cooperative), on the other hand, tend to decrease utility. The model indicates, however, that there is strong heterogeneity in agricultural producers' preferences for all cropping system attributes.

Two-way interactions refine the initial model and allow us to examine whether regional specificities capture heterogeneity in preferences. The results derived from the RPL model indicate that some heterogeneity is indeed related to county categories. Variance of net margins, for example, is less of a concern for agricultural producers located in county category 2. Agricultural producers located in county categories 1 and 3 have a homogeneous preference for cropping systems that do not require any acquisition of machinery. Cropping systems that require low intensity of production practices are homogeneously preferred to producers located in county categories 1 and 2. While producers located in 3-counties seem to be indifferent to the coordination arrangement used to govern transactions with buyers, producers from 2-counties have heterogeneous preferences without a typical preference.

In any case, interpreting the magnitudes of coefficients is discouraged because only relative parameter values matter (Scarpa, Thiene, and Train 2008). The conventional alternative in these circumstances is to estimate agricultural producers' WTA based on model estimates. Table 7 reports mean WTA estimates, 95 percent confidence intervals, and statistical evidence of differences among county categories derived from the RPL model.

The estimates of WTA for net margin variance indicate that Midwestern producers are risk-averse individuals in general, and that the level of aversion differs across county categories. Producers located in county category 1 show the highest aversion to variable annual returns. These producers would be willing to adopt a cropping system with high variance of returns if the ENM were on average \$380.19 higher than the average net margin of a cropping system characterized by low variance of returns, maintaining all other attributes fixed. This result might be associated with revealed net margins (from the survey). Producers located in county category 1 reported the thinnest net margins (\$152.69/acre/year—Table 5), which is 33.6 percent lower than the average revealed net margin in the sample (\$229.90/acre/year). Therefore, it is intuitive that

Table 6. Random Parameter Logit Estimates for Cropping Systems

Variable	RPL model	RPL model (two-way interactions)	St. Dev.
Net margin per acre per year	1.390 (0.074)**	—	—
County cat. 1	—	1.279 (0.174)**	—
County cat. 2	—	1.249 (0.120)**	—
County cat. 3	—	1.495 (0.142)**	—
County cat. 4	—	1.586 (0.160)**	—
Variance of net margin	−1.546 (0.325)**	—	1.901 (0.567)**
County cat. 1	—	−2.41 (0.837)**	2.623 (1.244)*
County cat. 2	—	−0.632 (0.551)	0.885 (1.229)
County cat. 3	—	−1.972 (0.665)**	2.475 (0.958)**
County cat. 4	—	−1.894 (0.715)**	2.569 (0.939)**
Does not require acquisition	0.714 (0.097)**	—	0.713 (0.126)**
County cat. 1	—	1.237 (0.212)**	0.091 (0.335)
County cat. 2	—	0.375 (0.135)**	0.508 (0.177)**
County cat. 3	—	0.634 (0.180)**	0.672 (0.348)
County cat. 4	—	0.772 (0.238)**	0.935 (0.248)**
Low intensity of practices	0.540 (0.060)**	—	0.402 (0.101)**
County cat. 1	—	0.855 (0.149)**	0.390 (0.219)
County cat. 2	—	0.510 (0.091)**	0.179 (0.192)
County cat. 3	—	0.471 (0.117)**	0.509 (0.171)**
County cat. 4	—	0.428 (0.142)**	0.435 (0.176)*
Cooperative	−0.189 (0.063)**	—	0.511 (0.085)**
County cat. 1	—	−0.245 (0.173)	0.813 (0.206)**
County cat. 2	—	−0.187 (0.1)	0.353 (0.154)*
County cat. 3	—	−0.068 (0.109)	0.127 (0.389)
County cat. 4	—	−0.264 (0.153)	0.752 (0.176)**
Specification contract	−0.248 (0.056)**	—	0.457 (0.08)**
County cat. 1	—	−0.321 (0.146)*	0.607 (0.178)**
County cat. 2	—	−0.171 (0.096)	0.451 (0.134)**
County cat. 3	—	−0.134 (0.098)	0.242 (0.172)
County cat. 4	—	−0.415 (0.125)**	0.519 (0.169)**
Opt-out	1.858 (0.325)**	—	3.442 (0.28)**

(*Continued*)

Table 6. (*Continued.*)

Variable	RPL model	RPL model (two-way interactions)	St. Dev.
County cat. 1	—	2.152 (0.815)**	5.906 (1.096)**
County cat. 2	—	2.060 (0.538)**	3.282 (0.464)**
County cat. 3	—	1.858 (0.546)**	2.668 (0.428)**
County cat. 4	—	1.689 (0.607)**	2.051 (0.44)**
Log-likelihood function	−1,915.63	−1,878.10	—
AIC	3,857.3	3,860.2	—

Notes: The models were estimated using Nlogit 5.0, with Halton draws and 800 replications for simulated probability. Standard errors are reported in parentheses.
*and **indicate statistical significance at 5 percent and 1 percent levels, respectively.

1-county producers are more risk averse than producers located elsewhere. Unexpected reductions in net margins could lead to financial complications or farm bankruptcy. Producers located in county category 2 present the lowest aversion to variable net margins. This result may relate to operation size, given that 2-county producers lead the largest operations, on average, in our sample. The ability to diversify returns from different crops or parcels serves as a plausible reason for this finding. Producers located in county categories 3 and 4 would need an additional $263.74/acre/year and $239.34/acre/year, respectively, to adopt a cropping system with high variance of returns, keeping other attributes equal. These results should be used with caution, however, since the mean estimates of WTA for net margin variance are not statistically different (Table 7).

The absence of specific investments in machinery is preferable to producers, regardless of the location. Estimates of WTA for investment requirements computed from the coefficients of the two-way interactions RPL model indicate that producers would be WTA $103/acre/year less, on average, to adopt a cropping system that does not require any acquisition of new machinery, *ceteris paribus*. There are differences across county categories, however. Producers from county category 1 would be willing to give up $196/acre/year to adopt a cropping system that uses machinery and/or equipment already available at the farm. Producers located in county categories 2, 3, and 4 would request an additional $60.83/acre/year, $85.43/acre/year, and $97.85/acre/year, respectively, to engage in cropping systems that require new investments in machinery, leaving other attributes unaltered.

It is interesting to observe that economies of scale seem to correlate with the preference for investments in machinery. While producers located in county category 2 operate the largest farms in the sample, they also require the lowest "fee" to engage in a cropping system that requires the acquisition of machinery. Their low aversion to risk may also serve as a plausible explanation for being less reluctant to make investments. On the other hand, producers located in 1-counties have the highest WTA estimates because of the relatively small operation size and high aversion to risk. In addition, producers from 1-counties demonstrate little ability to cope with investments due to the lowest revealed net margins. The WTA estimate for producers located in 1-counties is statistically different at a 5 percent significance level from estimates computed for producers located elsewhere. These results are consistent and corroborate with the findings of Khanna, Louviere, and Yang (2017) and Bergtold, Fewell, and Williams

Table 7. Mean Willingness to Accept (WTA) and 95 Percent Confidence Intervals (CIs)

Variable	Mean WTA [95% CI]		*1
Variance of net margin	−222.54 [−313.87, −133.79]	—	—
County cat. 1	—	−380.19 [−659.01, −118.54]	a
County cat. 2	—	−101.20 [−278.82, 73.82]	a
County cat. 3	—	−263.74 [−438.57, −93.58]	a
County cat. 4	—	−239.34 [−410.67, −65.82]	a
Does not require acquisition	102.92 [75.35, 131.07]	—	—
County cat. 1	—	196.00 [132.21, 273.15]	a
County cat. 2	—	60.83 [17.46, 106.86]	b
County cat. 3	—	85.43 [38.94, 135.52]	b
County cat. 4	—	97.85 [39.67, 160.54]	b
Low intensity of practices	77.85 [61.32, 95.06]	—	—
County cat. 1	—	135.06 [90.83, 186.89]	a
County cat. 2	—	82.01 [54.15, 113.05]	b
County cat. 3	—	63.02 [33.02, 93.63]	b
County cat. 4	—	54.12 [18.98, 91.65]	b
Cooperative	−27.18 [−44.68, −9.38]	—	—
County cat. 1	—	−38.66 [−91.94, 14.99]	a
County cat. 2	—	−30.06 [−61.11, 1.27]	a
County cat. 3	—	−9.00 [−37.33, 19.99]	a
County cat. 4	—	−33.24 [−70.98, 4.94]	a
Specification contract	−35.69 [−51.70, −19.89]	—	—
County cat. 1	—	−50.57 [−97.79, −5.70]	ab
County cat. 2	—	−27.65 [−58.06, 3.03]	ab
County cat. 3	—	−17.87 [−43.72, 7.76]	a
County cat. 4	—	−52.34 [−83.22, −21.98]	b

Notes: Mean WTA estimates followed by the same letter do not differ at 5 percent significance level within each attribute.
*1: Complete combinatorial test results (Poe, Giraud, and Loomis 2005).

(2014). The authors found that crop-specific investments create disincentives for the adoption of bioenergy crops.

Producers expressed overall preference for crops that require low intensity of production practices. The mean WTA for a low-intensity cropping system is $77.85/acre/year. Looking into specific counties, agricultural producers from 1-counties require an additional $135.06/acre/year to engage in a high-intensity cropping system. Producers located in counties 2, 3, and 4 would demand an additional $82/acre/year, $63/acre/year, and $54.13/acre/year, respectively, to cultivate high-intensity crops. An underlying factor leading to this difference might be farm income participation in the total household income. Because producers from 1-counties are more dependent on off-farm income, crops with moderate production practices give them more flexibility to seek full-time positions outside the farm. Producers located in 3-counties and 4-counties, on the other hand, are more attached to farm work, making them accept a considerably lower "fee" for a high-intensity crop.

When it comes to coordination arrangements, agricultural producers indicate strong preference for spot markets. Regardless of the location, producers would be WTA an additional of $27.18/acre/year to trade via cooperatives and an additional of $35.69 to trade via specification contracts. Producers from county category 3 are the least averse to trading through hybrid governances (i.e., specification contracts or cooperatives). County 3 farmers would be willing to join a cooperative if the ENM were on average $9/acre/year higher than trading via spot markets or willing to sign a specification contract if the ENM were $17.87/acre/year more than trading through spot markets. Producers from county category 1 are the most reluctant to joining a cooperative, while producers from county category 4 are the most averse to signing production contracts. The former group would require an additional net margin of $38.66/acre/year to become a cooperative member and the latter group would demand $52.34/acre/year net to sign a written agreement of supply.

Stated preference results for the pecuniary attribute net margin behave as expected. The unconditional probability of a cropping system being chosen increases with net margin, over all counties as well as for each separate county category. On average, producers located in 1-counties would engage in any production activity if the annual net margin was $222/acre. Producers in county category 2 would accept $247/acre/year on average to grow any crop. In counties 3 and 4, producers would need higher returns and would engage in production if net margins averaged $269/acre/year and $289/acre/year, respectively. These results are aligned to revealed net margins and rental rates in every county category (Table 5). Except for the estimated net margin in 3-counties, producers state that they would engage in production if returns were above revealed net margins. Producers in county category 3 would accept net margins slightly below what they have revealed, on average. The estimated net margins are consistently above county category averages of rental rates. Figure 2 summarizes producers' preference for net margins in each county category.

Implications for bioenergy crops

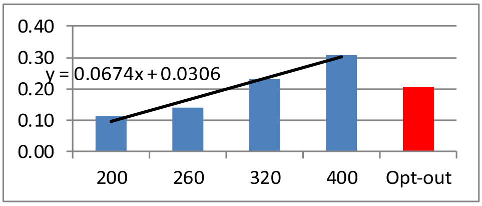
Producers located in all county categories show considerable preference for low-intensity cropping systems. This result translates into producers' WTG bioenergy crops given that switchgrass resembles low-intensity crops, while corn–soybean rotation resembles a high-intensity cropping system (Khanna, Dhungana, and Clifton-Brown 2008). Therefore, our initial hypothesis on the WTG bioenergy crops is satisfied but must be interpreted with caution, because we use an unlabeled choice experiment with the intention to circumvent skepticism and hesitation toward bioenergy crops, as demonstrated in other studies. County-specific preferences for bioenergy crops stemming from WTA estimates are also aligned to our original hypothesis: the WTG bioenergy crops decreases orderly from county category 1 through 4. And because results indicate that producers located in 1-counties are more emphatic about their preferences for low-intensity crops, it provides support to studies focused on idle or marginal lands (Skevas, Swinton and Hayden 2014; Timmons 2014; Saha and Eckelman 2015; Jiang et al. 2019).

Prob(Choice = 1)

All counties

Net Margins	Abs. Obs.	Freq.
200	288	0.11
260	357	0.14
320	582	0.23
400	779	0.31
Opt-out	513	0.20
Total (n)	2519	

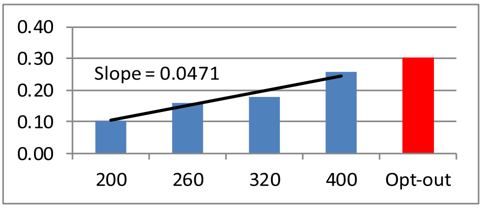
Weighted average of margins: **$257.35**



County Category #1

Net Margins	Abs. Obs.	Freq.
200	56	0.10
260	86	0.16
320	95	0.18
400	137	0.26
Opt-out	161	0.30
Total (n)	535	

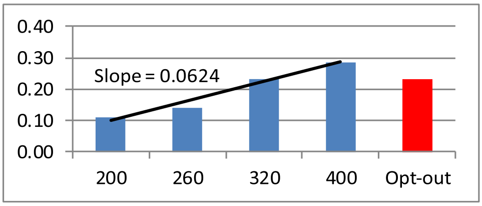
Weighted average of margins: **$221.98**



County Category #2

Net Margins	Abs. Obs.	Freq.
200	81	0.11
260	103	0.14
320	172	0.23
400	212	0.29
Opt-out	172	0.23
Total (n)	740	

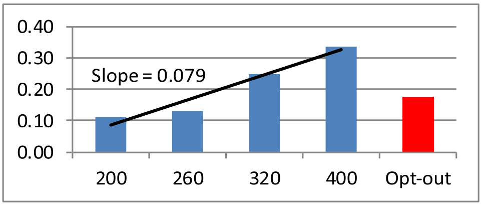
Weighted average of margins: **$247.05**



County Category #3

Net Margins	Abs. Obs.	Freq.
200	72	0.11
260	84	0.13
320	160	0.25
400	217	0.34
Opt-out	114	0.18
Total (n)	647	

Weighted average of margins: **$269.30**



County Category #4

Net Margins	Abs. Obs.	Freq.
200	79	0.13
260	84	0.14
320	155	0.26
400	213	0.36
Opt-out	66	0.11
Total (n)	597	

Weighted average of margins: **$288.84**

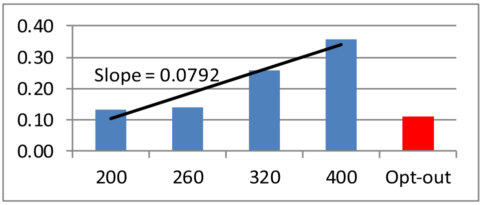


Figure 2. Producers' Preference for Net Margins by County Category.

https://doi.org/10.1017/age.2021.8 Published online by Cambridge University Press

The WTA estimates for machinery acquisition requirement also follow our original hypothesis. When a given cropping system does not require any acquisition or access to new equipment, producers are more willing to adopt that system. Although intuitive, this result, combined with other findings, is insightful and should be used to design targeted extension initiatives and entry strategies of biomass processors (e.g., bioenergy generators, cellulosic biorefineries, etc.). As potential producers become aware of the agronomic characteristics of switchgrass, appreciation for bioenergy crops is likely to increase. Targeted extension initiatives could stress the benefits of growing bioenergy crops in 1-counties in terms of allowing more time for professional activities off farm without compromising productivity and returns from the crops. Reduced levels of exposure to yield variations (and unstable economic returns, consequently) could also be exploited to meet producers' aversion to risk. As a native crop to the region under analysis, switchgrass copes well with risk-aversion concerns presented by producers, especially in county category 1, where the level of risk aversion seems to be the highest. Producers located in counties 2, 3, and 4 would also like to learn more about the underlying characteristics of switchgrass as they stated preference for low-intensity crops and showed concerns to variance of net margins. These implications relate to the findings of Caldas et al. (2014) and of Khanna, Louviere, and Yang (2017). In the former study, risk-averse growers were 5.9 percent more willing to adopt switchgrass. In the latter, the results suggest that variability in income leads to a lower likelihood of bioenergy crop adoption.

In addition to educate agricultural producers that switchgrass holds attributes they value, we also argue that well-devised extension trainings could alleviate development barriers associated with hesitation and skepticism. As producers become more informed and acquainted with switchgrass, some of the concerns presented in Rossi and Hinrichs (2011) and Qualls et al. (2012) would be cleared, reducing hesitation and skepticism. This would be particularly the case if biomass processors also used a part of these results to design entry strategies in the Midwest, meeting producers' need to *see to believe*.

It must be stressed, however, that interested producers are likely to require region-specific demonstrations before shifting away from conventional crops. As the yield performance of switchgrass depends on weather, soil characteristics, seed quality, and cultivar traits among other biotic and abiotic factors, producers are likely to require a comprehensive demonstration that engaging in switchgrass production will deliver value as they want to perceive. Furthermore, potential switchgrass producers will want to learn how relevant factors will be accommodated in a partnership agreement, especially when it comes to the concession of control rights and risk sharing.

Because subgroups of producers show different levels of interest for bioenergy crops, entrant biomass processors could segment suppliers and offer different compensation structures to different subgroups. Departing from estimated net margins, producers located in 1-counties represent the greatest opportunity for biomass processors. Offering them \$222/acre/year as normalized net margins appears to be large enough to offset revealed net margins (\$153/acre/year—Table 5) and the negative appreciation for production contracts. Supporting extension sessions to present the underlying characteristics of switchgrass would strengthen the partnership offer as the crop itself meets key preferences stated by producers in this study. Nevertheless, the \$222/acre/year compensation would not be sufficient to motivate the acquisition of new equipment, given that producers in county category 1 show the greatest reluctance to do so.

The entry strategy could be similar in 2-counties. Normalized net margins of \$247/acre/year might encourage supply partnerships as these amounts overcome revealed net

https://doi.org/10.1017/age.2021.8 Published online by Cambridge University Press

margins ($212/acre/year) and cope with negative estimates for engaging in production contracts. The alignment of this compensation structure to well-devised training sessions would help potential partners understand that switchgrass carries attributes they value such as low intensity of operations and reduced yield variance. The compensation amount, however, would not suffice to motivate the acquisition of new pieces of equipment.

On these lines, biomass processors would need to aim entry strategies and procurement efforts at producers who have current access to forage crop equipment in counties 1 and 2. Estimated net margins for producers located in counties 3 and 4 are not large enough to counterbalance revealed net margins and engagement in specification contracts. Although reduced levels of variance in yield and low intensity of agricultural practices are appreciated switchgrass characteristics, these attributes seem marginal to motivate adoption in counties 3 and 4.

A plausible but unlikely entry strategy alternative for processors would be to rely on spot markets (the preferable coordination arrangement for producers) to procure and access biomass feedstock. The transaction cost economics literature explains quite effectively why spot markets are not efficient coordination strategies for new entries when idiosyncratic assets and uncertainty are not trivial (Williamson 1985; Peterson, Wysocki, and Harsh 2001).

It is worth noting that the net margins estimated in this study for county categories 1 and 2 are comparable to compensations to producers estimated in other studies. Timmons (2014) estimated a mean WTA at $266/acre/year for Western Massachusetts, while Griffith et al. (2012) report payments of $450/acre/year (equivalent to $317/acre/year net margins) used in the UTBI. Epplin et al. (2007) found that Oklahoma growers would be willing to lease farmland for switchgrass production for rates between $202/acre/year and $290/acre/year, and Tennessee growers would sign long-term contracts for returns between $198/acre/year and $300/acre/year. If net margins between $222/acre/year and $247/acre/year became a reality in the Midwest, the production costs of cellulosic ethanol would fall between $1.26 and 1.32 per gallon under the assumptions made in Pacheco (2006). Despite the gains in accuracy and competitiveness when compared with some studies, the estimated compensation to Midwestern producers would still lead cellulosic ethanol to higher production costs than corn ethanol, currently estimated at $1.01 per gallon (CARD 2020).

Conclusions

This article utilizes an innovative choice experiment to estimate the WTG bioenergy crops, while circumventing deterring factors associated with hesitation and skepticism. Based on choice data collected throughout Midwestern states with RPS and RFS mandates in place, the results indicate that agricultural producers with existing operations in field and forage crops value nonpecuniary attributes: (i) cropping systems that require low intensity of production practices to obtain average yield; (ii) the absence of required investments in machinery; (iii) low variance of net margins; and (iv) coordinating transactions through spot markets.

Based on survey results, we discuss that hesitation and skepticism are deterring factors for the development of a thriving bioenergy industry that can be overcome through extension training. As agricultural producers learn more about switchgrass and its conveniences, they are likely to understand that the crop itself carries multiple attributes they show preference for. In addition, entrant biomass processors can devise segmented strategies to accommodate expectations and preferences stated by potential producers. A segmented strategy would be key not only to motivate partnerships of supply, but also to strengthen feasibility and returns on investments on power generation or fuel production.

Despite the opportunities for rural development and diversification observed in this study, Midwestern states have relied on wind- and solar-based technologies to meet RPS mandates (Barbose 2019). These decisions, however, discourage farm conversion and crop diversification in less privileged rural areas, which are highly correlated with marginal areas for the production of conventional field and forage crops. They also discourage the entry of biorefineries, which could benefit from an emerging industry to procure biomass feedstock for the production of cellulosic ethanol. The renewable fuel industry, nevertheless, still faces additional challenges in the technology arena.

Our results are corroborative with previous studies that focused solely on marginal farmland as potential resources to be allocated for biomass production (Skevas, Swinton, and Hayden 2014; Timmons 2014; Saha and Eckelman 2015). This study shows that producers located in places where conventional cropping systems (e.g., corn–soybean rotation) are less competitive across the Midwest tend to prefer crop attributes found in switchgrass. In other words, low intensity of production practices has diminishing mean WTA estimates as one moves from county category 1 to county category 4.

Farming capabilities also influence preference for cropping system attributes. As expected, producers value crops that do not require investment in machinery. Our results go beyond the common sense and not only estimate magnitudes for such preference, but also find underlying reasons for it. The results indicate that the absence of investment is placed first in the overall rank of preferable attributes, highlighting the conservative behavior and risk aversion of Midwestern producers. Preference for investments varies across locations and relate to demographic characteristics, however. Producers located in 2-counties are the least concerned about purchasing equipment, whereas 1-county producers are the most concerned. The results suggest that operation size, off-farm income participation in the total household income, and current net margins play important roles in county-specific preferences.

The combination of these results leads to interesting insights for decision and policy makers. Net margins of $222/acre/year and $247/acre/year might suffice to motivate farmland conversion and the adoption of switchgrass in county categories 1 and 2, respectively, when acquisition or access to new equipment is not needed. These compensations would hold even if production contracts must be signed between producers and a biomass processor. However, it is estimated that under a set of previously documented assumptions, these net margins would lead to the production of cellulosic ethanol at costs above current production costs for corn ethanol. Estimated net margins for county categories 3 and 4 are less likely to motivate producers to grow switchgrass.

In terms of econometric model design, this study provides evidence that modeling preference heterogeneity through individual deviations to mean utility weights reaches superior performance than modeling individual scale effects. The results show that log likelihood improves about 18 percent when the RPL model is utilized versus 4 percent improvement when the S-MNL model is used.

This article leaves an important question unattended. Although it has been observed that producers from county category 2 and 3 do not have homogeneous preferences for coordination arrangements, while producers from counties 1 and 4 do, this study does not address how contract provision or cooperative membership should be drafted. It might be important to assess agricultural producers' preferences for provisions or cooperative membership rules, as these points may have substantial influence on producers' behavior.

Acknowledgments. An earlier version of this article was presented at the International Food and Agribusiness Management Association World Conference. We would like to acknowledge the comments and suggestions received on that occasion. It is also pertinent to thank the survey participants for their time and effort. This study would not have been possible without their honest involvement and commitment.

Funding statement. This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

Conflicts of interest. None.

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Appendix

Table A1 provides an example of choice scenario used in the experiment. Estimates for the S-MNL models are presented in Table A2.

Table A1. Sample Choice Scenario Used in the Unlabeled Experiment

Which crop rotation would you prefer?			
System attributes	Crop rotation A	Crop rotation B	Neither
Net margin per acre per year	$260	$400	I am indifferent between these cropping systems
Net margin variance	±10% (±$40)	±40% (±$160)	—
Requires acquisition of machinery	No	Yes	—
Intensity of production practices*	Low	High	—
Marketing arrangement	Cooperative	Spot Market	—
I would grow:	☐	☐	☐

*Cropping systems with LOW intensity of production practices require 31 percent less labor time and effort to obtain average yield than cropping systems with HIGH intensity of production practices.

Table A2. Scaled Multinomial Logit Estimates for Cropping Systems

Variable	S-MNL model	S-MNL model (two-way interactions)
Net margin per acre per year	1.441 (0.221)**	—
County cat. 1	—	1.038 (0.239)**
County cat. 2	—	1.356 (0.269)**
County cat. 3	—	1.953 (0.473)**
County cat. 4	—	1.849 (0.509)**
Variance of net margin	−1.546 (0.350)**	—
County cat. 1	—	−2.474 (0.843)**
County cat. 2	—	−0.388 (0.462)
County cat. 3	—	−1.842 (0.665)**
County cat. 4	—	−0.994 (0.805)
Does not require acquisition	0.681 (0.117)**	—
County cat. 1	—	0.899 (0.218)**
County cat. 2	—	0.391 (0.131)**
County cat. 3	—	0.687 (0.218)**
County cat. 4	—	1.078 (0.366)**
Low intensity of practices	0.592 (0.099)**	—
County cat. 1	—	0.697 (0.164)**

(*Continued*)

Table A2. (*Continued.*)

Variable	S-MNL model	S-MNL model (two-way interactions)
County cat. 2	—	0.538 (0.135)**
County cat. 3	—	0.630 (0.182)**
County cat. 4	—	0.648 (0.169)**
Cooperative	−0.173 (0.068)*	—
County cat. 1	—	−0.096 (0.131)
County cat. 2	—	−0.256 (0.102)*
County cat. 3	—	−0.073 (0.127)
County cat. 4	—	−0.064 (0.141)
Specification contract	−0.176 (0.056)**	—
County cat. 1	—	−0.048 (0.110)
County cat. 2	—	−0.302 (0.100)**
County cat. 3	—	−0.132 (0.116)
County cat. 4	—	−0.299 (0.122)*
Opt-out	2.302 (0.448)**	—
County cat. 1	—	1.920 (0.619)**
County cat. 2	—	2.727 (0.627)**
County cat. 3	—	3.371 (0.975)**
County cat. 4	—	1.958 (0.700)**
τ	—	1.095 (0.153)**
σ	—	0.97613 (1.314)
Log-likelihood function	−2,245.00	−2,213.89
AIC	4,506.0	4,485.8

Notes: The models were estimated using Nlogit 5.0, with Halton draws and 800 replications for simulated probability. Standard errors are reported in parentheses.
*and **indicate statistical significance at 5 percent and 1 percent levels, respectively.

Cite this article: Signorini G, Ortega DL, Ross RB, Peterson HC (2021). Heterogeneity in farmers' willingness to produce bioenergy crops in the Midwest USA. *Agricultural and Resource Economics Review* **50**, 367–393. https://doi.org/10.1017/age.2021.8