Risk, cost-share payments, and adoption of cover crops and no-till

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Risk, cost-share payments, and adoption of cover crops and no-till

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Abstract: The objective of this research is to determine the effect of producer risk preferences on the willingness to adopt cover crops and no-till, given cost-sharing incentives, operator attributes, and farm management characteristics. The analysis extends previous research by showing how producer risk preferences affect the adoption of best management practices (BMPs). Risk aversion was quantified using a risk preference elicitation method that was included in a lottery choice experiment. A survey was conducted with Tennessee row crop producers. Probit regressions were used to determine how risk preferences, cost-share incentives, and respondent characteristics were associated with the adoption of these BMPs. An increase in the cost-share payment for cover crops was associated with an increase in the likelihood of its adoption, but adoption of no-till practices was unaffected by the offered incentive. Cover crop adoption was uncorrelated with risk preferences, but as producer risk aversion increased, the likelihood of adopting no-till diminished. The results could be useful in revising BMP cost-share programs to increase adoption while considering risk preferences. Also, this study will contribute to the academic literature by better guiding future studies in the measurement and assessment of risk and its role in BMP adoption.

Key words: cost sharing—cover crops—lottery choice—no-till—risk

US farm conservation policy shifted in the late 1990s from removing farmland from production to encouraging producers to adopt best management practices (BMPs) on working farmland (Cattaneo 2003; Claassen et al. 2008). Programs such as the Environmental Quality Incentives Program (EQIP) were introduced in the Federal Agriculture Improvement and Reform Act of 1996 to partially reimburse producers for voluntarily adopting BMPs on working farmland (Aillery 2006). These conservation programs were designed to maximize environmental benefits per dollar disbursed by targeting land where BMP adoption would provide the greatest environmental benefit without removing land from agricultural production (Claassen et al. 2008; Reimer and Prokopy 2014).

Eligible producers who participate in working farmland programs can select from a suite of BMPs to moderate the off-site effects of agriculture on soil and water quality. No-tillage (referred to as "no-till" hereafter) planting minimizes soil disturbance. Cover crops and no-till also mitigate water-induced erosion by covering bare soil over the winter (i.e., nongrowing period) (Snapp et al. 2005; Derpsch et al. 2010). Winter cover crops (EQIP Practice Code 340) and no-till planting (EQIP Practice Code 329) are two BMPs sponsored by the USDA Natural Resources Conservation Service (NRCS) to producers in the southeastern United States (USDA NRCS 2017). Winter cover crops are planted after cash crops are harvested (typically fall) and terminated before the next crop is planted (typically spring).

Studies find that adoption of BMPs increases with higher cost-share payments (Cooper 1997; Cooper 2003; Lichtenberg 2004; Lichtenberg and Smith-Ramirez 2011; Chabé-Ferret and Subervie 2013; Mezzatesta et al. 2013; Fleming 2017; Fleming et al. 2018). Cooper (1997) found that BMPs adoption increased as cost-share payments increased, but producers' response to the incentive varied, depending on the BMP considered. For example, producer responsiveness to a cost-share payment increase for conservation tillage was low compared to the other BMPs studied, but producer response to incentives encouraging the adoption of soil-moisture testing was comparatively high. Cooper (2003) analyzed producer decisions to accept payments in return for the adoption of BMP bundles. Cooper's (2003) study found that increasing cost-share payments for one BMP could increase the likelihood a producer adopted a related BMP. Lichtenberg (2004) used survey data, combined with information on BMP installation costs, to estimate producer demand for multiple BMPs. Willingness to adopt all BMPs increased at higher cost-share payment levels and all practice-incentive relationships that exhibited standard upward-sloping supply curves. More recent studies have found similar results for a wide array of BMPs (Chabé-Ferret and Subervie 2013; Mezzatesta et al. 2013; Fleming 2017; Fleming et al. 2018).

Despite the availability of cost-share payments and increased soil fertility benefits, adoption of cover crops and no-till remains limited in the United States. Winter cover crop use remains low nationally, with only 4% of harvested cropland planted with winter cover crops in 2017 (USDA NASS 2017). While more widely practiced than cover crops, no-till still has significant room to expand, with approximately 26% of total US cropland planted using no-till (USDA NASS 2017). Adoption of cover crops and no-till varies largely by region and is higher in the Economic Research Service's (USDA ERS) Southern Seaboard and Mississippi Portal production regions than in other parts of the country (USDA ERS 2015).

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Producers may be reluctant to adopt cover crops and no-till because they are uncertain about the practices' economic benefits (Snapp et al. 2005; Tripplett and Dick 2008; Levidow et al. 2014; Schipanski et al. 2014). Cooper and Signorello (2008) showed theoretically and empirically that one potential driver of producers' adoption of BMPs could be due to risk associated (or uncertainty) with these BMPs' impact on yields and net returns. They found farmers' uncertainty about their income from adopting BMPs could require a risk premium payment to cover uncertainty in income along with a cost-share payment to cover the cost of the technology. Thus, the hypothesized impacts of nonfinancial willingness-to-adopt factors, such as risk, were the impetus behind several studies investigating producer risk perceptions and BMP adoption (Prokopy et al. 2008; Baumgart-Getz et al. 2012; Tudor et al. 2014; Arbuckle and Roesch-McNally 2015; Liu et al. 2018). Arbuckle and Roesch-McNally (2015) reported that respondents associated cover crops with a variety of risks including decreased yields, crop insurance complications, and delayed planting. Producers who believed cover crops were associated with increased production risk and increased planting difficulty were less likely to adopt the BMPs. However, Baumgart-Getz et al. (2012) concluded the risk producers associated with BMP adoption diminished because of an increase in the availability of information and other learning resources pertaining to the establishment and implementation of these BMPs. For example, Anderson et al. (2020) reported corn (*Zea mays* L.) and soybean (*Glycine max* L.) yield variability to be lower (declining risk) when no-till and cover crops were used relative to conventional tillage.

The previous research mainly used self-assessment questions or variables hypothesized to proxy risk to measure producer risk preferences. For example, in their study of conservation tillage use, Schoengold et al. (2014) used enrollment in crop insurance to proxy risk aversion. They found that enrollment in crop insurance programs was uncorrelated with the adoption of conservation tillage. Producer age has also been used to proxy risk aversion, under the assumption that younger farmers are more likely to experiment with new technologies (Boyer et al. 2016). Farm size has also been used to proxy producer risk, with the assumption that operators of larger farms were more likely to take risks with respect to the adoption of precision agriculture technologies (Boyer et al. 2016). Jensen et al. (2015) asked producers if they tended to wait to adopt new technologies until their neighbors had as an indicator of producer risk attitudes. Proxy variables are useful for controlling what is a priori assumed to represent risk preferences, but direct elicitation methods are an alternative, more systematic approach for measuring producer risk preferences (Holt and Laury 2002; Brick et al. 2012; Eckel and Grossman 2002, 2008; Ihli et al. 2016). While proxy variables are useful for controlling what is hypothesized as risk, the strength of the correlation between these variables and actual preferences for risk is usually conjectural. A direct elicitation method would provide an actual measurement of risk preferences, removing conjecture and providing a novel contribution to the impact of risk preferences on BMP adoption (Holt and Laury 2002; Brick et al. 2012; Eckel and Grossman 2002, 2008; Ihli et al. 2016).

This study estimates the effect of producer risk preference and other factors such as cost-share payments on the willingness of Middle and West Tennessee row crop producers to adopt cover crops and no-till. The analysis uses data from a stated preference survey examining the adoption of conservation tillage and cover crops, given incentives to adopt these practices and producer aversion toward risk. Risk aversion is measured directly from the survey using a risk preference elicitation method.

We believe the contribution from this study is two-fold. First, results could be useful in revising BMP cost-share programs to increase adoption while considering risk preferences. For example, one possible policy alternative to encourage the use of BMPs while mitigating producers' risk aversion level might be coupling BMP cost-share payments with crop insurance subsidies. Second, this study will contribute to the academic literature by better guiding future studies in the measurement and assessment of risk and its role in BMP adoption. However, a shortcoming of this study is the low response and potential non-response and sample selection bias from the survey. The low response rate warrants some caution in generalizing the results.

Literature Review: Risk Preference. An extensive literature has developed around the measurement and representation of individual risk preferences. A variety of risk preference elicitation methods have emanated from this literature, including lottery-choice tasks, self-assessment questions, hypothetical gambles, and willingness-to-pay experiments (Holt and Laury 2002; Brick et al. 2012; Eckel and Grossman 2002, 2008; Ihli et al. 2016). However, risk preference elicitation methods are difficult to apply in the context of agricultural producer decisions because crop yield and farm income depend on a number of related, largely exogenous factors such as weather and market prices (Menapace et al. 2013; Ihli et al. 2016). We will focus our literature review on work that has applied these methods in an agriculture context.

Holt and Laury (2002) use a series of binary-choice lottery tasks to elicit individual risk preferences. In their experiment, participants make 10 choices between paired lotteries, with each of the two lotteries having two possible payoffs. The amounts of the lottery payoffs remain constant across the 10 choices, but the lottery probabilities vary across each choice. The change in probabilities is such that the expected value of the risky lottery is significantly less than the safe lottery for the first choice but increases with each choice and is significantly more than the safe lottery for the tenth choice. Thus, only an extremely risk loving participant would choose the risky lottery on the first choice and only an extremely risk averse participant would choose the safe lottery on the last choice. The expectation is that the majority of participants will choose the safe lottery for the first few choices and then switch to the risky lottery at some point, with the switching point providing a measure of the participant's risk preferences.

Brick et al. (2012) used a similar series of binary-choice lottery tasks except that the probabilities were constant while the payoffs varied. The "safe" lottery in this case is a sure thing (100% chance of receiving the payoff) while the "risky" lottery is a 50-50 gamble. They applied this approach in a survey to fisherman in South Africa about their risk preferences. They presented respondents with a paired lottery-choice where they varied the probabilities of high and low payoffs, holding payoffs constant. They found that respondent education and age impacted risk aversion.

Ihli et al. (2016) extended Brick et al.'s (2012) analysis by measuring the responses of Ugandan coffee producers using a Holt and Laury (2002) paired lottery-choice and a Brick et al. (2012) paired lottery-choice experiment.

The Holt-Laury method holds payoffs constant for different lotteries but varies the probability of receiving a payout. Ihli et al. (2016) found that the propensity to avert risky scenarios was lower for individuals with more education but higher for older respondents.

Menapace et al. (2013) modified Eckel and Grossman's (2008) risk preference elicitation approach to measure risk preferences among apple (*Malus domestica*) farmers from Trento, Italy. They examined the correlation between risk attitudes and producer beliefs that a crop value loss would occur following a damaging weather event. They found that the more risk averse a producer was, the stronger their prior belief that a farm loss would occur. A producer's decision-making under risk is therefore determined not only by their aversion toward risky propositions, but also by their beliefs about the likelihood of an event occurring.

While these studies are insightful, they did not use these results to determine how risk preferences affected other decisions. However, Barrowclough and Alwang (2018) estimated the effect of risk aversion on the willingness of Ecuadorian farmers to adopt four conservation agricultural practices (cover crops, crop rotation, reduced tillage, and contour cropping), where willingness to adopt was elicited by a hypothetical discrete choice experiment and risk is an attribute. The coefficient on the risk aversion parameter was negative and significant, suggesting that risk aversion was negatively correlated with willingness to adopt the practices.

This study used a modified lottery-choice risk elicitation method that combines elements of the methods used by Brick et al. (2012) and Menapace et al. (2013) to measure producer risk preferences. The elicitation method used in this study differs from those used in these earlier studies in a couple of key ways. First, like Brick et al. (2012), but unlike Menapace et al. (2013), respondents are asked to make a series of choices over a series of lotteries. In Menapace et al. (2013), respondents are asked to choose their most preferred lottery from a number of different options. Second, the lottery choices in this study are narrowly framed in terms of a decision whether or not to adopt a series of increasingly risky technologies. The main contribution of this study will be the application of this risk elicitation method to the adoption of cover crops and no-till.

Materials and Methods

Adoption Framework. Using McFadden's (1974) random utility framework, producers are assumed to maximize expected utility and use or convert additional cropland to a BMP when the expected utility (U^j) of using or converting additional land (j = 1) exceeds the expected utility of not using (j = 0), or when $U^1 \geq U^0$. In this case, producer utility is assumed to be a function of (1) the characteristics of the BMP being considered (x_b); (2) the amount of any cost share offered for use of the BMP and the requirements or characteristics of the associated cost-share program (x_c); and (3) the farmer's tolerance for risk and such other farm and farmer characteristics likely to influence the use or conversion decision (x_r). This study uses an Arrow-Pratt measure of risk aversion (r) such that higher values of r indicate a greater willingness to sacrifice higher expected net benefits from BMP use for lower variability in these expected net benefits. The elicitation and construction of r is described in more detail in the following section.

Data. Data were collected from a 2017 survey of row crop producers in West and Middle Tennessee. A mailing list of corn, cotton (*Gossypium hirsutum* L.), soybean, and wheat (*Triticum aestivum* L.) producers was obtained from the USDA Farm Service Agency (FSA) using the Freedom of Information Act (FOIA). The mailing list included all producers and landowners in the region who received a payment from USDA FSA from 2012 to 2016. The population in the list frame was 9,569. Unequal probability sampling without replacement was used to select the sample from the list frame (Tillé 1996). This cluster-based sampling procedure assigns probability weights to respondents. Respondents with larger probability weights were more likely to be selected into the sample. Probability weights were determined as the number of irrigated acres in a county relative to the total number of irrigated acres in the state of Tennessee. County-level irrigated acres were from the 2012 AgCensus (USDA NASS 2012). County-level irrigated acres were used to develop the proportional weights because the objective of the project was to analyze the adoption of water-conserving practices by producers in West Tennessee (defined as counties west of Nashville) who were most likely to use irrigation. Thus, producers in counties with relatively more irrigated acres were more likely to be selected from the FSA/FOIA list frame. This procedure increases the likelihood of selecting members belonging to a specific segment of a population of interest in the absence of farm-specific information on, for example, whether or not irrigation was used to produce row crops.

The survey was administered following Dillman's (2007) mail survey total design method. A postcard was first mailed to the sample of respondents on January 26, 2017, to inform row crop producers about the mail survey they would be receiving. Mail surveys were sent out on February 8, 2017. A prepaid postage envelope was included, as well as a cover letter explaining the purpose of the survey and an insert detailing the benefits and requirements of winter cover crops and no-till. A reminder postcard was mailed on February 17, 2017, followed by a second round of questionnaires on March 8, 2017. This mailing also included a postage-paid return envelope and cover letter reiterating the purpose of the survey. A 3% margin of error and a 95% confidence interval corresponds with a finite-population corrected sample of 960 (Lohr 1999). Previous experience led us to expect that we could expect a response rate of 19%. Based on this prior, the sample was inflated to 5,184. The survey was mailed to these randomly selected individuals, with declines to participate, undeliverable addresses, and replies that the recipient did not farm, reducing the survey pool to 3,841. A total of 344 surveys were returned for a 9% response rate. A major limitation of this study is the low response and potential nonresponse and sample selection bias. The low response rate warrants some caution in generalizing the results.

The survey included six sections. The first section included questions about farmland owned and leased, yield, and production costs. The second, third, and fourth sections covered questions on no-till, cover crops, and irrigation practices, respectively. Each of these sections included a question that asked producers if they would adopt no-till or cover crops, given a cost-share payment.

There were five cost-share payment levels corresponding with the no-till and cover crop practices. These amounts were uniformly randomly assigned to respondents. Cover crop adoption costs were set at US$190 ha^{-1}, with cost-share payments of US$37, US$74, US$111, US$153, and US$190 ha^{-1}. The exact question from the survey was "The expected cost of planting cover crops is US$190 per ha. Would you plant cover crops next season if you were offered a cost-share payment of [one of the cost-share payments listed] per ha?" Producers could state "yes" or "no." Adoption costs of no-till were set at US$62 ha^{-1}, and the cost-share payments for no-till were set at US$12, US$25, US$37, US$49, and US$62 ha^{-1}. The exact question from the survey was "The expected cost of converting to no-till is US$62 per ha. Would you convert acres to no-till if you were offered a cost-share payment of [one of the cost-share payments listed] per ha?" Producers could state "yes" or "no." Since few respondents used irrigation, data on irrigation adoption were limited. For this reason, adoption of best irrigation management practices was omitted from the analysis.

The fifth section of the survey elicited risk preferences. This study followed similar structure to Menapace et al.'s (2013) modified Eckel and Grossman (2008) lottery-choice risk elicitation method to measure producer risk preferences, considering the adoption of technologies. Producers were given a menu of technology options that included consecutive choices between paired lotteries (figure 1). For each pair, "Option One" was assigned a sure outcome of 100% of their expected farm net income (π). The second option in each contrast is a 50-50 gamble. In this case, the respondent's net farm income could be higher or lower than the sure outcome, given the adoption of the hypothetical technology. The technology generates higher gains or losses in net farm income as the menu advances. Respondents were instructed to consider their personal net farm income during the experiment. The number of times a producer selected the 50-50 outcome is converted to a constant relative risk aversion coefficient (r) assuming an isoelastic utility function $U(\pi) = (\pi^{1-r})/(1 - r)$, where π is net farm income. The constant relative risk aversion coefficient (r) solves equation 1:

$$U(\pi) = 0.5\,\frac{(1+\eta)\pi^{1-r}}{1-r} + 0.5\,\frac{(1+\theta)\pi^{1-r}}{1-r}\,, \quad (1)$$

where η is the potential decrease in net farm income with the adoption of the BMP (η = –10%, –20%, –30%, –40%, –50%, –60%); and θ is the potential increase in net farm income with the adoption of the BMP (θ = 20%, 40%, 60%, 80%, 100%, 120%) (Menapace et al. 2013). Excel solver (Microsoft Corporation, Redmond, Washington) was used to find the bounds of r for each generic technology A, B, C, D, E, and F. The midpoints of these bounds for each technology were assigned as the risk preference level for the producer. For example, the bounds of the value of r for the constant relative risk aversion coefficient was 2.489 and 6.889 for technology A. The midpoint of these bounds, 4.689, was used as the risk aversion level for a respondent. Producers who did not adopt any technologies were assigned a value of r just above the upper bounds of technology A's r range, and those who adopted all technologies A through F (F was the riskiest technology) were assigned a risk aversion level just below the lower bounds of technology E. The final section of the survey collected information on producer demographics, including age, education, and income. Table 1 shows the summary statistics of the data used in this study.

Figure 1
Lottery choice question used to elicit producer risk preferences.

Q31. Indicate if you would or would not adopt ***each*** of the following technologies:

Farm Technology	---------IMPACTS ON YOUR FARM INCOME--------- *ADOPT* the technology, and you have a 50/50 chance of: *DECREASING* your farm income by:		*INCREASING* your farm income by:	*DO NOT ADOPT*, and your farm income is:	Would you adopt this technology? (Please check one box in each row) *Yes*, I would adopt	*No*, I would not adopt
A	-10%	or	+20%	Unchanged	☐	☐
B	-20%	or	+40%	Unchanged	☐	☐
C	-30%	or	+60%	Unchanged	☐	☐
D	-40%	or	+80%	Unchanged	☐	☐
E	-50%	or	+100%	Unchanged	☐	☐
F	-60%	or	+120%	Unchanged	☐	☐

Estimation. We estimate willingness-to-adopt cover crops and no-till with two separate probit regressions. The cover crop and no-till adoption equations are as follows:

$$q^*_{CC,i} = \beta_0 + \beta_1 C_{cci} + \beta_2 risk_i + \beta_3 corn_i + \beta_4 cotton_i + \beta_5 beans_i + \beta_6 ha_i + \beta_7 weeds_i + \beta_8 age_i + \beta_8 edu_i + \beta_9 income_i + \varepsilon_{CC,i}\text{ , and} \quad (2)$$

$$q^*_{NT,i} = \gamma_0 + \gamma_1 C_{NTi} + \gamma_2 risk_i + \gamma_3 corn_i + \gamma_4 cotton_i + \gamma_5 beans_i + \gamma_6 ha_i + \gamma_7 weeds_i + \gamma_8 age_i + \gamma_8 edu_i + \gamma_9 income_i + \varepsilon_{NT,i}\text{ ,} \quad (3)$$

where $C_{cc,i}$ is the cost-share payment offered for cover crop adoption for individual i; $C_{NT,i}$ is the cost-share payment offered for no-till adoption; $risk_i$ is the risk preference level measured from the lottery game; $corn_i$ is the percentage of the total 2016 farmland that was corn; $cotton_i$ is the percentage of the

Table 1
Summary statistics of independent variables.

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Adoption regressions					
C_{CC}	204	111.49	55.04	37	190
C_{NT}	247	36.91	16.95	12	62
risk	173	3.36	2.576	0.823	6.889
corn	284	0.24	0.30	0	1
cotton	284	0.09	0.23	0	1
beans	284	0.56	0.34	0	1
ha	288	707	534	6	4,046
weeds	249	0.69	0.46	0	1
edu	281	0.42	0.49	0	1
age	269	62	14.18	21	98
Income	262	1.80	1.06	1	6

total 2016 farmland that was cotton; $beans_i$ is the percentage of the total 2016 farmland that was soybeans; ha_i is sum of the farm's total farmland in 2016; $weeds_i$ is an indicator variable equal to one if the respondent has identified herbicide resistant weeds on his or her operation, zero otherwise; edu_i is a binary variable that is one if the producer has a college degree, zero otherwise; age_i is a continuous variable and is the age of the respondent; $income_i$ is a Likert scale rating of 2016 household income; $\beta_0,\ldots,\beta_9$ and $\gamma_0,\ldots,\gamma_9$, are parameters to be estimated; and $(\varepsilon_{CC,i}, \varepsilon_{NT,i})$ are random errors each with an expected value of zero and a constant variance of one.

The coefficients of a probit do not directly translate to the marginal change in the probability of participation (Greene 2011). The sign of the estimated coefficients indicates the ceteris paribus directional effect of an explanatory variable on BMP adoption, but not its magnitude. Marginal effects indicate the size of the impact of a one-unit change in an explanatory variable on the dependent variable. Marginal effects were calculated for the probit following Greene (2011). If the explanatory variable is binary, its marginal effect on the probability of adoption is interpreted as a *ceteris paribus* change in the likelihood of adopting cover crops and no-till when the attribute is present (Greene 2011). For continuous variables, a change in an explanatory variable is interpreted as a *ceteris paribus* change in the likelihood of adopting cover crops or no-till, given a one-unit change in the explanatory variable. The model was estimated by maximum likelihood using the PROC QLIM procedure in SAS (SAS Institute 2009). Model significance was evaluated with a likelihood ratio statistic, testing the null hypothesis that the (β,γ)'s were jointly equal to zero. Overall model fit was also evaluated by calculating the percentage of observations correctly predicted where any probability above 0.5 is one and any probably below 0.5 is zero.

Variable Hypotheses. Coefficients for the cost-share payments for cover crops (C_{CC}) and cost-share payment for no-till (C_{NT}) are expected to be positive for the respective BMP (table 2). Studies consistently conclude that as cost-share payments increase, so too does the likelihood of adopting a BMP (Cooper and Keim 1996; Cooper 1997; Prokopy et al. 2008; Baumgart-Getz et al. 2012). The variables corn, cotton, and beans are the percentage of the total 2016 farm area a producer allocated to the production of these crops. We hypothesize the coefficients for corn (*corn*), cotton (*cotton*), and soybean (*beans*) would be positive for no-till adoption since producers in the region have successfully implemented this practice for these crops. For cover crops, producers reporting higher percentages of their area farmed in corn and cotton were assumed less likely to adopt cover crops. This is because corn and cotton are planted in April and early May; thus, there may be additional managerial burden to terminate the cover crop and plant the cash crop in time. On the other hand, soybeans can be planted late May and early June, providing producers a wider planting window following termination of the cover crop. Therefore, we hypothesize that the effect of planted soybean area (*beans*) will be positively associated with the adoption of cover crops. In Tennessee, double cropping soybean with wheat is a common practice because of the longer planting window with soybeans.

No-till and planting cover crops could affect weed management decisions and aid in weed control. We hypothesize that farmers who identified herbicide resistant weeds on their farms (*weeds*) would be more likely to adopt cover crops because of their potential to suppression of weed growth during the winter and early spring. The expected relationship between no-till and the identification of herbicide resistant weeds is negative because mechanical weed control may be required to control herbicide resistant weeds. It was also hypothesized that farm size (*ha*) would be positively associated with the adoption of either BMP, since previous studies have reported that larger farms are more willing-to-adopt (Prokopy et al. 2008; Baumgart-Getz et al. 2012). Following other studies, we hypothesize age (*age*) will have a negative coefficient and income (*income*), and education (*edu*) will likely have a positive coefficient. This means that older producers would be less likely to adopt but higher income and education would be more likely to adopt (Prokopy et al. 2008; Baumgart-Getz et al. 2012; Boyer et al. 2016).

Arbuckle and Roesch-McNally (2015) indicated that producers who associated cover crops with risky returns were less likely to implement the practice. It was

Table 2
Definition and predicted signs for the independent variables.

Variable	Description	Predicted sign for cover crop adoption	Predicted sign for no-till adoption
Adoption regressions			
C_{CC}	Cost-share payment assigned for adoption cover crops per hectare	+	
C_{NT}	Cost-share payment assigned for adoption of no-till per hectare		+
r	Latent risk coefficient	–	–
corn	Percentage of 2016 farmland that produced corn	+	–
cotton	Percentage of 2016 farmland that produced cotton	+	–
beans	Percentage of 2016 farmland that produced soybean	+	+
ha	Total number of hectares farmed in 2016	+	+
weeds	Have you identified herbicide resistant weeds on your farm? Yes =1, No = 0	+	–
edu	= 1 when if the producer has a college education; otherwise zero	+	+
age	Age of primary operator in years	–	–
income	= 1 if 2016 household income was less than US$99,999, = 2 if between US$100,000 and US$299,999, = 3 if between US$300,000 and US$499,999; = 4 if between US$500,000 and US$699,999; = 5 if between US$700,000 and US$999,999; and = 6 if greater than US$1,000,000	+	+

therefore hypothesized that elicited risk (*risk*) would be negatively associated with adoption of cover crops and no-till. Furthermore, Barrowclough and Alwang (2018), who used a risk elicited method, estimated the effect of risk aversion on the willingness of Ecuadorian farmers to adopt four conservation agricultural practices (cover crops, crop rotation, reduced tillage, and contour cropping), and found the coefficient on the risk aversion parameter was negative and significant. This suggested that risk aversion was negatively correlated with willingness to adopt the practices.

Results and Discussion

Summary Statistics. Table 3 shows the bounded risk aversion coefficients resulting from the lottery-choice question and the percentage of producers willing to participate in each lottery. A lower risk aversion coefficient indicates greater tolerance for risk. Just over half of the respondents indicated they would adopt generic technology A, which means over half of the respondents would choose a slightly riskier outcome than not adopting any technology. This is a slightly higher percentage of adopters than what Menapace et al. (2013) observed. However, this percentage decreased as the potential losses associated with each technology increased, with approximately a fifth of the respondents indicating they would adopt technology F. Menapace et al. (2013) also observed a decrease in participation in the lottery games as risk was increased. In this analysis, however, we find that a higher percentage of the respondents were willing to take greater risks than what Menapace et al. (2013) reported. The average constant relative risk aversion coefficient was 3.36 (table 1).

The average cover crop cost-share payment (C_{CC}) offered was US\$111 ha^{-1}. The percentage of producers willing to adopt cover crops at the US\$37 ha^{-1} cost-share payment was approximately 40% (figure 2). This percentage dropped slightly (but not significantly) to 37.5% when the cost-share increased to US\$74 ha^{-1} (figure 2). However, willingness-to-adopt cover crops increased when cost-share increased from US\$74 ha^{-1} to US\$190 ha^{-1} (figure 2). At the 100% cost-share payment (US\$190 ha^{-1}), 91% of the respondents were willing to adopt cover crops (figure 2). The average no-till cost-share payment (C_{NT}) offered to producers averaged US\$37 ha^{-1} (table 3). For no-till, most respondents (64%) indicated they would adopt the practice when a US\$12 ha^{-1} cost-share payment was offered (figure 3). Willingness-to-adopt no-till increased as the cost-share payment increased, with about 89% of the respondents indicating they would adopt no-till at the 100% cost-share payment (figure 3).

About 70% of the respondents identified herbicide resistant weeds on their farm. Of the responses, 24% of all 2016 hectares were planted in corn (*corn*), 9% of all 2016 hectares were in cotton (*cotton*), and 56% of all 2016 hectares were in soybeans (*beans*). The remaining percentage included commodities such as wheat and sorghum (*Sorghum bicolor* L.). The average farm size in 2016 was 707 ha, which is higher than the state average of 383 ha, according to the 2017 Agricultural Census (USDA NASS 2017). The average age of survey respondents was 62 years old, which is slightly older than the average age of principal operators in the state (59 years old in 2017) (USDA NASS 2017). Roughly half of respondents had a total of farm and nonfarm income for 2016 of less than US\$99,999, and roughly 5% of respondents reported their 2016 income to be US\$500,000 or above.

Model Fit Statistics. For the cover crop model, the likelihood ratio test that the coefficients of the explanatory variables were jointly zero was rejected (table 4). The cover crop adoption model correctly classified 51% of observations. For the no-till adoption model, the likelihood ratio test that the included factors had no effect on adoption was also rejected. The no-till adoption model correctly classified 65% of the observations. McFadden's

Table 3
Elicited constant relative risk aversion coefficients (r).

Technology	Constant relative risk aversion coefficient (r) bound	Percentage of farmers adopting technology (%)	Assigned r	n
Not adopt	$r > 6.889$	—	6.889	55
A	$2.489 < r < 6.889$	53.70	4.689	14
B	$1.672 < r < 2.489$	49.75	2.081	31
C	$1.256 < r < 1.672$	35.47	1.464	25
D	$1.000 < r < 1.256$	24.63	1.128	10
E	$0.823 < r < 1.000$	22.17	0.912	4
F	$0.823 < r$	20.20	0.823	37

Figure 2
Percentage of respondents adopting cover crops at a given cost-share payment.

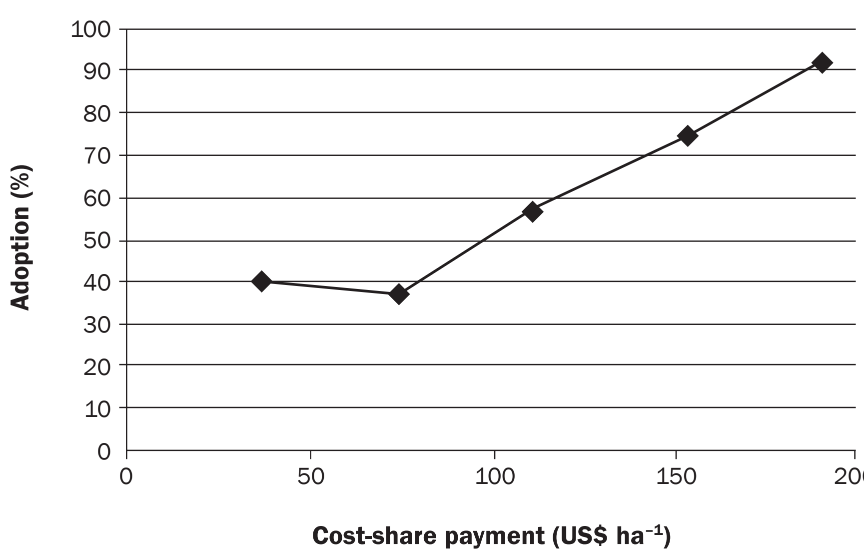

Figure 3
Percentage of respondents adopting no-till at a given cost-share payment.

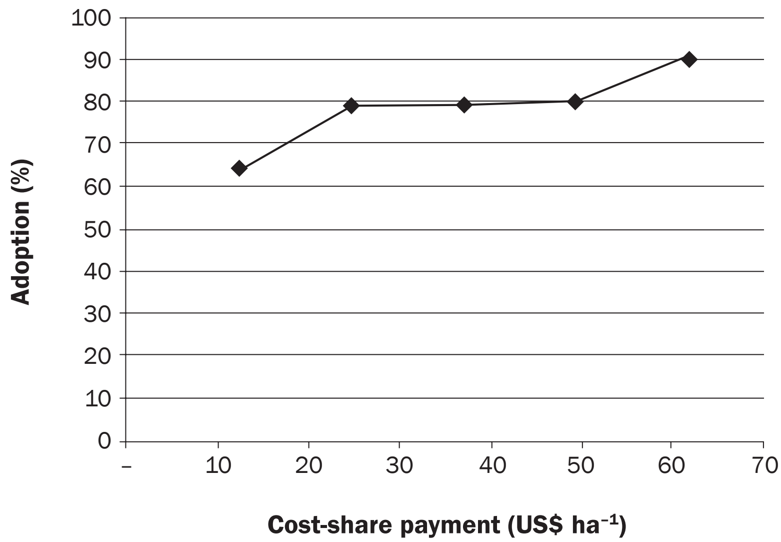

Table 4
Parameter estimates and significant marginal effects for the probit models.

	Cover crop adoption probit (n = 168)		No-till adoption probit (n = 160)	
Parameters	Parameter estimates	Marginal effects	Parameter estimates	Marginal effects
Intercept	0.005 (0.996)	—	0.4404 (1.222)	—
C_{CC}	0.0035*** (0.0065)	0.009***	—	—
C_{NT}	—	—	0.0035 (0.244)	—
risk	–0.0535 (0.057)	—	–0.1532* (0.0812)	-0.0323*
corn	–0.0065 (0.008)	—	–0.0007 (0.007)	—
cotton	–0.0013 (0.009)	—	–0.0009 (0.009)	—
beans	–0.0007 (0.007)	—	0.0066 (0.007)	—
ha	–0.0004 (0.011)	—	0.0345 (0.025)	—
weeds	–0.1087 (0.345)	—	–0.3685 (0.437)	—
age	0.002 (0.011)		0.0011 (0.013)	—
edu	0.025 (0.268)		–0.053 (0.364)	—
income	–0.097 (0.128)		0.399* (0.236)	0.084*
Likelihood ratio	<0.001		<0.001	
McFadden R^2	0.185		0.123	
Correctly predicted	0.51		0.65	

*, **, and *** are significant at the 0.10, 0.05, and 0.01 levels, respectively.

pseudo-R^2s were 0.19 and 0.12 for the cover crop and no-till models, respectively.

Adoption. The cost-share payment coefficient and marginal effect were positive and significant for cover crop adoption ($p < 0.01$). This indicates a US$1 ha^{-1} increase in the cost-share payment would increase the likelihood of a producer adopting cover crops by 0.09 (table 4). These results are similar to previous BMP adoption studies (Cooper 2003; Lichtenberg 2004; Lichtenberg and Smith-Ramirez 2011). Cooper (2003) and Lichtenberg (2004) found increasing cost-share payments for a BMP would increase the likelihood a producer adopted a related BMP. The hypothetical cost share for adopting no-till was uncorrelated with willingness-to-adopt this practice (table 4). Cooper (1997) found that producers were more responsive to increases in cost-share payments for some BMPs relative to others. According to USDA NASS (2014), 76% of all farmland in Tennessee is planted using no-till technology, suggesting that there is some motivation besides cost-share payment that drives no-till use in Tennessee.

The sign of the constant relative risk aversion coefficient was negative and significant ($p < 0.10$) for no-till adoption (table 4), but risk preference was uncorrelated with willingness-to-adopt cover crops. This is an interesting result given the high adoption of no-till in Tennessee. There could be several possible explanations for this result. One explanation that might deserve future research is with the assumed timeframe in elicitation method. Recent studies have reported no-till planting increased production risk and reduced profits for cotton production in Tennessee relative to conventional tillage (Zhou et al. 2017; Boyer et al. 2018). Adoption, while might increase risk, might be driven more out of environmental preferences than risk preferences. Crop production in this region primarily occurs on sandy or silty soils, which are susceptible to soil erosion (Bradley and Tyler 1996), and Campbell (2018) showed about 75% of Tennessee crop producers believe no-till would reduce soil erosion, which would be a risk reducing practice in the long run. This raises an interesting question—do these risk preference elicitation methods only value risk in the short run? Research should consider developing risk preference elicitation methods to look at how these tools evaluation short- and long-run risk preference.

Regardless, the stated preference results suggest that producer attitudes toward risk impact the likelihood of adopting a hypothetical no-till practice. A possible policy to encourage the use of BMPs, while acknowledging risk preferences, might be to couple cost-share payments with crop insurance premium subsidies (Boyer et al. 2017). This policy could possibly increase crop insurance subsidies if producers adopt a suite of BMPs. Risk-averse producers would receive some protection from possible downside variability associated with learning, start-up, and implementation costs (perceived or real) while encouraging the use of crop insurance and the adoption of BMPs.

Finally, 2016 household income was found to have a positive and significant impact on the adopt of no-till. This result matches previous research findings (Prokopy et al. 2008; Baumgart-Getz et al. 2012) and makes logical sense for no-till, which would require an investment into a no-till planter. A higher income would likely provide needed capital to purchase this equipment.

Summary and Conclusions

Regardless of the cost-share payments and environmental benefits from adopting cover crops and no-till, the use of these BMPs remains limited in the United States. Previous research finds that producers may be reluctant to implement some BMPs due to perceived uncertainties about the economic costs and returns from adopting certain practices. This research applied a risk elicitation method during a lottery choice experiment presenting a hypothetical program encouraging the adoption of cover crops and no-till planting by row crop producers in West Tennessee. The objective of this research was to determine how producer attitudes toward risk affected willingness-to-adopt cover crops and no-till, holding monetary incentives, respondent characteristics, and farm attributes constant. This study contributes to the research literature by demonstrating how risk preferences impact the BMP adoption.

The cost-share payment coefficients were significant in cover crop adoption and insignificant in no-till adoption. Thus, more producers would plant cover crops if the cost-share payment increased; however, no-till planting will be used without a cost-share payment. Cover crop adoption was uncorrelated with producer risk preferences, but risk-averse producers are less likely to adopt no-till planting.

Based on these findings, policymakers might consider reallocating cost-share funding for no-till to other BMPs that are responsive to cost-share payments. Furthermore, this study builds on Boyer et al.'s (2017) work by suggesting a possible policy revision might be to couple BMP cost-share payments with crop insurance premium subsidies. Finally, future research could investigate what drives risk preferences and if crop insurance is a suitable proxy for risk aversion. This study, while impactful, is not without limitations. The low response rate and potential sample bias from using FOIA to access producer contact information could limit the implication of the results.

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