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Assessing the Impact of Fresh Vegetable Growers' Risk Aversion Levels and Risk Preferences on the Probability of Adopting Marketing Contracts: A Bayesian Approach

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Abstract

One of the most frequently cited theoretical statements to explain the use of contractual arrangements is that risk drives the choice of contracts. However, there is limited empirical support for this argument. A Bayesian ordered probit formulation is used in this study to determine the importance of fresh vegetable producers' and farm operation characteristics on the probability of adopting marketing contracts. The findings of the study indicate that younger farmers, with larger farm size and with the ability to expand their operations are more likely to participate in marketing contract agreements. On the other hand, the results do not support the risk shifting hypothesis.

Keywords: marketing contracts, risk management, Bayesian ordered probit

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Introduction

In the Wealth of Nations Adam Smith criticized sharecropping[1] as an unsatisfactory intermediate stage between slavery and the English fee based system (Newbery 1977). Building on Adam Smith's argument, Alfred Marshall (1920) illustrated that sharecropping leads to moral hazard and, consequently, to Pareto inefficient resource allocation. The "Marshallian inefficiency" argument remained undisputed for several decades (Allen and Lueck 1999). However, despite its theoretical shortcomings, highlighted by Marshall and the majority of classical economists, sharecropping remained a popular method of agricultural production both in the Old and the New world (Newbery 1977).

Gale Johnson (1950) tried to explain this phenomenon. As a result of his endeavors, the focus of the research on contractual arrangements shifted from the resource allocation to the factors influencing the selection of contracts. Following the seminal works of Cheung (1969), Stiglitz (1974) and Newberry and Stiglitz (1979) the principal – agent framework has been adopted by many scholars as a theoretical explanation for the farmers' decision to utilize contractual agreements. Under this approach, the rationale for contract participation is risk sharing between a risk-averse agent (the farmer), who has the ability to shrink in performing the agreed tasks, and a risk neutral principal (i.e. landlord, buyer etc.), who is not able to perfectly observe the agent's activities (Allen and Lueck 1995, 1999; Sheldon 1996).

Despite the theoretical appeal of the risk-shifting hypothesis, there is no consensus in the empirical research regarding the significance of risk-sharing in farmers' decisions to utilize contracts. For instance, Ackeberg and Botticini (2002), Dubois and Vukina (2004), Hudson and Lusk (2004) illustrate that growers' risk aversion levels play an important role in the selection of contracts. On the other hand, Allen and Lueck (1992, 1995, 1999), Hobbs (1997) and Vassalos et al. (2013) argue that it is the reduction of transaction costs rather than the risk sharing that drives the selection of contracts.

A related strand of the literature focuses on the observable characteristics of the farmers (i.e. demographic characteristics) and of their farm operations (i.e. farm size, location etc.) and how these characteristics influence the choice of contractual agreements. Similarly to the risk shifting hypothesis, the empirical evidence regarding the role of the aforementioned characteristics is mixed. For instance, Katchova and Miranda (2004) illustrate that the age and education level of the farm manager do not influence the decision to participate in contractual agreements for corn and wheat producers in the U.S.A. Paulson et al. (2010) have similar findings for corn and soybean producers in U.S.A. However, Katchova and Miranda (2004) indicate that older and more educated soybean producers are more likely to participate in contractual agreements. Other studies (i.e. Asplund et al. 1989; Musser et al. 1996; Bellemare 2012) indicate that the age of the farm manager has a negative and statistically significant effect on the decision to participate in contractual agreements. Furthermore, Musser et al. (1996) and Goodwin and Schroeder (1994) indicate that more educated farm managers are more likely to participate in contractual agreements. The aforementioned discussion indicates the need for further research regarding the

[1] Sharecropping is a form of land leasing in which a tenant and a landlord share the final output as compensation for the managerial labor supplied by the tenants and the land capital supplied by the landlord.

role that: growers' risk aversion levels, growers' demographic characteristics and farm characteristics play in the choice of contracts.

The main objective of the present study is to examine the role of: i) risk, ii) producers' characteristics and iii) farm operation characteristics on the probability of adopting marketing contracts by U.S. Mid-South fresh vegetable producers. Marketing contracts typically refer to a written or oral agreement between a grower and a buyer who sets a price and possible price adjustments as well as a market outlet. Under this type of agreement producers assume all risk related to yield, but, share the risk related to price fluctuations with the buyer (MacDonald et al. 2004).

The contribution of the study to the literature is threefold. First, the present article focuses on fresh vegetable production (tomatoes), in contrast to grain crops that have been the major interest of similar studies (Musser et al. 1996; Katchova and Miranda 2004; Paulson et al. 2010). The unique characteristics of vegetable production (i.e. perishability and seasonality of production, higher price fluctuation etc.) in conjunction with the potential heterogeneity of contract preferences across different products are the underlying reasons for examining vegetables. Second, we incorporate a broader measure of growers' risk aversion and risk perception levels. Specifically, both the expected utility framework and answers to Likert-scale questions are utilized to elicit growers risk attitudes. Third, while several studies have used binary models to examine the relationship between contract choice and the characteristics of the farm or the grower, to the best of the authors' knowledge, this is the first endeavor that uses a Bayesian approach to analyze ordered multi-level responses. The adoption of multi-level response can reveal more about the dynamics of contractual agreements compared to a simple binary model.

The main data source for the study is a survey administered via US mail to tomato growers in four states: Kentucky, Illinois, Ohio and Indiana. A Bayesian ordered probit model is utilized to analyze the dataset. Growers age (in years), education (in years), risk aversion level, risk perception, location, income, farm size and the ability to expand the farm, if required, are included as explanatory variables in the analysis. The selection of these explanatory variables is based on previous literature, indicating that personal and farm characteristics influence the probability of adopting marketing contracts (Musser et al. 1996; Katchova and Miranda 2004; Goodwin and Schroeder 1994; Pennings and Leuthold 2000) and on feedback received by industry leaders.

The findings of our study have important theoretical and practical implications. From a theoretical perspective, the results do not provide empirical support for the risk shifting hypothesis (growers' risk aversion is not a determining factor of contract choices). Regarding the latter the results provide helpful insights to the vegetable production industry and especially to retailers who use marketing contracts as a vehicle to meet the changing consumer demand and improve market efficiency (Bellemare 2012; Sykuta and Parcell 2003). For instance, retailers can use this information to more efficiently identify growers that are willing to participate in a contractual agreement. This is especially important considering that the cost of writing and enforcing the contractual arrangements. Lastly the results may be used to target specific education programs related to marketing contracts.

Data Collection

The data for the present study were obtained from a mail survey. The survey instrument was initially mailed on April 1st, 2012 to three hundred fifteen (315) tomato growers in four states: Kentucky, Illinois, Ohio and Indiana. Two reasons justify this selection. First, although the U.S. Mid-South is not a major vegetable producing area, in the last decade the importance of vegetable production in the agricultural economy of this region has been constantly increasing. This is illustrated by the substantial increase in the number of farms with some type of vegetable production between 2002 and 2012, in conjunction with the increase in the market value of vegetable production (Table 1). The aforementioned factors highlight a very dynamic and changing market. This dynamic, indicates opportunities for new marketing options in the examined area. Second, tomatoes are selected because they are among the top three vegetables cultivated in these four states.

Table 1. Importance of Vegetable Production in the Examined Region

	2012	**2007**	**2002**	**% Change 2002- 2012**
		A. Number of Vegetable Farms		
State				
Illinois	1,370	1,377	1,107	23.76
Indiana	1,376	1,363	1,139	20.80
Kentucky	2,222	2,123	1,424	56.04
Ohio	2,440	2,873	2,323	5.03
		B. Number of Tomato Farms[2]		
State				
Illinois	587 (573)	525 (516)	334 (347)	75.75
Indiana	687 (628)	600 (554)	511 (470)	34.44
Kentucky	1,387 (1,297)	1,142 (1,102)	659 (618)	110.47
Ohio	1,285 (1,221)	1,351 (1,272)	1,083 (995)	18.65
		C. Market Value of Vegetable Production ($1,000)		
State				
Illinois	127,592	103,914	98,067	30.11
Indiana	104,411	78,719	77,583	34.58
Kentucky	28,787	20,937	17,575	63.79
Ohio	133,796	135,355	136,884	- 2.26

Source. 2012, 2007 USDA, Census of Agriculture

Following Dillman's (1978) guidelines, in addition to the questionnaire, the survey package included a personalized cover letter and a return-postage paid envelope. The cover letter was printed with a university letter head, signed by the researchers, emphasized the importance of the study and the fact that the responses will be anonymous and confidential. A personalized reminder was emailed to the producers two weeks later. A second mailing of the survey package was distributed to the growers during the last week of April, 2012. With the aim of increasing the response rate a monetary incentive ($25) was offered to the producers if they completed the survey.

The mailing information for the growers was gathered from MarketMaker, after obtaining permission to use the database of the website. MarketMaker is a free online marketing tool

[2] The number of farms that harvested tomatoes for fresh produce is included in the parenthesis

developed by the University of Illinois Extension Service. The primary objective of MarketMaker is to facilitate buying relationships between consumers (i.e. households, wholesalers, local restaurants etc.) and producers (Zapata et al. 2013). Currently, MarketMaker operates in 19 different states and includes a database of more than 8,600 producers.

Of the 315 survey packages initially mailed, 10 were returned as undeliverable and 5 indicated that they were not farmers or had retired leaving a total population of 300 producers. From the 300 producers 55 returned completed surveys for an effective response rate of 18.3%. The response rate is higher compared to similar studies that used mail surveys to examine producers' preferences towards contractual arrangements or used MarketMaker to obtain producers information. For instance: Zapata et al. (2013), Roe et al. (2004) and Carpio et al. (2013) reported response rates of 15.7%, 12.4% and 18% respectively.

Summary statistics of the demographic variables for the sample growers are provided in Table 2. The average age of the responders is 49.8, and the majority of the responders were male producers. These compare favorably with the data from census of agriculture for vegetables, potatoes and melons, where the average age of the vegetable producers was 55.9 and 17% were female. All of the farmers who participated in the survey use some form of direct marketing for their products (i.e. farmer's market, on farm sales etc.) with the second most common marketing option being local wholesalers. This finding is not surprising, considering that the study sample included growers who participate in the MarketMaker website. The "ability to expand" variable refers to a grower's ability to expand his/hers operation if the right opportunity occurs, based on their responses to the survey instrument.

Table 2. Sample Descriptive Statistics

Variable	Average	Std.	Min.	Max.
Gender (1=female)	0.25	0.43	0	1
Age	49.8	12.95	30	70
Farm Size (Acres)	70	40.7	1	110
Ability to expand	0.8	0.37	0	1
Household size	2.4	1.28	1	6
Household income	71,480	33,169	20,000	137,500
Education	15.5	2.56	5	19
Farm income	59,722	38,089	15,000	95,000
n=55				

Source. Survey questionnaire

Survey Description

The survey questionnaire consisted of five sections. The first section included general questions to attract producers' interest. The second section contained questions regarding producers' perception and experience with marketing contracts. The third section included the risk aversion level and risk preference elicitation questions. The fourth section included a choice experiment. Demographic information (including age, gender, education, income etc.) was collected at the end of the survey. Questions that required growers to check their records were not included in the survey instrument (Pennings et al. 2002).

The survey questionnaire (clarity of questions, layout of the survey, wording of instructions etc.) was modified following the feedback from five focus group discussions as well as pilot tests of the survey instrument. The focus group participants included vegetable growers, extension specialists and individuals involved with the marketing process of fresh vegetables. The focus group discussions took place during the 2011 Kentucky Farm Bureau Convention and the 2012 Kentucky Fruit and Vegetable Trade Show. Farmers who participated in the focus groups were not excluded from the mailing of the survey.

Risk Aversion and Risk Preferences Elicitation

A plethora of techniques has been adopted in the applied economics literature to elicit growers risk aversion levels and risk attitude. The majority of these measures can be derived from either: a) the expected utility framework, b) responses to Likert-scale questions, c) safety-first risk preference measures or d) the prospect theory (Pennings and Garcia 2001; Sartwelle et al. 2000).

For the objectives of the present study a combination of a "multiple price list" design and of Likert-scale questions was employed. The former is a modification of the design proposed by Binswanger (1980, 1981). Specifically, Binswanger's design was modified to resemble tomato growers' decisions. In detail, growers were asked to select among two hypothetical tomato varieties. The varieties had different resistance to diseases and, depending on whether or not the disease occurred, different economic returns. The probability that a disease would occur was set at 0.5. In accordance with Binswanger (1980), higher expected returns were offered at a cost of higher variance (Figure 1).

Please consider the choice you would make in the following hypothetical situation:

You will be given 150 tomato plants (in 5 bundles of 30 plants each) for free, to use in the coming season. There are two types of plants, A and B, and you can choose any combination of the two that totals 5 bundles.

The A and B plants have different levels of resistance to tomato diseases. The A plants have potentially higher harvests but are more vulnerable to disease. If disease does not occur, the A plants will produce a harvest worth $30 per bundle. However if disease occurs (50% of the time), the A plants' harvest is worthless ($0 per bundle). The B plants are disease-resistant and always produce a harvest worth $10 per bundle.

The following table illustrates the different combinations of type A and B plants that you could receive, and the value of their combined harvests based on the weather. Please **check one box** to indicate which combination of plants you would choose.

I choose: Check one of the six combinations A-F below	Bundles of 30 type A plants	Bundles of 30 type B plants	If disease does not occur (50%)	If disease occurs (50%)
o A	0	5	$50	$50
o B	1	4	$70	$40
o C	2	3	$90	$30
o D	3	2	$110	$20
o E	4	1	$130	$10
o F	5	0	$150	$0

Figure 1. Risk Preferences Elicitation Question

The basic advantage of this approach is that it can be used even if producers do not fully understand probabilities (Lusk and Coble, 2005). Table 3 illustrates the corresponding risk classification levels and the estimated partial risk aversion coefficient. Following Binswanger (1980), under the assumption that producers' exhibit constant partial risk aversion, the partial risk aversion coefficient can be estimated using a utility function of the following form:

$$(1)\ U = (1 - S)M^{1-s}$$

where M is the certainty equivalent and S is the approximate partial risk aversion coefficient[3]. In line with Lusk and Coble (2005), the measure used in the analysis as an individual's risk aversion coefficient (S) is the midpoint of the possible minimum and maximum range of S[4].

Table 3. The Payoffs and Corresponding Risk Classification for the Risk Game

Choice	Low Payoff (Disease occurs)	High Payoff (No disease)	Risk Aversion Class[a]	Approximate Partial Risk Aversion Coefficient (S)	Percentage of Choices in Experiment
A	50	50	Extreme	∞ to 2.48	16.3%
B	40	70	Severe	2.48 to 0.84	22.45%
C	30	90	Intermediate	0.84 to 0.5	34.69%
D	20	110	Moderate	0.5 to 0.33	18.37%
E	10	130	Slight to Neutral	0.33 to 0.19	6.12%
F	0	150	Neutral to Negative	0.19 to -∞	2.04%

Note. [a]Based on Binswanger (1980) classification

In addition to the multiple price list design, producers risk perceptions were elicited from three Likert-scale questions. The main advantage of this technique is that it is easier for the growers to answer these questions (Lusk and Coble 2005). To estimate producers' risk attitude we adopted three Likert-scale questions (Table 4) from Pennings and Garcia (2001). Following Pennings and Garcia (2001) if the sum score of the responses was negative, then, producers were classified as risk seeking. On the other hand, if the score was positive producers were classified as risk averse. Based on this scale, 59% of the producers in our sample are classified as risk averse, 25% as risk seeking and 16% as risk neutral. This finding compares favorably with results from previous research that used similar techniques to elicit growers risk aversion. For instance, Franken et al. (2014), using a sample of corn and hog producers from Illinois, estimated that 69% of the producers can be classified as risk averse, 11% as risk neutral and 20% as risk seeking. Similarly, Pennings and Garcia (2001) using a sample of Dutch hog producers estimate that 43% of them can be classified as risk averse.

[3] In order to calculate S (Table 3) we have to solve for the indifference point among two consecutive choices using equation 8. For instance, for choices A and B the S is calculated from the following equation: $50^{(1-s)} + 50^{(1-s)} = 40^{(1-s)} + 70^{(1-s)}$. This equation was solved in Excel after graphing the equations to estimate where the functions cross the x-axes.

[4] Following Binswanger (1981), for the regression analysis alternative F (Table 3) was given a value near zero (0.18) and the value for alternative A was set to 2.47

Table 4. Growers' Risk Perception: Response to Scale Questions
(-4= strongly Disagree, 4= Strongly Agree)

Question	Definition	Mean (Std. Dev.)
1	With respect to the conduct of business I avoid taking risk	0.51 (2.07)
2	With respect to the conduct of business I prefer certainty to uncertainty	1.50 (1.72)
3	I like "playing it safe"	0.81 (1.85)

Note. N=55

Econometric Procedures

After providing the definition of marketing contracts, in the second section of the survey instrument, growers were asked if they would be interested in participating in fresh produce marketing contract agreements. Producers were provided three ordinal choices to select from: i) no, I am not interested, ii) maybe, depending on the terms of the contract or iii) yes, I am willing to participate in a marketing contract agreement. This approach was preferred instead of a typical binary question (i.e. do you have a marketing contract for your fresh produce) because, currently, the use of marketing contracts for fresh vegetables is limited in the area of interest (Kentucky, Illinois, Ohio and Indiana)[5]. Given the discrete nature of the dependent variable, and the relatively small sample size of the study, we utilize a Bayesian ordered probit formulation to achieve the study objectives. The present section discusses in detail the formulation of the economic model used in this article.

Assume that a vegetable grower, indexed by i, is considering participation in a marketing contract agreement. The grower's decision, denoted Y_i, can be specified as a discrete variable with three possible values: a) the grower will not adopt the marketing contract, b) the grower may adopt the contract, depending on the terms and c) the grower will adopt the contract. In our sample 24% percent of the growers indicated that they are not interested in marketing contracts, 64% indicated that they may consider a marketing contract agreement depending on the terms and 11% indicated that they will adopt a marketing contract agreement.

Because the response variable is a non-numerical ordinal variable, an ordered probit model was implemented for the empirical estimation. Following Greene (2008), we first introduced a latent variable y* expressed as:

$$(2)\ y^{*} = BX + \varepsilon,$$

where B is the vector of the parameters to be estimated, X is the vector of explanatory variables and ε is a random term that follows normal distribution.

The value of the dependent variable Y_i (growers' decision) depends on the aforementioned latent variable and satisfies the following model:

[5] However, there is a great opportunity for increased use of contractual agreements considering the growth in fresh vegetable production (both in acres and farm number) in conjunction with the local food demand in the examined region.

$$(3)\ Y_i = \begin{cases} 0, \text{ if } y^* \leq A_1, \\ 1, \text{ if } A1 < y^* \leq A_2 \\ 2, \text{ if } y^* > A_2 \end{cases}$$

where, A_1 and A_2 are unknown cutoff values to be estimated with B.

The explanatory variables used can be broadly categorized in the following groups: i) producer characteristics (age, education, risk aversion level, risk perception), ii) farm characteristics (farm size, ability to expand, farm income), iii) location (Kentucky, Illinois, Ohio, and Indiana). Selection of these variables is based on previous literature (Musser, et al. 1996, Franken et al. 2014; Goodwin and Schroeder 1994) in conjunction with discussions with industry experts.

Empirical Estimation

Traditionally, to estimate the regression slopes and cutoff points we use maximum likelihood estimators (MLE). However, MLE is found to be unstable and easily affected by extreme cases when the sample size is small (Xie et al. 2009). Considering the small sample size of our study, in order to avoid this instability, we estimated the ordered probit model from a Bayesian perspective. This approach has a number of desirable properties. Specifically: i) when the sample size is small, the Bayesian method provides more stable parameter estimation and better model fitting compared to MLE, ii) the confidence intervals provided by the Bayesian approach are more reliable and do not depend on large sample assumptions, and iii) the Bayesian method facilitates the use of prior information or experts' belief through the specification of prior distributions.

Under the Bayesian inference, model parameters θ are considered as random. For the ordered probit model θ = (A, B). Before the data collection the researchers specify prior distributions based on findings from previous literature. Alternatively, one can adopt non-informative priors. Suppose that we denote the prior density function as π(θ). Then, according to Bayes theorem, the density of the posterior distribution can be expressed as:

$$(4)\ p(\theta|\ y) = \frac{f\ (y\ |\theta)\ \pi(\theta)}{f(y)}$$

where, f (y|θ) is the likelihood function and f(y) is the marginal likelihood.

Once the posterior density is computed we can use point estimators (i.e. posterior mean, median or mode) to estimate the model parameters. For the present study the posterior mean is used since it represents the center of the posterior distribution and can be obtained via Monte Carlo approximation when a tractable form of p(θ|y) is unavailable. To estimate the credible intervals[6] we utilized the Highest Posterior Density (HPD) interval that has the shortest length (Hoff, 2009).

Regarding the choice of prior distribution, for the present study, the non-informative approach, suggested by Gelman et al. (2008), is implemented. Specifically, we first standardize the continuous predictors to have mean zero and standard deviation 0.5. Then, we let the coefficients B have independent Cauchy prior with scale 2.5 and intercepts (i.e. the cutoffs) A have independent Cauchy prior with scale 10.

A Markov chain Monte Carlo (MCMC) algorithm is utilized to draw samples from posterior distributions. In particular, Gibbs sampler[7] is used to generate simulations from the joint posterior distribution of the model parameters (Gelfand and Smith 1990). For the present study we generate a Markov chain of length T= 1,000,000 iterations, as a large T guarantees convergence from any starting point of the chain. However, the simulation requires a burn-in starting period to allow for the chain to converge and make accurate approximations. The first S =200,000 iterations are treated as the burn-in period and are discarded. The posterior means of A and B are approximated using sample means of the remaining MCMC samples. Similarly, posterior standard deviations are approximated by sample standard deviations. Furthermore, for each regression coefficient its 90% and 95% HPD intervals are estimated.

Estimation of Marginal Effects

In an ordered probit formulation the sign of the estimated coefficients can be easily interpreted as determining if the latent variable increases, or not, with the explanatory variables (Cameron and Trivedi, 2005). However, the interpretation of the magnitude of the coefficients is not as straightforward. To overcome this problem, the marginal effect (ME) for each of the explanatory variables is estimated to reveal the exact impact of the explanatory variables on the probability of participating in a marketing contract agreement.
The marginal effects for the maximum likelihood estimation (MLE) are calculated following Cameron and Trivedi (2005) as:

$$(5)\quad \frac{\partial P(y=k|X_i)}{\partial X_{Kj}} = [\,\varphi\,(A_{k-1} - X_i\beta) - \varphi(A_k - X_i\beta)]\beta_j$$

where, the function φ(.) is the pdf of the standard normal distribution. Since we have three categories, we estimate three marginal effects. The Monte Carlo estimate of the $ME_{y=0,j}$ is calculated by taking the average of all iterations after the burn-in:

[6] A credible interval is the Bayesian analogue of the confidence interval. In contrast to the confidence interval, it incorporates information for the prior distribution. A 90% credible interval indicates the range that the true parameter value will fall into with 90% probability.
[7] A Gibbs sampler is an MCMC approach for generating random variables from a distribution without having to calculate the density (Casela and George 1992).

$$(6)\ \widehat{ME_{y=0,j}} = \frac{1}{T-S}\sum_{t=S+1}^{T} -\varphi(A_1^{(t)} - \overline{X}'B^{(t)})B_j^{(t)}$$

where, $A^{(t)}$ and $B^{(t)}$ are the samples in the t[th] iteration of the MCMC chain, and $\overline{X}$ is the column-wise mean of the design matrix.

Similarly, the marginal effects at y=1 and 2 are estimated using the following formulas:

$$(7)\ \widehat{ME_{y=1,j}} = \frac{1}{T-S}\sum_{t=S+1}^{T} -\varphi[\left(A_2^{(t)} - \overline{X}'B^{(t)}\right) - \Phi\left(A_1^{(t)} - \overline{X}'B^{(t)}\right)]B_j^{(t)}$$

$$(8)\ \widehat{ME_{y=2,j}} = \frac{1}{T-S}\sum_{t=S+1}^{T} -\varphi(A_2^{(t)} - \overline{X}'B^{(t)})B_j^{(t)}$$

Empirical Results

The regression results for the ordered probit and Bayesian ordered probit formulations are reported in Table 5[8]. The marginal effects for the Bayesian formulation are presented in Table 6. In a general framework, the sign of the coefficients indicates whether the latent variable y* increases or decreases with the explanatory variable. The marginal effects indicate the increase/decrease in the probability of signing a contract associated with a one unit increase in the explanatory variable. Lastly, for the ordered probit/logit models, inference regarding the threshold parameters, i.e., comparing each cutoff parameter with zero, is meaningless (Green and Hensher 2009; Dayking and Moffat 2002). However, testing whether the cutoff parameters are statistically different from each other can help us assess if the three categories should be collapsed into two (Gebrezgabher et al. 2010; Cameron and Trivedi 2005). For the present study, a chi-square statistic for the MLE approach (Williams 2015) and the HPD interval for the Bayesian approach, verify that the two cut-off points A_1 and A_2 are significantly different from each other.[9] Thus, the three categories should not be collapsed into two, and the use of an order probit model is justified.

In line with our initial hypothesis, the findings indicate that the probability of signing a marketing contract is lower for older producers (Table 5). Specifically, a one year increase in the age of the producer is associated with being 1.36% more likely not to sign a contract, 0.83% less likely to maybe sign a contract depending on the terms and 0.53% less likely to sign a contract (Table 6). A number of reasons justify this finding. First, older growers have a shorter planning

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[8] In addition to the main effects estimation, models with interaction terms were also estimated. In line with the findings of Hudson and Lusk (2004), the interaction terms were not statistically significant. The only exception was the interaction term between risk perception and Kentucky that was found to have a statistically significant positive coefficient indicating that more risk averse growers in the state are more likely to participate in contractual agreements.

[9] For the MLE approach, prob > χ^2 =0.00. The Bayesian model yields an estimated value of $A_2 - A_1$ of 2.69, with a 95% HPD interval [1.87, 3.50], confirming that the difference between the two cutoff points is significant.

horizon, thus they may be less likely to participate in contractual agreements especially if they require long term commitments (Musser et al. 1996). Second, older/more experienced growers may be able to better time their production and achieve greater net returns from the cash market (Franken et al. 2014). Furthermore, older growers are less willing to diversify their practices, especially in areas where contracting is not common (Franken et al. 2014). On the other hand, younger producers may prefer contractual agreements in order to improve their financing capabilities (Davis and Gillespie 2007).

Table 5. Ordered Probit Estimation Results for the Probability of Signing Contracts[1]

	Ordered Probit (MLE)		**Bayesian Ordered Probit**	
Variables	Coefficient	Standard Error	Coefficient	Standard Error
Risk Aversion	-0.2751	0.3027	-0.3241	0.2919
Risk Perception	0.0407	0.0416	0.0354	0.0401
Age	-0.0544**	0.0166	-0.0564**	0.0171
Farm Size	0.0085*	0.0047	0.0083*	0.0047
Ability to Expand	1.1607*	0.6220	1.1007**	0.6011
Education	-0.0758	0.0739	-0.0719	0.0709
Farm Income	0.4868	0.6514	0.5010	0.6531
Kentucky	1.0929*	0.5536	1.0355**	0.5182
Indiana	0.2960	0.5378	0.2029	0.4946
Ohio	0.0458	0.5796	-0.0608	0.5475
A_1	-2.8058	1.6058	-3.0569	1.5642
A_2	-0.2397	1.5336	-0.3680	1.4776
Pseudo R^2	0.2508			
Fitting[10]	0.2642		0.2642	
Prediction[11]	0.3774		0.3774	

Note. * and ** denote significance level of 0.10 and 0.05 respectively

Moreover, the results indicate that the farm size and the ability to expand the operations, if needed, have a positive impact on the probability of adopting a marketing contract agreement (Table 5). For instance, a grower that has the potential to expand his/her operations is 10.49% more likely to participate in a marketing contract agreement, compared to a grower that does not have the ability to expand (Table 6). This finding is not unexpected considering that the majority of farmers who participate in contractual agreements are large scale producers (Franken et al. 2014; MacDonald et al. 2004, Katchova and Miranda 2004). This result is also consistent with the statement of Wang et al. (2014), who mentioned that buyers are more likely to offer contractual agreements to larger farms in order to reduce transaction costs.

Following Goodwin and Schroeder (1994) and Musser et al. (1996) our initial hypothesis was that education would have a positive impact on the probability to participate in contractual agreements, since more educated growers may be able to utilize contractual agreements more efficiently. However, in line with Goodwin and Kastens (1996), Katchova and Miranda (2004) Paulson et al. (2010), and Bellemare (2012), our results indicate that the education level of the farm manager does not have a statistically significant impact in the probability that a grower will participate in contractual agreements (Table 5).

[10] Misclassification rate in the fitted data is 0.2642 for both MLE and BOP, i.e., 14 misclassified cases out of 53 observations.
[11] Misclassification rate in out-of-sample prediction by a ten-fold cross validation is 0.3774 for both MLE and BOP, i.e., 20 misclassified cases out of 53 observations.

Two of the purported benefits of contractual agreements include a reduction in income risk and a steady cash flow that can improve growers' access to credit (Katchova and Miranda 2004; MacDonald and Korb 2011; Wang et al. 2014). Therefore, a plausible hypothesis is that producers with lower farm income may be more likely to participate in contractual agreements (Musser et al. 1996; Wang et al. 2014). Our findings indicate that farm income does not have a statistically significant impact in the probability that a grower will use marketing contracts (Table 5). Although surprising, this result is consistent with the findings of Katchova and Miranda (2004) who indicated that gross farm income does not affect the probability of participating in marketing contracts for U.S.A. soybeans and wheat producers and with Simmons et al. (2005) who indicated that credit constraints do not have a statistically significant impact in the decision to participate in contractual agreements for corn and rice producers in Indonesia. This finding may suggest to potential buyers that just designing a monetary scheme is not enough to attract producers to participate in contractual agreements

None of the explanatory variables related to risk (risk aversion levels and risk perception) have a statistically significant impact on the probability of adopting marketing contracts (Table5). Consequently, our findings, in line with Allen and Lueck (1992, 1995, 1999), do not provide support for the risk shifting hypothesis.

Regarding the location variables, producers in Kentucky are more likely to sign a marketing contract compared to growers in Illinois (the base category), while, producers in Indiana and Ohio are not significantly different from those in Illinois. For instance, the probability of a producer in Kentucky signing a marketing contract is 9.81% higher compared with a grower in Illinois (Table 6). The change in the available marketing outlets in conjunction with the rising importance of vegetable production in the economy of Kentucky provides justification for this finding. Specifically, it has been noticed in the literature that when production of a certain agricultural product in one area increases substantially, like the case of tomato production in KY, there is an expectation for increased participation in contractual agreements (Davis and Gillespie 2007). Furthermore, until 2008, fresh produce cooperatives were among the major marketing outlets (Woods et al. 2012). However, after 2008 the majority of them declined, or went out of business (Woods et al. 2012). Consequently, vegetable producers seek alternative options. Considering the increased demand for local foods in the state, and the promotion programs, such as Kentucky Proud, contractual agreements with restaurants and grocery stores is an attractive marketing alternative (Woods et al. 2012).

Table 6. Marginal Effects for the Bayesian Ordered Probit Formulation

Variable	**No**	**Maybe**	**Yes**
Risk Aversion	0.0783	-0.0469	-0.0314
Risk Perception	-0.0840	0.0051	0.0034
Age	0.0136**	-0.0083**	-0.0053**
Farm Size	-0.0020*	0.0012	0.0008*
Ability to Expand	-0.2675*	0.1626	0.1049*
Education	0.01740	-0.0108	-0.0067
Farm Income	-0.1218	0.0759	0.0458
Kentucky	-0.2514**	0.1533	0.0981**
Indiana	-0.0503	0.0302	0.0200
Ohio	0.0140	-0.0092	-0.0048

Note. * and ** denote significance level of 0.10 and 0.05 respectively

Conclusions

Contractual agreements account for, almost, 40% of the value of U.S. agricultural production. However, only 12% of the producers participate in any type of contractual arrangements (MacDonald and Korb 2011). Considering the low participation rate and the expenses associated with writing a contract (monetary costs, time requirements etc.) a better understanding of the factors that influence producers probability of signing a contract is especially important for reducing costs and writing contracts that can be beneficial for the buyer and the grower. Although numerous theoretical explanations for the increased use of contracts have been proposed, there is limited empirical support for them (Hudson and Lusk 2004; Paulson et al. 2010).

The present study used a Bayesian ordered probit approach to investigate how different producer and farm operation characteristics affect fresh vegetable growers' decision to sign a marketing contract. Fresh vegetable growers were selected as the sample of the present study due to the increased sources of risk they face and the limited opportunities they have to reduce this uncertainty.

The findings indicate that the producers' age, the farm size, the ability to expand and the location are factors that influence the probability of signing a marketing contract. On the other hand, farm income and education level did not have a statistically significant impact on the probability of signing a marketing contract agreement.

An important research question is whether or not growers risk aversion levels affect the probability of participating in contractual agreements. The present study used a multiple price list game and three Likert scale questions to elicit growers risk aversion and risk perception levels. The findings of the empirical analysis do not provide support for the risk shifting hypothesis.

A limitation of the present study is associated with the relatively small sample. However, the use of Bayesian analysis can help overcome this problem. Further research is needed to estimate if the results of this study are consistent across regions. Furthermore, future research may try to examine which elements of a contractual arrangement make them more attractive to producers.

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