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Crop Production Contracts and Marketing Strategies: What Drives Their Use?

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ABSTRACT

Numerous crop marketing and risk management tools are available. Research relating producers' risk attitudes to their use of these tools has produced mixed results, and most studies focus on individual tools, neglecting potential complementarities in information they provide. Little is known about the proportion in which individual tools are used, e.g., the percentage of the crop that is forward sold as opposed to hedged. This study identifies factors, including risk attitude, that impact the proportion of corn and soybean producers' sales through spot markets, futures, and options, as well as forward and production contracts, and investigates contract complementarity and substitutability using survey and accounting data, and causal modeling. [Econ Lit classification: Q130]. © 2012 Wiley Periodicals, Inc.

1. INTRODUCTION

Numerous marketing and risk management tools are available for agricultural producers facing substantial price risks (Martin & McLeay, 1998; Pennings, Isengildina-Massa, Irwin, Garcia, & Good, 2008; White & Dawson, 2005). Most research focuses on relatively simple choices, such as whether to use futures and options contracts (Pennings & Leuthold, 2000a, 2000b) or crop insurance (Knight & Coble, 1997), and few studies examine a broader array of marketing and risk management choices. Although Pennings et al. (2008) identify factors influencing the portfolio of marketing and risk management tools that producers adopt, less is known about how such factors influence the *proportion* in which these tools are used (e.g., the percentage of the crop that is forward sold as opposed to hedged). Other studies examine the *proportion* of crop sales made using a particular marketing method but offer little insight regarding how the use of one marketing tool influences the use of another (e.g., Goodwin & Schroeder, 1994; Katchova & Miranda, 2004; Musser, Patrick, & Eckman, 1996; Sartwelle, O'Brien, Tierney, & Eggers, 2000; Shapiro & Brorsen, 1988). In addition, research on producers' use of these tools has produced relevant but sometimes puzzling results. For instance, the role of risk aversion is unclear, as some studies find a strong relationship between risk aversion and the use of risk management instruments, while others do not (e.g., Pennings & Garcia, 2001; Rabin & Thaler, 2001).

This study identifies factors, including risk attitude, that impact the proportion of corn and soybean producers' sales through spot markets, futures and options, forward contracts, and production contracts using survey and accounting data in a hurdle model framework. We also investigate relationships among marketing methods using more rigorous causal modeling procedures.[1] Such procedures allow causal inferences, and inform structural equation modeling

[1]Bryant et al.'s (2006) evaluation of causal hypotheses stemming from theories of futures markets is perhaps the most familiar application of causal analysis. The authors rejected hypotheses regarding the hedging pressure theory

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(Chong, Zey, & Bessler, 2010), which permits a more complete understanding of the interaction among marketing alternatives. Secondary accounting data control for farm size and their financial state (e.g., debt structure), whereas primary survey data capture producers' age and risk attitude. We elicit risk attitude measures directly (Roe, 1982), instead of computing indirect measures from observed behavior (e.g., Antle, 1987; Moscardi & de Janvry, 1977) or using proxies (e.g., wealth) that may cause endogenous matching (Ackerberg & Botticini, 2002; Braido, 2008) or identification problems (Bellemare & Brown, 2010). Two main approaches to directly elicit risk attitudes exist: measures derived from the expected utility framework and measures derived from responses to multi-item scales (c.f., Pennings & Garcia, 2001, for a measure combining both approaches). We use the lower-cost multi-item scale approach and factor analysis (Hair, Anderson, Tanham, & Black, 1995) of producers' responses to limit measurement error of latent risk attitudes and thereby reduce potential for the endogenous matching bias associated with correlation among those errors and regression residuals.

The remainder of the article is organized in a straightforward manner. The literature on crop producers' use of risk management and marketing tools is reviewed in the next section. Sample representativeness and data collection are discussed in the research design section, followed by a description of the empirical methods. Next, empirical results are presented followed by a discussion of the findings and suggestions for future research.

2. LITERATURE REVIEW

To facilitate comparisons and discussion, selected findings on factors influencing the proportion of crops producers sold using various marketing tools are summarized in Table 1. Shapiro and Brorsen (1988) used Tobit models to examine the factors influencing 41 Indiana corn, soybean, and wheat producers' use of futures markets. The debt-to-asset ratio and farm acreage had significantly positive effects, while years of farming experience and formal education had significantly negative effects. The most important factors were perceptions regarding income stability (not shown in Table 1), followed by the debt-to-asset ratio.

Using similar data on 62 Indiana corn and soybean producers and Tobit models, Musser, Patrick, and Eckman (1996) investigated the factors influencing the percentage of expected harvest that was forward priced using any type of marketing arrangement. The debt-to-asset ratio had a significantly positive impact on the maximum percentage of expected soybean production that producers would forward price, which is consistent with Shaprio and Brorsen's (1988) previous results. Age and education had significantly negative and positive effects, respectively, on the forward pricing of corn, as younger producers have more time to recover the costs of learning forward pricing methods and further education facilitates their use. Farm size, as measured by gross income, had a significantly negative impact on the forward pricing of corn. Risk aversion toward losses had a significantly positive impact on the maximum percentage that producers would forward price for both corn and soybeans. Dummy variables for options/minimum-price contracts and for futures hedges generally had significantly positive impacts on forward pricing for both corn and soybeans, suggesting that joint portfolio effects may exist.

Goodwin and Schroeder (1994) used probit and Tobit models to investigate factors influencing whether 509 Kansas producers forward price their output using futures and/or forward contracts and how much of it they forward price. In general, experience had a significantly negative effect on the probability of forward pricing (i.e., probit results), whereas farm size in acres, education, the debt-to-asset ratio, and risk aversion had significantly positive effects. Acreage and education had similar positive effects on the proportion of output forward sold (i.e., Tobit results), but results were less consistent for other variables and risk aversion was significantly positive only for cattle producers.

of futures market risk premiums (i.e., the generalized version of Keynes' [1930] normal backwardation theory) and theories that speculative activity affects price volatility.

TABLE 1. Selected Results for the Proportion of Crops Sold

Dependent variable	Shapiro & Brorsen (1988) % hedged using futures	Goodwin & Schroeder (1994) % forward and futures	Musser, Patrick, & Eckman (1996) % forward priced	Sartwelle, O'Brien, Tierney, Eggers & (2000) % cash sales	forward contracted	futures and options	Katchova & Miranda (2004) % sold with marketing contracts[a]
Age	–	–	<0, C	–	–	–	0
Experience	<0	0	–	0	0	<0	–
Education	<0	> 0, C, S	> 0, C	–	–	–	0
Risk aversion	0	0	> 0, C, S	0	0	0	–
Debt/asset	> 0	0	> 0, S	–	–	–	0
Acres	> 0	> 0, C, S	–	<0	> 0	0	–
Gross income (size)	–	–	<0, C	–	–	–	> 0, C
Futures hedging	–	–	> 0, C, S	–	–	–	<0, S
Forward contracting	0	–	–	–	–	–	–
Crop insurance	0	0	–	<0	> 0	> 0	0
R^2	0.84	–	–	0.17	0.16	0.19	–
N	41	171, C, 238, S	43 & 53, C 45 & 54, S[b]	35	35	35	503, C, 335, S

Note. See references for full citations. Unless denoted, results are for an aggregate of multiple commodities. > 0 denotes statistically positive effects, < 0 denotes statistically negative effects, and 0 denotes effects that are not statistically different from zero. "–" indicates that the variable was not included in the analysis. C = corn; S = soybeans; N = sample size.

[a]In this study, marketing contracts is an aggregate variable including categories of forward contracts that either set a price or tie it to futures markets and other specialty marketing contracts (e.g., seed, non-GM, identity-preserved).

[b]Sample sizes correspond to Musser et al.'s (1996) analyses of the percentage of expected production forward priced by July 15, 1993 and the maximum percentage of expected production forward priced by August 1 for corn and soybeans, respectively.

Sartwelle et al. (2000) used Tobit and multinomial logit models to examine the factors that influence 351 Kansas, Texas, and Iowa grain producers' use of cash sales, forward contracts, and futures and options. Cash sales decreased and forward contracting increased significantly with farm size (i.e., crop acreage) in Tobit regressions. A survey item regarding farm size relative to others in their region also significantly decreased cash sales in the Tobit analysis and increased use of forward contracts and futures and options relative to cash sales in multinomial logit regressions. Both Tobit and multinomial logit models indicated that use of futures and options decreased with experience in agriculture. Diversifying into livestock production increased cash sales and decreased forward contracting significantly in both analyses. Use of forward contracts and futures and options increased and cash sales decreased significantly with purchase of crop insurance in both analyses. Their measure of risk attitude was statistically insignificant in all regressions.

Katchova and Miranda (2004) raised doubt about much of this prior research by identifying that previous results may have confounded explanatory variables' contract adoption effects with their influence on the quantity contracted. Using U.S. Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) data on corn, soybean, and wheat producers, the authors demonstrated that results of Tobit models performed on samples with observations of zero contracting are strongly influenced by and almost identical to the adoption decision, i.e., binary probit results.[2] Hurdle models explaining the proportion of crop contracted, the frequency of contracting, and contract type (i.e., forward or specialty marketing

[2]Subsequently, Katchova and Miranda (2004) performed three hurdle models per commodity to explain the proportion contracted, the frequency of contracting, and the contract type (i.e., forward or specialty marketing contract), where the models estimated respectively truncated Tobit, truncated count (i.e., Poisson), and binomial logit regressions conditional on a binary contract adoption choice (i.e., probit).

contract) conditional on contract adoption revealed few consistent impacts across commodities for the conditional or truncated regressions. In some cases, the signs of significant effects were the opposite of those for Tobit regressions in their own work and in previous studies. Unfortunately, the study was unable to provide any insights into the impacts of risk aversion due to unavailability of measures in the ARMS dataset.

Identifying that crop producers utilize numerous combinations of marketing and risk management tools, Pennings et al. (2008) employed multinomial logit analysis and a choice bracketing framework to investigate the factors that influence the portfolio of tools adopted. The sample consisted of commercial producers that subscribe to agricultural market information and advisory services from a U.S. firm via satellite. At a broad bracketing level, adoption of forward pricing tools and crop insurance in combination was significantly more likely for younger producers, larger farms, and farms that had not diversified into livestock production. These variables were also important at medium bracketing levels that included forward pricing categories of exchange, exchange-derived, and non-exchange-derived instruments (i.e., futures and options, hedge-to-arrive and basis contracts, and forward contracts, respectively) and insurance categories of catastrophic, yield insurance, and revenue insurance products. Though essentially unimportant at broader bracketing levels, risk aversion mattered at the narrowest bracketing level for choices of combined use of futures and options and for choices of combined use of hail and other yield insurance products. Although the study provided interesting insights into combinations in which marketing and risk management tools are adopted, it did not consider the proportion in which each tool in the portfolio was utilized.[3]

3. DISCUSSION OF THE DATA SAMPLE

3.1. Research Context and Data Sources

A unique dataset was assembled by surveying a sample of crop producers by personal on-farm interviews, for whom annual accounting and production records are kept through the University of Illinois Farm Business Farm Management (FBFM) Extension program. FBFM is a cooperative educational-service available to all agricultural producers in the state for a fee (Lattz, Cagley, & Raab, 2005). The program is designed to assist producers with management decisions by providing business analysis through computer-assisted processing of records for income tax management. The secondary production and accounting data are collected annually by 58 fulltime field staff specialists serving nine FBFM associations.

Extensive pretesting of survey materials enhances the reliability of primary data. Four rounds of pretests—two with FBFM personnel and two with producers—were performed. In each case, survey items were modified, eliminated, and added based on comments. One-hundred fifty producers were contacted and as encouragement for their participation were offered a chance at one of ten $100 lottery prizes. Personal interviews, averaging just over an hour, limited the sample size, but enhanced the reliability of responses. Producers were assured of their anonymity and then acquainted with definitions of key terms. A paper survey led the interview process, collecting information on marketing methods. Along with specific survey items, participants made additional comments that were also recorded. In total, 48 producers participated in interviews from December 2006 through April 2007. Although the relatively small sample obtained may pose modeling constraints and concerns for representativeness that are addressed throughout the manuscript, interviews allow greater insights through discussions with producers.

Because producers' use of marketing arrangements may vary from year to year, producers were asked to select from predefined ranges to approximate the percentage of their expected

[3] Using a multinomial logit framework similar to that employed by Sartwelle et al. (2000) and Pennings et al. (2008), Bezabih (2009) investigates the impacts of tenants' and landlords'' time preferences and production risk preferences on choice of land rental contract (i.e., fixed rent, pure sharecropping, and cost-sharing). In this setting, as in commodity marketing, a portfolio of (or the proportion of land rented using) various contract types may be of interest for future research in instances when a tenant rents from multiple landlords or a landlord rents to multiple tenants.

TABLE 2. Representativeness of Sample in Terms of Size, Returns, and Operator Age

	2006 FBFM	2007 Census	Pennings et al. (2008)		
Distribution of farms by size	Surveyed producers	Farms with harvested cropland	Corn	Soybeans	
Over 2,000 acres	8.33%	4.98%	4.50%	2.90%	
1,000–1,999 acres	35.42%	5.94%	58.60%	45.10%	
500–999 acres	35.42%	9.12%	7.90%	14.40%	
Under 499 acres	20.83%	79.96%	9.80%	14.50%	
Mean Statistics		Corn	Soybeans		
Size (acres)	1,044	745	731	1,500 to 1,999 range	
Producer age	55	55	56	40 to 44 range	
Market value of products sold	$417,260[a]	$335,767	$322,157	–	–
Crop returns per acre[b]	$488.94	$467.61	$254.84	–	–

[a]Total crop returns for Farm Business Farm Management (FBFM) producers.
[b]http://www.ers.usda.gov/Data/Costs AndReturns/testpick.htm

production that they sold using various marketing arrangements in marketing year 2006. Averages of these ranges are used here to construct the dependent variables. Because the respective minimum and maximum available responses were 0% and from 75–100%, the resulting dependent variables are truncated with a minimum of 0% and a maximum of 88% [= (75% + 100%)/2]. The marketing arrangements included categories of futures and options, forward contracts, production contracts for seed, and nongenetically modified crop production, and a category for any proportion sold on the spot with no form of price protection.

Producers were asked to respond to a series of survey items previously validated by Pennings and Garcia (2001) for the construction of factor analytic measures of latent risk attitudes. Items were scaled −4 to +4, so that negative numbers indicate risk-seeking, positive numbers indicate risk-aversion, and zero indicates risk-neutral. Producers responded to these items separately for corn and soybeans, so that separate risk attitude measures could be computed to correspond specifically to respective corn and soybean marketing contexts. The reliability of the measures of latent variables is indicated by Cronbach's (1951) alpha. Values exceeding 0.70, specifically 0.80 for corn and 0.79 for soybeans, indicate that the resulting risk attitude measures are highly reliable.

3.2. Representativeness and Summary Statistics

Presently, about one out of five Illinois commercial farms with over 500 acres or over $100,000 total farm sales participate in the FBFM Extension Program. "(T)he data from recordkeeping farms may be used with reasonable confidence, even though the recordkeeping farms as a group do not represent a cross section of all commercial farms in the state" (Lattz et al., 2005, p.1). Consistent with prior research on producers participating in farm management associations (e.g., Goodwin & Schroeder, 1994) and subscribing to advisory services (e.g., Pennings et al., 2008), surveyed FBFM farms are larger and more commercial than typical U.S. farms (Table 2). Relative to 2007 U.S. Department of Agriculture (USDA, 2007) Census data, the distribution of FBFM farms by size is also more similar to the sample obtained by Pennings et al. (2008). Producers in our sample range in age from 39 to 76 with a mean of 55 and a standard deviation of about 8 years. Using a binary measure of education (4-year college degree = 1; otherwise = 0), about 33% of producers in our sample have completed 4 or more years of college. Mean education levels are about 14 years in Shapiro and Brorsen (1988) and in Goodwin and Schroeder (1994) and 15 years in Musser et al. (1996). The debt-to-asset ratio for producers in the sample ranges from 1–69% with a mean of 24% and a standard deviation of about 16%, which suggests degrees of leverage that are similar to Shapiro and Brorsen's (1988) and Musser

TABLE 3. Representativeness of Sample in Terms of Contract Use

	Our FBFM sample (2006)		Pennings et al. (2008)		Goodwin & Schroeder (1994)	
	Corn	Soybean	Crop[a]		Corn	Soybeans
Portion of producers adopting						
futures & options	41.67	39.58	Futures:	40.4	10.73	5.22
			Options:	37.0	9.6	4.42
Forward contracts	87.50	83.33		82.20	34.46	30.92
Production contracts	10.42	25.00		–	–	–
Portion of crop contracted by contracting producers						
futures & options	36.25	31.68	Futures:	–	33.84	28.65
			Options:	–	29.24	36.59
Forward contracts	43.11	39.82		–	37.18	33.27
Production contracts	29.00	34.67		–	–	–

Note. FBFM = Farm Business Farm Management.
[a]In this study, reported statistics pertain to the percentage of corn, cotton, soybean, and wheat crops sold.

et al.'s (1996) samples. As in prior research (e.g., Pennings et al., 2008; Shapiro & Brorsen, 1988), the majority of producers in the sample are risk-averse with respect to both corn (59%) and soybeans (58%), and the average producer is moderately risk-averse.

Surveyed FBFM producers' use of contracts is also more representative of large commercial producers than it is of typical U.S. producers (Table 3). In the USDA-ARMS dataset analyzed by Katchova and Miranda (2004), only 12% of corn producers, 8% of soybean producers, and 5% of wheat producers use *marketing* contracts including flat or fixed price, formula pricing, delayed price, minimum price, fixed basis, futures fixed, and other contracts. By comparison, of the 48 producers in the sample growing corn (soybeans), about 42% (40%) use futures and options, 88% (83%) use forward contracts, and 10% (25%) use production contracts. Similarly, in the sample studied by Pennings et al. (2008), about 40% of producers use futures, 37% use options, and 82% use forward contracts. Though adoption rates are somewhat lower in Goodwin and Schroeder (1994), producers using contracts in their study market similar proportions of output using those contracts as in our sample. Specifically, producers using the respective contracts to market corn (soybeans) in our sample make 36% (32%) of sales using futures and options, 43% (40%) using forward contracts, and 29% (35%) using production contracts. Producers using the respective contracts to market corn (soybeans) in Goodwin and Schroeder (1994) make 34% (29%) of sales using futures, 29% (37%) using options, and 37% (33%) using forward contracts.

4. EMPIRICAL METHODS

4.1. Regressions

Several studies investigating determinants of the proportion of a crop contracted have employed Tobit procedures (e.g., Goodwin & Schroeder, 1994; Musser et al., 1996; Shapiro & Brorsen, 1988). The log-likelihood for the Tobit model contains probabilities of nonuse of contracts from a Probit regression in the first term and a classical regression for positive amounts contracted in the second term:

$$\ln L = \sum_{\alpha_i = 0} \ln \Phi\left(-\frac{\beta'_\alpha x_i}{\sigma}\right) + \sum_{\alpha_i > 0} \ln\left[\frac{1}{\sigma}\phi\left(\frac{\alpha_i - \beta'_\alpha x_i}{\sigma}\right)\right], \tag{1}$$

where $\Phi(\cdot)$ is the standard normal probability density function, $\boldsymbol{x}_i$ and β_α are vectors of independent variables and coefficients, σ is the standard deviation, and α_i denotes the proportion contracted.[4] Following Katchova and Miranda (2004), α_i is not constrained from above since a producer conceivably may contract more than his actual ex post production. Under the Tobit formulation, the independent variables and associated coefficients are constrained to be the same for the contract adoption and proportion contracted decisions. Cragg's (1971) less restrictive hurdle or two-step model does not require the variables and coefficients for both decisions to be the same. The log-likelihood is the sum of the log-likelihood of a Probit regression (the first two terms) and the log-likelihood of a truncated regression (the second two terms) and is given by

$$\ln L = \sum_{c_i=0} \ln \Phi\left(-\gamma' z_i\right) + \sum_{\alpha_i>0} \left\{ \ln \Phi\left(\gamma' z_i\right) + \ln\left[\frac{1}{\sigma}\phi\left(\frac{\alpha_i - \beta'_\alpha x_i}{\sigma}\right)\right] - \ln \Phi\left(\frac{\beta'_\alpha x_i}{\sigma}\right)\right\}, \quad (2)$$

where $\mathbf{z}_i$ and γ are vectors of independent variables and coefficients pertaining to contract adoption and, and as before, $\mathbf{x}_i$ and β_i are vectors of independent variables and coefficients pertaining to the proportion contracted. When $\mathbf{z}_i = \mathbf{x}_i$ and $\gamma = \beta_\alpha/\sigma$, these models are equivalent.

4.2. Causal Models

Recently, researchers have used mathematical models building on counterfactual logic to investigate causal relationships (Pearl, 1986, 1995, 2000; Salmon, 1998; Spirtes, Glymour, & Scheines, 2000). Such models are depicted as directed graphs designed to represent conditional independence as implied by the recursive production decomposition (Chong, Zey, & Bessler, 2010):

$$pr(v_1, v_2, \ldots v_m) = \prod_{j=1}^{m} pr(v_j \mid \pi_j), \quad (3)$$

where pr is the probability of variables $v_1, v_2, \ldots, v_m$; π_j refers to a realized subset of variables that precede (in a causal sense) v_j in order ($j = 1, 2, \ldots, m$); and $\prod$ is the multiplication operator. Pearl (1986, 1999) suggested d-separation for graphical characterization of independence relations. As a simple example, in a directed acyclic graph (DAG) with variables X, Y, and Z in variable set V, the correlation between X and Y conditional on Z equals zero ($X \perp Y \mid Z$) if and only if X and Y are d-separated given Z (Chong et al., 2010).[5]

Various algorithms are available for searching observational data for causal structure in this manner, including Pearl's (2000) IC algorithm and Spirtes et al.'s (2000) PC algorithm. Here we use the PC algorithm which is freely available online through TETRAD IV software (http://www.phil.cmu.edu/projects/tetrad/).[6] Once the causal directions of relationships are established, structural equation models (SEM) are used to determine the magnitude and statistical significance of the effects (Bollen, 1989).[7] Using SEM and survey data on Scottish agricultural producers' attitudes toward various aspects of farming, including financial risk, Willock et al. (1999) show business and environmentally oriented behavior are influenced directly by some

[4]The proportion contracted α_i equals the latent variable α_i^* for $\alpha_i^* = \beta'_\alpha X_i + \varepsilon_{\alpha i} > 0$ and equals zero otherwise, where $\varepsilon_{\alpha i}$ are independently and normally distributed residuals with mean zero and variance σ^2.

[5]In a directed acyclic graph or DAG, one cannot return to a starting variable by following arrows leading away from it, meaning that chain relationships such as X→Y→X are not allowed.

[6]Readers are directed to Chong et al. (2010) for a more complete description of d-separation. Also, see Bryant et al. (2009) for a simplified three-variable example (i.e., variables A, B, and C) applying a subset of Spirtes et al.'s (2000b) PC algorithm to evaluate the null hypothesis H_0: A causes B based on unconditional correlations.

[7]Pennings and Leuthold (2000b) provide a detailed description of structure equation modeling in an investigation of the impact of producers' behavioral attitudes on futures contract usage.

TABLE 4. Correlations

	Age	Education	Acres	Debt/Asset	Risk attitude	Spot%	Fut&Opt%	Fwrd%	Prod%
Age		0.03	−0.06	−0.46***	−0.23*	0.42***	−0.26**	−0.33**	0.12
Education	0.03		−0.07	−0.07	−0.27**	−0.16	0.01	0.28**	0.11
Acres	−0.06	−0.07		0.23*	0.13	−0.11	−0.14	0.25**	0.04
Debt/Asset	−0.46***	−0.07	0.23*		0.31**	−0.37***	0.38***	0.22*	−0.14
Risk attitude	−0.23*	−0.26**	0.12	0.31**		−0.39***	−0.05	0.34***	0.13
Spot%	0.36***	−0.14	−0.18	−0.35***	−0.29**		−0.24*	−0.80***	−0.27**
Fut&Opt%	−0.28**	−0.05	−0.06	0.34***	−0.01	−0.33**		−0.06	−0.19
Fwrd%	−0.17	0.24**	0.21*	0.07	0.32**	−0.71***	−0.18		0.29**
Prod%	−0.11	−0.12	0.27**	0.08	0.04	−0.14	−0.17	−0.05	

Note. $N = 48$. Soybean correlations in upper off-diagonal, and corn correlations in lower off-diagonal. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively. Spot% is the percentage of sales made in spot markets without any price protection. FUT&OPT% is the percentage of sales made using futures and options. Fwrd% is the percentage forward contracted. Prod% is the percentage of sales made under production contracts.

selected attitudes and indirectly by others through mediating variables representing producers' objectives.

5. EMPIRICAL RESULTS

5.1. Correlations

Correlations for marketing arrangements and producer characteristics are presented in Table 4. Correlations for soybean and corn data are in the upper and lower off-diagonals, respectively. As the same producers raise both soybeans and corn, correlations between producer characteristics are identical in both upper and lower diagonals with the exception of correlations with risk attitude. Conceptually, risk attitude can be context specific; hence, corresponding survey items distinguish producers' preferences by crop. Here, risk attitudes are similar across crops. Significant correlations of 0.31 with the debt-to-asset ratio and −0.23 with age for both crops and of −0.27 and −0.26 with education for soybeans and corn, respectively, evidence this invariance.

Statistically significant correlations suggest that producers farming greater acreages carry more debt and that older producers carry less debt. Greater reliance on spot sales and lower proportional use of futures and options are associated with age and are inversely related to the debt-to-asset ratio. Similarly, forward contracting of soybeans is significantly less with age and greater with the debt-to-asset ratio. Forward contracting is significantly associated with education and size of farm for both crops. Risk aversion is also significantly associated with forward contracting and less use of spot markets. The percentage of the corn marketed through production contracts is significantly associated with size. For soybeans, production contracting is significantly associated with forward contracting and (nearly significantly) inversely related to futures and options usage (p value = .103).[8] Discussion with producers revealed that production contracts often specify a premium over the cash price for carrying out special activity (e.g., raising seed or nongenetically modified crops), and give the buyer the right to call for quantities of grain, often stored on-farm, as needed. This uncertain timing of delivery is not conducive to the use of futures and options; hence, some production contracts allow a portion of the secured grain to be forward priced based on futures market prices.

[8] Discussions with surveyed producers provide insight on these findings. Production contracts often specify a premium over the cash price for carrying out some special activity (e.g., raising seed or nongenetically modified crops or identity preservation), and give the buyer the right to call for quantities of grain, often stored on-farm, as needed. This uncertainty regarding timing of delivery is not conducive to the use of futures and options, and hence, some production contracts offer the opportunity to forward price a portion of the secured grain based on current futures market prices.

TABLE 5. Marginal Effects for Spot Regressions

	Corn spot sales			Soybean spot sales		
		Hurdle model			Hurdle model	
	Tobit	Binary probit	Truncated OLS	Tobit	Binary probit	Truncated OLS
Age	0.0071	−0.0021	0.0108	0.0085*	−0.0037	0.0154***
	(0.0050)	(0.0046)	(0.0067)	(0.0051)	(0.0049)	(0.0054)
Education	−0.1272	−0.0135	−0.1870*	−0.1629**	−0.0185	−0.2127***
	(0.0798)	(0.0823)	(0.1108)	(0.0822)	(0.0826)	(0.0820)
Acres	3.28×10^{-5}	0.0001	−0.0001	0.0000	3.98×10^{-5}	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt/Asset	−0.0036	−0.0036	−0.0013	−0.0042	−0.0053*	0.0025
	(0.0027)	(0.0024)	(0.0040)	(0.0029)	(0.0031)	(0.0033)
Risk attitude	−0.0608	−0.0287	−0.0649	−0.0988***	−0.0341	−0.0768**
	(0.0371)	(0.0352)	(0.0512)	(0.0384)	(0.0361)	(0.0393)
Sigma	0.3796	–	0.2691	0.2572	–	0.2262
	(0.0663)		(0.0445)	(0.0285)		(0.0301)
Observations	48	48	44	48	48	43
Censored	4 at 0%	–	–	5 at 0%	–	–
Log likelihood	−5.9327	−11.2983	7.7303	−8.0250	−10.7690	7.6800

Note. OLS = Ordinary least squares. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

TABLE 6. Marginal Effects for Futures and Options Regressions

	Corn futures and options			Soybean futures and options		
		Hurdle model			Hurdle model	
	Tobit	Binary probit	Truncated OLS	Tobit	Binary probit	Truncated OLS
Age	−0.0163	−0.0178	−0.0057	−0.0140	−0.0192*	0.0004
	(0.0110)	(0.0115)	(0.0117)	(0.0101)	(0.0114)	(0.0114)
Education	0.0828	0.2571	−0.3133*	0.0944	0.1982	−0.1143
	(0.1614)	(0.1661)	(0.1820)	(0.1474)	(0.1672)	(0.1614)
Acres	−0.0001	0.0000	−0.0001	−0.0001	−0.0001	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Debt/Asset	0.0103*	0.0068	0.0123**	0.0117**	0.0055	0.0206***
	(0.0054)	(0.0054)	(0.0057)	(0.0050)	(0.0053)	(0.0063)
Risk attitude	−0.0640	−0.0501	−0.0424	−0.0649	−0.0297	−0.1003
	(0.0783)	(0.0797)	(0.0839)	(0.0729)	(0.0784)	(0.0882)
Sigma	0.4236	–	0.2476***	0.3793	–	0.2271
	(0.0753)		(0.0612)	(0.0684)		(0.0612)
Observations	48	48	20	48	48	19
Censored	28 at 0%	–	–	29 at 0%	–	–
McFadden's Pseudo R^2	0.1524	0.1339				
Log likelihood	−26.2935	−28.2357	6.735	−23.3443	−28.4432	9.8561

Note. OLS = Ordinary least squares. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

5.2. Regression Results

Marginal effects for Tobit and hurdle models of spot market, futures and options, and forward contract usage are reported in Tables 5 through 7. Corresponding model results are presented for production contracting of soybeans in Table 8. As only four production contracts for corn exist in our dataset, this aspect of corn marketing cannot be considered. Two-limit or double-censored Tobit regressions are useful when several observations exist at upper as well as lower

TABLE 7. Marginal Effects for Forward Contract Regressions

	Corn forward contracts			Soybean forward contracts		
		Hurdle model			Hurdle model	
	Tobit	Binary probit	Truncated OLS	Tobit	Binary probit	Truncated OLS
Age	−0.0039	–	−0.0057	−0.0090**	0.0002	−0.0175***
	(0.0041)		(0.0054)	(0.0046)	(0.0008)	(0.0079)
Education	0.1887***	–	0.2147**	0.2461***	0.0006	0.3801**
	(0.0672)		(0.0855)	(0.0744)	(0.0037)	(0.1181)
Acres	0.0001	–	0.0001*	0.0001*	0.0000	0.0001*
	(0.0001)		(0.0001)	(0.0001)	(0.0000)	(0.0001)
Debt/Asset	−0.0019	–	−0.0028	−0.0001	0.0004	−0.0018
	(0.0023)		(0.0028)	(0.0025)	(0.0016)	(0.0033)
Risk attitude	0.0951***	–	0.1041**	0.1028**	0.0015	0.1476***
	(0.0312)		(0.0412)	(0.0347)	(0.0070)	(0.0545)
Sigma	0.2109	–	0.2310	0.2303	–	0.2538
	(0.0218)		(0.0313)	(0.0248)		(0.0395)
Observations	48	48	47	48	48	44
Censored	1 at 0%	–	–	4 at 0%	–	–
Log likelihood	5.4518	–	9.7681	−1.3956	−5.6597	11.2084

Note. OLS = Ordinary least squares. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

TABLE 8. Marginal Effects for Production Contract Regressions

	Corn production contracts			Soybean production contracts		
		Hurdle model			Hurdle model	
	Tobit	Binary probit	Truncated OLS	Tobit	Binary probit	Truncated OLS
Age	−0.0088	−0.0013	–	0.0016	−0.0007	−0.0298
	(0.0192)	(0.0058)		(0.0155)	(0.0087)	(0.0219)
Education	−0.1027	−0.0241	–	0.1232	−0.0250	0.7679**
	(0.3070)	(0.0890)		(0.2465)	(0.1389)	(0.3032)
Acres	0.0003	0.0001	–	0.0002	0.0001	0.0003
	(0.0002)	(0.0001)		(0.0002)	(0.0001)	(0.0003)
Debt/Asset	−0.0021	−0.0006	–	−0.0075	−0.0020	−0.0462**
	(0.0097)	(0.0030)		(0.0088)	(0.0046)	(0.0220)
Risk attitude	0.0877	0.0386	–	0.1955	0.0952	0.4222**
	(0.1429)	(0.0414)		(0.1219)	(0.0655)	(0.1745)
Sigma	0.5136	–	–	0.5622	–	0.2230
	(0.2000)			(0.1337)		(0.0688)
Observations	48	48	5	48	48	12
Censored	43 at 0%	–	–	36 at 0%	–	–
Log kikelihood	−13.1180	−14.7285	–	−24.3095	−24.7337	7.9622

Note. OLS = Ordinary least squares. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

limits of the dependent variable (Goodwin & Schroeder, 1994; Sartwelle et al., 2000). Following Katchova and Miranda (2004), we compare the results of Tobit models censored only at zero and hurdle models because we surveyed producers on the proportion of expected production that was contracted which conceivably may exceed the realized production. Particularly, in the case of futures and options, quantities contracted may exceed expected production due to speculative behavior (Musser et al., 1996). Two-limit Tobit regressions yield results that are largely similar to the Tobit regression results presented here and are available from the authors upon request.

Unlike Katchova and Miranda's (2004) analysis, where Tobit results appeared to be driven by the binary Probit results for contract adoption, Tobit results presented here are mostly consistent with truncated regression results for the proportion contracted in hurdle models. Specifically, the sign and significance of marginal effects are mostly the same, though their magnitudes differ. This result is not surprising for our sample because in several instances the number of censored observations is small. As most of the sample use forward contracts, the consistency in this case likely reflects that there are so few zero observations that Tobit models are unlikely to confound independent variables' adoption effects with effects on the proportion contracted (Table 7). In fact, binary Probit regressions are unable to detect significant effects for soybean forward contracting and are infeasible for corn forward contracting due to the limited number of zero observations. Thus, for research with samples indicating nearly universal adoption of the marketing method considered, Tobit analyses may be appropriate.[9] The potential value of the hurdle approach is apparent, though, as certain variables at times have opposite effects on the adoption and proportion decisions. No instance exists, however, in which the opposing effects are both statistically different from zero. The insignificantly positive marginal effect of education on the adoption of corn futures and options and the significantly negative marginal effect on the proportion of the crop for which they are used is an example (Table 6). For simplicity, the remainder of the discussion focuses on the hurdle model results unless otherwise stated.

Spot regressions suggest that for each additional year of age, a producer will sell about 1–2% more soybeans in spot markets (Table 5). The marginal effect in the truncated regression for corn is of similar magnitude and nearly significant (p value = .108). Age also decreases the adoption of futures and options significantly for soybeans (Table 6) and significantly decreases the proportion of soybeans sold using forward contracts (Table 7). The results for futures and options adoption are consistent with the findings of Musser et al. (1996), who argued that older producers have less time before retirement to recover the learning and adjustment costs associated with risk management instruments; therefore, they are less likely to adopt them. Alternatively, older producers may just be more reluctant to switch from familiar, conventional cash marketing methods, or they may feel that experience selling in cash markets limits their need to use futures markets. Shapiro and Brorsen (1988) and Goodwin and Schroeder (1994) find similar negative effects for experience on the proportion forward priced and the proportion hedged, respectively.

Producers possessing Bachelor of Science degrees sell about 19% and 21% less corn and soybeans in spot markets (Table 5) and about 21% and 38% more corn and soybeans using forward contracts (Table 7) than those that had not completed a 4-year degree. Education also has a significantly positive influence on the proportion of soybeans sold on production contracts (Table 8). The results are consistent with prior findings for education's impact on the proportion forward priced using various types of contracts (e.g., Goodwin & Schroeder, 1994; Musser et al., 1996). Shapiro and Brorsen (1988) find that education has a significantly negative effect, however, on the proportion hedged in futures markets, which is consistent with our findings for corn (Table 6).

Intuitively, as risk aversion increases, spot sales of soybeans decrease significantly (Table 5), and forward contracting of corn and soybeans increases significantly and by over 10% (Table

[9] Obviously, at least some of the prior research on forward pricing utilized samples that do not share the characteristic of nearly universal adoption of forward contracts found in the sample used here. Only around 55% of the producers used forward pricing tools in Goodwin and Schroeder (1994); in Shapiro and Brorsen's (1998) analysis of futures hedging, only 63% used futures. Such data sets would be interesting applications for hurdle models. Reported high usage of forward and futures contacts in the Musser et al. (1996) study may be indicative of sufficient adoption of forward pricing to justify Tobit analysis, though it is difficult to say for certain as the adoption rate was not reported for the aggregate forward pricing category that was ultimately modeled. Ninety-six percent, 70 percent, and 52 percent of respondents used cash markets, forward contracts, and futures and/or options, respectively, in Sartwelle et al.'s (2000) analysis of each marketing method. Tobit analysis would likely be appropriate for the cash market variable, whereas a hurdle model analysis seems more suitable for the forward contract and futures/options variables.

7). Risk aversion also significantly increases the proportion of soybeans sold on production contracts by 42% according to truncated regressions (Table 8). Although risk attitude is nearly significant (p value = .109) in the corresponding Tobit regression, the results are otherwise dissimilar to the truncated regression.[10] Unexpectedly, risk attitude has a statistically insignificant effect on the use of futures and options (Table 6). The result may reflect that motivations for hedging other than risk aversion may exist, as identified by Pennings and Leuthold (2000a). Consistent with Shapiro and Brorsen (1988) and Musser et al. (1996), higher debt-to-asset ratios significantly increase the proportional use of futures and options, as relatively more leveraged producers likely use these tools to ensure stable cash flows to repay debt. The same logic should apply to forward contract use, but does not show up statistically.

5.3. Causal Model Results

Complementarity and substitutability of risk management and marketing tools are relatively unexamined aspects of crop marketing. One impediment in assessing these relationships is that including one marketing alternative as an explanatory variable for another marketing arrangement poses simultaneity issues for conventional regression procedures because the same producer characteristics influence the use of each marketing method. We deal with this issue by employing causal modeling to represent detected relationships among marketing methods and producer attributes graphically (Bryant, Bessler, & Haigh, 2006) and subsequently estimating the relationships using structural equation modeling (Bollen, 1989) to account for measurement error. Due to the limited number of corn production contracts in our sample, this analysis is conducted only for soybean marketing.

Exploratory searches for causal relationships can be performed over a full set of possible relationships, or hypotheses of causation among specific variables may be targeted (Bryant, Bessler, & Haigh, 2009, p. 372). We conduct the latter analysis by searching for a superior alternative to a directed graph established based on existing knowledge. Specifically, the initial graph uses relationships among producer attributes and marketing methods for the effects that were statistically significant in the preceding regression analysis.[11] Further, endogenous variables were prohibited from impacting obviously exogenous variables, like producers' age. Finally, based on discussions with producers who indicated that buyers' right to call for delivery in production contracts made forward pricing options in the contracts more attractive than hedging, we direct causality from production contracting (PROD%) to futures and options (FUT&OPT%) and from PROD% to forward contracting (FWRD%), and subsequently from FWRD% to FUT&OPT%. A search for a superior structure using the PC algorithm in TETRAD IV cannot reject the specified relationships, supporting the direction of causality depicted by Model 1 (Figure 1).

As a sensitivity check, we formulate an identical initial graph except that we leave the direction of relationships among the three marketing methods unspecified. The causal search then yields the structure represented by Model 2 in Figure 1. However, the χ^2 fit statistic rejects the null hypothesis that Model 2 estimates of the correlation matrix are not statistically different from the data at the 5% level. In contrast, Model 1 does not significantly diverge from the data at the 5% level.

The standardized coefficients and significance levels corresponding to the relationships in the models in Figure 1 are obtained using a structural equation framework estimated in AMOS (Arbuckle, 2010), as are the additional fit statistics. Structural equation modeling in TETRAD IV produces similar nonstandardized coefficients as in AMOS, but the standardized coefficients from AMOS identify the relative magnitude of effects.

It is apparent that the primary difference between the two models is in terms of the direction of effects among marketing methods. Model 1 registers more statistical significance for the

[10]The dissimilarity in results for Tobit and truncated regressions of production contract usage reflects the further censoring by Tobit regressions of the already small sample.

[11]Similarly, Bryant et al. (2006) filtered their data using vector autoregression prior to the causal analysis.

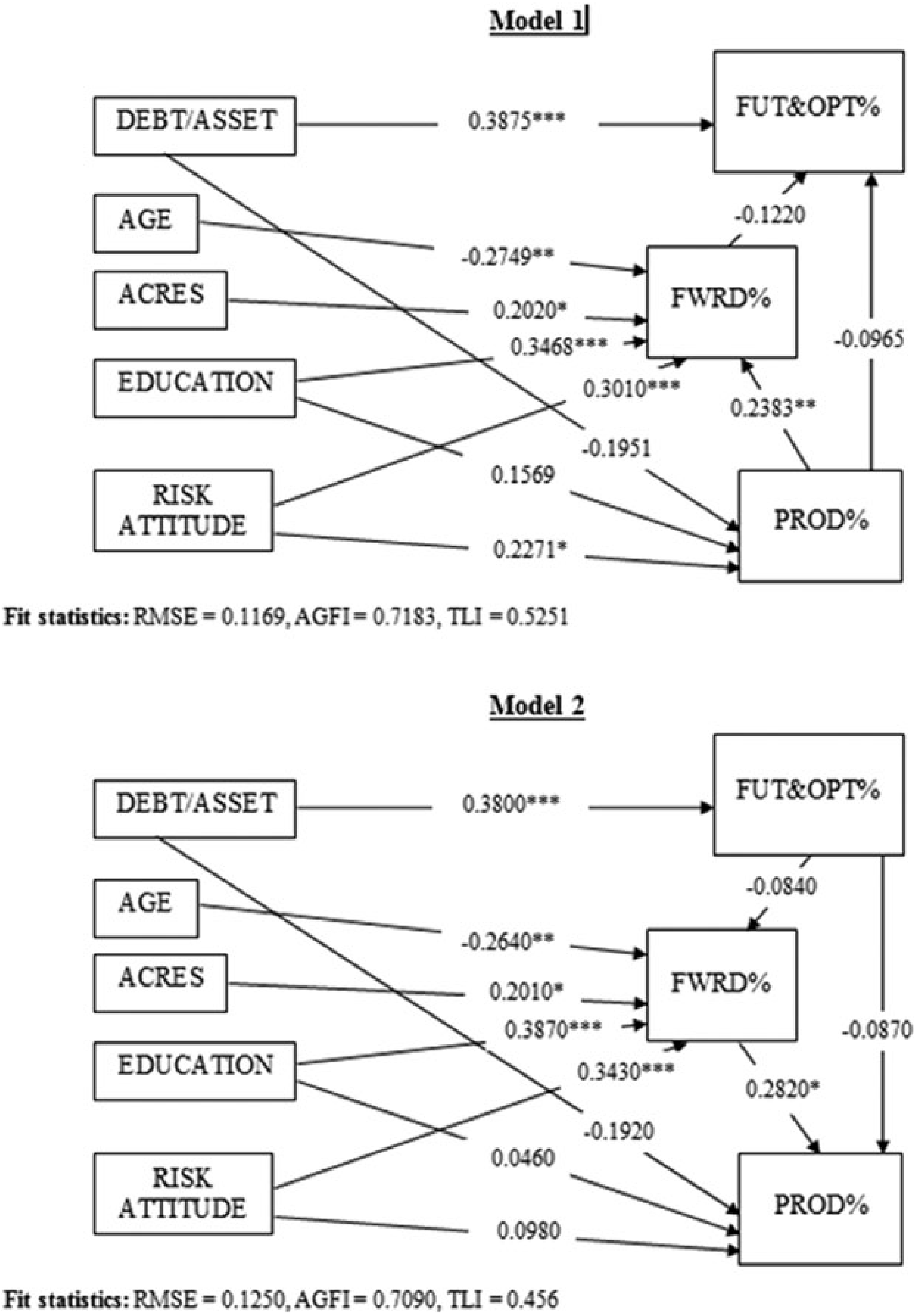

Figure 1 Alternative models of producers' contract use.

impact of RISK ATTITUDE on PROD% and the impact of PROD% on FWRD% than Model 2. Otherwise, the signs, magnitudes, and statistical significance of the effects are mostly consistent across the models, so the primary difference is in terms of the direction of effects among marketing methods. Fit statistics indicate that Model 1 adheres to the data slightly better than Model 2, supporting the relationships described by producers.[12] Regardless of (the direction of) causation, the signs of the coefficients, much like the correlations in Table 4, support complementarity among production and forward contracting and noncomplementarity or even substitutability with futures and options. The only relationship between marketing methods that is statistically significant, however, is that between production contracting and forward contracting.

6. DISCUSSION AND CONCLUSIONS

Most research on crop marketing and risk management focuses on one aspect such as hedging (e.g., Shapiro & Brorsen, 1988) or analyzes aggregate contracting variables (e.g., proportion forward priced), which makes it difficult to identify differential effects of producer characteristics on different contracts or capture complementarities among marketing alternatives (e.g., Goodwin & Schroeder, 1994; Katchov & Miranda, 2004; Musser et al., 1996). Although Pennings et al. (2008) identify factors influencing the portfolio of marketing and risk management tools producers adopt, they do not identify how factors influence the degree to which the tools are used.

This study investigates the factors influencing Illinois corn and soybean producers' proportional use of futures and options, forward contracts, production contracts, and spot sales without price protection. Following Katchova and Miranda (2004), we employ Cragg's (1971) hurdle model, which may be more appropriate than commonly used Tobit procedures if producers' marketing practices reflect separate decision processes of adopting a marketing method first and choosing the quantity marketed under that method second. In contrast to Katchova and Miranda (2004) who analyze a contracting variable aggregated across several types of contracts, we examine more disaggregated sets of marketing methods using both Tobit and hurdle models. Results logically suggest that Tobit models are appropriate when nearly all producers use a particular marketing method (i.e., confounding adoption effects with an explanatory variable's influence on proportional use is unlikely).

Importantly, hurdle model results largely corroborate prior research using Tobit models, and thereby increase confidence in previous inferences made regarding proportional contract usage with these less refined procedures. Consistent with earlier findings for producers' age (Musser et al., 1996) and experience (Goodwin & Schroeder, 1994; Shapiro & Brorsen, 1988), older producers are less likely to adopt futures and options and sell relatively less using forward and production contracts and more using spot markets. Consistent with Goodwin and Schroeder (1994) and Musser et al. (1996), higher education significantly increases the proportion of the crop forward contracted. Shapiro and Brorsen (1988) and Musser et al. (1996), respectively, find that the proportion of the crop hedged and the proportion forward priced increase with the debt-to-asset ratio, which may reflect needs for steady cash flows to repay debt. Here, debt obligations are supported as a motivation for hedging. Although the debt-to-asset ratio significantly increases the proportion sold using futures and options, it has no effect on forward contracts, and oddly a negative significant effect on the proportion of soybean sales through production contracts. Overall, the results are consistent with findings that agribusiness managers' behavior in a number of contexts—from choice of land rental contracts (Bezabih, 2009) to livestock producers risk management strategies (Martin & McLeay, 1998), the timing of

[12]The root mean squared error of (RMSE) estimates how well the fitted model approximates the population covariance matrix, with values below 0.08 indicating a close fit (Pennings & Leuthold, 2000b). The adjusted goodness-of-fit index (AGFI) ranges from 0 (poor fit) to 1 (perfect fit) and is measured by the squared residuals between predicted and actual data, accounting for available degrees of freedom. The Tucker–Lewis index (TLI) accounts for parsimony in a comparative index between the proposed and null models, with recommended values of 0.9 or greater.

producers' crop sales and purchases (Stephens & Barrett, 2011), and other business and environmentally oriented behavior (Willock et al., 1999)—are influenced by financial and credit constraints and/or risk considerations.

Intuitively, increasing risk aversion decreases spot sales and increases the proportion sold using forward and production contracts, but has no impact on futures and options usage, which may reflect that motivations for hedging other than risk aversion (e.g., avoidance of conflicts among trade partners with differential bargaining power) may exist (Pennings & Leuthold, 2000a). Mixed evidence of risk aversion effects in prior research may reflect variation in the measures of risk aversion and aggregate measures of contracting. By using validated measures of risk aversion and making greater distinction among contract types, we show that risk aversion is more important for some contract types (i.e., forward and production contracts) than others (futures and options).

The use of the causal inference procedures permits a more integrated and clearer view of producer contracting and the factors that influence contract use. Risk aversion has its primary effects on production and forward contracting alternatives; heightened risk aversion increases the use of both contracts. Forward contracting complements the use of production contracting, and both are (weak) substitutes for futures contracting. The use of futures contracts is mainly and positively influenced by debt-to-asset ratios, which suggests futures and options are playing their most significant direct role in these economic activities by providing a steady cash flow to repay debt. Age, acreage, and education were the factors influencing forward contracting. In our context, producers were using forward contracts to make pricing decisions, and these factors assumed importance in determining the proportion of the crop to be marketed using this alternative. On balance, it is clear that the use of directed graphs (Bryant et al., 2006) permits inference of causal relationships among marketing methods, which supports producer statements that production contracts spur greater utilization of forward pricing arrangements. Allowing for the interactions across contracts also eliminates some of the effects that were difficult to understand (i.e., the significant negative effect of debt-to-asset ratios on production contracts) in the hurdle models.

Using a combination of survey and accounting data, we detect significant effects despite a limited sample size. A larger sample, especially with greater proportional use of production contracts, may allow detection of relationships not apparent here and permit a wider range of possible specifications. Although the categories of marketing methods considered are more disaggregated than in prior research, further disaggregation could be informative. For instance, the futures and options category might be broken apart into separate futures and options categories or into categories for hedging and speculation. The forward contracting category could also be split into cash forward sales and hedge-to-arrive contract categories. Our findings suggest in a more disaggregate context, causal models and a structural equation framework may provide a richer understanding of the relationships between marketing methods.

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