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

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Abstract

One of the most frequently used arguments to explain the increased 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 utilized in this study to examine the impact of fresh vegetable producers' personal characteristics on the probability of adopting marketing contracts. Among the characteristics examined are: risk aversion levels, risk perception, age, education, income, location. The findings indicate that age, farm size and the potential to expand the operation are parameters that affect the choice of contracts. On the other hand, the results do not support the risk shifting hypothesis.

Keywords: Marketing Contracts, Bayesian Ordered Probit, Risk

JEL Classifications: Q12, Q13

Introduction

In The Wealth of the Nations Adam Smith criticized sharecropping[1] as an unsatisfactory intermediate stage between slavery and the English 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).

Despite its theoretical shortcomings, mentioned by Marshall and the majority of classical economists, sharecropping remained a popular method of agricultural production both in the Old and the New world. 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 work of Stiglitz (1974) and Cheung (1969) risk aversion has been adopted by many scholars as a theoretical explanation of contract choice. However, this premise has limited empirical support and has been challenged by a number of researchers especially during the last 15 years (Allen and Lueck, 1995; Hudson and Lusk, 2004).

The main objective of the present study is to examine the role of: i) risk, ii) personal characteristics and iii) farm 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 main data source for the study is a mail survey administered to tomato growers in four states: Kentucky, Illinois, Ohio and Indiana. A Bayesian ordered probit model is utilized to

[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.

analyze the data set. 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 (Musser et al. 1996; Katchova and Miranda, 2004; Goodwin and Schroeder, 1994; Pennings and Leuthold, 2000).

The contribution of the study to the literature is threefold. First, 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. Second, the present study focuses on fresh vegetable production, in contrast to grain crops that has 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 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. Lastly, to the best of the authors' knowledge, this is among the first research endeavors to examine how growers' risk perception affect the choice of marketing contracts for fresh vegetable production.

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 increasing demand for local foods. For instance, retailers can use this information to identify more efficiently growers that are willing to participate in a contractual agreement. This is especially important considering the cost of writing and enforcing the contractual arrangements.

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. 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. 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 was offered to the producers ($25) if they completed the survey.

The mailing information for the growers was gathered from MarketMaker, after obtaining permission to use the data base of the web site. MarketMaker is a free online marketing tool developed by the University of Illinois Extension Service. Its' primary objective 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 data base of more than 8,600 producers.

Of the 315 survey packages initially mailed, 10 were returned as undeliverable and 5 indicated that they are 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,

To assess the representativeness of responders, we compared demographic variables from the study sample with statistics obtained from the 2007 Census of Agriculture for Vegetables Potatoes and Melons (Table 1).

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 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. Two of the major focus groups took place during the 2011 Kentucky Farm Bureau Convention and the 2012 Kentucky Fruit and Vegetable Trade Show.

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 occur different economic returns. The probability that a disease will occur is set at 0.5. In accordance with Binswanger (1980), higher expected returns were offered at a cost of higher variance (Figure 1).

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 2 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[2]. 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[3].

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

[2] In order to calculate S (Table 2) we have to solve for the indifference point among two consecutive choices using equation 5. 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 can be solved in Excel or in Mathematica after graphing the equations to estimate where the functions crosses the x-axes.

[3] Following Binswanger (1981), for the regression analysis alternative F (Table 2) was given a value near zero (0.18) and the value for alternative A was set to 2.47

we adopted three Likert-scale questions (Table 3) 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.

Econometric Procedures

Theoretical Model

Assume that a vegetable grower, indexed by i, is considering adopting a marketing contract. 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. Twenty four percent of the growers in our sample 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:

$$(2)\ y^* = B'X_j + \varepsilon,$$

where, B´ is the vector of the parameters to be estimated, X_j 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 is estimated by the following model:

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

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

The explanatory variables can be broadly categorized in the following groups: i) Producer characteristics (age, education, risk aversion levels, risk perception), ii) Farm characteristics (farm size, ability to expand, farm income), iii) Location (Kentucky, Illinois, Ohio, Indianna). The selection of these variables is based on previous literature (Musser et al. 1996; Katchova and Miranda, 2004; Goodwin and Schroeder, 1994; Pennings and Leuthold, 2000).

Age is expected to have a negative effect on the probability of adopting a marketing contract for the following reasons: i) because of their shorter planning horizon older producers may be less willing to participate in long-term contractual agreements, and ii) the shorter planning horizon makes it more difficult to recover from the learning and adjustments costs (Musser et al., 1996). On the other hand, education is expected to have a positive impact on the adoption of marketing contracts, since more educated growers are more likely to understand the concept and responsibilities associated with such an agreement (Musser et al., 1996, Goodwin and Schroeder, 1994).

Considering that the majority of farms that adopt contractual agreements are large scale operations (MacDonald et al., 2008), farm size is hypothesized to have a positive effect on the probability of adopting marketing contracts. Finally, the effect of farm income, risk aversion levels and risk perception is uncertain (Musser et al., 1996).

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 easy to be 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 danger, we estimated the ordered probit model from a Bayesian perspective, which is more reasonable and stable under small sample sizes compared to

MLE. Furthermore, the confidence intervals provided by the Bayesian approach are more reliable and do not depend on large sample assumptions. Lastly, the Bayesian method facilitates the use of prior information or experts' belief through the specification of a prior distribution.

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 for of p(θ|y) is unavailable. To estimate the credible intervals[4] 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 continuous predictors to have mean zero and standard deviation 0.5, then let the coefficients B had independent Cauchy prior with scale 2.5 and intercepts A have independent Cauchy prior with scale 10.

[4] 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.

A Markov chain Monte Carlo (MCMC) algorithm is implemented to draw samples from posterior distributions. With the aid of the latent variable y*, the conditional posterior distributions of all parameters have closed forms so that a Gibbs sample can be implemented (Gelfand and Smith, 1990). The posterior means of A and B are approximated using sample means and standard deviations of the MCMC samples. Furthermore, for each regression coefficient 90% and 95% HPD intervals are estimated. Lastly, the marginal effects for each coefficient are also estimated.

Empirical Results

The regression results for the ordered probit and Bayesian ordered probit formulations are reported in Table 4. The marginal effects for the Bayesian formulation are presented in Table 5. 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.

In line with our initial hypothesis, the findings indicate that the probability of signing a marketing contract is lower for older producers (Table 4). Specifically, a one year increase in the age of the producer is associated with being 0.04% more likely to not sign a contract, 0.03% less likely to maybe sign a contract depending on the terms and 0.01% less likely to sign a contract (Table 5). In line with Paulson et al. (2010) and Goodwin and Kastens (1996) education level was not found to have a statistically significant impact on the decision to participate in a marketing contract agreement.

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 (Table 4).Consequently, our findings 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). For instance, the probability of a producer in Kentucky signing a marketing contract is 0.31% higher compared with a grower in Illinois (Table 5). This finding probably reflects the greater increase in the number of farms and in the market value of vegetable products in Kentucky compared to Illinois.

Lastly, in line with our initial expectations, 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 4). For instance, a grower that has the potential to expand his/her operations is 0.35% more likely to participate in a marketing contract agreement, compared to a grower that does not have the ability to expand (Table 5).

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 farm characteristic, personal characteristics and risk preferences 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 effect 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.

Figure 1: Risk Preferences elicitation question

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

Table 1: Descriptive Statistics Associated with Commercial Tomato Growers

Variable	Average	Std.	Min.	Max.
Gender	0.24	0.43	0	1
(1=female)	(0.17)[a]			
Age	49.8 (56)[a]	12.95	30	70
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

[a] Numbers in parenthesis come from 2007 census of agriculture for vegetables, potatoes and melons.

Table 2: 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%

[a] Based on Binswanger (1980) classification

Table 3: Growers' Risk Perception: Response to Scale Questions (-4= strongly Disagree, 4= Strongly Agree)

Question	Definition	Mean
1	With respect to the conduct of business I avoid taking risk	0.51 (2.07)[a]
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)
n=49		

[a] Number in parentheses are standard deviations

Table 4: Ordered Probit Estimation Results for the Probability of Signing Contracts

	Ordered Probit (MLE)		**Bayesian Ordered Probit**	
Variables	Coefficient	Standard Error	Coefficient	Standard Error
Risk Aversion	-0.2751	0.3027	-0.3241	0.2919
Risk Peception	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
Able to Expand	1.1607*	0.6220	1.1007**	0.6011
Education	-0.0758	0.0739	-0.719	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			1.0976	1.4943
A_2			3.7865	1.6003

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

Table 5: Marginal Effects for the Bayesian Ordered Probit Formulation

Variable	No	Maybe	Yes
Risk Aversion	0.0021	-0.0016	-0.0004
Risk Peception	-0.0003	0.0002	0.0001
Age	0.0004	-0.0003	-0.0001
Farm Size	-0.0001	0.0000	0.0000
Able to Expand	-0.0096	0.0061	0.0035
Education	0.0002	-0.0002	0.0000
Farm Income	-0.0045	0.0028	0.0017
Kentucky	-0.0084	0.0052	0.0031
Indiana	-0.0021	0.0010	0.0011
Ohio	-0.0003	-0.0006	0.0009

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