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Improving targeting of farmers for enrollment in agri-environmental programs

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Abstract

Agricultural cost-share research and planning tend to focus on one program at a time, and hence overlook additional efficiencies that might be obtained by considering the possibility that enrollment decisions are related across different programs. Models of multiple-program participation decisions enable these relationships to be considered as part of conditional enrollment predictions, providing more complete and accurate understanding of enrollment behavior. Analysis of data from farmer surveys in Maryland and Ohio show complementary drivers across program participation. Results are consistent with economies of scale and/or scope among different agri-environmental programs. The data also show the gains in prediction accuracy when the model accounts for participation in other programs, thereby enabling improved targeting and program design. For instance, enrollment in commodity-type programs causes a much larger marginal increase (12.6%) in the probability of Maryland cover crops participation than does the increase from Conservation Reserve Program enrollment (4.4%).

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Government agencies often seek to increase the effectiveness of agri-environmental payment programs (c.f. Claassen et al., 2008; Huber et al., 2017; Palm-Forster et al., 2019; Pannell & Claassen, 2020), and a rich research literature informs both adoption decisions and the evaluation of program effectiveness. Farmers often enroll in multiple programs simultaneously. For instance, US farmers may enroll in several federal programs, including the Conservation Reserve Program (CRP), Wetlands Reserve Program, Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), and might also enroll in state programs that incentivize similar land practices, such as the Maryland Agricultural Water Quality Cost-Share Program (MACS). When seeking to understand farmers' enrollment in programs such as these, researchers typically evaluate only one program at a time, which matches how governments tend to compartmentalize program administration. This paper shows that models that enable farmers' program enrollment decisions to be considered as a simultaneous portfolio rather than as independent choices may provide additional insight.

There are several economic reasons why—from the farmer's perspective—participation decisions ought to be related and, therefore, modeled simultaneously. For example, program enrollment involves a farmer–agency interaction and often a practice adoption or production adjustment. Although programs have different selection criteria or mechanisms, the farmer–agency interactions are often similar in information gathering, application forms, interactions with government staff, willingness to be monitored, and other features. As a result of these similarities, a farmer might experience a lower marginal cost of enrolling in an *additional* program once they are already enrolled in others. This argument is consistent with recent research that frames the "complexity" and "stringency" of agri-environmental program contracting in terms of transaction costs (respectively, Palm-Forster et al., 2016; Peterson et al., 2014), wherein a reduced marginal cost of enrolling in an additional program (conditional on prior enrollment in other programs) represents an economy of scale as one enrolls in a larger number of programs.

There may also be potential economies of scope among individual programs.[1] For example, the variety of agronomic, technological, eligibility, learning, and budget constraints on participation might create opportunities for an optimizing farmer to earn more profit by strategically mixing cost-shared agricultural best management practices (BMPs) and more traditional agricultural policies (such as disaster relief, commodity support, and crop insurance). As an illustration, enrolling farmland in CRP that is most likely to suffer flood losses would raise actual production history and, in turn, might create opportunities to increase net returns from crop insurance or anticipated disaster relief. These potentially joint CRP and insurance choices might also create different incentives to enroll remaining farmland in EQIP or CSP's soil/nutrient retention practices such as cover crops (CC). There are also explicit examples where governments provide purposeful monetary scope incentives, such that participating in one program provides a bonus in another program.[2] A final reason why optimizing farmers might

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consider a portfolio of programs is that farmers recently have relied more on direct government payments. These payments accounted for 20%–34% of net cash income in 2018–2021, up from 8% to 14% in 2012–2017.[3] Obtaining payments of this magnitude typically requires simultaneous enrollment in multiple programs of different types, and hence farmers who are heavily reliant on these payments may seek to enroll in multiple complementary programs.

If indeed program enrollments are potentially related in ways such as these, then program design cannot be truly optimized (e.g., for efficiency or other program goals) without an understanding of how farmers make decisions across a portfolio of programs. For example, empirical evidence of this type might reveal systematic patterns wherein farmers' operational characteristics (size, cash crop, age, etc.) lead to increases in the probability of participation in multiple programs (i.e., complementary enrollment). When participation is complementary across multiple programs, then the marginal incentive needed to induce *one additional* program participation should be lower if a farmer is already enrolled in others, because the conditional likelihood of participation is greater.[4] Accounting for enrollment patterns such as these can therefore enable agencies to incentivize program participation in a more cost-effective manner. Other issues such as eligibility and inter-program competition arise when enrollment is substitutable.

Conversely, without systematic information on how enrollment is related across different programs, administrators and policy makers have no way to capitalize on such behaviors in program design. Although a few studies have sought to understand related enrollment decisions such as these (see the next paragraph), this type of decision-making and the forces that inform it are generally underappreciated in both the literature and in applied program design, which tends to be compartmentalized as noted above. This paucity of insight and attention motivates the joint estimation presented in this paper.

Although many single adoption and single agri-environmental program enrollment studies exist, only a small set of studies have sought insight from simultaneous models that seek to explain farmer enrollment decisions in multiple programs or the adoption of multiple practices or technologies. Several well-cited early efforts used multinomial logit and tended to address the adoption of multiple technologies or management practices (Caswell & Zilberman, 1985; Cooper, 2003; Dorfman, 1996; Wu & Babcock, 1998; Zepeda, 1990). However, given that the independence of irrelevant alternatives assumption limits the applicability of multinomial logit model (Greene, 2018), recent studies emphasize multivariate probit (MVP) models. Examples include MVP models used to study the adoption of multiple conservation practices (Cooper & Keim, 1996; Fleming, 2017; Fleming et al., 2018; Ward et al., 2018), partial versus whole-farm participation in CRP (Chang & Boisvert, 2009a), joint participation in CRP and off-farm work (Chang & Boisvert, 2009b), soil fertility management practices (Kamau et al., 2014; Khanna, 2001; Weber & McCann, 2015), and climate adaptation (Maguza-Tembo et al., 2017; Trinh et al., 2018).

These and other prior multiple-decision studies tend to emphasize practice or technology adoption rather than enrollment. Multiple-program enrollment studies are an important complement to adoption studies such as these because, though enrollment usually implies adoption, the decision is somewhat different, and the link is more direct for increasing program participation. To our knowledge, Duke (2004) and Chang and Boisvert (2009a, 2009b) are the only published MVP papers that have studied agri-environmental program participation decisions directly—as opposed to practice or technology adoption. Duke (2004) applies a trivariate probit model to evaluate enrollment in Delaware's agricultural lands preservation program, federal commodity programs, and federal conservation programs. Although this study provides relevant insight, it is limited by a focus on a single state and comparably small and homogeneous

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set of programs. Given the heterogeneity of farming operations, government programs and other relevant considerations across states and regions, it seems unlikely that any one single-state study of this type can fully inform whether and how joint enrollment decisions are made across other programs and states. Chang and Boisvert (2009a, 2009b) used US data to examine the CRP enrollment decision with two types of related decisions. The second decision in Chang and Boisvert (2009a) involved whether a farmer put all or part of their farm in CRP. Chang and Boisvert (2009b) examine whether to work off the farm. Both of these related studies model non-CRP program enrollments as independent variables. For instance, Chang and Boisvert (2009b) included farmland preservation, EQIP, and the commodity program payment-type measure as explanatory variables after testing for exogeneity.

Building on this prior work, the present article seeks to provide broader and (arguably) more generalizable evidence on multiple-program enrollment, considering new data, a larger and more diverse set of programs, and results compared over multiple states in two different US regions (Mid-Atlantic versus Midwest). We also introduce a method to generate conditional enrollment predictions into the agri-environmental enrollment literature; this method of converting MVP results into more policy-relevant behavioral predictions differs from Chang and Boisvert (2009b) and was adapted from a paper in health policy evaluation (see below).

To enable the modeling outlined above, this article presents a new, original data set on farmers' enrollment behavior across multiple types of agri-environmental programs, within two US states. The data are drawn from an original survey of Maryland and Ohio farmers, with 2028 total observations. We use this dataset to extend prior modeling in a way that provides more comprehensive and accurate enrollment predictions over multiple programs. The model first uses observable characteristics to explain enrollment in three types of conservation programs (CC cost-share, the CRP, and other conservation programs) and a composite indicator of agricultural commodity programs/crop insurance. We then convert these MVP model estimates into predictions of conditional enrollment probabilities that control for farm and farmer characteristics (such as acreage, household characteristics, and land management) and other voluntary program enrollments. The method used to calculate these probabilities is adapted from an approach developed for health policy research by Ramful and Zhao (2009).[5] Results enhance the ability of policy makers to make use of multiple-program studies by providing information in a more intuitive and usable form than is found in the prior literature.

Results identify significant drivers of enrollment across four types of programs within two states. Among these is acreage, which increases the probability of enrollment in almost all programs. However, most drivers are state-specific—highlighting the importance of evaluating these patterns on a state-by-state basis. Within each state, there is substantial evidence of complementary in enrollment decisions. Evidence of statistically significant correlation across program enrollment decisions suggests that the MVP model is more efficient and informative than four independent univariate probit (UVP) models, thereby leading to more accurate predictions of enrollment probability. Because a principal interest of program managers is predicting enrollment (rather than testing hypotheses, which is a common focus of academics), the enhanced prediction accuracy of these models is a key advantage.

Illustrative examples of conditional CC enrollment decisions clarify how and why these multiple-program enrollment patterns are relevant. For instance, enrollment in commodity-type programs causes a much larger marginal increase (12.6%) in the probability of Maryland CC participation than does the increase from CRP enrollment (4.4%). Results such as these can help program managers target enrollment to those most likely to participate (i.e., given their prior enrollment decisions in other programs). For example, as with the recent 2021 Pandemic

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Cover Crop Program, program managers could design bonus payments for farmers who are signing up for one program if they add additional programs; if program enrollments are complementary, these bonus payments should be less in an optimal program design than payments offered in single-signup programs. However, this guidance does not apply if enrollments are independent (or instead act as substitutes). Results also demonstrate that the potential advantage of MVP predictions over single UVP counterparts increases as the number of potential programs (and hence related enrollment decisions) grows. Taken together, these results suggest the need for greater attention to joint program enrollment decisions across different agricultural settings.

AN ECONOMIC EXPLANATION OF MULTI-PROGRAM ENROLLMENT

The standard single-program adoption/enrollment model assumes that a farmer has only one program decision, though this is analytically equivalent to multiple-program decisions when the decisions are independent; we refer to these situations as "univariate" enrollment models in that the farmer maximizes utility by independently choosing whether to enroll in a series of programs. An independent random utility model (RUM) represents each decision, where a farmer accepts cost-share to enroll in the program if the farmer's indirect utility with the program is larger than the utility level without the program.

Univariate approaches of this type imply that farmers' enrollment decisions in different types of programs are independent—an assumption that is almost certainly incorrect for many agricultural contexts. Here, instead, we assume that farmers consider a portfolio of potentially (although not necessarily) related enrollment decisions. This assumption leads naturally to the presented MVP model. We assume that each farmer decides the combination of available voluntary agricultural conservation and production programs in which to enroll based on the incentives that are provided by each program (or cost-share), moderated by characteristics of the farming operation and surrounding context. Participation may require various types of BMP adoption and/or adjustments to status quo production. To simplify the model, we assume that all adoption without cost-share has already occurred and hence focus on marginal enrollment decisions.

Theoretical and empirical advantages of multivariate modeling

The MVP model has a number of well-known advantages for explaining interrelated decision processes (Greene, 2018; Khanna, 2001). First, independent UVP models are inefficient when used to model decisions that are made jointly. In such cases, otherwise correctly specified UVP models may provide *consistent* estimates of model parameters, but the resulting *inefficiency* reduces accuracy[6] (Greene, 2002, 2018; Khanna, 2001). When decisions are correlated, MVP models provide more precise predictions—a theoretically anticipated result that is verified by our empirical findings below.

Perhaps more importantly, however, the inherent relationships between simultaneous enrollment or adoption decisions are often of direct relevance to policy makers. Ward et al. (2018, p. 29) argue that MVP captures "the richness and complexity of the decision-making process," where the joint estimation framework is not only able to "quantify the effects

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of observed characteristics on two or more decisions" (Chang & Boisvert, 2009a, 2009b, p. 83), but also address "the same unobserved characteristics that may influence adoption decisions for all inter-related components" (Khanna, 2001, p. 37). Moreover, as noted by Greene (2018, p. 818), the estimate of ρ between any two models represents the "correlation between the disturbances in the equations, the omitted factors. That is, ρ measures (roughly) the correlation between the outcomes after the influence of the included factors is accounted for." Hence, the MVP model not only provides statistical evidence for whether a correlation exists but the direction of this correlation. In the present application, this estimate thereby provides insight into whether program enrollments are viewed as substitutes or complements from the perspective of the farmer—an important result from the perspective of program targeting and design. This information is unavailable from standard UVP models.[7]

For reasons such as these, MVP approaches are simultaneously expected to be more precise, informative, and tractable than UVP alternatives. Moreover, the significance of ρ for each model pair provides evidence on whether the use of joint modeling is warranted. The results presented below illustrate these advantages for our case study.[8]

Theoretical foundations and empirical methods

Theoretical models underlying these types of joint decisions in the literature reflect relatively standard applications of RUM applied to a portfolio of related enrollment decisions and allowing correlated errors. Given the standard structure of these theoretical models, we present the details formally in Part I of the Appendix and focus discussion here on the intuition, assumptions, and caveats of the resulting empirical application (which is specific to our enrollment case study application).

When developing models of this type, it is important to recognize implicit assumptions and issues that are (and are not) modeled explicitly. Among these, we acknowledge that program enrollment is not a unilateral decision made by a farmer. Many programs have budget constraints, which lead to selection criteria, eligibility constraints, and/or the use of auction-type mechanisms by sponsoring agencies. For instance, programs like EQIP fund only 27.7% of applications (CRS 2020). However, the complexity of modeling and surveying the processes that lead to enrollment result in an economic literature wherein almost all single-and two-program empirical analyses largely or entirely abstract from these issues (c.f. Chang & Boisvert, 2009a, 2009b; Jang & Du, 2018; McCann & Claassen, 2016; Mishra & Khanal, 2013; Suter et al., 2008). That is, to promote tractability, it is standard practice to model enrollment decisions from the perspective of the farmer while abstracting from selection processes by sponsoring agencies. The present analysis follows in this tradition: we abstract from selection processes and assume that all respondents can potentially enroll in all programs.[9] As we restrict attention to a subset of farmers who are likely to be eligible (landowning farmers growing commodity crops) and we measure whether respondents have ever enrolled in a program over a long time period (2000–2016), we believe selection processes should exclude few if any of our respondents in a systematic way. Finally, we follow conventions in most of this literature by using "program enrollment" and "program participation" interchangeably.

We also emphasize that the farmer's decision is assumed to be based on utility maximization, where utility is assumed to be determined—among other things—by the net cost of program enrollment and the cost-share provided by the program. Models of this type are more appropriate than alternatives based on purely financial considerations (e.g., calculating the

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farmer's costs and comparing these costs to the provided cost-share). For reasons described below, the researcher cannot directly observe the net cost of program enrollment (prior to receipt of the cost-share). However, following standard practice, this cost is assumed to be composed of all net costs of the farmer's full set of marketed and unmarketed activities within the program relative to not being in the program (i.e., all the private benefits and costs of adoption are included). We further assume that these costs are determined by underlying farm characteristics that can be considered exogenous. Hence, any systematic cost differences across farms can be captured in the model via the inclusion of the underlying farm characteristics that determine those costs. Given this foundation, farmers are assumed to enroll in a single program if the cost-share is larger or equal to the farmer's cost, with the latter assumed known to the farmer and determined by farm characteristics and other exogenous variables.

We emphasize that the resulting model is not a simple "financial" model, wherein we attempt to calculate single-period farmer costs and compare them to the provided cost-share. There are multiple reasons for the specification of the model in "utility space" rather than "financial space." For example, incentivizing farmers to adopt new conservation practices may require cost-share payments that are greater than the short-term financial (or accounting) cost of the practices alone (Gramig & Widmar, 2018). With CC, for instance, Bowman and Lynch (2019) argue that soil health practice adoption requires an extended period of time before benefits are realized, which implies that the farmer's private benefits affecting willingness to accept (WTA) will tend to be lower because of discounting. Cost-share today can offset some of the costs of waiting for private benefits, and hence will not necessarily be available to cover all future costs of ongoing adoption. Further, multiple programs are available to farmers, and it would be too strong an assumption to generalize the prior condition by simply adding up all cost-share payments and comparing them to the sum of all assumed costs.

The presented RUM specification reflects this situation (see Appendix), wherein it is impossible for the researcher to directly observe the present value of costs perceived by the farmer for a combined set of program enrollments but where it is reasonable to assume the enrollment decisions are made by each farmer based on a benefit–cost criterion, where each farmer is aware of their own costs. Our decision rule further allows for possible economies in multiple adoptions, which we test empirically.

The model also reflects a situation wherein agencies exogenously assign cost-share from the farmer's perspective. Notwithstanding recent programs like the Pandemic Cover Crop Program, cost-share is typically separable and additive within actual programs, because payments do not vary if the farmer enrolls in multiple programs. However, the farmer's cost with multiple programs is unlikely to be separable and additive because of the spillovers from the farmer's perspective (see arguments on economies of scope and scale in the introduction). The intuition for the theoretical model is that farmers can identify the set of program enrollment decisions that provide the highest utility—including the cost-share payments and their internal knowledge of net costs—and that this relationship can be modeled probabilistically.

The resulting theoretical model is presented in the Appendix and leads to an empirical specification in which enrollment in each program may be modeled empirically as a function of underlying farm and farmer characteristics, along with formal cross-program relationships accommodated via the MVP specification. The econometric model (the MVP) has separate equations for each observed program. Explanatory variables are selected from survey data to describe farm and farmer characteristics: these are used to estimate observable effects in the RUM across the equations. Both observable and unobservable effects estimated across the program equations suggest spillovers, and measuring the unobservable effects requires

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simultaneous estimation. We hence adapt the MVP model of Greene (2018) to a quadrivariate choice version.

DATA

The data are derived from an online-mail, mixed-mode survey of Maryland and Ohio farmers conducted from January through March 2018. The sampling list was drawn randomly from the Farm Service Agency (FSA) master list of farmers and supplemented with lists from the state program participant list and the Maryland Grain Producers and Utilization Board list for Maryland's farmers. This survey covered potential CC growers who grow corn, soybeans, wheat, and small grains such as commodity crops in Maryland[10] and eight counties of northwest Ohio (Allen, Fulton, Hancock, Henry, Lucas, Putnam, Seneca, and Wood). The targeted farmers from the two states were invited to complete the online survey using *Qualtrics* or could request a matching paper version. Adjusting the sample for deceased individuals, duplicates, etc., led to a final mailing list of 2983 potential respondents in Maryland and 5411 in Ohio who were contacted. The survey response rate was 36.8% and 41.0% for Maryland and Ohio, respectively. Screening questions allowed us to isolate a subsample of landowners currently farming commodity crops, thereby excluding respondents who might not be making decisions about potential program enrollment.[11] The subsample of usable data included 60% of Maryland respondents and 78% of Ohio respondents. Maryland farmers were less likely to be landowning farmers growing commodity crops. Further data cleaning dropped respondents with missing values for any of the explanatory variables, leaving the sample used for data analysis: 2028 observations with 1372 from Ohio (67.7%) and 656 from Maryland (32.3%).

The dependent variables derive from a survey question that addressed enrollment in different types of agri-environmental programs. For example, the Ohio question was:

Between 2000 and 2016, did you sign up for any of the following government programs? (check all that apply)

1. *USDA commodity programs or crop insurance*
2. *USDA CRP*
3. *Other USDA conservation programs for cover crops (for example, EQIP, CSP)*
4. *Other USDA conservation programs for things other than cover crops (for example, EQIP, CSP, CREP, WRP)*
5. *Any state or local farm/conservation programs for cover crops (for example, TMACOG, GLRI, Beaver Creek, Tontogany)*
6. *Other state or local farm/conservation programs for things other than cover crops (for example, Beaver Creek, Bull Creek, GLRI NRP)*

The Maryland version had different state and local programs but was otherwise identical. A footnote defined abbreviations. The first two options were used to define the variables *PROGCOMM* and *PROGCRP* (Table 1). The option for local, state, or federal cost-share programs for CCs became the variable *PROGCC*; the principal program in Ohio is EQIP, while in Maryland it is MACS.[12] The last category represents all federal and state/local programs for BMPs other than CC (*PROGOTH*). For the explanatory variables, 15 variables in Table 1 control farm and farmer characteristics.

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TABLE 1 Summary statistics for program enrollment and farm characteristics from the survey of Maryland and Ohio farmers

		Maryland		Ohio		
Variables	**Explanation**	**Mean**	**SD**	**Mean**	**SD**	**Difference**
Dependent variable						
PROGCC	Federal and state cover crop programs	0.80	0.40	0.21	0.41	0.60***
PROGCRP	USDA Conservation Reserve Program	0.34	0.47	0.37	0.48	−0.03
PROGCOMM	USDA Commodity program or crop insurance	0.56	0.50	0.67	0.47	−0.12***
PROGOTH	Federal and state conservation programs for things other than cover crop	0.38	0.49	0.18	0.38	0.20***
Explanatory variable						
LNACRE	Acreage of cropland in log form	5.51	1.41	5.47	1.21	0.04
CONVTILL	Indicator: 1 = Conventional tillage in 2017	0.29	0.45	0.53	0.50	−0.25***
CONSTILL	Indicator: 1 = Conservation tillage in 2017	0.40	0.49	0.50	0.50	−0.10***
NOTILL	Indicator: 1 = No-till in 2017	0.86	0.34	0.65	0.48	0.21***
CORN	Indicator: 1 = Produce corn in 2017	0.80	0.40	0.85	0.36	−0.05**
SOYBEANS	Indicator: 1 = Produce soybeans in 2017	0.89	0.31	0.96	0.19	−0.07***
WHEAT	Indicator: 1 = Produce wheat in 2017	0.47	0.50	0.55	0.50	−0.08***
OTHERCROP	Indicator: 1 = Produce crops other than corn, soybeans, and wheat in 2017	0.37	0.48	0.20	0.40	0.17***
EXPERIENCE ≤ *20*	Indicator: 1 = Farming experience less than or equal to 20	0.20	0.40	0.18	0.38	0.02
EXPERIENCE21-40	Indicator: 1 = Farming experience between 21 and 40	0.41	0.49	0.44	0.50	−0.03
EXPERIENCE40+	Indicator: 1 = Farming experience above 40	0.39	0.49	0.38	0.49	0.01
IRRIGATION	Indicator: 1 = Use irrigation	0.30	0.46	0.03	0.18	0.26***
GCFIUNDER150	Indicator: 1 = GCFI under 150,000	0.49	0.50	0.62	0.49	−0.13***
GCFI150TO350	Indicator: 1 = GCFI between 150,000 and 349,999	0.19	0.39	0.19	0.39	−0.00
GCFIOVER350	Indicator: 1 = GCFI over 350,000	0.32	0.47	0.19	0.39	0.13***

Note: After dropping missing observations, the final dataset is 2028 with 1372 from Ohio and 656 from Maryland. Original data collection by authors. Conventional tillage refers to the case that less than 30% of the soil surface is covered by residue after planting. Conservation tillage refers to the case that at least 30% of the soil surface is covered by residue after planting. No-till refers to no soil disturbance prior to planting. GCFI was developed by USDA ERS to measure farm income. Total sample size is 2028. Difference of means *t* test, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Abbreviation: GCFI, gross cash farm income.

Within the MVP, these explanatory variables are hypothesized to explain farmers' choices of whether to enroll in the four types of programs. Although one could form ex ante hypotheses on the direction of effects (e.g., larger farms are more likely to enroll in commodity programs) linked to individual parameters, we refrain from this exercise given the very large number of these hypotheses that could be stated ($N = 104$) and because the primary focus of the analysis is comparison across programs, the extent to which joint estimation enhances model predictions,

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the possibility of complementary or contrary drivers across program types, and potential economies of scale/scope as discussed above. That is, the key hypotheses of interest relate to the additional information provided via joint MVP estimation—not individual variable effects within each model in isolation.

As an illustrative example, results shown below demonstrate that larger farm acreage leads to higher probabilities of enrolling in commodity programs; however, the effect of acreage on the farm operation is greater than the effect on commodity program enrollment alone. For example, acreage has a similar effect on CRP and cover crop program enrollment. A UVP study of commodity program enrollment alone would be unable to discern and therefore underestimate the acreage effect on broader enrollments. The driver hence has a complementary effect across enrollment multiple programs, which suggests an underlying efficiency that would not be captured by studies of each program in isolation. Correlation coefficients in the MVP model can further identify relationships between enrollment across programs due to unobserved effects captured in the model disturbances. Finally, comparison of results across two states, in two distinct US regions (Ohio in the Midwest and Maryland in the Mid-Atlantic), helps to illustrate the extent to which patterns of this type can vary across agricultural settings.

Table 1 shows descriptive statistics for model variables, with *t*-tests comparing the means for Maryland and Ohio respondents. As expected, farm characteristics and program enrollments differ across the two states. In Maryland, 80% of respondents received CC cost-share between 2000 and 2016 in contrast to 21% in Ohio. Maryland respondents also had higher enrollment in other conservation programs; the Ohio enrollment rate was only 18% over the period studied. Yet Ohio respondents were more likely to enroll in commodity programs. Approximately one-third of respondents report enrollment in CRP in both states.[13] As respondents could report more than one program, Table A1 presents multiple-enrollment patterns. Of 16 possible enrollment combinations, few farmers enroll in all programs (13% in Maryland and 5% in Ohio) or in none (7% in Maryland and 16% in Ohio). The modal enrollment combination in Maryland was commodity and CC programs (18%) followed closely by CC programs alone (17%), while in Ohio, the modal response was the commodity program alone (32%).

Table 1 further shows that respondents in Ohio and Maryland report different average farm characteristics, as revealed by several explanatory variables. In contrast to the 2017 Census of Agriculture, our samples have larger acreage, more farming experience, higher adoption rates of conservation practices (e.g., conservation tillage); our focus on landowners who farm commodity crops explains this difference, which overrepresents landowners and CC adopters relative to a Census survey. Variables that were statistically indistinguishable across states included acreage, farming experience indicators, and some gross cash farm income (GCFI) indicators. The mean and median acreages from raw data (without log-transformation) are 572 acres and 260 acres for Maryland respondents, and 487 acres and 250 acres for Ohio respondents. In both states, 80%–82% of our respondents report more than 20 years of farming experience.

Farming practices also differ across the two states—these variations can be relevant if particular types of practices (e.g., crops grown or tillage types) act as substitutes or complements for program enrollments. For example, Ohio farmers were more likely to pursue conventional and conservation tillage, while Maryland farmers were more likely to use no-till. The high no-till adoption rate in Maryland may be the result of Chesapeake Bay restoration efforts and/or the complementarity of no-till and CC (78% of MD farmers plant in the CC program and use no-till). Among survey respondents, the two most common crops planted are corn (80% in Maryland and 85% in Ohio) and soybeans (89% in Maryland and 96% in Ohio). Wheat is the third most common crop. The t-tests show that planting corn and wheat are significantly more

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common in Ohio than Maryland, but the "other" crop category is more common in Maryland. Irrigation is far more common in Maryland (30%) than in Ohio (0.03%). Maryland respondents have a higher percentage of GFCI over $350,000 (32%), but a smaller percentage in the category of GCFI under $150,000 (49%).[14] These underlying differences in farm characteristics across surveyed farmers within the two states leads to an ex ante expectation that program enrollment behaviors might also differ. This expectation is supported by MVP results, as discussed below.

RESULTS

Table 2 shows MVP results for both states along with measures of model fit. The Maryland and Ohio models are both significant at $p < 0.01$ (Wald $\chi^2 = 231.79$ and 368.41). Results provide strong evidence of correlations in program enrollments, as captured by joint MVP estimation. In Maryland, five of six pairwise program combinations have statistically significant ρ correlations, while in Ohio there are three of six combinations with statistically significant correlations. The many statistically significant positive correlations in the unobserved components of enrollment indicate that the MVP model is superior to a parallel collection of UVPs, with the latter being both inefficient and unable to accommodate enrollment correlations within model predictions (Greene 2002, p. 17-1; Greene 2018, p. 818).

These advantages of MVP are clear in a side-by-side comparison with UVP results, as shown by Table A2 and A3. Beyond the ρ correlations, which are absent from the UVPs, the MVP reveals statistical significance for an additional three coefficients.[15] All correlations between the disturbances in the equations are positive, which indicates the complementarity between the cost-share programs' unobserved effects across most of the equations; this is consistent with Duke (2004), who finds positive correlation between federal commodity and conservation programs.

Enrollment drivers in four programs

We begin our more detailed discussion of model results by first considering joint enrollment decisions revealed by the MVP model, following prior work. We then convert these results into conditional enrollment predictions, adapting methods originally developed for health policy evaluations to provide a novel approach for joint prediction within the agri-environmental literature.

State-level MVP regressions explain the drivers of each enrollment decision, controlling for the influence of other drivers and correlations among the other three enrollment decisions due to unobserved factors. Results suggest that Maryland respondents are more likely to enroll in CC programs when they have larger acreages, more than 20 years of experience, and GCFI over $150,000. CRP enrollment increases with acreage but decreases with corn and when GCFI was over $350,000. For commodity programs, enrollment increases with acreage, conservation tillage, conventional tillage, wheat, and those who have more than 20 years of farming experience; the only decreasing driver is "other" crops. Enrollment in other conservation programs (*PROGOTH*) increases with *OTHERCROP* and farms in the highest GCFI category. Looking across program types, results indicate that Maryland respondents with larger acreages and more experience are more likely to have enrolled in both CC and commodity programs.

TABLE 2 Multivariate probit regressions explaining farmer program enrollment decisions in Maryland and Ohio

	Maryland				Ohio			
Variables	**PROGCC**	**PROGCRP**	**PROGCOMM**	**PROGOTH**	**PROGCC**	**PROGCRP**	**PROGCOMM**	**PROGOTH**
LNACRE	0.22*** (0.07)	0.14** (0.07)	0.17*** (0.06)	−0.02 (0.06)	0.19*** (0.05)	0.15*** (0.05)	0.12** (0.05)	0.20*** (0.06)
CONVTILL	0.04 (0.14)	0.01 (0.12)	0.22* (0.12)	0.11 (0.12)	−0.36*** (0.08)	−0.09 (0.07)	0.10 (0.08)	−0.17* (0.09)
CONSTILL	0.18 (0.15)	−0.11 (0.12)	0.20* (0.12)	0.01 (0.12)	0.07 (0.09)	0.14* (0.08)	0.17** (0.08)	0.16* (0.09)
NOTILL	0.16 (0.17)	−0.05 (0.15)	0.23 (0.16)	0.18 (0.15)	0.40*** (0.09)	0.20** (0.08)	0.13* (0.08)	0.49*** (0.10)
CORN	0.10 (0.16)	−0.24* (0.15)	0.00 (0.15)	0.05 (0.14)	0.17 (0.14)	−0.02 (0.11)	0.21** (0.11)	−0.12 (0.14)
SOYBEANS	0.03 (0.20)	−0.13 (0.19)	0.17 (0.19)	0.10 (0.19)				
WHEAT	−0.07 (0.14)	0.08 (0.12)	0.29** (0.12)	−0.12 (0.12)	0.07 (0.09)	0.06 (0.08)	0.01 (0.08)	0.02 (0.09)
OTHERCROP	0.04 (0.14)	−0.16 (0.12)	−0.19* (0.12)	0.22** (0.11)	0.39*** (0.10)	0.09 (0.09)	−0.01 (0.09)	0.38*** (0.10)
EXPERIENCE21-40	0.41*** (0.16)	−0.10 (0.14)	0.31** (0.14)	0.03 (0.14)	−0.22* (0.12)	0.07 (0.10)	0.21** (0.10)	−0.27** (0.12)
EXPERIENCE40+	0.29* (0.16)	−0.06 (0.14)	0.38*** (0.14)	−0.17 (0.14)	−0.36*** (0.12)	−0.03 (0.10)	0.07 (0.10)	−0.27** (0.12)
IRRIGATION	0.03 (0.16)	0.18 (0.12)	−0.15 (0.13)	0.134 (0.13)				
GCFI150TO350	0.71*** (0.21)	−0.11 (0.16)	0.13 (0.16)	0.20 (0.16)	0.22* (0.12)	0.06 (0.11)	0.24** (0.12)	0.13 (0.13)
GCFIOVER350	0.41** (0.21)	−0.30* (0.18)	0.12 (0.18)	0.47*** (0.18)	0.45*** (0.14)	0.13 (0.13)	0.19 (0.14)	0.28* (0.15)
Constant	−1.08*** (0.32)	−0.65** (0.30)	−1.63*** (0.29)	−0.70** (0.29)	−2.26*** (0.27)	−1.37*** (0.23)	−0.80*** (0.22)	−2.25*** (0.28)
Correlations								
ρ(*PROGCC*, *PROGCRP*)	0.12 (0.08)				0.17*** (0.05)			
ρ(*PROGCC*, *PROGCOMM*)	0.33*** (0.08)				0.02 (0.05)			
ρ(*PROGCC*, *PROGOTH*)	0.22*** (0.08)				0.37*** (0.06)			
ρ(*PROGCRP*, *PROGCOMM*)	0.24*** (0.07)				−0.03 (0.05)			

(Continues)

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TABLE 2 (Continued)

	Maryland				Ohio			
Variables	**PROGCC**	**PROGCRP**	**PROGCOMM**	**PROGOTH**	**PROGCC**	**PROGCRP**	**PROGCOMM**	**PROGOTH**
ρ(*PROGCRP*, *PROGOTH*)	0.53*** (0.07)				0.31*** (0.05)			
ρ(*PROGOTH*, *PROGCOMM*)	0.23*** (0.07)				−0.08 (0.06)			
Observations	656				1372			
Log pseudolikelihood	−1464.77				−2838.21			
Wald χ^2	231.79				368.41			
Prob > χ^2	0.00				0.00			

Note: original data collection by authors. $N = 2028$. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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Many of these results differ in Ohio, showing the importance of state-by-state analysis. For Ohio, two common drivers increase enrollment in all four programs: larger acreages and no-till. Ohio CC enrollment also increases with "other" crops and GCFI over $150,000 but declines with conventional tillage and more than 20 years of farming experience. Ohio CRP enrollment increases with conservation tillage. Ohio commodity program enrollment increases in conservation tillage, corn, and the middle categories of farm experience (21–40 years) and GCFI ($150,000–$350,000). Enrollment in other conservation programs increases with conservation tillage, "other" crops, and GCFI over $350,000 but decreases with conventional tillage and farm experience over 20 years.

Several patterns emerge across states for the same program types. A CRP farmer in both states will tend to have larger acreage. A commodity program farmer in both states will tend to have larger acreage, 21–40 years of experience, and use conservation tillage. A farmer enrolled in an "other-conservation" program in both states will tend to plant *OTHERCROP* and have the highest income category. Importantly, no driver increases enrollment in CRP, commodity programs, and other conservation programs in one state but decreases enrollment in the other state. That said, no-till has different impacts on enrollment in Ohio, relative to Maryland. Ohio no-till farmers are more likely to enroll in all programs, while no-till has no significant enrollment effects in Maryland.[16]

Comparisons across states are more complicated for CC programs, as related to the different extent and type of CC programming available in Ohio versus Maryland. Herein, we compare the econometric results from the two states on CC enrollments, acknowledging that there are many institutional, historical, and economics differences for which a model of this type cannot control. Hence, these results should be interpreted as reduced-form econometric conclusions rather than a structural perspective on the CC enrollment process within each state.

The results in both states show that CC enrollment increases with acreage and with farms in the two highest income categories. These findings are consistent with those from the Prokopy et al. (2019) study on conservation practice adoption. However, experience has different effects by state. Ohio farmers with more than 21 years of experience are less likely to enroll in CC program than those with less experience. The opposite result is found in Maryland, where those with the most experience are more likely to enroll. This means that CC participation via EQIP, CSP, or state/local programs has proven more attractive to less-experienced farmers in Ohio, while Maryland's programs have encouraged greater enrollment by more experienced farmers.

These CC results contribute an institutional-driver explanation to the broad literature on the role of experience in adopting new agricultural technologies. As Abadi Ghadim and Pannell (1999) and Bergtold et al. (2012) have argued, farming experience may increase or decrease the likelihood of technology adoption. For instance, Bergtold et al. (2012) argue that experience (1) might lower the costs of learning but raise opportunity costs of switching; (2) could increase risk aversion, increasing the cost of a new effort; and (3) may lower the costs of a new effort by reducing uncertainty about the outcomes. Our results show that experienced farmers in Maryland tend to favor the year-to-year state CC program, while young (and perhaps innovative or risk-taking) farmers in Ohio respond to the temporally limited federal CC program.

Mean prediction probabilities for enrollment in cover crop programs

Based on the MVP model results above, we adapt the approach of Ramful and Zhao (2009) to enable predictions of the conditional probability of CC program enrollment given information

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on farm operation and enrollment in other programs. For comparison, we also report comparative probabilities derived from naïve and less precise predictions drawn from (1) raw data with no control over the sample's farm or farmer characteristics and (2) UVP models for both Ohio and Maryland, which arise when correlations between enrollments are unacknowledged.

Table 3 shows predicted probabilities of CC enrollment for both states and with progressively increasing enrollment in other programs. The means and 95% confidence intervals (CIs) in parentheses of regression predictions (MVP and UVP) are calculated using predictions at individual level instead of evaluating at the sample means. The conditional probabilities for the MVP model are equal to the joint probability divided by the marginal probabilities, which are also evaluated at individual level. In contrast, in the UVP model, conditions are used to restrict the subgroup for estimation. Thus, the predicted probabilities from UVP model are conditional probabilities from a smaller number of farmers.[17] The first row predicts the unconditional probability that a Maryland and an Ohio farmer enrolls in a CC program. The estimates from all three methods are almost identical for the unconditional case, as expected: about 80.4% in Maryland and 20.8% in Ohio. The 95% CIs of predictions overlap for the raw data, MVP prediction, and UVP prediction, and the CIs from MVP and UVP have a narrower range than the raw percentages. These results imply that a random commodity crop farmer would have an 80.4% (20.8%) chance of being enrolled at least once in Maryland's (Ohio's) CC program between 2000 and 2016.

Predictions of CC enrollment change when one incorporates additional information on other program enrollments. For example, the CC enrollment prediction in Maryland increases from 80.4% to between 83.3% and 86.8% when one knows that the farmer has enrolled in a single other program. Knowing that a farmer enrolled in CRP, commodity programs, and other conservation programs increases the prediction of CC enrollment to 90.1%. For Ohio, predictions range from 21.0% to 35.5% if conditioned on one known program, whereas the predicted probability increases to 38.6% if conditioned on all three programs.

These results have important policy implications, demonstrating the value of joint enrollment modeling (compared to more naïve UVP). Program administrators may have information about farmers' participation in various programs, and this information may be used to help identify farmers who are more likely to enroll in additional programs. Knowing, for example, that a Maryland farmer has participated in CRP suggests that this farmer is 83.3% likely to have enrolled in the CC program, which increases prediction by 2.9% over the uninformed state-average prediction (from MVP). For instance, the Chesapeake Bay Watershed Implementation Plans benefit from monitoring of all practices, not just the ones receiving cost-share, so this method can help make more informed predictions when information about farmer-specific details is limited. A related policy implication is that the value of conditional information is likely higher in low-enrollment states. For example, comparing CC enrollment probabilities conditional on enrollment in zero and three other programs shows a difference of 17.8% in Ohio but only 9.7% in Maryland.

Results also demonstrate how predictions change conditional upon the number of other enrolled programs and how these results compare to parallel UVP estimates that do not account for multiple-program enrollment. In Maryland, for example, MVP predictions are from 0.4% to 3.6% different from parallel UVP predictions when conditioning on enrollment in one other program. When conditioning on two or three programs, these differences can be much larger (0.2%–7.0% versus raw data, 0.2%–23.6% versus UVP). The predictions from UVP struggle to predict CC enrollment conditional on two or three programs because of the limited observations. Similar results are found in Ohio, except that the raw data and UVP predictions (1) are

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TABLE 3 Predicted conditional program enrollment probabilities for Maryland and Ohio

	Maryland			Ohio		
Probabilities	**Raw data with 95% CI**	**MVP with 95% CI**	**UVP with 95% CI**	**Raw data with 95% CI**	**MVP with 95% CI**	**UVP with 95% CI**
$p(y_{CC}=1\|X)$	80.3 [77.3, 83.4]	80.4 [79.2, 81.6]	80.3 [79.1, 81.6]	20.7 [18.6, 22.9]	20.8 [20.0, 21.6]	20.7 [19.9, 21.5]
$p(y_{CC}=1\|y_{CRP}=1,X)$	82.9 [77.9, 87.9]	83.3 [82.2, 84.4]	82.9 [80.3, 85.5]	29.1 [25.2, 33.1]	24.9 [24.0, 25.7]	29.2 [27.5, 30.9]
$p(y_{CC}=1\|y_{COMM}=1,X)$	89.6 [86.4, 92.7]	86.8 [86.0, 87.7]	89.6 [88.5, 90.7]	22.8 [20.1, 25.6]	21.0 [20.3, 21.8]	22.8 [21.9, 23.8]
$p(y_{CC}=1\|y_{OTHER}=1,X)$	87.7 [83.6, 91.8]	85.8 [84.8, 86.8]	87.6 [85.2, 89.9]	46.2 [39.9, 52.41]	35.5 [34.6, 36.3]	46.2 [43.5, 48.9]
$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,X)$	93.7 [89.7, 97.7]	88.0 [87.2, 88.8]	79.6 [73.3, 85.9]	34.2 [29.2, 39.2]	25.2 [24.4, 26.1]	34.3 [32.4, 36.2]
$p(y_{CC}=1\|y_{CRP}=1,y_{OTHER}=1,X)$	86.6 [80.6, 92.6]	86.4 [85.4, 87.4]	86.6 [83.4, 89.8]	52.0 [43.9, 60.2]	37.6 [36.8, 38.5]	52.0 [47.9, 56.2]
$p(y_{CC}=1\|y_{COMM}=1,y_{OTHER}=1,X)$	97.0 [93.4, 99.6]	90.0 [89.3, 90.7]	79.8 [72.4, 87.2]	50.9 [43.3, 58.4]	36.4 [35.6, 37.3]	50.8 [47.8, 53.9]
$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)$	94.6 [89.8, 99.3]	90.1 [89.4, 90.8]	66.5 [54.7, 78.3]	56.9 [47.4, 66.3]	38.6 [37.8, 39.5]	56.9 [51.7, 62.1]

Note: Original data collection by authors. Numbers in the cells are percentages. The means and 95% CIs in parentheses in MVP and UVP model are calculated using predictions at individual level. The conditional probabilities of MVP model are equal to the joint probability divided by the marginal probabilities, which are also evaluated at individual level. In contrast, the UVP conditional predictions are generated based on estimation using subgroup of the whole samples.

Abbreviations: CI, confidence interval; MVP, multivariate probit; UVP, univariate probit.

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always higher than the MVP probability of CC enrollment and (2) have differences that tend to be larger than in Maryland. For example, the predicted probability of CC enrollment from MVP (conditional on three other programs) is about 39%, while the other predictions are over 56%. In other words, using the MVP regression results provides conditional CC enrollment probabilities that can be more informative, especially in Ohio.

Results also suggest the possibility of substantial economies of both scope and scale in farmer program enrollment decisions. Both estimates of ρ from the MVP model and the conditional enrollment predictions demonstrate that CC enrollment predictions depend both on (a) whether farmers enroll in specific other types of programs, for example, CRP, and (b) the number of other programs in which farmers enroll. Hence, models that simultaneously estimate decision-making over multiple-enrollment decisions provide more accurate and informative predictions of behavior than otherwise identical UVP models—even with the behavioral drivers evaluated at their means. This reflects expectations from econometric theory, suggesting that MVP models are more efficient in this context and also reveal potentially important correlations in decision-making that are invisible to UVP counterparts. Here, these correlations could reflect policy-relevant economies of scope and scale in enrollment decisions.

Heterogeneity in prediction for enrollment in cover crop programs

In some settings, the average prediction probability is not the best metric for policy makers to use because it does not consider heterogeneity in farm characteristics and operating conditions (c.f. Chavas & Nauges, 2020; Pannell & Claassen, 2020). For example, policy makers might desire information not on the behavior of average farmers but rather on whether and how programs might be targeted to those who are most likely to enroll and/or who might offer the greatest program additionality. Accordingly, a planner might wish to predict enrollment for a specific farm with fully or partially known characteristics X.

To illustrate the capacity of the model to provide predictions of this type, we use individual respondent observations on X to predict, through the estimated MVP models, participation under the eight information scenarios in Table 3. Results are shown in Figure A1 for Maryland and Figure A2 for Ohio. Both Maryland and Ohio show a large degree of heterogeneity in the probability of enrolling in CC programs. Even though the mean and mode predictions in Maryland are high and increase with additional enrollments, we also find that certain farmers are far less likely to enroll, as a function of farm characteristics.

The results of this type can be used directly to help target currently unenrolled farmers with the greatest predicted CC enrollment probability, based on observable dimensions of X and any available information on other enrollment choices (sample means can be assumed for unobserved farm characteristics). For example, one might contact the unenrolled farmers with the highest estimated probability first and then continue until either the budget is exhausted or enough resistance on the margin suggests the program has reached its (approximate) maximum participation level. Here, the relatively greater degree of heterogeneity in Ohio (i.e., a wider and flatter distribution) implies greater potential opportunities for targeting this type in that state, compared with Maryland.

The results in Table 2 can also be used to examine the extent to which farm and farmer heterogeneity affect enrollment predictions. In Maryland, the average farm has an 80.3% overall enrollment probability in the state CC program. However, among farmers with 20 or less years of experience, the enrollment probability for a Maryland small farm at the 25th percentile of

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acreage would have a lower CC enrollment probability (70.5%) than one at the 75th percentile of acreage (83.4%). These results suggest that, in Maryland, planners who have limited time to recruit—but who know what farms are not enrolled—would tend to have more success marketing the CC program to larger farms and those farmers with 21–40 years of experience. A similar example in Ohio shows a different pattern. A planner will do better by targeting large farms run by farmers with less than 20 years of experience (29.7% versus 19.0% for a smaller farm). Prokopy et al. (2019) also found that older farmers were less likely to adoption conservation. Indeed, a planner would have almost three times the likelihood of success by targeting a larger farm with a lower-experienced farmer than a smaller farm with a farmer with the highest experience. Additional examples of this analysis of heterogeneity are provided by Table A4.

Marginal value on CC enrollment of other programs

Beyond results in Table 3, the method presented above also offers a way to estimate how enrollment in other programs increases the likelihood of CC enrollment on the margin. To demonstrate these results, we calculate in Table 4 the marginal increases for selected combinations of enrollment in one, two, or three other programs. For instance, a farmer in Maryland (Ohio) who is known to be enrolled in CRP is 4.4% (6.9%) more likely than one who is not in CRP to enroll in CC programs. In contrast to similar effects observed for CRP, commodity programs have different effects in Maryland and Ohio. In Maryland, a known commodity program farmer is 12.6% more likely to enroll in CC programs than a farmer who is not in commodity programs. This effect is only 1% in Ohio. Table 4 presents nine marginal effects conditioned on two conditional program enrollments and seven marginal effects conditioned on three-program enrollments. These marginal effects of adding one, two, or three other programs have marginal CC enrollment increases between 1.2% and 24.3%. In other words, Table 4 shows that farmers with some enrollments combinations are far more likely than others to enroll in CC programs. This offers targeting opportunities.

There are several ways for researchers and planners to use these results. First, the results show what single program has the largest effect on the margin, driving enrollment in CC programs. This is the most complementary program and can help identify where potential economies of scope/scale likely emerge. In Maryland, conditioning on commodity program enrollment alone has a marginal effect that is approximately 50% greater (12.6% vs. 8.1%) than other conservation programs and 200% greater (12.6% vs. 4.4%) than CRP. This is surprising because one might expect the conservation programs to vary with the conservation-oriented CC programs rather than with commodity programs. These results are almost reversed in Ohio, where the largest marginal effect comes from other conservation programs, which is 165% greater (18.4% vs. 6.9%) than the CRP effect and almost 1800% greater (18.4% vs. 1.0%) than commodity programs. These results imply that planners and researchers should use caution when drawing generalizations across states about how farmers plan their portfolio of program enrollments, as these results can vary dramatically across states.

Second, as more conditioning information on program enrollment is added, there are certain program combinations wherein the impact on CC enrollment is further increased. These results can help identify the types of farmers who are most likely to respond to CC program offerings. For instance, in Maryland, the impact of commodity program enrollment is persistent even in the two-program and the three-program scenarios. Commodity program enrollment in combination with CRP (+14.7%) or with other conservation programs (+18.1%) leads to a large

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TABLE 4 Marginal effect of enrollment in other programs on predicting probability of cover crop enrollment

Item	Probabilities	Maryland (%) 95% CI	Ohio (%) 95% CI
Single program	$p(y_{CC}=1\|y_{CRP}=1,X)-p(y_{CC}=1\|y_{CRP}=0,X)$	4.37 [4.18, 4.56]	6.94 [6.79, 7.09]
	$p(y_{CC}=1\|y_{COMM}=1,X)-p(y_{CC}=1\|y_{COMM}=0,X)$	12.62 [12.13, 13.11]	0.98 [0.96, 1.00]
	$p(y_{CC}=1\|y_{OTH}=1,X)-p(y_{CC}=1\|y_{OTH}=0,X)$	8.14 [7.79, 8.49]	18.41 [18.15, 18.68]
Two programs	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=0,X)$	14.71 [14.14, 15.29]	8.07 [7.90, 8.24]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,X)-p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=0,X)$	11.36 [10.90, 11.83]	1.26 [1.23, 1.29]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=1,X)$	2.04 [1.95, 2.14]	7.04 [6.89, 7.19]
	$p(y_{CC}=1\|y_{CRP}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{OTH}=0,X)$	9.39 [8.98, 9.79]	22.26 [21.94, 22.59]
	$p(y_{CC}=1\|y_{CRP}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{CRP}=1,y_{OTH}=0,X)$	6.73 [6.45, 7.04]	17.62 [17.38, 17.86]
	$p(y_{CC}=1\|y_{CRP}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{OTH}=1,X)$	1.32 [1.26, 1.39]	4.99 [4.91, 5.06]
	$p(y_{CC}=1\|y_{COMM}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{COMM}=0,y_{OTH}=0,X)$	18.12 [17.42, 18.83]	20.45 [20.15, 20.74]
	$p(y_{CC}=1\|y_{COMM}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{COMM}=1,y_{OTH}=0,X)$	5.28 [5.03, 5.53]	18.98 [18.73, 19.24]
	$p(y_{CC}=1\|y_{COMM}=1,y_{OTH}=1,X)-p(y_{CC}=1\|y_{COMM}=0,y_{OTH}=1,X)$	9.78 [9.36, 10.21]	2.70 [2.67, 2.73]
Three programs	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=0,y_{OTHER}=0,X)$	18.55 [17.83, 19.27]	24.27 [23.92, 24.62]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=0,y_{OTHER}=0,X)$	17.04 [16.38, 17.70]	19.90 [19.63, 20.17]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=1,y_{OTHER}=0,X)$	5.61 [5.35, 5.87]	22.90 [22.58, 23.21]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=0,y_{OTHER}=1,X)$	10.03 [9.59, 10.47]	7.77 [7.66, 7.87]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=0,X)$	4.93 [4.70, 5.16]	18.11 [17.88, 18.34]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=0,y_{OTHER}=1,X)$	9.74 [9.32, 10.17]	2.75 [2.72, 2.78]
	$p(y_{CC}=1\|y_{CRP}=1,y_{COMM}=1,y_{OTHER}=1,X)-p(y_{CC}=1\|y_{CRP}=0,y_{COMM}=1,y_{OTHER}=1,X)$	0.28 [0.23, 0.32]	5.03 [4.96, 5.10]

Note: Original data analysis by authors. The means and 95% CIs in parentheses in multivariate probit model are calculated using predictions at individual level.
Abbreviation: CI, confidence interval.

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increase in CC enrollment probability relative to enrollment in neither of the two programs. Another example is a representative farmer in Ohio, where one knows enrollment in commodity, other conservation, and CRP. If this farmer was enrolled in all three, then the probability of enrolling in CC programs is 24.3% higher than that same farmer who enrolled in none of the three programs. Table 4 offers many other combinations.

These results demonstrate the stacking effect among agri-environmental programs, wherein farmers make joint decisions over a portfolio of programs. Table 4 also reveals a measure of overlapping decisions over multiple programs, in which the independent marginal increases from the three other programs are greater than their joint marginal effects. This further suggests that research studies on independent programs, program enrollment, or technology adoption may overstate costs when there are possible economies across different types of enrollments.

CONCLUSION

There is increasing interest among both governments and researchers in understanding whether and how the efficiency of agri-environmental cost-share programs can be improved. Economic research is helping to shape these designs but does not always offer the most actionable or accurate guidance for program design. Among the simplifications that are common in past work is the use of independent program-by-program analysis that overlooks the possibility that farmers might make program enrollment decisions jointly—univariate empirical models are unable to capture important inter-program relationships that can exert significant influences on farmer enrollment decisions. The resulting models provide incomplete and imprecise guidance for program design, overlooking important dimensions of how to enhance enrollments while potentially reducing costs.

Responding to this paucity of relevant information in the literature, this paper offers a feasible yet powerful reduced-form method to both (a) model joint practice, adoption, or enrollment decisions made by farmers, and (b) convert results into targeted predictions of conditional enrollment probabilities. A corollary benefit of this approach is the provision of insight regarding areas in which economies of scale/scope in these decisions may arise, that is, which programs offer the most complementarity in decision-making.

As always, multiple caveats and limitations must be considered when interpreting these results. As in all economic models, simplifications and assumptions are required to promote tractability and to enable a focus on key issues of interest, as detailed under the discussion of theoretical foundations and empirical methods above. For example, like all reduced-form econometric models, the presented MVP specification is designed to capture and test causal relationships between variables and predict empirical outcomes (here program enrollment)—not to reflect the explicit structural function of the underlying systems. Although assumptions and simplifications are required to implement any applied empirical model of this type, the presented approach provides insights unavailable via common univariate analyses and relaxes the implicit but often misplaced assumption of these models that program enrollment decisions are made independently. The resulting estimates provide heretofore unavailable insight on whether and how information on joint program enrollments can provide information to enhance agri-environmental program design.

Planners can employ empirical estimates of this type in various ways to provide information that enhances farmer recruitment and hence program efficiency. Although many of these uses are illustrated above, others are possible. For example, the results could be used to evaluate

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how cost-share rates might be reduced without necessarily reducing enrollment—for example, as a tool to enhance cost-effectiveness.[18] Although detailed applications of this type would require additional empirical modeling (perhaps with additional case study locations) so that greater variability in incentives could be studied, results here suggest the type of results that might emerge. Potential applications of this type are not merely speculative or academic in nature. For example, the 2021 Pandemic Cover Crop Program suggests that program managers are beginning to think along the same lines: (1) Can a bonus payment be offered to farmers who are signing up for program X if they will add program Y? and (2) How much less can be paid for program Y when it is a bonus on program X? Further research could help explore whether and how economics of scale/scope such as these might affect agri-environmental enrollment and adoption across various settings, thereby providing additional guidance on how programs might be "stacked" to enhance efficiency. If farmers make decisions over the space of available programs, then planners should potentially design cost-share that accounts for the *other* government agencies' efforts to incentivize the provision of agri-environmental services.[19]

The results presented here are derived from information on farmer decisions over an extended period (2000–2016). A forward-thinking planner, however, could also use these multi-program past decisions to begin to design new portfolio enrollment options for future farmers. The probabilistic results presented herein should align with a price-discriminating monopsonist's effort to drive farmers to their minimum WTA across multiple, correlated programs. Experimental economics researchers could further use these results to design induced-value schedules in a discriminatory-price auction experiment across multiple programs.

A separate literature explores the cost-effectiveness with which auctions and other mechanisms address hidden information, where WTA is unknown to the government's agri-environmental procurement agency. There may be opportunities for future research where our empirical approach dovetails with the hidden information literature. Specifically, our enrollment probabilities for farmers with a given set of characteristics and conditional on other enrollments ought to be transformable—through a simple function—into unobservable WTA. As we add information on more characteristics and enrollments, the relevant group narrows. In effect, one should be able to sort an out-of-sample set of Maryland and Ohio farmers in terms of their probabilities of enrolling in, say, a CC program. The patterns in this sorting ought to relate closely to the patterns in WTA. Future research could explore the value of this approach in constructing an empirically based counterfactual match or informing induced-value schedules in an auction-based economic experiment.

Taken together, and notwithstanding the assumptions and caveats explicated above, results from the analysis illustrate the type of insight that is possible when one evaluates and predicts farmer decisions as a portfolio rather than in isolation. As implied by the results presented above, accounting for related decision-making interdependencies can in some cases be more important for predicting enrollment variations across farmers than other influences that have been given far greater attention in the literature.

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ENDNOTES

[1] By economies of scope, we mean the efficiencies formed by the variety of agri-environmental programs. That is, a farmer has lower average costs because costs are spread over a variety of programs. By economies of scale, we refer to the cost advantages that farmers obtain due to the number of enrollments. These efficiencies may arise among programs that seem quite different, such as programs that idle land and other programs that address working lands.

[2] Iowa's Cover Crop/Crop Insurance Project pays farmers enrolled in federal crop insurance for cover crops with a $5/acre reduction in insurance premiums (see https://www.cleanwateriowa.org/cropinsurancediscount, accessed June 25, 2021). The Pandemic Cover Crop Program in 2021 offered the same type of $5/acre incentive (see https://www.farmers.gov/pandemic-assistance/cover-crops, accessed June 25, 2021).

[3] 2020–21 data are forecasted. Source USDA ERS Data files U.S. and State-Level Farm Income and Wealth Statistics, https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/data-files-us-and-state-level-farm-income-and-wealth-statistics/.

[4] The flip side of targeting for lower-cost enrollment on the margin is program cost ineffectiveness. If programs do not recognize that farmers perceive a lower marginal cost of an additional program enrollment—that is, programs are complementary—then they may overcompensate farmers. In other words, program managers may be underestimating how attractive their programs are to farmers, the net result of which are surplus payments above those actually required to obtain conservation services from farmers. Overspending of this type reduces program cost-effectiveness.

[5] Chang and Boisvert (2009b) derived direct and indirect marginal effects from their MVP. Conditional on one dependent variable being observed, they decomposed each independent variable's total marginal effect into a direct effect on the current dependent variable and an indirect effect from the conditional decision. This approach is valuable for understanding the drivers of a program-enrollment decision. We instead will focus on the conditional relationship among the enrollment decisions themselves.

[6] Here, we follow Bishop and Boyle (2019) and define accuracy as determined by the combination of validity (lack of bias) and reliability (efficiency).

[7] As an alternative to MVP models, one might seek to specify a set of independent UVP models for each program of interest (say, "Program A") that include independent variables to indicate enrollment in other program types (e.g., Program B, C, etc.). However, alternative UVP models of this type would face the obvious challenge of endogeneity in the other program enrollments in a model of Program A enrollment, thereby necessitating IV, control variable, or other approaches to avoid bias and inconsistency. The complexity and challenges of such models (e.g., considering issues such as exclusion restrictions for identification) render MVP models a more tractable and defensible approach, and one that is arguably more consistent with the behavioral underpinnings of the model.

[8] Some past literature argues, without formal econometric proofs, that UVP estimation leads to *bias* as well as inefficiency when decisions are made jointly (c.f. Ward et al., 2018; Kamau et al., 2014; Maguza-Tembo et al., 2017). However, a more general conclusion of the econometric literature is that UVP models enable consistent but inefficient estimation in such cases, while failing to provide insight into correlations across simultaneous decisions as outlined above (Greene, 2002, 2018).

[9] Given the complexity of the presented MVP model, simultaneously accounting for agency selection processes would require development of novel and heretofore unavailable econometric approaches that are beyond the scope of the present paper. We hence leave exploration of the tractability of such models for future work.

[10] Maryland is an outlier in CC adoption and agri-environmental programming more broadly because it has long been developing and implementing innovative policies to address Chesapeake Bay water quality problems. As such, the lessons from data in Maryland are less reflective of general CC patterns in other states today. However, it is still valuable to better understand the complex agri-environmental policy environment for Maryland

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farmers and identify a potential path to further improve the adoption rate. Considering that program development is a dynamic process, more states will become similar to Maryland in terms of CC adoption, not less.

[11] Examples include retired farmers, landowning nonfarmers, and those with all their land in CRP retirement programs.

[12] The CC program indicator is coarse but was a limitation resulting from design decisions for the survey instrument. Future work may better disentangle the various CC programs. This is likely important because not only are the federal programs imperfect substitutes in terms of payments, constraints, etc., but also because recent research suggests potentially complex interactions; Park et al. (2021) show that at a county level EQIP payments increase CC adoption while CSP payments lead to decreases, ceteris paribus.

[13] CRP participation is higher than yearly participation data from USDA because we counted the CRP enrollee if respondent signed up CRP in any year between 2010 and 2016.

[14] One modeling challenge arises because *SOYBEANS* and *IRRIGATION* are, respectively, very common in Maryland and rare in Ohio. Including such variables to explain regression outcomes is inappropriate in Ohio because of insufficient variation; thus we exclude these two variables in the Ohio estimation. In addition, the farm characteristic variables were measured in a "check all that apply" survey format, so we are unable to connect, say, a given tillage practice to a given crop.

[15] The specific differences were that, in Maryland, two coefficients were significant at the 10% level in the MVP, but not in the UVP. Also, in Maryland, two coefficients were significant at the 5% level in the MVP, but the 10% level in the UVP. In Ohio, only one coefficient was significant at the 10% level in the MVP, but not in the UVP. In both models, the standard errors tended to be the same or slightly smaller on average in the MVP relative to the UVP.

[16] The difference may arise due to the different prevalence of no-till: 86% in Maryland and 65% in Ohio (table 1). Because almost all Maryland farmers already use no-till, there may be too few observations to reveal a statistical tendency. However, Ohio no-till farmers are likely different from those who do not use no-till.

[17] For the MVP probabilities, the steps followed were: (1) estimate MVP with the entire state sample; (2) predict the joint probabilities and marginal probabilities using the individual data in the estimated MVP model; (3) calculate the conditional probabilities at individual level with the data of joint probabilities and marginal probabilities; and (4) calculate the average effect and 95% CI. However, the conditional probabilities from UVP are calculated differently. For example, to calculate the probability of CC enrollment conditional on CRP enrollment: (1) estimate a UVP ($y_{cc} = 1,0$) using the subgroup of that enrolled in CRP (CRP = 1); (2) predict the probability at individual level, which automatically becomes the conditional probability; and (3) calculate the average effect and 95% CI. Therefore, in UVP when more program enrollment conditions are included, fewer observations are used in the estimation.

[18] If a farmer, for instance, is highly likely to enroll in one more program given their prior observed enrollments, then perhaps a lower incentive could be offered. If a farmer is unlikely to enroll in one more program, then perhaps the incentive could be increased.

[19] Our cost-effectiveness argument matches the way in which many researchers study procuring environmental services—that is, by looking for cost savings in payments to farmers but also holding constant the benefits of each procured unit. Another literature focuses on the benefit side, recognizing that benefits will be heterogeneous and there will be complicated by dynamic effects and spatial externalities. We direct the reader to one benefit-side study in particular (Huber et al., 2017), which examined the overlapping benefits of four types of Swiss agri-environmental policies. Huber et al. (2017, p. 49) warrant their study in similar terms to ours, writing, "Existing literature, however, often focuses on single measures without considering that policies are usually bundles of different measures addressing multiple non-marketed goods and services. Thus, interaction effects of a set of policies in a given policy mix may influence the cost-effectiveness of single measures." The implication is that the true optimal targeting requires that researchers bring together the government's cost and benefit sides.

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