doi:10.2489/jswc.2022.00062

Barriers to cover crop adoption: Evidence from parallel surveys in Maryland and Ohio

J.M. Duke, R.J. Johnston, A.L. Shober, and Z. Liu

Abstract: This paper evaluates perceived barriers to cover crop adoption, using data from an original survey of farmers in two US states. Barriers are compared in a high adoption state (Maryland) and a more typical adoption state (Ohio). Although 25.5% in Maryland and 22.3% in Ohio reported no barriers, the remainder reported at least one barrier. Financial barriers are most frequently cited (investment return, seed cost, labor cost, and equipment needs), while barriers related to education and information are mentioned less frequently (doubts on cover crop importance, knowledge issues, and risk). Multivariate probit regressions explain how farm characteristics and cover crop information sources influence these barriers, while allowing perceived adoption barriers to be related in unobservable yet systematic ways. Results show that these effects differ systematically across states. For example, barriers related to investment return are more commonly cited by large-acreage farmers in Ohio who use conservation or conventional tillage, relative to no-till. Contrasting results are found in Maryland, where there is no acreage pattern and the use of no-till increases concern about investment return. The findings on the importance of financial barriers suggest the importance of cost-share in encouraging adoption, access to which should be emphasized in educational programming. If educators believe farmers' perceptions of financial barriers do not match scientific results—say because farmers' financial fears are myopic—then the design and targeting of educational materials such as enterprise budgets may allay financial concerns.

Key words: conservation agriculture—conservation policy—cost-share—EQIP

Cover crop adoption is widely promoted by US federal and state cost-share programs due to established benefits for soil health and water quality. Yet adoption rates in many areas remain low as a share of overall cropland acreage. For instance, 3.9% of US cropland had cover crops (CC) planted in 2017, and only Maryland (29%) and Delaware (20%) had shares at or exceeding 20% (USDA NASS 2017). Adoption is increasing in many states. For instance, in Ohio CC acres increased by 101% while Maryland increased by 25% between the agricultural censuses of 2012 and 2017 (USDA NASS 2017).

An expansive literature has emerged studying why farmers adopt best management practices (BMP), including CC (Baumgart-Getz et al. 2012; McCann and Claassen 2016; Lee and McCann 2019; Ranjan et al. 2019; Prokopy et al. 2019). These studies tend to emphasize barriers (or related transactions costs) as independent variables in the adoption decision. That is, the focus is on BMP adoption, and barriers are assumed to influence farmers' adoption decisions. Many of these studies seek to identify a broader set of factors that affect farmers' adoption of CC and then identify barriers as those variables with negative and statistically significant effects on adoption (Lichtenberg 2004; Bergtold et al. 2012; Stuart and Gillon 2013; Arbuckle and Roesch-McNally 2015; Dunn et al. 2016; Burnett et al. 2018). Commonly reported barriers include certain farm and farmer characteristics (e.g., farmer age) and various self-reported or perceived measures (e.g., lack of information, hours spent on paperwork, etc.). With relatively few exceptions (McCann and Claassen 2016), however, the literature gives less attention to the determinants of adoption barriers. That is, these barriers are (perhaps inaccurately) viewed as fixed and independent over time and across farmers. Yet, some perceived barriers to adoption—such as those related to farmers' attitudes, knowledge, and risk perceptions—may change over time, and may themselves be affected by a myriad of determinants. In formal terms, they may be viewed as latent endogenous variables in the adoption decision. For example, certain types of information sources for farmers may be associated with variations in adoption barriers related to risk or cost perceptions.

That is, some types of adoption barriers may be explained as a function of measurable independent variables. This is an important observation because it implies that some types of barriers might be reduced by targeted policies or programs, thereby providing a mechanism to enhance adoption. For example, financial considerations are a commonly reported barrier for CC adoption in previous studies (Miller et al. 2012; Carlisle 2016; Daryanto et al. 2019). CC use requires farmers to invest in establishing and terminating the crop, and these costs can vary across CC types (Roesch-McNally et al. 2017). For instance, Roley et al. (2016) showed that the average annual cost for using winter rye (*Secale cereale* L.) was US\$61 ac^{-1} (US\$150.70 ha^{-1}), which includes the costs of seeding, planting, terminating, additional time and labor, and the effects on cash crops. However, these costs might also vary across farmers as a function of their experience, field types, etc. Hence, it is reasonable to expect that perceived financial barriers to CC adoption might vary across farmers, as a function of a variety of farm and farmer characteristics.

It is also possible that some CC adoption barriers might be nonindependent (correlated), or related in unobservable yet systematic ways. There is clear evidence of

Received April 8, 2021; Revised August 3, 2021; Accepted September 13, 2021; Published online February 10, 2022.

Joshua M. Duke is the head and professor in the Department of Agricultural Economics and Rural Sociology, Auburn University, Auburn, Alabama. **Robert J. Johnston** is a professor in the Department of Economics, Clark University, Worcester, Massachusetts. **Amy L. Shober** is a professor and extension specialist in the Department of Plant and Soil Sciences, University of Delaware, Newark, Delaware. **Zhongyuan Liu** was a postdoctoral fellow in the Department of Agricultural Economics and Rural Sociology, Auburn University, Auburn, Alabama.

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

such correlation in different types of BMP adoption decisions (Kara et al. 2008; Fleming et al. 2018), suggesting the possibility that similar correlations may apply to the underlying adoption barriers. These correlations can be identified using multivariate statistical approaches that model barrier determinants simultaneously for different barriers—thereby providing insight into the extent to which different barriers are correlated across farmers, *ceteris paribus*. Evidence of such correlation (or lack thereof) can be instrumental in helping to develop effective barrier-reducing agronomic education efforts. For example, evidence that barriers due to financial considerations and risk perceptions are correlated might suggest the efficacy of educational programs that target these two barriers jointly, rather than treating them as independent concerns.

Understanding determinants of adoption barriers can inform potential approaches to ameliorate these barriers over time, and hence promote greater CC adoption. Although the existing literature on barriers is reviewed further below, among the key gaps is that quantitative research does not yet offer a comprehensive comparison of (1) the perceived importance of different types of perceived financial and educational barriers, (2) what farm characteristics and CC information sources are associated with perceived barriers, (3) whether there are unobserved correlations across perceived barriers such as these, and (4) whether raw barrier responses and multivariate probit model (MVP) results vary across different states.

To address gaps in understanding CC adoption barriers, this paper develops a statistical model of perceived adoption barriers using data from a survey of farmers built upon the most recent existing literature and an original set of focus groups. Data analysis applies a multivariate regression technique that controls for unobserved/unobservable variation in farmers' opinions about the relevance of different barriers. Results from the same model and survey instrument are compared across a relatively high adoption state (Maryland) and a more typical adoption state (Ohio). This allows for a systematic comparison in barrier determinants across two states with different CC cost-share and educational programming.

Materials and Methods

In the sections that follow we use the term "barriers" rather than "perceived barriers" for conciseness, while acknowledging that the analysis solely addresses barriers as perceived by farmers. Of course, there may be a perception-reality divergence in modeling CC barriers. A farmer's perceptions about barriers might not match those perceived by agronomic experts. This paper focuses on farmer perceptions of these barriers, under the recognition that behavior is likely to be motivated by these perceptions, whether or not these perceptions are consistent with reality. The current data cannot (and is not intended to) evaluate the extent to which respondents' perceptions match objective reality. However, to the extent that a divergence exists, educational programming might close any perception-reality gaps. It is also possible that better, targeted education might be as or more effective than cost-share in overcoming barriers. The goal of the paper is to inform these and other programs that explicitly target perceived barriers to enhance CC adoption. To preface the analysis that follows, the following section reviews the institutional backgrounds on CC programming in the two states studied. Then, the survey design, data collection, and variables are described.

Cover Crop Programs in Ohio and Maryland. CC adoption barriers are potentially affected by a variety of variables reflecting relevant government policies, available cost-share programs, education and extension activities, the CC input subsector, equipment availability, and the behavior of other farmers. Here, we compare Ohio and Maryland, which differ substantially in terms of programs available to support CC, agricultural production, and the context in which adoption is promoted. Primary cash crops in both states include corn (*Zea mays* L.), soybean (*Glycine max* [L.] Merr.), and small grains. Maryland has among the highest CC adoption rates among US states at 20% to 25% of total cropland (327,689 ac [132,611 ha]) (Weil and Kremen 2007; USDA NASS 2017). In contrast, CC acreage in Ohio is estimated at 357,292 ac (144,591 ha), which is approximately 3.3% of total cropland (USDA NASS 2017). Adoption of CC is promoted in the two states in part to reduce nutrient loads to the Chesapeake Bay (Maryland) and western Lake Erie basin (Ohio); both waterbodies have total maximum daily loads established. With respect to available CC programs, both states provide federal cost-share through the Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP). However, enrollment in federal programs and the scale of state and local programs differ considerably between the two states. Meanwhile, programs in the two states cannot be compared directly since the EQIP and CSP in Ohio cover all BMPs while the dominant program in Maryland incentivizes CC adoption and use.

In Ohio, the nonfederal local/state/watershed-based programs have relatively low budgets such that federal programs incentivize more planting. According to the data from USDA NRCS (2019b), EQIP funding in the fiscal year 2019 in all of Ohio totaled US$36.124 million, an increase of 43% compared to the US$25.338 million in 2010. About 70% of the total EQIP funding went to program participants as payments for implementing conservation practices, and the remainder was used for technical assistance or reimbursement funds. In 2019 there were 1,496 active contracts in EQIP, with 223,842 contracted acres (90,586 ha). CSP also provided US$11.5 million for Ohio in fiscal year 2019 (USDA NRCS 2019a). Of this total, US$9.02 million, or 78%, of CSP funding in Ohio was paid directly to the participants for maintaining and improving existing conservation practices. There were 111 active contracts in 2019, with 27,544 total acres (11,147 ha).

The presented analysis relies on data collected in eight contiguous counties in northwest Ohio, where farmers have several state and local conservation CC programs available. For the sample discussed in this paper, 5.6% of respondents reported planting CC in EQIP in 2017, 2.2% in CSP, 0.8% in other federal programs, and 8.2% in state/local programs such as the Great Lakes Restoration Initiative (GLRI), Ottawa River watershed project, Miller City Cuttoff & Pike Run Watershed Grant, and Central Fulton Conservation Project.

In contrast, the Maryland Agricultural Water Quality Cost-Share (MACS) Program is a large state initiative with comparatively high budgets that allow nearly 100% of applicants to obtain some type of cost-share. In 2019 to 2020, the total funding for this program was US$22.5 million, and farmers could receive up to US$90 cost-share ac^{-1} (US$222.40 cost-share ha^{-1}) of CC planted. There were 1,687 farms that participated in the program with 558,976 ac (226,210 ha) during 2016 to 2017 (Maryland Department

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

of Agriculture 2017). Maryland farmers are also eligible for federal programs. EQIP funding in Maryland in 2019 was US$18.56 million, or roughly half of the funding in Ohio (USDA NRCS 2019b). The total active contracts and acreage for EQIP in Maryland are 341 and 14,045 ac (5,684 ha), which are about 22.8% of total active contracts and 6.3% of the enrolled acreage in Ohio. For the sample discussed in this paper, 0.9% of respondents planted CC in EQIP during 2017, 1.3% in CSP, 1.1% in other federal programs, and 66.0% in MACS. Hence, there are considerable differences in CC program use across the two states.

Barriers to Cover Crop Adoption and Survey Variables. There is an extensive CC adoption literature (Lee and McCann 2019), summaries of which are provided elsewhere (Carlisle 2016; Miller et al. 2012). Rather than repeating the general insights in prior reviews, the following section highlights more recent findings of this literature as related to the variables included in the empirical analysis. In this way, we summarize the primary ways in which existing work motivated our research design. In supplementary materials, we develop an updated version of the summary table in Miller et al. (2012), focusing solely on barriers to adoption (our table S1 lists 13 barriers from prior studies, which we reduce to 7 key barriers and an "other" category). The 7 dependent variables in our empirical analysis take the form of binary indicators identifying whether farmers perceive certain types of barriers as affecting CC use on their farm.

The survey was developed over a two-year process, including (1) an initial literature review, (2) six structured interviews with CC program personnel and other experts in both states and the federal government, and (3) focus groups with farmers in each state. The purpose of the structured interviews was to understand relevant state and federal CC programs, patterns in enrollment, perceived challenges in maintaining and increasing CC adoption/enrollments, etc. Information from these interviews was supplemented with the results of four focus groups conducted with 25 farmers in Ohio and Maryland (held in December of 2016 and January of 2017). These focus groups explored the way farmers and local CC program personnel thought about CC, available CC programs, and different types of barriers to adoption. This insight was used to develop the set of barriers for which information was elicited by the survey instrument and that were ultimately included as dependent variables in the quantitative models. Focus groups also provided information on the factors hypothesized to cause systematic variations in these barriers across different farms and farmers—these comprise the explanatory variables. A final goal of focus groups was to refine and pretest the language in the survey instrument, following survey design guidelines in Johnston et al. (2017).

Barriers were identified for each farmer who responded to the survey via the following question: "What do you think are the barriers to using cover crops on your farm? (…whether that means planting a cover crop for the first time or planting more than you currently plant) Please check all that apply." This was followed by a list of seven statements (detailed in supplementary table S2), along with an "other" category. Those who checked the "other" category were able to describe this barrier in a follow-up text box.

Most literature cites economic or financial challenges as one of the primary barriers to adoption (Carlisle 2016; SARE 2017; Daryanto et al. 2019). CC have direct costs associated with the purchase of seed, labor, and equipment used in planting and termination (Lichtenberg 2004; Arbuckle and Ferrell 2012; Bergtold et al. 2012). Studies show that the absence of cost-share programs or insufficient cost-share rates in some states contribute to farmers' financial concerns (Maryland Department of Agriculture 2005; Singer et al. 2007; Baumgart-Getz et al. 2012; Dunn et al. 2016). The overall concern that CC do not pay for themselves was captured by the variable *ROI* for return on investment, or the financial sustainability of planting CC. This variable takes a value of 1 if the survey respondent identified the following as a barrier within the survey: "I am not confident that cover crops are financially sustainable." The use of the term "sustainable" implies a focus on long-term returns. A qualification is that some respondents may have conflated their other financial concerns with CC, being more pessimistic about CC ROI than in some other years. This might be expected because 2016 and 2017 were 2 of the 12 years between 2000 and 2019 when net farm income was below the average (USDA ERS 2021). Indeed 2015 to 2019 was an extended low period for this measure. Although the frequency with which this barrier is reported might be higher than in some years, we do not anticipate a systematic bias in the effect of the explanatory variables on *ROI* in the presented empirical analysis.

Many studies find that the costs of seed, labor, and equipment can also prevent broader CC adoption, apart from more general ROI concerns. The survey therefore asks separate questions about each of these costs: *COSTS-LABOR*, *COSTS-SEED*, and *EQUIPMENT* (we report the survey questions and summary statistics by state in supplementary table S2). For example, seed costs are variable (they depend on whether CC are planted) while equipment costs are fixed in the short run (they occur regardless of whether CC are planted, and the survey question focuses on buying equipment rather than operating and maintaining it). Labor costs might be fixed or variable. As a result of these and other differences, these costs might present different types of barriers to different types of farming operations, for example as a function of factors such as financial position, experience, level of capitalization, and size of operation. *ROI* addresses respondents' overall concern with the financial sustainability over a long term—which considers both revenues and costs—while *COSTS-LABOR*, *COSTS-SEED*, and *EQUIPMENT* emphasize specific sources of cost.

CC might introduce perceived risks to a farming operation, captured by the variable *RISK* and linked to the statement "I believe there are risks to my farm introduced by planting cover crops." One possible risk is that CC may interfere with the fall harvest or spring planting of the cash crop (Snapp et al. 2005; Dunn et al. 2016; Roesch-McNally et al. 2017). Other risks may be farm- or farmer-specific. For instance, during focus groups in Ohio, respondents expressed concern that CC might provide winter food for nuisance animals, thereby increasing pest impacts in future years. Farmers may also fear that planting CC might increase some diseases and/or that CC could become a weed (Snapp et al. 2005). Farmers might also be concerned about financial risks and impacts on yield variability.

Lack of farmer experience (or related information and education challenges) may further discourage the use of CC. Some farmers lack sufficient information, such as information on the benefits of planting CC (Singer et al. 2007; Arbuckle and Ferrell 2012; Miller et al. 2012) or related to selection of CC species within a crop rotation

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

(Miller et al. 2012; SARE 2017). Prokopy et al. (2019) review 35 years of adoption literature, and one conclusion is that future research should measure the impact of different "avenues of reaching farmers." Here, we distinguish between two potential barriers related to experience and knowledge. The first reflects basic knowledge about CC (*KNOWLEDGE*), whereas the second reflects a more general disagreement that CC are important (*IMPORTANCE*). The former is linked to the statement "I don't know enough about cover crops" while the latter is linked to the statement "I don't think of cover crops as being an important part of my farming." Both of these barriers may be addressed with continuing education about the private benefits and costs of CC. Research also can test whether specific avenues of educational programming are most effective at reaching farmers who were unpersuaded by previous efforts to promote adoption. Some novel approaches may even be effective, such as peer mentoring programs (we thank an anonymous referee for this suggestion).

The "other" option with an open-ended follow-up question allows respondents to discuss other types of barriers that are not explicitly addressed by other survey questions. The survey did not ask farmers to consider an exhaustive list of all possible CC adoption barriers. This was done intentionally. First, listing all possible adoption barriers would have led to an exceptionally long list that would risk frustrating survey respondents. Second, and most importantly, many types of barriers do not vary systematically across farmers and hence cannot readily be addressed by farm-level interventions. For example, there may be macro-scale barriers to CC adoption related to factors such as the structure of the state or regional farm economy. Our study does not address barriers of this type because they apply similarly to all farmers in a region.

Explanatory Variables and Hypotheses. Two types of variables potentially influence barriers: 12 farm and farming operation characteristics and 13 information sources (table 1). *LNACRE* measures the *log* of acres of cropland for commodity crops in 2017. Studies show that farmers with larger acreage may perceive fewer barriers to use CC or conservation practices, in general, because they have economies of scale in the fixed costs of learning, equipment, etc. (Featherstone and Goodwin 1993; Upadhyay et al. 2003; Gabrielyan et al. 2010; Vitale et al. 2011). In contrast, Bergtold et al. (2010) found that larger acreage has a negative impact on CC adoption due to the lack of time and labor (Bergtold et al. 2012). Other studies find an insignificant relationship between farm size and conservation practices (Prokopy et al. 2008; Bergtold et al. 2012). Various explanations have been offered for the mixed results on the farm-size/adoption relationship. For instance, there may be different measures of farm size, either acreage managed or acreage owned (Prokopy et al. 2008). Or, there may be scale-related challenges with capital investment, risk tolerance (Carlisle 2016), and/or anticipated environmental benefits (Arbuckle and Ferrell 2012). In this paper, we expect that *LNACRE* should have no effect, or a negative effect, on the two barriers (*EQUIPMENT* and *ROI*) due to economies of scale. However, acreage should be positively associated with labor because of lumpiness in labor supply, or an inability to hire more labor, especially for the small farms in our sample (76.5%) with gross cash farm income (GCFI) less than US$350,000 for whom hiring new labor may not be routine.

Farming experience is measured using four binary indicators for the years of farming by the principal operator: *EXPERIENCE<16*, *EXPERIENCE16-30*, *EXPERIENCE31-45*, and *EXPERIENCE46+*. Our survey also included measures of farmer's age and GCFI; however, these two measures were correlated with farming experience. Therefore, we use experience in the regressions alone, which also partially captures age and GCFI effects. To evaluate whether this specification choice has a significant impact on model results, we also estimated preliminary models that included all three of these types of variables, but only 1 of 32 new coefficients was significant. Because these new variables introduce multicollinearity and the existing results are robust, we proceed with the model that incudes experience alone, as a proxy for combined age, income, and experience. We hypothesize that the relationship between farm experience and adoption barriers will depend on farmers' risk preferences (Abadi Ghadim and Pannell 1999; Bergtold et al. 2012), but also on age because younger farmers are more likely to use CC (Clay et al. 2020). That said, older farmers would tend to have more years of opportunity to experiment with CC and identify an optimal mix of inputs to enhance profits. Thus, in concept, greater experience should lead to reduced concern about CC labor requirements (*COSTS-LABOR*) because accumulated skills should substitute for labor quantity. However, more experienced farmers might also be resistant to change. More experience might also proxy for financial security, so more experience should lead to fewer financial barriers. Considering these factors, we hypothesize that less experienced farmers will be more likely to report barriers, while those with more experience will be less likely.

The set of explanatory variables also includes indicators for the use of conventional tillage (*CONVTILL*), conservation tillage (*CONSTILL*), and no-till (*NOTILL*). Within the survey, conventional tillage was defined as "less than 30% of the soil surface is covered by residue after planting," while conservation tillage refers to "at least 30% of the soil surface is covered by residue after planting." No-till is the case in which there is "no soil disturbance prior to planting." Survey respondents were allowed to select multiple options in this question. Because CC management under no-till often incorporates equipment for termination, such as a "roller-crimper" (Miller et al. 2012), one possible hypothesis is that farmers who use no-till (*NOTILL*) will be more likely to report barriers related to equipment (*EQUIPMENT*). However, Bergtold et al. (2010) found that farmers who already adopted conservation tillage were more likely to adopt CC. Thus, the use of conservation tillage (*CONSTILL*) or no-till (*NOTILL*) is expected to have negative relationship with CC barriers.

The variables *CORN*, *SOYBEANS*, and *WHEAT* indicate whether the respondent planted the crop. The survey also includes a single variable, *OTHERCROP*, which includes those who reported "any other crops" and the few respondents who (perhaps erroneously) selected "no crops." Participants selected all that apply (and table 2 shows that >80% of respondents planted corn and soybeans). The use of any irrigation (*IRRIGATION*) was an indicator variable. Studies show that farmers in areas with a dominant corn–soybean production system can find it challenging to integrate CC into the crop rotation because most of the agricultural infrastructure is oriented toward corn and soybeans (Arbuckle and Ferrell 2012; Roesch-McNally et al. 2017). Accordingly, there may be a positive tendency

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Table 1
Explanatory variables and expected relationships to barriers to cover crop adoption.

Variable	Explanation	Hypothesized sign ROI	Labor	Seed	Equipment
Farm and farming operation characteristics					
LNACRE	Acreage of cropland in log form	–	?	+	–
EXPERIENCE<16	Indicator: 1 = Farming experience less than 15 years	+	?	+	+
EXPERIENCE16-30	Indicator: 1 = Farming experience between 16 and 30 years	+	?	+	+
EXPERIENCE31-45	Indicator: 1 = Farming experience between 31 and 45 years	–	?	–	–
EXPERIENCE46+	Indicator: 1 = Farming experience above 46 years	–	?	–	–
CONVTILL	Indicator: 1 = Use conventional tillage			+	
CONSTILL	Indicator: 1 = Use conservation tillage	–	–	–	–
NOTILL	Indicator: 1 = Use no-till	–	–	–	–
OTHERTILL	Indicator: 1 = Use other tillage				
CORN	Indicator: 1 = Produce corn	?	+	+	+
SOYBEANS	Indicator: 1 = Produce soybeans	?	+	+	+
WHEAT	Indicator: 1 = Produce wheat				
OTHERCROP	Indicator: 1 = Produce other crops				
IRRIGATION	Indicator: 1 = Yes	–	?	–	–
Information sources					
INFOEXTAGENT	Indicator: 1 = Extension agent				
INFODEALERS	Indicator: 1 = Seed dealers				
INFOEXTWEB	Indicator: 1 = Cooperative extension web services				
INFODISTICT	Indicator: 1 = Soil Conservation District Office				
INFOSTATE	Indicator: 1 = Maryland/Ohio Department of Agriculture				
INFOOHNOTILL	Indicator: 1 = Ohio No-Till Council				
INFONRCS	Indicator: 1 = USDA Natural Resources Conservation Service				
INFOGROWERS	Indicator: 1 = Growers' associations				
INFOFB	Indicator: 1 = Farm Bureau				
INFOFARM-NEIGH	Indicator: 1 = Other farmers—neighbors				
INFONOFARM-NEIGH	Indicator: 1 = Other farmers—not neighbors				
INFOOTHER	Indicator: 1 = Other				
INFONONE	Indicator: 1 = None of the above				

for corn–soybean farmers to report one or more of labor, seed, or equipment barriers. As irrigation should reduce crop yield risks and indicate high levels of capitalization, we anticipate that *IRRIGATION* will be negatively associated with *ROI*, *COSTS-SEED*, and *EQUIPMENT*.

Farmers can learn about CC in many ways, and we consider 10 possible information sources identified by our interviews and focus groups as being particularly relevant to farmers in at least one of the two states: the USDA Natural Resources Conservation Service (NRCS) (*INFONRCS*), Soil Conservation District Office (*INFODISTICT*), Cooperative Extension web services (*INFOEXTWEB*), the Departments of Agriculture in each state (*INFOSTATE*), extension agents (*INFOEXTAGENT*), seed dealers (*INFODEALERS*), growers' associations (*INFOGROWERS*), Farm Bureau (*INFOFB*), and informal channels like neighboring farms (*INFOFARM-NEIGH*) or other farmers (*INFONOFARM-NEIGH*). Respondents were asked which of these information sources were used and could select more than one source. The information source of the Ohio No-Till Council (*INFOOHNOTILL*) only exists in the Ohio survey. This survey lists 11 specific information sources and two possible answers for other sources. Although it may seem possible that our barriers and information sources could have dual causation, we ran separate regressions with and without the information sources and find no compelling evidence that the inclusion of (potentially endogenous) information sources lead to potential biases in other conclusions drawn from the model (table S6 in the supplementary files). Hence, although we lack the data to address any possible endogeneity of information sources formally, other model results are robust to the inclusion or exclusion of these variables. We proceed with models that include the information-source variables, while noting that results for these variables should be interpreted with at least some caution due to possible endogeneity.

Existing studies highlight the importance of CC information for adoption (Snapp et al. 2005; Arbuckle and Ferrell 2012; Miller et al. 2012; Carlisle 2016), and we seek insight about the relative impact of different information sources in reducing barriers. Indeed, the naïve hypotheses are that each source should reduce barriers. However, we also hypothesize that farmers who obtain information on CC from public agencies (e.g., Departments of Agriculture, USDA NRCS, and extension agents) would be less likely to report barriers of all types because these agencies provide information that is designed to help farmers overcome barriers. In contrast, it is possible that information from private networks might have some built-in

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Table 2
Summary statistics of variables used in regressions.

Variable	Maryland Mean	Maryland sd	Ohio Mean	Ohio sd	*t*-test
Dependent variables					
ROI	0.29	0.45	0.38	0.49	−0.09***
COSTS-LABOR	0.34	0.47	0.36	0.48	−0.02
COSTS-SEED	0.41	0.49	0.39	0.49	0.02
EQUIPMENT	0.14	0.35	0.28	0.45	−0.14***
Explanatory variables					
Farm and farmers characteristics					
LNACRE	5.51	1.38	5.53	1.19	−0.02
EXPERIENCE <16	0.12	0.32	0.12	0.32	0.00
EXPERIENCE16-30	0.20	0.40	0.23	0.42	−0.03
EXPERIENCE31-45	0.40	0.49	0.41	0.49	−0.01
EXPERIENCE46+	0.29	0.45	0.23	0.42	0.06**
CONVTILL	0.29	0.45	0.55	0.50	−0.26***
CONSTILL	0.41	0.49	0.51	0.50	−0.10***
NOTILL	0.87	0.34	0.65	0.48	0.22***
CORN	0.80	0.40	0.86	0.35	−0.06***
SOYBEANS	0.90	0.30	0.97	0.18	−0.07***
WHEAT	0.46	0.50	0.55	0.50	−0.09***
OTHERCROP	0.36	0.48	0.20	0.40	0.16***
IRRIGATION	0.29	0.45	0.04	0.18	0.25***
Information sources					
INFOEXTAGENT	0.51	0.50	0.44	0.50	0.07***
INFODEALERS	0.29	0.45	0.40	0.49	−0.11***
INFOEXTWEB	0.23	0.42	0.16	0.37	0.07***
INFODISTICT	0.75	0.43	0.48	0.50	0.27***
INFOSTATE	0.69	0.46	0.23	0.42	0.46***
INFOOHNOTILL	—	—	0.12	0.32	—
INFONRCS	0.44	0.50	0.22	0.41	0.22***
INFOFB	0.17	0.37	0.17	0.38	0.00
INFOFARM-NEIGH	0.36	0.48	0.40	0.49	−0.04
INFONOFARM- NEIGH	0.21	0.41	0.23	0.42	−0.02
INFOOTHERS	0.09	0.08	0.08	0.08	−0.01
N	546		1,250		

Notes: Original data collection by authors. The option of *INFOOHNOTILL* only exists for respondents in Ohio. Given that the Maryland and Ohio survey only has few observations for *INFOGROWERS* (0.05 for Maryland and 0.04 for Ohio), *INFOOTHER* (0.04 for Maryland and 0.04 for Ohio), the researchers grouped these two options in both states and renamed as *INFOOTHERS*.
*** $p < 0.01$, ** $p < 0.05$.

biases that attenuate barrier-reducing potential; for instance, a seed company might favor a more capitalized model of agriculture and thus this information source might be associated with an increase in labor barriers. We also expect the two farmer-information sources to be the least likely to reduce barriers because their objective functions do not necessarily involve CC promotion.

Statistical Methods. CC adoption studies often have dichotomous dependent variables (adopt/not adopt) analyzed with discrete choice regression techniques such as logit or probit models. The model in this paper is similar; however, four response variables (barriers) are simultaneously modeled using a more general MVP (Greene 2012) (equation 1):

$$y^*_m = x'_m \beta_m + \epsilon_m,\ m = 1,\dots, M, \tag{1}$$

$$y_m = 1 \text{ if } y^*_m > 0,\ y_m = 0 \text{ otherwise,}$$

where the y^*_m is a vector of unobserved latent variables of respondents' perceptions about whether barriers $m = 1,\dots, M$ exist (subscript m references each barrier), x_m is a vector of observable influences, and ϵ_m is a vector of unobservable influences that are treated as errors. The equation error distributions are assumed multivariate normal with zero means and a variance-covariance matrix R, where R has 1s on the leading diagonal and correlated coefficients ρ_{mn} between equation m and n on the off-diagonal elements.

If the unobserved latent variable for a farmer's opinion on a specific barrier (y^*_m) is positive, then the farmer has reported this factor (y_m) to be a barrier to CC use. These perceptions may overlap across different barrier types—for instance, the perception of a *ROI* barrier may be related to concerns about the equipment needed to plant CC. The MVP model allows one to test whether the observed variables affect one barrier in the same way or differently than other barriers (e.g., $\boldsymbol{\beta}_{1l} \neq \boldsymbol{\beta}_{1k}$ where l and k indicate different set of barriers).

The MVP model also tests for variation across barriers through unobserved components via the correlation coefficients (ρ). The unobserved variations may come from the potential connections between farmers' perceptions of barriers to adopt CC. However, the omitted variables that are unmeasurable (or costly to measure) explanatory variables, such as awareness of and concern about the environmental impact and farmland quality, can also contribute to the unobserved variations. For example, some types of farmers may simply be predisposed to perceive many types of CC adoption barriers, *ceteris paribus*. Because the adoption barriers are binary outcomes with potential correlation in unobserved components, the MVP model is more appropriate than a univariate model. The univariate models, which ignore the unobserved and common factors and correlation among adoption barriers and estimate the models independently, can lead to inefficient and less informative estimates (Kassie et al. 2013; Lin et al. 2005; Mulwa et al. 2017). The model is estimated using maximum likelihood with GHK simulation (Cappellari and Jenkins 2003).

Survey Methods. The survey was implemented using a mixed-mode mail/internet approach from late January to March of 2018. The survey sample frame was all potential CC growers in Maryland and the eight counties of northwest Ohio (Allen, Fulton, Hancock, Henry, Lucas, Putnam, Seneca, and Wood). To obtain a mailing list for this group, we obtained a list of commodity crop

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

(corn, soybean, and small grains) farmers from the USDA Farm Service Agency, and supplemented this list in Maryland with an additional state program participant list and the Maryland Grain Producers and Utilization Board list. The combined mailing list was cleaned manually to remove duplicates, nonspecific location addresses (like post office boxes), corporation names that suggested an individual farmer might not be answering the survey, and businesses like golf courses and cemeteries. This procedure yielded 8,774 names to which survey invitation letters were sent (5,551 in Ohio; 3,223 in Maryland).

Survey implementation followed the tailored design method for mixed-mode surveys outlined by Dillman et al. (2014). The first contact was a letter sent by postal mail that explained the purpose of the research and invited the respondents to complete an online version of the survey. This letter provided the URL and subject identification number necessary to access the survey. Paper surveys could also be requested. Three rounds of follow-up (reminder) mail contacts were sent to those who did not respond to earlier contacts, with a paper copy of the survey included with the third contact letter. This procedure yielded a total sample size of 2,804 completed surveys, with 1,845 from Ohio (65.8%) and 959 from Maryland (34.2%). Various respondents were subsequently excluded from this analysis based on survey responses, suggesting they were not potential CC growers. These included farmland owners who did not farm or had land entirely out of production, and hence were not making decisions with regard to CC planting. The overall response rate is 41.7% in Maryland and 37.4% in Ohio, but only some of the observations were usable and came from commodity crop farmers (59% in Maryland and 77% in Ohio). CC were familiar to the respondents; respectively, 95.4% and 74.5% of Maryland and Ohio respondents reported having planted CC at some point in the past.

The data used for the analysis are drawn from sections of the survey that asked about barriers to CC adoption (see above), with explanatory variables derived from questions on demographic, farming, and farm characteristics. The survey defined CC as "any crop planted for late fall, winter, or early spring seasonal vegetative cover." After initial data screening (see above) but before accounting for missing data on individual variables used within the model (due to incomplete survey questions), the data included 1,518 observations from Ohio and 716 from Maryland. There were 2,804 observations in total from the survey, but the presented models are estimated using survey responses only from landowners who plant commodity crops. This screen left 2,277 observations, and a further 481 observations were dropped because of missing values (table S3 in the supplementary files). However, as the regression analysis below models the two states separately and controls these factors in each analysis, the impact of missing values on parameter estimation is likely small. The final usable sample size is n = 1,796, with 546 from Maryland and 1,250 from Ohio.

Results and Discussion

The first subsection below explains the average respondent's view about which barriers affected CC use. The raw data show different orders and intensities among Maryland and Ohio samples, but in both states the four most important barriers are *ROI*, *COSTS-LABOR*, *COSTS-SEED*, and *EQUIPMENT*. The following two subsections explore the Ohio and Maryland responses using MVP regressions on the relationship among farm and agronomic characteristics and the four most important barriers. A final subsection compares the results for the two states.

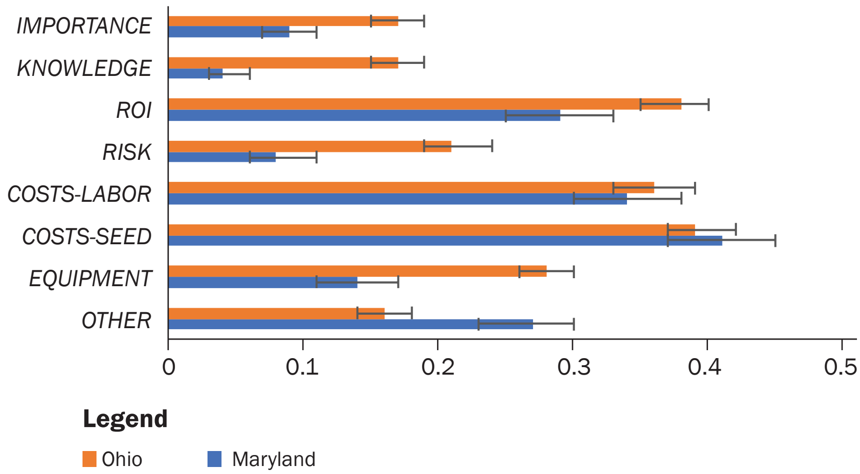
Descriptive Analysis. Figure 1 (the data in figure 1 are also presented in table form in supplementary materials, table S2) shows the percentage of respondents that reported whether each of the barriers affected their CC use. Given Maryland's robust CC program, it is not surprising that the three least-reported barriers for this state involved public education: *KNOWLEDGE* (4%), *IMPORTANCE* (9%), and *RISK* (8%). Instead, Maryland respondents were more likely to report barriers involving the financial viability of CC: *EQUIPMENT* (14%), *ROI* (29%), *COSTS-LABOR* (34%), and *COSTS-SEED* (41%). *OTHER* barriers were reported by 27% of Maryland respondents and 16% of Ohio respondents, but this category will not be analyzed as it means different things to different respondents. The "other" category was included to prevent respondents from forcing a missing category of barrier into one of the seven principal categories. Some respondents who answered "other" also filled in an open-ended answer. We did not recode open-ended answers back into the seven categories. In both Maryland and Ohio, 4% of respondents answered "other" and then wrote that there were no barriers to CC. Besides that answer-in-error, the most common "other" responses in Maryland were that the state program rules on planting were too restrictive (10%), weather (2%), and lack of funding (2%). In Ohio, the most common were program restrictions (3%), weather (2%), and a skepticism that CC improve environmental outcomes (2%).

Ohio respondents were more likely than those in Maryland to report five of the barriers as being relevant: *IMPORTANCE* (17%), *KNOWLEDGE* (17%), *ROI* (38%), *RISK* (21%), and *EQUIPMENT* (28%). Once again, this matches expectations given the relative lack of robust and longstanding state-level CC programs in Ohio, compared to Maryland. The most commonly reported four (out of seven) barriers in Ohio were the same as in Maryland. The MVP regression analyses focuses only on *EQUIPMENT*, *ROI*, *COSTS-LABOR*, and *COSTS-SEED*. This decision to exclude *KNOWLEDGE*, *IMPORTANCE*, and *RISK* is motivated by the lower importance of these barriers to farmers. This lesser degree of importance (along with other patterns common in these less-important barriers) also contributes to statistical challenges for the MVP model. The MVP regression, like dichotomous choice models in general, are less reliable when the dependent variable is dominated by a single outcome (e.g., when a barrier is rarely identified as relevant) or when the data set has little variation in both dependent and independent variables. In such cases, the data do not provide sufficient variation to support reliable statistical inference (i.e., it is difficult to identify statistically significant effects due to lack of variation in the data).

As respondents could identify more than one barrier, another set of descriptive statistics involve the patterns over multiple possible barriers that could be identified. Figure 2 (same data as supplementary table S4) shows the percentage of respondents in each state that identified zero, one, two, three, or four of the most important barriers. The most common permutation in both states was zero reported barriers, followed by one barrier (labor in Ohio and seed in Maryland). Not surprisingly, Maryland respondents were more likely to report zero

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Figure 1
Barriers to cover crop adoption from Ohio and Maryland.



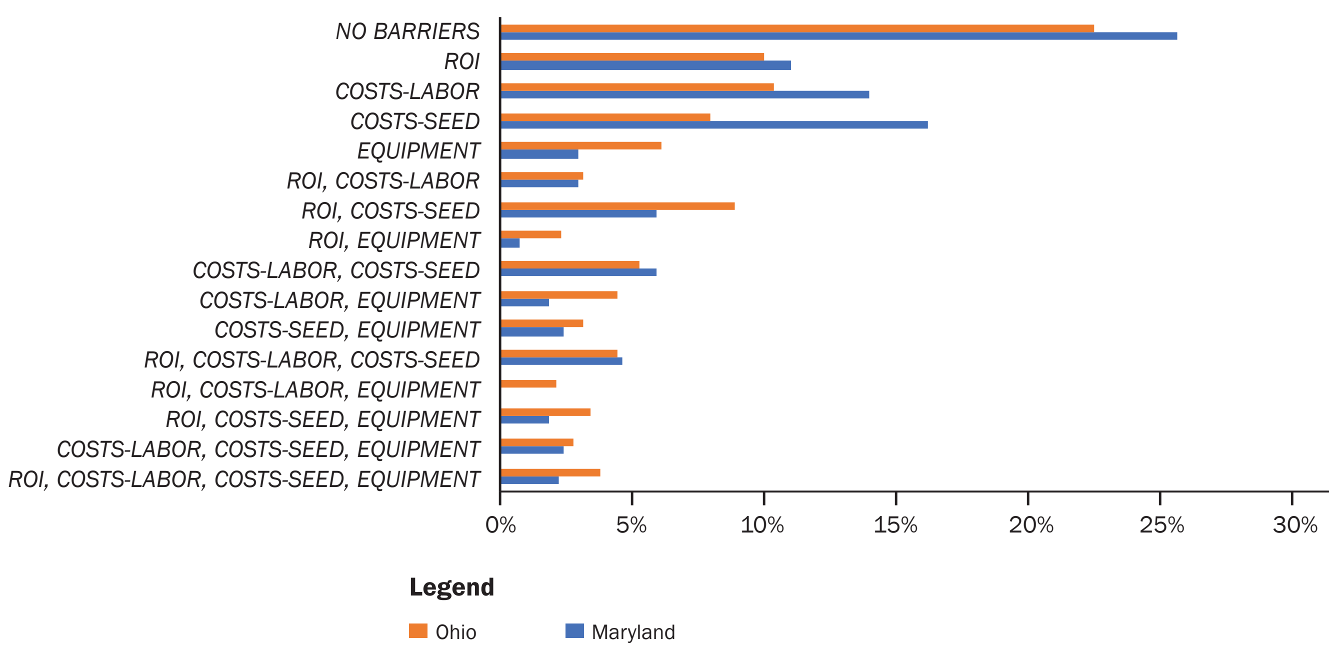
or one total barriers (69% versus 57%), while Ohio respondents were more likely to report two or three barriers (40% versus 28%). Only a small number of respondents in both states reported all four barriers as being relevant.

Table 2 includes summary statistics and *t* tests on the equality of means for all variables. The results show that most explanatory variable means are statistically different between Maryland and Ohio. Yet the states are similar in terms of acreage and farming experience. The mean and median acreages are almost identical (median acreage is 268 ac [108.5 ha] in Maryland and 250 ac [101.2 ha] in Ohio). Compared to the average harvested cropland acreage in 2017 Census of Agriculture (165 ac [66.77 ha] in Maryland and 173 ac [70 ha] in Ohio) (USDA NASS 2017), our samples have larger average acreages. Because we restrict our samples to farmers who are landowners and plant commodity crops (such as corn, soybeans, and small grains), this is expected. Over 65% of respondents in both Maryland (69%) and Ohio (65%) have farming experience over 30 years. Meanwhile, less than 12% of respondents are new farmers whose farming experiences are less than or equal to 15 years. The percentage of respondents in Maryland who have at least 46 years of farming experience is significantly higher than those in Ohio ($p = 0.022$).

Conventional and conservation tillage are more prevalent in Ohio (*CONVTILL* = 55%, *CONSTILL* = 51%) than in Maryland (*CONVTILL* = 29%, *CONSTILL* = 41%). Given the prevalence of CC in Maryland, tillage practices tended to be conservation till or no-till; 87% of respondents from Maryland claim that they use no-till, which is higher than the percentage in Ohio (65%). The corn–soybean cropping system is dominant in both Maryland and Ohio. Not surprisingly, over 90% of respondents from both states plant soybeans (97% in Ohio and 90% in Maryland) and over 80% plant corn (Ohio: 86% and Maryland: 80%). Wheat (*Triticum aestivum* L.) is third with about 50%, followed by other types of crops. *T*-tests show that the percentages of corn, soybeans, and wheat

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Figure 2
Reported patterns in barriers to cover crop adoption in descending order: survey responses from Ohio and Maryland.



adoption in Ohio are significantly higher than the percentages in Maryland (all $p < 0.01$). Another significant difference in farming operations is the adoption of irrigation between Maryland (29%) and Ohio (4%).

In terms of information sources about CC, the survey shows that Soil Conservation District Office is dominant for farmers to learn about CC in both Maryland (*INFODISTICT* = 75%) and Ohio (*INFODISTICT* = 48%). Except for the leading information source, respondents from Maryland and Ohio rank information sources differently; the top sources in Maryland are the state Department of Agriculture (*INFOSTATE* = 69%), extension agents (*INFOEXTAGENT* = 51%), USDA NRCS (*INFONRCS* = 44%), neighboring farmers (*INFOFARM-NEIGH* = 36%), and seed dealers (*INFODEALERS* = 29%). The top sources in Ohio are extension agents (*INFOEXTAGENT* = 44%), seed dealers (*INFODEALERS* = 40%), neighboring farmers (*INFOFARM-NEIGH* = 40%), nonneighboring farmers (*INFONOFARM-NEIGH* = 23%), and Ohio Department of Agriculture (*INFOSTATE* = 23%). We grouped *INFOGROWERS* (5%) and *INFOOTHER* (4%) because each option had few observations, and we named the combined variable *INFOOTHERS*.

Ohio Regression Results. Table 3 presents the MVP model using Ohio data. All statistically significant results on farming characteristics match prior hypotheses and expectations, though many variables lack statistical significance. Results provide multiple insights into the determinants of CC barriers in the state. The probability of reporting the *ROI* barrier increased with larger farms ($p = 0.0003$) and farmers that use conventional tillage ($p = 0.003$) or conservation tillage ($p < 0.0001$). In contrast, the probability that *ROI* is cited as a barrier decreases in farmers with extensive farming experience; this includes farming experience between 31 and 45 years ($p = 0.051$) and over 46 years ($p = 0.034$). The *ROI* barrier was less likely to be reported among those that planted *OTHERCROP* ($p = 0.074$). In Ohio, 20% reported planting other crops, which was much lower than corn, soybeans, and wheat. There was no statistical tendency to indicate the *ROI* barrier among those who plant corn, soybean, and wheat and among farmers with less than 31 years of experience, all else equal.

Table 3
Multivariate probit regression explaining barriers to cover crop use for Ohio.

Variables	*ROI*	*COSTS-LABOR*	*COSTS-SEED*	*EQUIPMENT*
Farm and farmers characteristics				
LNACRE	0.14***	0.10***	0.05	−0.06
	(0.04)	(0.04)	(0.04)	(0.04)
EXPERIENCE16-30	−0.21	−0.16	0.06	0.03
	(0.13)	(0.13)	(0.13)	(0.14)
EXPERIENCE31-45	−0.24*	−0.05	−0.10	0.18
	(0.12)	(0.12)	(0.12)	(0.13)
EXPERIENCE46+	−0.28**	−0.39***	−0.20	0.17
	(0.13)	(0.14)	(0.13)	(0.14)
CONVTILL	0.24***	−0.04	0.07	0.24***
	(0.08)	(0.08)	(0.08)	(0.08)
CONSTILL	0.39***	0.08	0.25***	0.11
	(0.08)	(0.08)	(0.08)	(0.08)
NOTILL	−0.05	0.03	0.11	−0.11
	(0.08)	(0.08)	(0.08)	(0.08)
CORN	−0.05	0.40***	−0.17	0.09
	(0.12)	(0.13)	(0.12)	(0.12)
SOYBEANS	0.26	−0.07	−0.15	0.47*
	(0.23)	(0.23)	(0.21)	(0.25)
WHEAT	0.02	−0.03	0.14*	−0.12
	(0.08)	(0.08)	(0.08)	(0.08)
OTHERCROP	−0.17*	0.09	0.07	−0.18*
	(0.10)	(0.09)	(0.09)	(0.10)
IRRIGATION	0.09	0.02	−0.02	−0.03
	(0.20)	(0.21)	(0.20)	(0.21)
Information sources				
INFOEXTAGENT	0.17**	0.01	−0.06	0.02
	(0.08)	(0.08)	(0.08)	(0.09)
INFODEALERS	−0.14*	0.22***	0.07	0.03
	(0.08)	(0.08)	(0.08)	(0.08)
INFOEXTWEB	0.07	0.05	−0.16	−0.18
	(0.11)	(0.11)	(0.11)	(0.12)
INFODISTICT	−0.14*	0.18**	−0.12	0.04
	(0.08)	(0.08)	(0.08)	(0.08)
INFOSTATE	−0.06	0.03	0.13	0.00
	(0.10)	(0.10)	(0.10)	(0.10)
INFOOHNOTILL	−0.03	−0.21*	−0.21*	−0.16
	(0.13)	(0.13)	(0.12)	(0.13)
INFONRCS	−0.02	−0.05	−0.02	−0.02
	(0.10)	(0.10)	(0.10)	(0.10)
INFOFB	−0.07	−0.18*	0.14	0.07
	(0.10)	(0.11)	(0.10)	(0.11)
INFOFARM-NEIGH	0.17**	0.04	0.29***	0.05
	(0.08)	(0.08)	(0.08)	(0.08)
INFONOFARM- NEIGH	−0.01	0.05	0.10	0.22**
	(0.09)	(0.10)	(0.09)	(0.10)
INFOOTHERS	−0.22	0.29**	−0.09	0.31**
	(0.14)	(0.13)	(0.10)	(0.14)

Table 3 continued

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Table 3 continued

Variables	*ROI*	*COSTS-LABOR*	*COSTS-SEED*	*EQUIPMENT*
CONSTANT	−1.34***	−1.28***	−0.60**	−1.04***
	(0.27)	(0.27)	(0.26)	(0.30)
Correlations				
ρ(*ROI, COSTS-LABOR*)		−0.06		
		(0.05)		
ρ(*ROI, COSTS-SEED*)		0.36***		
		(0.05)		
ρ(*ROI, EQUIPMENT*)		0.09*		
		(0.05)		
ρ(*COSTS-LABOR, COSTS-SEED*)		0.10*		
		(0.05)		
ρ(*COSTS-LABOR, EQUIPMENT*)		0.25***		
		(0.05)		
ρ(*COSTS-SEED, EQUIPMENT*)		0.16***		
		(0.05)		

Notes: Original data collection by authors. *n* =1,250. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The probability of identifying the labor-cost (*COSTS-LABOR*) barrier increased among farmers with large acreage (p = 0.008) and who plant corn (p = 0.002). Reporting the *COSTS-LABOR* barrier decreased among farmers with the most experience (p = 0.004). The *COSTS-SEED* barrier also had few associations; the results show that reporting this barrier increased with farmers who use conservation tillage (p = 0.002) and who plant wheat (p = 0.072). Respondents were more likely to report the *EQUIPMENT* barrier when using conventional tillage (p = 0.003) and planting soybeans (p = 0.059), but less likely when planting *OTHER* crops (p = 0.080).

No other patterns were detected on the *COSTS-LABOR*, *COSTS-SEED*, and *EQUIPMENT* barriers. Some of the results without significance may be due to the lack of variation in the independent variables. For instance, almost all Ohio respondents planted soybeans and corn—and two-thirds used no-till—so the limited variation in these farming techniques might reduce the ability of the model to identify significant effects (due to a lack of statistical power). However, in other cases the lack of significance may be due to a lack of true effect. For example, results show no statistically significant results linked to the use of irrigation, despite 29% the sample reporting that they use irrigation.

The regression also tests for patterns in information sources. We do not have strongly held hypotheses on the significance or direction of these relationships. In concept, we would expect information to be more strongly associated with the less-frequently reported education-type barriers (*IMPORTANCE*, *KNOWLEDGE*, and *RISK*), which were not studied in the MVP model. Nevertheless, some significant patterns were found. Farmers who received CC information from seed dealers (p = 0.095) and Soil Conservation District Offices (p = 0.087) are less likely to report that *ROI* is a barrier. This could be due to the private incentives of the organizations delivering information. As farmers are more likely to worry about the ROI if they received information from extension agents (p = 0.035) and neighbors (p = 0.036), it is possible that extension agents and neighbors are unbiased and/or communicate benefit and cost information separately. A possible reason is that extension agents and neighbors may have little systematic incentive to promote CC, so they should be less likely to overestimate CC's ROI relative to some of the other sources whose business/performance derives from greater CC use/program participation, and therefore may have incentives to (over-) promote the positive ROI from CCs. This could also be explained by certain types of farmers choosing to seek information from extension agents or perhaps the type of information provided by Ohio extension materials and programs, among other possible explanations.

Concerns about *COSTS-LABOR* increased among farmers who received CC information from seed dealers (p = 0.007), Soil Conservation District Offices (p = 0.027), and other information sources (p = 0.031). The first two results are interesting in that they almost perfectly counterbalance the lower probability results on reporting the *ROI* barrier. These results suggest that Ohio farmer interactions with seed dealers and conservation districts are systematically associated with the lower level of *ROI* concerns but the higher level of labor-cost concerns. Farmers who received CC information from Ohio No-Till Council (p = 0.100) and Farm Bureau (p = 0.082) are less likely to report the *COSTS-LABOR* barrier. Seed cost is more likely to be considered a barrier when farmers obtain information from neighbors (p = 0.0003), but less likely when the information comes from the Ohio No-Till Council (p = 0.063). Interestingly, the use of seed-dealer information sources is not systematically associated with lower perception of the *SEED-COST* barrier. Lastly, farmers are more likely to report the *EQUIPMENT* barrier if they received information from farmers other than their neighbors (p = 0.024) and other information sources (p = 0.026).

Table 3 also includes joint correlation tests for unobserved variation in each pair of adoption barriers. The results on the correlation between the equation error terms show that all correlation coefficients except for the one between *ROI* and *COSTS-LABOR* are statistically significant and positively correlated. The two highest estimated correlations were between *ROI* and *COSTS-SEED* (0.36, 95% CI: 0.26 to 0.46) and between *COSTS-LABOR* and *EQUIPMENT* (0.25, 95% CI: 0.15 to 0.35). Overall, the five correlations imply that there are complementary patterns in the reporting of barriers to CC use, which are not explained by the independent variables. That is, farmers who report one type of barrier as being relevant are more likely to report most others as being relevant. This may be due to a tendency of some farmers to perceive greater barriers to CC use of all types (and vice versa), *ceteris paribus*. It may also be due to influential factors that are not included in the model but could potentially be explored in future research.

Maryland Regression Results. Compared to Ohio, fewer statistically significant relationships were found in Maryland (table 4). Farmers who use no-till (p = 0.030) and who received information from neighboring farmers (p = 0.046) are more likely to identify the *ROI* barrier. Interestingly, this effect

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

of tillage practices appears to be the opposite of that in Ohio: in Ohio we observe a positive sign for *CONV* and *CONS* tillage with *ROI*, while in Maryland no-till has a positive relationship with *ROI*. The reason for this finding is unknown but suggests that the influence of current tillage practices on perceived *ROI* barriers can vary in important ways across different agricultural contexts. Although we lack the data to explore this divergence further, we highlight it as a potentially important issue for future research.

For the labor-cost barrier (*COSTS-LABOR*), the probability increased with larger acreage farms (p = 0.012), soybeans (p = 0.041), and obtaining CC information from the Maryland Department of Agriculture (p = 0.013). The labor-cost barrier was less likely to be reported when farmers use irrigation (p = 0.023). Only two associations were found for the seed-cost barrier (*COSTS-SEED*); farmers who use conventional tillage (p = 0.041) and obtain information from seed dealers (p = 0.052) were more likely to report the seed-cost barrier. Next, the *EQUIPMENT* barrier was less likely to be reported by farmers who have large acreage (p = 0.008) and plant wheat (p = 0.040), but more likely when planting other crops (p = 0.079) and receiving information from the Maryland Department of Agriculture (p = 0.001). Results show that three correlation coefficients are statistically significant, involving all four barriers. All three are positive, ranging from 0.21 to 0.38, indicating complementarity in the unobserved components of barriers.

Comparison. The Ohio models revealed 27 significant associations among the independent variables and the barriers, while the Maryland models revealed 12. In the unobserved variation, Ohio had five correlations, while Maryland had three. This implies that there are a greater number of systematic patterns that explain barriers in Ohio, compared to Maryland. These differences can potentially be explained by sample size difference between the two states or Maryland's greater funding for CC and longstanding state program, both of which may have reduced adoption barriers over time. In contrast, the less expansive state programs in Ohio may have contributed to larger, more variable and less idiosyncratic barrier perceptions. Beyond the Maryland CC programs, there also are significant differences between the two states

Table 4
Multivariate probit regression explaining barriers to cover crop use for Maryland.

Variables	*ROI*	*COSTS-LABOR*	*COSTS-SEED*	*EQUIPMENT*
Farm and farmers characteristics				
LNACRE	0.05	0.14**	−0.01	−0.17***
	(0.06)	(0.06)	(0.05)	(0.07)
EXPERIENCE16-30	−0.06	0.16	0.01	−0.12
	(0.22)	(0.22)	(0.21)	(0.25)
EXPERIENCE31-45	−0.02	−0.04	0.04	−0.23
	(0.20)	(0.20)	(0.19)	(0.23)
EXPERIENCE46+	0.05	−0.05	0.02	−0.34
	(0.21)	(0.21)	(0.20)	(0.24)
CONVTILL	0.09	−0.05	0.26**	0.15
	(0.13)	(0.14)	(0.13)	(0.16)
CONSTILL	0.12	0.08	0.02	−0.07
	(0.13)	(0.13)	(0.13)	(0.16)
NOTILL	0.42**	−0.15	0.13	0.22
	(0.19)	(0.19)	(0.18)	(0.21)
CORN	−0.10	0.19	0.06	−0.19
	(0.17)	(0.17)	(0.16)	(0.19)
SOYBEANS	0.07	0.48**	0.27	0.16
	(0.22)	(0.24)	(0.21)	(0.24)
WHEAT	−0.04	−0.06	−0.17	−0.31**
	(0.13)	(0.13)	(0.12)	(0.15)
OTHERCROP	0.05	0.18	0.13	0.28*
	(0.13)	(0.13)	(0.12)	(0.16)
IRRIGATION	0.11	−0.32**	0.02	−0.23
	(0.14)	(0.14)	(0.14)	(0.18)
Information sources				
INFOEXTAGENT	0.02	−0.07	−0.08	−0.17
	(0.13)	(0.13)	(0.12)	(0.15)
INFODEALERS	−0.19	−0.02	0.26*	0.15
	(0.14)	(0.14)	(0.14)	(0.17)
INFOEXTWEB	−0.04	0.07	−0.05	0.27
	(0.16)	(0.15)	(0.15)	(0.18)
INFODISTICT	−0.14	0.22	0.21	−0.02
	(0.14)	(0.14)	(0.14)	(0.16)
INFOSTATE	−0.18	0.35**	0.10	0.59***
	(0.14)	(0.14)	(0.13)	(0.18)
INFONRCS	0.12	0.12	−0.13	0.16
	(0.13)	(0.13)	(0.13)	(0.16)
INFOFB	0.03	−0.28	−0.09	−0.00
	(0.16)	(0.17)	(0.16)	(0.21)
INFOFARM-NEIGH	0.27**	0.03	−0.10	−0.25
	(0.13)	(0.13)	(0.13)	(0.17)
INFONOFARM-NEIGH	−0.15	0.23	0.06	0.08
	(0.16)	(0.16)	(0.15)	(0.19)
INFOOTHERS	0.11	−0.26	−0.29	−0.32
	(0.21)	(0.21)	(0.21)	(0.26)
CONSTANT	−1.15***	−2.10***	−0.81***	−0.50
	(0.34)	(0.39)	(0.31)	(0.35)

Table 4 continued

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

Table 4 continued

Variables	*ROI*	*COSTS-LABOR*	*COSTS-SEED*	*EQUIPMENT*
Correlations				
ρ(*ROI, COSTS-LABOR*)		–0.03		
		(0.08)		
ρ(*ROI, COSTS-SEED*)		0.21***		
		(0.07)		
ρ(*ROI, EQUIPMENT*)		0.12		
		(0.09)		
ρ(*COSTS-LABOR, COSTS-SEED*)		0.05		
		(0.07)		
ρ(*COSTS-LABOR, EQUIPMENT*)		0.20**		
		(0.09)		
ρ(*COSTS-SEED, EQUIPMENT*)		0.38***		
		(0.09)		

Notes: Original data collection by authors. n = 546. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in terms of tillage, crops, irrigation, and information sources (table 2).

In both cases, we find instances where one explanatory variable has the same effect on multiple adoption barriers within the state. In Ohio, five farm characteristics had the similar effects on multiple barriers. Respondents with more farmland are more likely to be concerned with the *COSTS-LABOR* and *ROI* for CC adoption. Respondents with the most farming experience are less likely to report those two barriers. Conventional tillage is positively associated with *ROI* and *EQUIPMENT*, while conservation tillage is positively associated with *ROI* and *COSTS-SEED*. In terms of information sources, farmers who learn about CC from farming neighbors are more likely to form barriers of *ROI* and *COSTS-SEED*.

However, results also identify several instances in which an explanatory variable has opposite effects on multiple barriers within a state. For example, farmers in Maryland who have large cropland acreage are more likely to report that labor costs are a barrier but less likely to be concerned with equipment as a barrier. Patterns such as these suggest the complexity of ways that different types of farm and farmer characteristics influence different types of barriers. They also suggest that actions taken to reduce some barriers might inadvertently increase others.

Among the most important comparative findings is the considerable difference between statistically significant barrier determinants identified in each state—as a whole, the farm and farmer characteristics that influence barriers in Ohio often differ from those in Maryland. This finding implies that one size does not fit all with respect to barrier determinants—a finding that a variable influences an adoption barrier in one state does not imply that the same pattern will apply in others. Hence, researchers should exercise caution when seeking to generalize case-study findings of this type in the literature.

For example, conservation tillage shows positive association with *ROI* for Ohio farmers but not in Maryland, whereas no-till has positive association with *ROI* for Maryland farmers but not in Ohio, and the coefficients are statistically different across states (p = 0.08 and 0.03, respectively). Planting soybeans and learning CC from the state Department of Agriculture are positively associated with *COST-LABOR* for Maryland farmers but not in Ohio, and the coefficients are again significantly different (p = 0.09 and 0.06, respectively). Farmers in Ohio who plant wheat and learn CC from their neighboring farmers are more likely to report *COSTS-SEED*, but not in Maryland. The coefficients for *WHEAT* and *INFOFARM-NEIGH* across states are significantly different (p = 0.04 and 0.008, respectively). Lastly, farmers in Maryland who use other crop or learn CC from the state Department of Agriculture are positively associated with *EQUIPMENT*, but not in Ohio, and the coefficients are significantly different across states (p = 0.02 and 0.004, respectively). The results of equality tests across equations are included in table S5 in the supplementary materials.

Discussion. The raw data on barriers and MVP model results provide insights that can be used to inform efforts to overcome CC barriers. First, the raw survey responses identify those barriers viewed as relevant by the largest proportion of farmers. For example, results suggest that concerns about CC seed (*COSTS-SEED*) are the most frequently identified. Other patterns in the raw responses might suggest challenges facing different types of farms—and thereby the type of issues that could be targeted by programs seeing to encourage greater CC adoption. For instance, a respondent who is more concerned with variable costs (labor and seed) might face different challenges than one who is capital constrained (equipment). Some respondents might be focused primarily on CC profitability (ROI) and not the costs—one sees this in about 10% of each sample. These respondents are possibly quite well informed about CC profitability and thus would be the most responsive to cost-share programs. Respondents reporting three or four barriers might be ones that CC programs should target last, for they would likely need the most incentive and/or education.

Second, we offer a more robust estimation technique (MVP model) that identifies what influences are associated with adoption barriers, including farm/farmer characteristics and CC information sources. This includes a set of potential factors that have not been studied extensively by prior work, particularly with respect to the types of barriers studied here. For example, our study identifies several systematic influences related to such dimensions as crop rotations, tillage, and information channels. The model also accounts for unobserved correlations across barriers that may have systematic effects beyond effects associated with observable factors. Hence, actions taken to address one barrier may have complementary effects on others.

Summary and Conclusions

This paper seeks to explain and better understand the factors associated with perceived barriers to CC adoption. The accumulated evidence suggests several conclusions. First, some farmers report no barriers (25.5% in Maryland and 22.3% in Ohio). Second, financial barriers are the most frequently mentioned by respondents. Financial barriers can be lowered with more cost-share, further agronomic research that results in strategies that lower the costs associated with planting CC, and other efforts that reduce information costs. Educational efforts could therefore emphasize how to best access cost-share.

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

However, if educators believe farmers' perceptions of financial barriers do not match scientific results—say because farmers' financial fears focus too much on short-term costs and not enough on long-term benefits—then the design and targeting of educational materials such as enterprise budgets may allay financial concerns. Indeed, as Arbuckle and Roesch-McNally (2015) concluded in their study, farmers need more information about CC benefits and risks.

Third and not surprisingly, CC education and cost-share will likely need to vary by state or region. This conclusion is more than a call for educational programming to vary among regions because CC cost-share programs, farmers' adoption patterns, and agriculture in general varies. Our results show that there are systematic differences across two states in factors that influence farmers' perceived barriers. In Ohio agriculture, where CC adoption is lower, more systematic patterns in barriers were found than in Maryland. This means that educators will be better positioned to develop targeted materials in Ohio. One example of many derived from the MVP coefficients suggests how to target materials. Materials that explain CC are financially sustainable after the first few years because of improved soil health (*ROI*) and explain how to best secure seasonal labor (*COSTS-LABOR*) should be delivered primarily to those with less than 30 years of farming experience who manage large acreages. This conclusion is available because those types of farmers are more likely to report those two barriers in Ohio. Delivering educational materials is costly, so better targeting allows for budgets to go farther and trigger more adoption. Further, location-specific challenges go beyond the scope of the model. For instance, in some areas agricultural input markets related to CC might be thin because there are few seed/equipment dealers or there may be few available CC species. Obviously, cost-share institutions will vary by region. Innovative educational programming will combine targeting information with active steps to overcome market challenges—one idea is to create web-based opportunities for farmers from one region to better access input markets from other regions. Arbuckle and Roesch-McNally (2015) made a related argument about the need for "facilitating infrastructure" to overcome technical hurdles—for instance, helping farmers access custom operators. In sum, the results imply that generic policies to reduce barriers are not likely to be as effective as possible across all states and regions, but opportunities to better target groups of farmers exist.

The study has limitations, which suggest several opportunities for further research. Of course, surveys in more states and regions would improve an educator's ability to understand barriers and design targeted materials. Additional research could help determine the extent to which similar findings apply to other study contexts and with different types of dominant crops and farming methods. Subsequent research could also examine whether results are sensitive to the specific description of barriers or the specific set of explanatory variables that may be relevant in different contexts. In addition, our results used statistical methods built on important assumptions. For instance, some might see the regression models as causal, while others might view them as correlations. We address endogeneity issues with respect to information sources but not with the choice of agronomic practices because we (1) viewed those practices as exogenous and (2) could not develop a better way to ask our survey questions. Nonetheless, this means that we cannot eliminate the possibility that the manner in which a farmer forms opinions about CC barriers might possibly affect decisions about crop type and tillage. Future surveys might be able to develop questions that improve causal inference by constructing agronomic measures that are unequivocally exogenous.

Another potential shortcoming in these results is that we do not present a model that accommodates heterogeneity in barrier perceptions between those who have adopted CC in the past (adopters) and those who have not (nonadopters). At the request of a referee, we present several prospective models in our supplementary materials that seek to answer this question in alternative, if preliminary, ways. One presents independent models for adopters and nonadopters (table S7 in the supplementary files), while another includes interactions with a variable that identifies past CC adoption (table S8 in the supplementary files). While these models provide suggestive evidence of limited differences between the two groups, they do not provide definitive results. For example, these results may be influenced by limitations on degrees of freedom and/or potential endogeneity between adoption behavior and barrier perceptions. The adoption measure used in these alternative models largely reflects past adoption behavior, while the barrier opinions reflect barriers to present and future adoption. Hence, one might argue that adoption behavior is temporally exogenous in a model of this type. Nonetheless, endogeneity and model specification remain a concern for these alternative models, largely because our study was not originally designed to test for these differences (hence the data are not well suited for this purpose). We therefore present these as supplemental models for comparison only, while highlighting this issue as an important area for future research. A final issue not considered here is the relative intensity of different barriers—we consider only a binary measure of whether a barrier is perceived as relevant (or not), not whether barriers are perceived as more or less important by each farmer.

Supplemental Material

The supplementary material for this article is available in the online journal at https://doi.org/10.2489/jswc.2022.00062.

Acknowledgements

This work is supported by Agriculture Economics and Rural Communities grant no. 2016-67023-24757 /project accession no. 1008736 from the USDA National Institute of Food and Agriculture and the Alabama Agricultural Experiment Station. We are grateful for assistance with Ohio focus groups from Ed Crawford, with Maryland focus groups from Anthony Riggi, and with the survey execution from TianHang Gao and Emerson Paradee.

References

Arbuckle, J.G., and J. Ferrell. 2012. Attitudes toward cover crops in Iowa: Benefits and barriers. Iowa Farm and Rural Life Poll. Ames, IA: Iowa State University Extension and Outreach 1–12.

Arbuckle, J.G., and G. Roesch-McNally. 2015. Cover crop adoption in Iowa: The role of perceived practice characteristics. Journal of Soil and Water Conservation 70(6):418–29. doi:10.2489/jswc.70.6.418.

Baumgart-Getz, A., L.S. Prokopy, and K. Floress. 2012. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. Journal of Environmental Management 96(1):17–25.

Bergtold, J.S., M. Anand, and J. Molnar. 2010. Limited access to conservation: Limited-resource farmer participation in the conservation security program in the southeast. Journal of Agricultural and Applied Economics 42(2):211-227.

Bergtold, J.S, P.A. Duffy, D. Hite, and R.L. Raper. 2012. Demographic and management factors affecting the adoption and perceived yield benefit of winter cover

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org

crops in the southeast. Journal of Agricultural and Applied Economics 44(1):99–116.

Burnett, E., R.S. Wilson, A. Heeren, and J. Martin. 2018. Farmer adoption of cover crops in the western Lake Erie basin. Journal of Soil and Water Conservation 73(2):143-155. https://doi.org/10.2489/jswc.73.2.143.

Cappellari, L., and S.P. Jenkins. 2003. Multivariate probit regression using simulated maximum likelihood. The Stata Journal 3(3):278–94.

Carlisle, L. 2016. Factors influencing farmer adoption of soil health practices in the United States: A narrative review. Agroecology and Sustainable Food Systems 40(6):583–613. http://dx.doi.org/10.1080/21683565.2016.1156596.

Daryanto, S., P. Jacinthe, B. Fu, W. Zhao, and L. Wang. 2019. Valuing the ecosystem services of cover crops: Barriers and pathways forward. Agriculture, Ecosystems and Environment 270–271(October 2018):76–78. https://doi.org/10.1016/j.agee.2018.10.021.

Dillman, D.A., J.D. Smyth, and L.M. Christian. 2014. Internet, Phone, Mail and Mixed Mode Surveys: The Tailored Design Method, 4th edition. New York: John Wiley and Sons.

Dunn, M., J.D. Ulrich-Schad, L.S. Prokopy, R.L. Myers, C.R. Watts, and K. Scanlon. 2016. Perceptions and use of cover crops among early adopters: Findings from a national survey. Journal of Soil and Water Conservation 71(1):29–40. https://doi.org/10.2489/jswc.71.1.29.

Featherstone, A.M., and B.K. Goodwin. 1993. Factors influencing a farmer' s decision to invest in long-term conservation improvements. Land Economics 69(1):67–81.

Fleming, P., E. Lichtenberg, and D.A. Newburn. 2018. Evaluating impacts of agricultural cost sharing on water quality: Additionality, crowding in, and slippage. Journal of Environmental Economics and Management 92:1-19.

Gabrielyan, G., S. Chintawar, and J. Westra. 2010. Adoption of cover crops and its effect on nitrogen use by farmers. *In* 2010 Annual Meeting, February 6-9, 2010. Orlando, FL: Southern Agricultural Economics Association.

Ghadim, A.K.A., and D.J. Pannell. 1999. A conceptual framework of adoption of an agricultural innovation. Agricultural Economics 21(2):145–54.

Greene, W.H. 2012. Prentice Hall Econometric Analysis, 7th edition. Hoboken, NJ: Prentice Hall.

Johnston, R.J., K.J. Boyle, W. Adamowicz, J. Bennett, R. Brouwer, T.A. Cameron, W.M. Hanemann, N. Hanley, M. Ryan, R. Scarpa, R. Tourangeau, and C.A. Vossler. 2017. Contemporary guidance for stated preference studies. Journal of the Association of Environmental and Resource Economists 4(2):319-405.

Kara, E., M. Ribaudo, and R.C. Johansson. 2008. On how environmental stringency influences adoption of best management practices in agriculture. Journal of Environmental Management 88:1530–1537.

Lichtenberg, E. 2004. Cost-responsiveness of conservation practice adoption: A revealed preference approach. Journal of Agricultural and Resource Economics 29(3):420–35.

Lee, S., and L. McCann. 2019. Adoption of cover crops by US soybean producers. Journal of Agricultural and Applied Economics 51(4):527-544.

Maryland Department of Agriculture. 2005. Maryland farmers' winter cover crop participation: Report on a mail survey and four focus groups of Maryland farmers. Baltimore, MD: Maryland Department of Agriculture. http://mda.maryland.gov/resource_conservation/Documents/ccreport.pdf.

Maryland Department of Agriculture. 2017. Maryland Department of Agriculture 2016-2017 Cover Crop Program. https://mda.maryland.gov/Documents/FY17ccplant.pdf.

McCann, L., and R. Claassen. 2016. Farmer transaction costs of participating in federal conservation programs: Magnitudes and determinants. Land Economics 92(2):256-272.

Miller, L., J. Chin, and K. Zook. 2012. Policy Opportunities to Increase Cover Crop Adoption on North Carolina Farms: A Report for the Union of Concerned Scientists. Master's project, Duke University.

Prokopy, L.S., K. Floress, J.G. Arbuckle, S.P. Church, F.R. Eanes, Y. Gao, B.M. Gramig, P. Ranjan, and A. S. Singh. 2019. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. Journal of Soil and Water Conservation 74(5):520-534. https://doi.org/10.2489/jswc.74.5.520.

Prokopy, L.S., K. Floress, D. Klotthor-Weinkauf, and A. Baumgart-Getz. 2008. Determinants of agricultural best management practice adoption: Evidence from the literature. Journal of Soil and Water Conservation 63(5):300–311. https://doi.org/10.2489/jswc.63.5.300.

Ranjan, P., S.P. Church, K. Floress, and L.S. Prokopy. 2019. Synthesizing conservation motivations and barriers: What have we learned from qualitative studies of farmers' behaviors in the united states? Society & Natural Resources 32(11):1171-1199. DOI:10.1080/08941920.2019.1648710.

Roesch-McNally, G.E., A.D. Basche, J.G. Arbuckle, J.C. Tyndall, F.E. Miguez, T. Bowman, and R. Clay. 2017. The trouble with cover crops: Farmers' experiences with overcoming barriers to adoption. Renwawable Agriculture and Food Systems 33(4):322–33.

Roley, S.S., J.L. Tank, J.C. Tyndall, and J.D. Witter. 2016. How cost-effective are cover crops, wetlands, and two-stage ditches for nitrogen removal in the Mississippi river basin? Water Resources and Economics 15:43–56. http://dx.doi.org/10.1016/j.wre.2016.06.003.

SARE (The Sustainable Agriculture Research and Education). 2017. Report of the 2016-17 national cover crop survey. College Park, MD: The Sustainable Agriculture Research and Education. https://www.sare.org/publications/cover-crops/national-cover-crop-surveys/.

Singer, J.W., S.M. Nusser, and C.J. Alf. 2007. Are cover crops being used in the US Corn Belt? Journal of Soil and Water Conservation 62(5):353–58.

Snapp, S.S., S.M. Swinton, R. Labarta, D. Mutch, J.R. Black, R. Leep, J. Nyiraneza, and K. O'neil. 2005. Evaluating cover crops for benefits, costs and performance within cropping system niches. Agronomy Journal 97(1):322–32.

Stuart, D., and S. Gillon. 2013. Scaling up to address new challenges to conservation on US farmland. Land Use Policy 31:223–36. http://dx.doi.org/10.1016/j.landusepol.2012.07.003.

Upadhyay, B.M., D.L. Young, H.H. Wang, and P. Wandschneider. 2003. How do farmers who adopt multiple conservation practices differ from their neighbors? American Journal of Alternative Agriculture 18(1):27–36.

USDA ERS (Economic Research Service). 2021. 2021 Farm Sector Income Forecast. Washington, DC: USDA ERS. https://www.ers.usda.gov/topics/farm-economy/farm-sector-income-finances/farm-sector-income-forecast/.

USDA NASS (National Agricultural Statistics Service). 2017. 2017 Census of Agriculture. Washington, DC: USDA NASS. www.nass.usda.gov/AgCensus.

USDA NRCS (Natural Resources Conservation Service). 2019a. NRCS Conservation Programs: Conservation Stewardship Program. Washington, DC: USDA NRCS. https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/fb08_cp_cstp.html.

USDA NRCS. 2019b. NRCS Conservation Programs: Environmental Quality Incentive Program. Washington, DC: USDA NRCS. https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/fb08_cp_eqip.html.

Vitale, J.D., C. Godsey, J. Edwards, and R. Taylor. 2011. The adoption of conservation tillage practices in Oklahoma: Findings from a producer survey. Journal of Soil and Water Conservation 66(4):250–64. https://doi.org/10.2489/jswc.66.4.250.

Weil, R., and A. Kremen. 2007. Thinking across and beyond disciplines to make cover crops pay. Journal of the Science of Food and Agriculture 87(4):551-557.

Copyright © 2022 Soil and Water Conservation Society. All rights reserved.
Journal of Soil and Water Conservation 77(2):198-211 www.swcs.org