September, 2016

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Forthcoming at ***Journal of Great Lakes Research***

Date: July 10, 2016

Title Page

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Abstract (250 words or less):

Phosphorus loadings from the Maumee River watershed have significantly compromised the Lake Erie ecosystem, as evidenced by the most severe harmful algal bloom in Lake Erie in 2015 and the shut-down of Toledo drinking water supply in 2014. Despite government payments for adoption of voluntary conservation practices, excess nutrient runoff from agricultural production remains a substantial challenge.

The right timing of nutrient application is a critical best management practice (BMP). Using a unique survey of 2,540 farmer respondents in the Maumee River watershed, this paper analyzes how socio-psychological, socio-demographic, and field-based spatial characteristics impact farmers' adoption of timing-related best practices for nutrient management, including delaying broadcast application before a storm event, avoiding winter application of nutrients, and avoiding fall application of nutrients.

Results reveal three unique classes of farmers for each of the timing-related management decisions. While the significance of most farmer and field characteristics varies across the three BMP adoption decisions, perceived efficacy--the belief that the particular practice will actually reduce dissolved phosphorus runoff from farm fields—is positively correlated with a higher likelihood of adopting each of the BMPs across almost all classes of farmers. For example, results from the ordered logit model suggests that a 20% increase in perceived efficacy would result in the likelihood of actual adoption of delaying broadcast from 35% to 48%. An implication is that policies and outreach efforts aimed at increasing farmers' perceived efficacy of practices could lead to higher adoption levels, but the effectiveness may vary across different classes of farmers.

Keywords (2-6 words)

water quality, farming, nutrient loss, fertilizer application, best management practices

Introduction

Nutrient runoff from agricultural production contributes to freshwater eutrophication and coastal hypoxia across the United States and globally, posing great risks to freshwater and marine ecosystems (Diaz and Rosenberg, 2008; Hudnell, 2010). A recent rise in the amount of dissolved reactive phosphorus (DRP) entering the western Lake Erie basin has increased the frequency and extent of harmful algal blooms (HABs) (Michalak et al., 2013), as evidenced by the record-breaking blooms in 2011 and 2015, and the two-day shutdown of the City of Toledo's public water system in summer 2014 due to algal toxins. These toxic blooms pose significant risks to many ecosystem services, including recreational opportunities, water clarity, public health and potable water (International Joint Commission, 2014). Experts believe that the increase in DRP is in part due to poor nutrient management planning (i.e., poor timing and over-application) as well as the broadcast application of fertilizer without incorporation (Ohio Lake Erie Phosphorus Task Force, 2013; Scavia et al., 2014). These factors, in combination with warmer than average temperatures in Lake Erie during the summer and an increase in heavy rain events, have amplified the spread of toxic algal blooms (Meehl et al., 2007; Michalak et al., 2013; Ohio Lake Erie Phosphorus Task Force, 2013; Thomson et al., 2005; van de Vijver et al., 2008). Additional regulations and strategies to improve farmers' management practices are needed to achieve recommended nutrient loading reductions.

In reaction to the Toledo incident, the Ohio House and Senate passed a new bill effective in June 2015 that bans nutrient application on frozen or saturated ground, and when there is a forecast of heavy rain (Ohio Senate Bill 1, 2015). At the same time, prior recommendations to avoid winter and fall application of nutrients are now being reconsidered due to the likelihood that applying under the appropriate conditions in the fall and winter could be more effective than applying in the spring when storm-based runoff will most likely contribute to harmful blooms (Stumpf et al., 2012). However, by delaying broadcast application of nutrients in the spring when a storm is forecasted, farmers could further reduce DRP loads flowing into western Lake Erie (Ohio Lake Erie Phosphorus Task Force, 2013). Recent studies of climate change impacts show that the Lake Erie region will see more frequent and more intense rainfall as well as greater spring precipitation (Diaz and Rosenberg, 2008), which suggests that farmers' adaptations in altering phosphorus timing could be even more significant in the future.

Nutrient runoff from agricultural fields varies with seasons and increases during periods of heavy precipitation events. For instance, less nutrients are lost if the nutrients are applied in the spring rather than the fall, but this difference is offset by a heavy (e.g., 25% or more) increase in mean annual precipitation during the spring season (Nangia et al., 2010). Even when nutrients are applied during the growing season, the amount of precipitation can have a significant impact on runoff. For example, an intense rain event 30 days after manure application can cause more runoff than a light rain event the day after application (Vadas et al., 2011). Increasingly the literature on agricultural pollution control and conservation practices recognizes that solving the "phosphorus pollution puzzle" depends critically on understanding the complex interplay

between agricultural production processes such as farmers' land management decisions and biophysical processes of nutrient flows (Garnache et al., in press), and altered nutrient application timing is being recognized as one key component of the solutions (Rabotyagov et al., 2014).

The purpose of this paper is to investigate the factors that motivate farmers to apply phosphorus at the "right" times. We do this by evaluating the impact of select socio-psychological, socio-economic, and field-based spatial characteristics on farmers' adoption of three timing-related best practices for nutrient management: delaying broadcast application before a storm event, avoiding winter application of nutrients, and avoiding fall application of nutrients. An ordered logit model is used to assess likelihood of adoption for each of these three timing related practices and latent class models are then used to identify unique subgroups of farmers who may vary in their likelihood of adoption given a range of both shared and unique explanatory factors.

The main results reveal that for each of the timing-related practices, three unique classes of farmers exist who vary in the way they think and act as it relates to the particular practice. While the level of adoption for each class does not necessarily vary across the classes, the characteristics of individuals in each class and the factors motivating their choices differ, suggesting that policies and outreach efforts aimed at increasing adoption will vary in their effectiveness across different groups of farmers. The only variable that is consistent across all three practices and across almost all classes is perceived efficacy—i.e., the belief that the particular practice will actually reduce dissolved phosphorus runoff from farm fields. This individual-level characteristic is positively correlated with a higher likelihood of adopting all of the timing-related BMPs for the majority of farmers.

This paper makes at least three contributions to the literature on modeling the adoption of best management practices. First, our paper offers one of the first analyses of the relative effect of socio-psychological, socio-economic and field-based spatial characteristics impacting farmers' decisions to apply phosphorus at the right time, both in terms of seasonal timing and timing applications in light of storm forecasts. Second, our analyses reveal that often-neglected socio-psychological characteristics, such as the perceived efficacy of a practice in reducing phosphorus runoff, are significant in driving the adoption decisions of these timing-related BMPs. This highlights the potential of improved education and extension to promote environmental stewardship and the importance of considering the efficacy of a practice in addition to other socio-psychological characteristics that are more commonly used to explain adoption decisions (e.g., environmental values and attitudes). Finally, while our models reveal substantial heterogeneity among farmers in their BMP adoption decisions, we are able to nonetheless identify classes of farmers who are most likely to have the practice in place and may be more amenable to changing their practices, e.g., as a result of more targeted education and extension efforts that provide farmers with the right tools and information to adapt their land management decisions.

Role of farmer and spatial heterogeneity in land management decisions

Some management decisions by farmers have been extensively studied individually or as part of a suite of practices including conservation tillage (e.g., Konar et al., 2014; Kurkalova et al., 2006), soil testing (Khanna, 2001), phosphorus application (Zhang, 2015), and crop rotation (Wu and Babcock, 1998). However, these studies typically focus on the profit motives of farmers, and ignore other behavioral considerations. In addition, very limited research exists about farmers' decision making regarding the timing of their nutrient applications. The small set of studies that have examined farmers' application timing decisions only investigate seasonal timing in nitrogen applications (e.g. Huang et al., 1994, 2000; Johnson et al., 1991) while neglecting socio-psychological characteristics such as the role of perceived efficacy of the practice in reducing nutrient runoff. Furthermore, even studies of non-timing related adoption that do address socio-psychological characteristics do not typically focus on perceived efficacy, but instead focus more on farmer identity as a conservationist or some measure of general environmental concern or values (e.g., Prokopy et al., 2008).

Most previous studies of phosphorus reductions in the Lake Erie agroecosystem (e.g., Bosch et al. 2013) assume a given amount and location of BMP adoption and ignore the factors influencing individual farmers' responses to policies and adoption decisions. With seasonality, weather forecasts, and other biophysical and farm-level characteristics to consider (e.g., soil moisture and nutrients, tillage practices, and crop schedules), the motivations behind timing decisions are complex and may encompass other concerns in addition to profit maximization. It is likely that the suite of factors contributing to the adoption of each best management practice is unique, and that both socio-psychological and socio-cultural influences play important roles (Burnett et al., 2015; Zhang, 2015). In addition, previous research has examined the significance of the field or farm-specific characteristics in affecting farmers' nutrient application decisions, including farmers' opportunity cost of time, machinery and equipment level, and different level of weather risks (Sheriff, 2005); adoption costs of the conservation practices (Kurkalova et al., 2006); as well as other farm enterprise characteristics that might impact nutrient applications. However, most existing studies of application timing decisions just focused on an individual farmer's tolerance for risk (e.g., Huang et al., 1994), and structural aspects like insurance programs designed to mitigate risk (Huang et al., 2000).

Spatially heterogeneous land characteristics have long been shown to influence the economic aspects of decision making related to tillage (Kurkalova et al., 2006; Wu et al., 2004), crop rotation (Wu and Babcock, 1998), crop choice (Hendricks et al., 2014), land allocation (Laukkanen and Nauges, 2014), and a variety of conservation practices (Rabotyagov et al., 2014). Because these spatial characteristics may interact with socio-psychological characteristics (e.g., farmers may put different weights on crop yield goals and soil erosion for high quality land vs. low quality land), these interactions add an important layer of contextual complexity in

driving farmers' timing-related land management decisions. Specific to phosphorus timing, for example, the dominant soil texture of the field could affect the farmers' seasonal timing decisions: farmers may be more likely to avoid fall application if their fields are sandier because most of the fertilizer applied would wash through the soil while more nutrients could be retained until the spring for plant use in the case of clay soils (McDowell et al., 2001). Spatial heterogeneity also plays an important role in understanding the environmental impacts of agricultural land management decisions, implying the potential for "hot spots" with high runoff levels and potential gains from spatial targeting of conservation practices (e.g., Bosch et al., 2013; Babcock et al., 1997).

In summary, existing studies of farmer land management decisions highlight the importance of heterogeneity both in terms of individual behaviors and land characteristics. On this basis, we hypothesize that both sources of heterogeneity are important in explaining the timing-related best practices that farmers adopt for nutrient management.

Methods

Survey sampling and administration

The sample population for this survey consists of corn and soybean farmers within the Maumee River watershed in the western Lake Erie basin (HUC6 #H041000), which is the largest drainage basin in the Great Lakes region (Figure 1). More importantly, the Maumee River watershed has been implicated as the largest source of phosphorus to Lake Erie (Scavia et al., 2014). Dissolved reactive phosphorus loads from the Maumee have increased by over 200 percent from 1995 to 2011, which has been a major cause of harmful algal blooms and other water quality problems in Lake Erie (Michalak et al., 2013). While the Maumee River watershed features a variety of environments (agricultural fields and concentrated animal feeding operations, wetlands, and urban/industrial settings), economies (extensive agriculture, manufacturing and chemical industries, and transportation networks), and administrative settings (three states and 25 counties), it is dominated by row crop agriculture, which covers more than 70% of the landscape.

As part of an NSF-funded coupled natural-human systems project (Martin et al., 2011), we conducted a mail survey of 7,500 randomly selected farmers in the Maumee River watershed, collecting data on their field, farm and operator characteristics between February and April 2014. The addresses came from a list of 12,000 farmers in the Maumee River watershed provided by a private vendor[1]. The survey was conducted following Dillman's Tailored Design method (Dillman et al., 2009). In February of 2014, an announcement letter was sent to the random sample of farmers informing them that they would soon be receiving a survey in the mail. A cover letter and a survey booklet with prepaid return postage were sent to all participants a week

[1] Addresses were provided by Farm Market ID who maintains a mailing list of farmers in the watershed based on government payment records and farm magazine subscriptions.

later. Included with this first survey was a token incentive of one dollar to increase response. In early March a reminder postcard was sent to participants who did not return the survey. In late March an additional mailing of the cover letters and survey booklets was sent out to those participants who had not yet responded. In late April, a final reminder letter was sent to participants. Several months before the initial mailings, we pilot tested the survey instrument with farmers recruited by local extension professionals to assess face validity. A total of 3,234 surveys were initially returned, of these 438 were no longer farming and 32 surveys did not answer sufficient number of questions. In total, we obtained 2,764 valid survey responses, yielding an adjusted response rate of 36.9%. A descriptive report on this survey can be found online at our project website at http://ohioseagrant.osu.edu/archive/maumeebay/ and Burnett et al. (2015).

Measurement

The dependent variables of interest are the likelihood of farmers adopting three timing-related practices: (i) avoiding broadcast application of nutrients when the forecast predicts a 50% or more chance of at least 1 inch of total rainfall in the next 12 hours, (ii) avoiding winter or frozen ground surface application of phosphorus, and (iii) avoiding fall application of phosphorus. We measured likelihood of adoption by asking farmers whether they had adopted the particular practice or not (where 0 = not adopted and 1 = adopted) for a representative field on his/her farm. Participants were randomly assigned to one of three conditions to ensure that the range of fields selected included low, average and high productivity fields. For those who had not already adopted the practice, we then asked them how likely they were to adopt, with possible responses ranging from 0 (will never adopt) to 3 (will definitely adopt). The two measures were combined to create a categorical measure of adoption (i.e., will never adopt = 0, unlikely to adopt = 1, likely to adopt = 2, will definitely adopt = 3, and already adopted = 4, Table 1). In other words, our dependent variable mainly relies on the future likelihood of adoption, while adjusting for the fact that farmers who have already adopted are likely to continue the adoption.

Explanatory variables were identified on the basis of their potential to impact the adoption of conservation practices. One set of variables included socio-psychological factors such as *efficacy*, *farmer identity*, *concern*, *familiarity*, and *risk attitude*. We hypothesized that the likelihood of adopting recommended practices would increase with an increase in the perceived efficacy of the practice, farmer identity as a conservationist, concern about nutrient loss, familiarity with 4R practices, and a more tolerant attitude toward risk. A single item for each of the practices measured *efficacy*, or the belief in the effectiveness of a specific practice at reducing nutrient loss, with possible responses ranging from 0 ('not at all') to 4 ('to a great extent'). Items measuring *farmer identity* were based on the good farmer concept (Burton, 2004; McGuire et al., 2013). Respondents were asked to rate the importance of production-oriented values (e.g., high profits, high yields) and conservation-oriented values (e.g., maintaining soil organic matter, minimizing nutrient runoff into waterways), with possible responses from 0 ('not

at all important') to 4 ('very important'). The variable farmer identity was then constructed as the difference between the conservationist values and the productionist values, which could range from -4 (greater identity as a productionist) to 4 (greater identity as a conservationist). A single item measured *concern* about nutrient loss occurring on his/her farm, ranging from 0 ('not at all concerned') to 6 ('extremely concerned'). A single item measured *familiarity* with 4R Nutrient Stewardship – applying the right fertilizer source at the right rate and the right time in the right place - with possible responses ranging from 0 ('not at all familiar') to 4 ('extremely familiar'). We measured *risk attitude* by asking respondents to rate their willingness to take risks in their farming occupation, with possible responses from 0 ('not willing to take risks') to 10 ('very willing to take risks').

A second set of socio-psychological factors was created to serve as a proxy for local norms. We hypothesize that farmers' likelihood of adopting best practices increases as the number of individuals in the community supporting the behavior increases (i.e., increasing social pressure to believe in and adopt the practice). In particular, we constructed several variables to account for social influences based on the township in which the farm field is located in, using the town-average values of selected socio-psychological variables, including *average perceived efficacy* of the practice, *average farmer identity*, and *average familiarity* with 4R Nutrient Stewardship.

As explained above, previous literature has established the role of farmers' demographic and socioeconomic characteristics as well as spatial land characteristics in driving farmers' land management decisions (Huang et al., 2000; Kurkalova et al., 2006; Sheriff, 2005). As a result, in our model we included key socio-demographic characteristics such as the respondent's gender, age, income, years of experience, and education, as well as relevant spatial, field-specific farm characteristics, including total planted acres, soil type, and field slope (Table 2). We also included several farm-enterprise characteristics that account for the opportunity cost of time and cost of production: 1) whether the farmer currently manages livestock or poultry on his/her farm (to account for the type of enterprise); 2) number of fields (to account for the needs for labor across the entire farm operation and the opportunity cost of time); 3) a binary dummy variable for custom phosphorus application that proxies whether the farmer hired labor or not; 4) the horsepower of the combine harvest used on that field indicating the size of equipment; and 5) the total variable cost of production for this particular field. These variables account for the opportunity cost of time and other aspects related to the specific practice, and thus control for some of the structural characteristics that might influence a farmer's ability to adopt a particular timing related practice.

Statistical Analysis

We estimated both an ordered logit model and a latent class model for each timing related practice. We chose the ordered logit model because our dependent variable – the future likelihood of adopting one particular time-related practice – is ordinal and categorical, and the

ordered logit model explicitly exploits the ordinal nature of the dependent variable and thus provides a more efficient estimate than other models like multinomial logit. This model is estimated using the "ologit command" via Stata 14.

One limitation of the ordered logit model is that all farmers are assumed to behave homogeneously conditional on their field, farm and operator characteristics. In contrast, previous literature has found evidence of heterogeneity among farmers' land use and conservation decisions (e.g., Konar et al., 2014; Wilson et al., 2014). A popular approach to accommodate the latent heterogeneity is a latent class model approach. The core assumption of the latent class model is that different and discrete classes of farmers exist (some more likely to adopt particular timing-related practices) and that individuals in each class share homogeneous preferences, but preferences of individuals vary across classes. The optimal number of distinct classes and which class a particular individual belongs to (e.g., whether someone is more likely to delay application with an impending storm or not) are determined by the data, in particular the socio-demographic characteristics of farmers.

A latent class model is estimated for each of the three timing related practices. In doing so, we assume that there is only one categorical latent, or unobservable variable and that this discrete latent variable represents the underlying subgroups or segments of decision makers, and that a suite of factors including those listed previously affects these underlying subgroups. These variables are then divided into two categories: predictors and covariates. The predictors affect the dependent variable directly. These include the socio-psychological variables such as perceived efficacy of the practice, conservation identity, and town-average 4R familiarity, field characteristics such as the slope of the field, soil quality and soil texture; as well as the farm enterprise characteristics that account for the opportunity cost of time and the costs and machinery of production. The covariates determine the probability of an individual belong to a particular latent class or group. These include socio-demographics like age, gender, education, years of farming experience, income, generation, and retirement status. The model is estimated via maximum likelihood estimation in Latent Gold 4.5.

Results

Descriptive summary

Over half of all farmers across the Maumee River watershed already avoid winter application, exceeding the adoption level of only a third of farmers for the other two practices (Table 1). In addition, farmers who haven't adopted these practices seem to be divided in their stated future likelihood of adoption: half stated that they are unlikely to adopt while half stated they are likely to adopt. Finally, farmers in Michigan seem to have higher likelihood of adopting these practices in comparison to Ohio farmers, who make up the majority of farmers in this watershed.

Table 2 shows the summary statistics of key variables for the farmer survey. The average age of operators in our sample is 58.9 years old, which is within the range of 54.8 to 61 years old

based on the county-level data from the 2012 Census of Agriculture. A comparison between our sample and the 2012 Census of Agriculture data for all farms within the HUC6 western Lake Erie subwatershed (# H041000) reveals that our sample is skewed towards larger farms with higher gross sales. According to the 2012 Census of Agriculture, there are a total of 18,116 farms in the watershed with harvested cropland, and the average farm size for these farms is 264 acres. In our sample of 2,615 farms the average farm size is 440 acres. According to the 2012 Census of Agriculture for counties in the watershed (U.S. Department of Agriculture, 2012a), the share of farms whose income are less than 50,000 is 38%, and the share for those who made more than $500,000 is 12.4%. Comparatively, annual gross income for 16.6% of our sample is less than $50,000, while 20.6% make between $50,000 and $100,000, 27.7% make between $100,000 and $250,000, 16.1% make between $250,000 and $500,000, and 19.0% made $500,000 or greater (Burnett et al. 2014). The majority of our sample population is male (91.7%) with an average age of 59 years old. Half of the respondents (50.9%) have only a high school degree or equivalent, while 10.7% have an associate's degree and 12.4% have a bachelor's degree. A small proportion (5.4%) of respondents have a graduate or professional degree.

While this may suggest that our sample is not statistically representative of all 18,116 farms in the Maumee River watershed, the 2012 Census of Agriculture data also shows that over 80% of all cropland in Ohio and Indiana are located in farms with at least 180 acres and over half of the acreage is on farms with at least 500 acres (U.S. Department of Agriculture, 2012b). As larger farms manage a greater relative proportion of cultivated lands in the Corn Belt (Lambert et al., 2007), they also have a disproportionate potential to impact environmental quality through adoption or non-adoption of conservation practices. In fact, in the western Lake Erie basin, almost 65% of the cropland is managed by farmers with operations of at least 500 acres, while those with operations under 50 acres manage less than 3% of the total acreage (U.S. Department of Agriculture, 2012b). Since the focus of our paper is farmers' timing-related management choices, it seems appropriate to focus on the larger farms, or the farmers who manage proportionally more acreage in the watershed, which is more important from both a behavioral and a water quality control perspective.

Ordered logit model

The ordered logit model compares five categories of adoption from "never intending to adopt" to "already adopted," and is separately estimated for each of the three timing-related practices. We controlled for time-invariant unobservables by including three crop reporting district fixed effects in these models. The results of the ordered logit model are presented in Table 3. Instead of showing the raw regression coefficients, we take the exponential of the reported coefficients and show these transformed coefficients in Table 3. Doing so provides a more intuitive interpretation in terms of the proportional odds ratio that compares the likelihood of adoption by farmers who are in groups greater than k versus less than or equal to k, where k is the ordered response variable. This effect is assumed to be equal across all k categories and therefore we interpret this proportional odds ratio as the change in the predicted odds of farmers'

likely future adoption vs. non-adoption, given a one-unit increase in the predictor variable and assuming that all other variables are held constant.

A key and consistent result from these three models is that socio-psychological variables are positive and significant factors in driving farmers' decisions to apply at the "right" time, both in terms of seasonal timing and timing with respect to storm forecast. In addition, all three models show that these predictors are significant in predicting the future adoption likelihood, explaining roughly 8-11% of the variance for any particular practice. Below we discuss the ordered logit results for each of the three adoption practices. We discuss these results in terms of the proportional odds ratio, which is calculated as the exponential of the estimated coefficients that are reported in the table.

Delayed broadcast application before a storm: We find that for every one-unit increase in a farmer's perceived efficacy associated with this practice (eff_delay_bc), the odds of likely future adoption vs. non-adoption are 2.65 times greater—in other words, a farmer is 2.65 times as likely to adopt the practice in the future versus not given a marginal increase in his or her perceived efficacy of the practice. Similarly, we find a positive correlation between higher conservationist identity (identity_farmer) and concern regarding nutrient loss (concern) with higher predicted probability of adoption. The results also show evidence of the effects of field and socio-demographic characteristics in determining the adoption of delaying the broadcast before rainstorm forecast. Specifically, we find that older farmers, farmers with higher farm income and a larger field size are more likely to delay broadcasting before a storm. In contrast, we find that farmers with livestock on farm are less likely to delay broadcasting before a storm, which could result from the fact that those farmers have less time in dealing with crop management practices or have greater need to dispose of manure.

Avoiding fall application: Farmers' perceived efficacy of avoiding fall application is an important predictor of the likelihood of avoiding fall application as well. Specifically, for every one-unit increase in a farmer's perceived efficacy associated with this practice, we expect that the odds of likely future adoption vs. non-adoption are 2.45 times greater. A stronger conservationist identity significantly correlates with an increase in adoption, as do several field-level spatial characteristics that seem to be more important in driving the adoption of avoiding fall application than delaying broadcast. Specifically, those who planted corn in the previous growing season (corn_2013) are more likely to avoid fall application, but those with better soil quality are less likely to avoid fall application of nutrients, maybe reflecting the desire to achieve higher yields on top quality fields. Therefore, those with sandier soils may be more likely to avoid fall application of nutrients compared to clay, which is intuitive because fertilizer applied in fall tends to be washed away in sandier soils, leaving less for crops to use in the spring (McDowell et al. 2010). The results also show that farmers who have phosphorus custom applied are less likely to avoid fall fertilizer application.

Avoidance of winter application: Perceived efficacy is also strongly correlated with the likelihood of avoiding winter application. Specifically, for every one-unit increase in a farmer's perceived efficacy of avoiding winter application (eff_avoidwinter), we expect that the odds of likely future adoption vs. non-adoption are 2.18 times greater. Other individual-level variables are also positively correlated with adoption, including behavioral characteristics such as conservationist identity (identity_farmer) and concern about nutrient loss on their farm (concern), as well as socio-demographic characteristics such as better education, higher annual income, and higher off-farm income. At a field level, for those whose field slope was greater than 10%, we expect the odds of likely future adoption vs. non-adoption are 2.58 times smaller. This may suggest that comparatively, farmers tend to take greater care in better quality and flatter fields to avoid winter application. We also find that farmers are less likely to avoid winter application on rented fields, and when they have livestock, which is similar to our previous finding for the delayed broadcast application before a storm. In addition, Michigan farmers have a statistically higher probability of avoiding winter applications, which may suggest the need for future research examining differences in state and the county-level regulations education and extension efforts.

Latent class model

The latent class model does not impose restrictions on the number of latent classes, and thereby the degree of heterogeneity, *ex ante*. Instead, this approach allows the data to determine the number of optimal latent classes by virtue of which number of classes minimizes the Bayesian Information Criterion (BIC) (Nylund et al., 2007). The results indicate that model fit was strongest for the three latent class solution for all three adoption decisions.[2] Table 4 presents the covariate results from the class membership regressions, while Tables 5-7 show the results on the direct predictors of adoption of P-timing conservation practices based on the 3-class latent class models. These results are estimated regression coefficients and standard errors rather than marginal effects, so the direction and significance of these coefficients are more important than the actual magnitude. As shown in Tables 5-7, the R-square statistics for the latent class models show that these 3-class latent class models are able to explain 55-76 percent of all variations for the adoption of timing-related practices, which represents significant improvements over the ordered logit model and suggests the importance for accounting for farmers' heterogeneous preferences when modeling the adoption of conservation practices.

Delayed broadcast application before a storm: the majority of individuals are in class 1 (61%), with the remaining individuals in class 2 (21%) and class 3 (18%) (Table 4). In terms of the covariates (Table 4), we see that age, years of experience, farm income, number of farming generations, and off-farm income are statistically significant in determining the probability of an individual belonging to a particular class. Specifically, those most likely to have adopted the

[2] Additional statistics on goodness of fit for alternative number of classes are available from the authors upon request.

practice (i.e., class 3 with 78% adoption) have a greater likelihood of off-farm employment and have a greater probability of farm income in the range of $50,000 to $100,000 or over $500,000. Although class 1 and 2 have lower likelihood of adoption (24% and 50% respectively), they make up the majority of farmers in our sample. Class 1, with the lowest current rate of adoption but greatest likelihood of future adoption, tends to be older, second-generation farmers with farm income ranging from $50,000 to $100,000. Class 2, with a fairly even split between adoption and likely adoption, tends to be younger, first-generation farmers with farm income in the range of $100,000 to $250,000.

In terms of the direct predictors of one's likelihood of delaying broadcasting in light of a storm event (Table 5), there are significant differences across classes in terms of whether and how a certain predictor affects the future likelihood of adoption. For the sake of brevity we will focus on the factors motivating adoption in class 3, the class of individuals most likely to have adopted the practice—i.e., "adopters." For these individuals, the likelihood of delaying broadcasting increases with greater perceived efficacy, and higher community-average perceived efficacy (eff_delaybc_avg) and conservationist identities (identity_farmer_avg), indicating a potential sensitivity to social norms. They are also sensitive to a range of field and farm characteristics. Specifically, adopters are more likely to delay broadcasting for low slope fields (0-2%) with better soil quality and enrolled in crop insurance programs. In addition, we also find that adopters with livestock on their farm are less likely to delay broadcast, possibly reflecting the fact that livestock operations decrease the time available for crop management. This is also consistent with the higher adoption by individuals in this class who hire professionals to custom apply (p_custom), which may help solve this time constraint. In contrast, farmers in class 1, which are the majority, are more likely to delay broadcasting with a higher perceived efficacy, greater conservationist identity, higher concern regarding nutrient loss, as well as higher community-average familiarity with 4R Nutrient Stewardship (familiar_4r_avg).

<u>Avoidance of fall application</u>: the majority of individuals are in class 1 (65%), with the remaining individuals divided between class 2 (22%) and class 3 (13%) (Table 4). Individuals in classes 3 and 1 are the most likely to have adopted the practice (47% and 40% adoption respectively), followed by class 2 (10% adoption). In terms of the covariates (Table 4), we see that age, experience, generation, farm income, and off-farm income are statistically significant in determining the probability of an individual belonging to a particular class. Specifically, while both class 3 and class 1 have similar levels of adoption, class 3 individuals are more likely to operate smaller farms (under $50K) but have off-farm income, while class 1 individuals are likely to be younger farmers with higher gross farm income and more farming experience. Class 2, the class with the lowest levels of adoption tends to be older, with less experience, and no off-farm income.

In terms of the direct predictors of one's likelihood of avoiding fall application (Table 6), there are significant differences across classes in terms of whether and how a certain predictor affects the future likelihood of adoption. As before, we focus on the factors motivating adoption

in class 3, the minority class that is also most likely to have either adopted or to be likely to adopt in the future. For these adopters, the likelihood of avoiding fall application increases with a stronger conservationist identity (identity_farmer) and increased tolerance for risk in farming (risk_farmer). With regards to field characteristics, adopters are more likely to avoid fall application on flatter, corn fields, and on a farm with fewer number of fields to take care of and no livestock. Interestingly, Class 3 individuals are negatively influenced by individual beliefs in the efficacy of the practice (eff_avoidfall), while individuals in the other classes, such as those in the majority class in class 1, experience significant increases in adoption with increases in perceived efficacy. The effect of soil texture on adoption is more mixed for the two classes with higher adoption: for the majority of farmers in class 1, higher clay content of the soil (soil_clay) leads to higher retention of nutrients applied in the fall for next spring, thus resulting in a lower adoption level which is consistent with the ordered logit model results and agronomic studies (McDowell et al., 2001); however, class 3 individuals experience the opposite, counterintuitive effects. The counterintuitive results for the class 3 individuals on soil clay content and perceived efficacy may result from a small class size, and thus might need to be interpreted with caution.

Avoidance of winter application: the majority of individuals are in class 1 (60%) and class 2 (30%), while a minority fall in class 3 (10%) (Table 4). Class 1 individuals are most likely to have already adopted the practice (63% adoption) followed by class 2 (57% adoption) and class 3 (24% adoption). In terms of the covariates (Table 4), we see that age, gender, experience, farm income, and off-farm income are statistically significant in determining the probability of an individual belonging to a particular class. Adopters (i.e., class 1) are younger and more likely to be operating farms with over $500,000 in gross farm income. Individuals in class 2 operate similar size farms but have more experience, while individuals in class 3 are older with less experience and operating farms with relatively lower gross farm income.

In terms of the direct predictors of one's likelihood of avoiding winter application (Table 7), there are significant differences across classes in terms of whether and how a certain predictor affects the future likelihood of adoption. We focus on the factors motivating adoption in class 1, the class of individuals most likely to have adopted the practice and that also represents the majority of the farmers. For these adopters, the likelihood of avoiding winter application increases with higher levels of efficacy and conservationist identity, and lower levels of risk tolerance. With regards to field characteristics, adopters are more likely to avoid winter application as the slope of the field decreases, and the parcel is further from the town. Similar to delaying broadcast, farmers with livestock on the farm are less likely to avoid winter application, possibly reflecting less time available for crop management given the time devoted to livestock operations.

Discussion

Characteristics of class membership

The results indicate that three unique classes of farmers exist who vary in the way they think and act as it relates to each timing-related best management practice. From a modeling standpoint, allowing for these three unique classes to emerge increases the explanatory power of the model by 45-65%. This again underscores the need for taking a more heterogeneous approach to modeling farmer adoption of conservation practices. Interestingly, the level of adoption for each class does not necessarily vary across the classes, but the characteristics of individuals in each class and the factors motivating their choices do differ. This supports the idea that policies and outreach efforts aimed at increasing adoption will vary in their effectiveness for different groups of farmers depending on the unique motivations and constraints of each class. Across the three classes, the level of formal education varies quite widely, as does the gender and status of the individuals as retired (or not) from an off-farm job. It appears that these factors are not a driver of farmer preferences. However, we do find that the generational status of the family farm and years of experience matters, where first generation farmers with more years of experience are more likely to belong to a class with increased adoption for some practices. Age is also a determinant of class membership with relatively younger farmers often belonging to classes with higher levels of adoption. These findings are consistent with previous literature such as Prokopy et al. (2008). Finally, having higher gross farm income generally increases the likelihood of one belonging to a class with higher adoption levels, while lower farm income tends to increase the likelihood of belonging to the class with lowest adoption levels. Similar trends are found for the effects of the off-farm income as well. This is also fairly consistent with past research highlighting the positive effect of income (Saltiel et al., 1994; Prokopy et al., 2008; Lambert et al., 2007; Gould et al., 1989), perhaps due to the increased ability to invest in new technologies, or adopt new technologies that may be both high risk and high reward.

Motivators of adoption

In terms of the socio-psychological characteristics directly influencing adoption, the only common predictor across all three classes and practices is perceived efficacy. This finding is consistent both with the behavioral literature on motivation (Floyd et al., 2000), as well as prior research on farmer conservation decisions (Tey and Brindal, 2012). If an individual is concerned about a problem, the final cognitive barrier that may prevent someone from acting on his or her concern is typically efficacy or behavioral control. Specifically, an individual will only act on their motivations when he or she believes they have the ability to implement actions that will actually achieve the desired outcome. Figure 2 shows the relationship between perceived efficacy of a timing-related practice with the predicted probability of “will definitely adopt’ the practice for two specific classes for each practice, which could be loosely termed as the “early adopter” class and the “likely future adopter” class. We chose the category of “will definitely adopt” in the future but haven’t already adopted because farmers in this category are most likely to switch from current non-adoption to adoption of the timing-related practice in the future. Figure 2 shows that an increase in perceived efficacy is almost always positively correlated with a higher predicted probability of “will definitely adopt” that practice in the future, but the

magnitude of this positive effect varies substantially among different classes or subgroups of farmers and also varies by types of practices. In particular, an increase in a farmer's perceived efficacy of avoiding fall application from "not at all" to "a good deal" would increase the probability of "will definitely adopt" avoiding fall application from 0 to 20% for the likely future adopter subgroup of farmers (class 2 shown in Table 6). In contrast, a similar change in the perceived efficacy of winter application would only induce half of the likely adopters in class 3 shown in Table 7 to increase their probability of "will definitely adopt" from 0 to about 10%.

While it is plausible that adoption of a particular practice can increase the perceived efficacy of that practice, there is a long history in behavioral theory identifying the significance of efficacy as a determinant of behavior and not the reverse. Specifically, the Theory of Reasoned Action/Theory of Planned Behavior identifies the role of perceived control or ability in explaining intentions to adopt a particular behavior (Ajzen, 1991). The motivational literature related to behaviors that are adopted to protect oneself from a hazard or risk focus almost exclusively on efficacy as the primary antecedent of behavior (Maddux and Rogers, 1983). In the context of farming and adoption of BMPs, we expect that farmers are well aware of the risks associated with nutrient loss (both economically, and ecologically or environmentally in some cases), but that it is their beliefs about the efficacy of a practice that may vary and be a greater driver of adoption. While it is difficult to rule out all endogeneity concerns, our model mainly relies on how current perceived efficacy affect future likelihood of adopting the timing-related practice in which the lagged explanatory variable should mitigate endogeneity problems, if any. Additional robustness checks using only farmers who haven't adopted yet or reframing the dependent variable into four categories did not change our main results on the positive and significant role of perceived efficacy in timing-related practice adoption.

In addition to efficacy being a motivator for the majority of farmers for all practices, relatively greater identity as a conservationist versus a productionist increases the likelihood of adoption for those individuals in the class identified as most likely to adopt each of the three practices. This finding is also consistent with prior research on farmer identity where pro-environmental or conservationist identities increase support for best management practices that may not be consistent with a purely productionist identity (McGuire et al., 2013; Prokopy et al., 2008). Here we see that for avoiding winter and fall application, the two classes with the greatest proportion of current and future adopters has an increased likelihood of adoption as the relative weight placed on one's conservationist identity increases. There is no effect of a conservationist identity on adoption for the classes with the lowest adoption rates, indicating that their motivation does not include conservation related farming motivations or values. For delaying broadcasting, an increased conservationist identity increases the probability of adoption for over 80% of the farmers in the sample who have already adopted or are willing to adopt the practice in the future.

The social influence variables measured as town-average socio-psychological characteristics vary in their significance as drivers of adoption across the three practices and by

subgroups of farmers. Social pressures seem to play a larger role for delaying broadcasting in the spring, and for the minority classes with the lowest likelihood of avoiding winter application. In this case, for example, we find that social pressure is associated with a lower likelihood of adoption. The class of individuals most likely to already be delaying their broadcasting in light of a storm event seem to be responsive to all measures of community norms, while the older class of likely adopters are more sensitive to increased familiarity in the community and the younger class of likely adopters are more sensitive to increased conservationist identities in the community. Normative measures of community familiarity, efficacy and identity have no effect on the adoption of avoiding winter application for the likely adopters, but have a negative effect for those in the minority class that are least likely to adopt. This group may not feel pressure to comply with social norms, as reflected by their position as the minority in the community (both in terms of total numbers and in terms of current adoption of BMPs). Similarly, for the decision to avoid fall application, the younger adopters tend to be positively influenced by perceived efficacy in the community, whereas the older adopters tend to be negatively influenced.

Finally, while results from the ordered logit model do not show a set of consistently significant socio-economic and field-level spatial characteristics across all three timing-related practices, the latent class model results suggest the strong and significant influences of these variables in driving farmers' adoption. Specifically, farmers with higher farm income and higher education level are more likely to adopt these timing-related practices; and farmers are more likely to adopt on flatter fields with better soil quality and sandier soils that are part of a farm with no or few livestock operations. In addition, the latent class models reveal that certain subgroups of farmers, typically those in the minority, tend to be more motivated or influenced by these field-level spatial characteristics and farm enterprise factors than others.

Conclusions

Using data from a unique farmer survey of 2,540 corn and soybean farmer respondents in the western Lake Erie basin, this paper analyzes how farmers' socio-psychological, socio-economic and spatial land characteristics affect their decisions to adopt three timing-related best management practices: delaying broadcast given storm forecast, avoiding fall application and avoiding winter application. For each of these three practices, the results consistently show the significance of socio-psychological factors in leading farmers to apply at the "right" time. In particular, our results clearly show the significance of perceived efficacy of the practice, suggesting the need to include measures of efficacy in future studies of farmers' land management decision-making and incorporate efficacy building mechanisms into policy and outreach. Specificallty, the ordered logit model suggests that a 20% increase in perceived efficacy would result in the likelihood of actual adoption of delaying broadcast increasing from 35% to 48%.

Our results also reveal key differences in the effects of socio-economic, farm enterprise and field factors across the three practices. The influence of these factors varies depending on the

practice. For example, avoiding winter application is more constrained by socio-economic characteristics of farmers such as having less gross farm income, as well as having land rental versus ownership status. Income also seems to be a limiting factor for the class least likely to have already adopted the practice of delaying broadcast application. Age is also a limiting factor with older farmers often being more likely to belong to a class with relatively lower levels of adoption. In contrast, delaying broadcast and especially avoiding fall application may be more constrained by external or structural factors, such as a higher percentage of clay in the soil texture or having a large farm with too much acreage to cover in the spring or fall. One explanation for these differences could be that farmers constrained by timing in the spring default to fall (versus winter application), and those who must apply in the winter are limited to those using manure as a source (a minority of farmers in the watershed). As a result, most farmers have more control over the decision to avoid winter application and may rely more on individual beliefs or social feedback to identify what is the "right" behavior.

Motivational theories would predict that an individual acts to solve a problem when they have high perceived behavioral control, or the ability to act on their values and motivations (Ajzen, 1991). In the context of best management practices in agriculture, this behavioral control is tied to the belief that the options available to achieve the conservation outcome are effective (i.e., able to reduce nutrient loss from the field to achieve either economic or environmental goals). What seems to be lacking in this context for many non-adopters is a high degree of perceived efficacy or behavioral control. One way to infuse more efficacy and control into farmer thinking would be to provide site-specific or field-level recommendations about what practices to implement in order to achieve both short-term production goals and long-term sustainability goals. In talking about these goals, the lowest common denominator would be to focus on production goals, as the productionist identity was shared equally among farmers in the watershed. However, it was the conservationist identity that was actually associated with greater adoption of timing-related best practices. As a result, extension and outreach efforts could be targeted to make the conservationist identity more salient when providing field-level support for selecting and implementing practices. Such targeting might involve highlighting how respected farmers in the community minimize soil erosion and nutrient runoff when making field management decisions in order to achieve long-term goals related to conservation (e.g., soil health, water quality).

Our results reveal that many field and farm level spatial characteristics are significant in driving farmers' application timing decisions, including field slopes, soil texture, field and farm size, land tenure status, as well as the farm's crop-livestock mix. These may suggest that, in addition to perceived efficacy being a significant cognitive barrier, there are also clear structural barriers that also decrease one's perceived control or ability to successfully implement a practice that will actually reduce nutrient loss. These may include a lack of time and machinery needed to implement a practice given farm size and number of fields, or having less time available for crop management given time devoted to livestock operations, or uncertainty in weather forecasts. The

significance of field and farm characteristics such as better soil quality, larger field size, and sandier soils in driving higher adoption level may also suggest roles of spatially targeted nutrient management policies such as greater policy and outreach emphasis on adoption on large farms with better soil quality. Our model also reveals the importance of socio-economic and farm enterprise characteristics: for example, farmers with higher farm income, higher education level and less livestock on the farm tends to have a higher likelihood of adopting timing-related practices, which may warrant stronger outreach and 4R Nutrient Stewardship training efforts targeted towards farmers who farm large acreage and do not have livestock. These results suggest the need of further research regarding the interplay between socio-psychological characteristics such as perceived efficacy and control and the spatial characteristics at the parcel level as well as the farm enterprise and socio-economic characteristics.

These results provide one of the first analyses of the adoption of timing-related conservation practices using actual farmer survey data, but nonetheless are also subject to several limitations that warrant future research. First, we do not observe the capital costs of adopting a specific practice for a specific field and thus cannot predict the influence of incentive-based policies, e.g., payments for specific practices, on the likelihood of adoption. Secondly, our survey was conducted in early 2014, collecting data on land management decisions farmers made in 2013, when the commodity prices were still high. To the extent that farmers make land management decisions differently in this new era of low to negative profit margins, our modeling results may not always apply. However, it is highly possible that when facing lower and negative profit margins now, farmers may be more likely to adopt or engage in practices that could be potentially cost-saving, making our current findings conservative. Lastly, our survey and models are based on the decisions made by row-crop farmers in western Lake Erie basin operating mid to large-scale farms, and thus may not necessarily extend to other places, especially beyond the Midwest.

Acknowledgements

This work was supported by the National Science Foundation Coupled Human and Natural Systems program [grant number GRT00022685]; and the NOAA/Ohio Sea Grant Program.

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Tables

Table 1 – Summary statistics on the adoption of time-related best management practices

	Avoiding fall application					
	No. Obs	Will never adopt	Unlikely to adopt	Likely to adopt	Will definitely adopt	Already doing it on the field
IN	367	5%	32%	25%	8%	30%
MI	151	5%	17%	13%	13%	52%
OH	2,005	5%	24%	26%	12%	33%
Total	2,523	5%	25%	25%	12%	33%

	Avoiding winter application					
	No. Obs	Will never adopt	Unlikely to adopt	Likely to adopt	Will definitely adopt	Already doing it on the field
IN	371	3%	7%	20%	13%	56%
MI	154	2%	8%	9%	17%	64%
OH	2,015	3%	6%	19%	18%	54%
Total	2,540	3%	6%	18%	18%	55%

	Delaying broadcast before storm forecast					
	No. Obs	Will never adopt	Unlikely to adopt	Likely to adopt	Will definitely adopt	Already doing it on the field
IN	367	5%	32%	25%	8%	30%
MI	151	5%	17%	13%	13%	52%
OH	2,005	5%	24%	26%	12%	33%
Total	2,523	5%	25%	25%	12%	33%

Table 2 – Summary of the variables and descriptive results for the sample

Variable	Description	# Obs	Mean	Std. Dev.	Min/Max
Dependent variables: Best Management Practices on Phosphorus Application Timing					
Adopt_winter	Dependent variable: future likelihood of avoiding winter application	2432	3.16	1.09	0/4
Adopt_fall	Dependent variable: future likelihood of avoiding fall application	2414	2.45	1.30	0/4
Adopt_delaybc	Dependent variable: future likelihood of delaying broadcast application before storm forecast	2434	2.76	1.14	0/4
Socio-psychological variables: Individual characteristics					

familiar_4r	Familiarity with 4R	2598	1.46	1.25	0/4
concern	Concern about nutrient loss on your farm	2555	3.49	1.03	0/6
identity_farmer	Farmer identity (conservationist/profit maximizer)	2554	1.28	0.84	-1.26/4
risk_farmer	Risk attitude in your primary occupation as farmer (higher value is a higher risk tolerance)	2574	5.42	2.39	0/10
eff_avoidfall	perceived efficacy of avoiding fall application	2562	2.23	1.13	0/4
eff_avoidwinter	Perceived efficacy of avoiding winter application	2570	2.99	0.99	0/4
eff_delay_bc	Perceived efficacy of delaying broadcast application	2573	2.66	0.99	0/4

Socio-psychological variables: Town-level differences

fam_4r_avg	Town-average of familiarity with 4R	2615	1.44	0.29	0.67/2.17
perc_loss_avg	Town-average of percep_loss	2615	4.22	0.34	2.93/5.01
iden_farm_avg	Town-average of farmer identity (conservationist/profit maximization)	2615	1.26	0.10	0.47/1.60
eff_fall_avg	Town-average of perceived efficacy for avoiding fall application	2615	2.22	0.18	1/2.77

eff_win_avg	Town-average of perceived efficacy for avoiding winter application	2615	2.97	0.17	2/3.42
eff_bc_avg	Town-average of perceived efficacy for delaying broadcast application	2615	2.64	0.17	0/3.17
Socio-economic characteristics					
gender	= 1 if female	2612	0.021	0.142	0/1
age	Age of farmers	2629	58.59	11.92	20/89
education	Education level	2600	2.98	1.29	1/6
experience	Years of farming experience	2615	37.60	13.60	2/70
generation	Number of farming generation	2571	2.56	0.67	1/3
retired	=1 if retired	2579	0.28	0.45	0/1
offfarm_inc	Amount of off-farm income	2610	1.67	1.35	0/4
farm_income	A farmer's annual gross income	2357	3.01	1.33	1/5
num_field	Number of fields	2785	10.7	20.4	1/75
livestock	= 1 if the farm has livestock	2608	0.29	0.45	0/1
Field-level characteristics					
harvester_hpw	Horsepower of harvester	2804	208.1	671.7	0/550
p_custom	=1 if phosphorus is custom applied	2810	0.45	0.50	0/1
cost_variable	Variable production costs	2794	231.0	150.0	27/598
field_acre	Acreage of the field	2615	45.83	56.01	0/1000
plant_acre	Total planted acres at the farm level	2602	440.10	646.34	0/7050

dist_town	Distance to a town or city with 10,000 people or more	2614	13.38	11.76	0/200
soil_top	=1 if soil is top quality based on expected corn/soybean fields	2615	0.33	0.47	0/1
soil_clay	=1 if dominant soil texture is clay	2615	0.22	0.41	0/1
soil_sand	=1 if dominant soil texture is sand	2615	0.02	0.15	0/1
field_rent	=1 if field is rented	2557	0.35	0.48	0/1
dist_4rdealer	Euclidean distance in kilometers to nutrient service providers	2613	35.54	18.83	0.97/114.65
corn_2013	=1 if the crop was corn in 2013	2615	0.47	0.50	0/1
slope	Slope of the field	2440	2.13	1.44	1/5
fe_Indiana	Crop reporting district fixed effect-NE Indiana	2868	0.13	0.34	0/1
fe_Michigan	Crop reporting district fixed effect-Michigan	2868	0.06	0.23	0/1
fe_NW_Ohio	Crop reporting district fixed effect-NW Ohio	2868	0.69	0.46	0/1
Fe_outside	Crop reporting district fixed effect-Other parts of Ohio	2868	0.12	0.33	0/1

Table 3 – Results of the ordered logit model for each timing related practice

	Delay broadcast before storm forecast		Avoid fall application		Avoid winter application	
Predictor	**Odds ratio**	**S.E.**	**Odds ratio**	**S.E.**	**Odds ratio**	**S.E.**
Socio-psychological variables: Individual characteristics						
Perceived efficacy of the practice	2.646***	0.140	2.447***	0.115	2.178***	0.117
Risk_farmer	0.976	0.019	0.964	0.019	0.974	0.020
Farmer_identity	1.201***	0.057	1.228***	0.069	1.185***	0.072
Concern	1.149***	0.053	1.033	0.047	1.094*	0.052
Socio-psychological variables: Town-level averages						
Familiar_4R_avg	1.083	0.115	1.137	0.121	1.035	0.116
Identity_farmer_avg	1.284	0.232	0.977	0.169	1.326	0.247
Efficacy_avg	1.079	0.184	1.127	0.148	0.756*	0.120
Socio-economic characteristics						

Age	0.994*	0.003	1.001	0.003	0.996	0.003
Gender	1.344	0.539	0.852	0.314	1.584	0.662
Retired	1.004	0.107	0.921	0.096	0.846	0.094
Experience	0.997	0.003	0.999	0.003	1.004	0.004
Education	1.041	0.037	1.005	0.036	1.146***	0.044
Farm_income	1.091**	0.048	0.972	0.043	1.171***	0.055
Off_farm_income	0.993	0.038	1.063	0.040	1.150***	0.046
Num_field	1.0003	0.002	-0.003	0.002	0.999	0.002
The farm has livestock	0.793**	0.079	-0.108	0.087	0.678***	0.071

Field (spatial) characteristics

Corn_2013	0.930	0.107	1.334***	0.149	0.939	0.112
Field_acre	1.001*	0.001	0.999	0.001	1.001	0.001
Plant_acre	0.999	0.000	0.999**	0.0001	1.000	0.0001
Dist_town	0.995	0.004	0.999	0.004	0.999	0.004
Soil_top	1.133	0.108	0.828**	0.078	1.024	0.103
Slope of field 2-5%	0.990	0.105	0.946	0.098	0.918	0.103
Slope of field 5-10%	0.989	0.170	1.165	0.199	1.082	0.196
Slope of field more than 10%	0.950	0.340	1.644	0.594	0.387***	0.128
Not sure about slope of field	0.723**	0.096	1.003	0.132	0.742**	0.101
Soil_clay	1.137	0.123	0.789**	0.083	1.045	0.119
Soil_sand	1.588	0.521	2.100***	0.699	0.364	0.345
Field_rent	0.907	0.087	1.119	0.105	0.838***	0.085
Crop_insurance	1.083	0.109	-0.0338	0.096	0.964	0.102
Custom apply phosphorus	0.982	0.088	-0.190***	0.087	1.025	0.097
Horsepower of harvester	1.000	0.0001	0.0001	0.0001	0.999	0.0001

Variable production costs	1.0004	0.0004	0.0001	0.0004	1.0006	0.0005
Crop reporting district fixed effects						
Fe_Indiana	0.988	0.163	-0.096	0.147	1.082	0.188
Fe_Michigan	1.301	0.286	0.596***	0.416	1.633**	0.399
Fe_NW Ohio	1.057	0.136	0.150	0.147	1.055	0.143
Ancillary parameters that define the changes in predicted probabilities among categories						
/cut1 between will never adopt and unlikely to adopt	-0.997	0.588	-1.157	0.498	-1.602	1.334
/cut2 between unlikely to adopt and likely to adopt	1.537	0.568	1.508	0.490	-0.095	1.329
/cut3 between likely to adopt and will definitely adopt	3.782	0.574	2.903	0.493	1.539	1.329
/cut4 between will definitely adopt and already doing it on the field	4.412	0.576	3.527	0.495	2.429	1.330

Number of Observations	1936	1912	2035
Log-likelihood	-2265.18	-2452.8	-2221.37
Pseudo R^2	0.108	0.1115	0.0844

Note: The asterisks indicate the rejection of the null hypothesis that the proportional odds ratio equals one, and *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

The proportional odds ratios presented in the tables are converted using the exponential of the regression coefficients.

Table 4. Coefficients from Class Membership Models from a 3-Class Latent Class Model

	Delay broadcast				Avoid fall application				Avoid winter application			
	Class1	Class2	Class3	p-value	Class1	Class2	Class3	p-value	Class1	Class2	Class3	p-value
Intercept	-0.061	0.991	-0.93		-0.061	0.991	-0.472	<0.01***	3.187***	-0.972	-2.215	0.015**
female	1.092	-3.94	2.849	<0.01***	1.092	-3.941	2.849	0.03**	1.547	3.159	-4.706	0.13
age	0.038***	-0.046***	0.008	<0.01***	-0.032***	0.026***	0.006	<0.01***	-0.023***	-0.007	0.030***	<0.01***
education				<0.01***				0.17				0.012**
-some high school, no diploma	3.804	-2.112	-1.693		1.443	-3.933	2.490		1.553	2.197	-3.750	
- high school degree	-0.273	0.175	0.098		-0.581	1.632	-0.582		-0.393	-0.854	1.247	
- some college, no degree	-0.661	0.130	0.532		-0.374	1.094	-0.720		-0.121	-0.020	0.141	
- Associate's degree	-0.701	0.285	0.416		-0.058	0.651	-0.593		-0.271	-0.882	0.153	
- Bachelor's degree	-0.771	0.258	0.513		-0.158	0.228	-0.070		-0.345	-0.745	1.090	
- Graduate or professional degree	-1.398	1.264	0.134		-0.273	0.797	-0.524		-0.423	0.304	0.120	
experience	-0.023***	0.036***	-0.014	<0.01**	0.0103*	-0.020***	0.009	0.11	0.0004	0.020***	-0.021**	0.066*
Generation of family farming				<0.01***				0.18				<0.01***
- first	-0.527***	0.336***	0.191		0.190	-0.104	-0.086		1.068	-2.910	1.842	
- second	0.390***	-0.050	-0.340**		-0.191	0.250*	-0.58		-0.590	1.320	-0.729	
-third	0.137	-0.286***	0.149		0.001	-0.146	0.145		-0.478	1.590	-1.112*	
farm_income				<0.01***				<0.01***				0.37

- less than 50k	0.173	0.278	-0.451***		-0.658***	0.159	0.499***		-0.164	-0.057	0.220	
- 50-100k	0.339*	-0.713***	0.375***		0.059	0.102	-0.160		0.029	-0.207	0.178	
- 100-250k	-0.138	0.472***	-0.334***		0.022	0.114	0.092		-0.078	-0.212	0.290	
-250-500k	0.058	-0.201	0.143		-0.025	0.160	-0.135		-0.104	-0.059	0.163	
- 500k or greater	-0.432***	0.165	0.268**		0.602***	-0.306	-0.296		0.316*	0.536***	-0.852***	
offfarm_inc	-0.002	-0.072	0.073*	0.41	0.089	-0.285***	0.197***	<0.01***	-0.052	0.057	-0.005	0.34
retired	0.1112	-0.090	-0.021	0.79	-0.095	0.200	-0.105	0.55	0.213	-0.131	-0.082	0.19
Class Size	61.3%	21.1%	17.6%		64.9%	22.2%	12.9%		59.8%	30.1%	10.1%	
Unlikely to adopt	14.7%	9.7%	15.6%		33.2%	20.5%	25.6%		9.1%	6.1%	7.4%	
Likely to adopt	61.3%	40.8%	6.7%		27.2%	69.1%	27.9%		28.3%	37.2%	68.3%	
Already adopted	23.9%	49.5%	77.7%		39.6%	10.3%	46.5%		62.6%	56.7%	24.3%	
No. Obs.		1885				1862				1877		

Note: *, **, *** indicate significance at 10%, 5% and 1% level

Table 5. Results of 3-Class Latent Class Model for the Adoption of Delaying Broadcast Before Storm Forecast

Predictors	**Class1**	**s.e.**	**Class2**	**s.e.**	**Class3**	**s.e.**	**Wald[a]**	**Wald(=)[a]**
Socio-psychological variables: Individual characteristics								
eff_delay_bc	0.861***	0.068	10.589***	3.340	3.034***	0.910	178.81***	14.17***
risk_farmer	-0.011	0.019	-1.011***	0.362	-0.211	0.229	9.18***	8.28***
identity_farmer	0.118***	0.058	12.153***	3.823	-9.961***	2.883	25.97***	22.18***
concern	0.084*	0.045	4.221***	1.426	-4.045***	1.277	22.26***	18.89***
Socio-psychological variables: Town-level averages								
fam_4r_avg	0.129	0.111	-8.264***	2.809	16.776***	4.738	22.70***	21.33***
iden_farm_avg	0.352*	0.183	-23.056***	7.417	15.662***	4.566	25.62***	21.22***
eff_delaybc_avg	-0.317*	0.172	21.525***	6.737	27.815***	8.062	25.60***	22.76***
Field (spatial) characteristics								
corn_2013	0.019	0.109	-9.659***	3.333	1.544	1.127	10.28***	10.26***
field_acre	0.000	0.001	0.070***	0.024	0.008	0.006	10.91***	10.88***
plant_acre	0.000	0.000	0.011***	0.004	-0.007	0.002	21.24***	20.65***
dist_town	-0.001	0.004	-0.215***	0.082	0.064	0.052	8.62***	8.46***
soil_top	-0.061	0.094	6.513***	2.195	7.509***	2.286	19.89***	19.85***
slope 0-2%	-0.094	0.096	3.675***	1.354	6.183***	1.917	35.04***	23.53***
slope 2-5%	-0.226**	0.104	3.789***	1.322	28.704***	7.970		
slope 5-10%	0.103	0.138	0.178	1.117	-2.577**	1.279		
slope > 10%	0.571***	0.279	-8.680****	3.313	-34.669***	9.895		
slope not sure	-0.353***	0.117	1.038	1.345	2.359**	1.239		
soil_clay	-0.110	0.108	4.478	1.768	14.368***	4.036	20.04***	19.51***
soil_sand	0.044	0.363	6.806	4.069	34.081***	9.843	14.74***	14.64***
Farm enterprise characteristics								
field_rent	-0.151	0.095	5.978***	2.149	2.708***	1.379	13.59***	12.21***
crop_insurance	0.188**	0.097	-15.421***	5.069	14.318**	3.972	25.57***	22.17***

livestock	-0.148	0.097	-3.244***	1.309	-10.837**	3.246	20.48***	16.10***
num_field	0.000	0.002	-0.254***	0.087	0.292***	0.089	19.55***	19.52***
harvester_hpw	0.125	0.091	-20.365***	6.453	18.130***	5.003	25.01***	23.11***
p_custom	0.000	0.000	0.003*	0.002	0.001	0.001	5.21	4.71
cost_variable	0.000	0.000	0.041**	0.014	-0.010**	0.005	13.53***	13.50***
Crop reporting district fixed effects								
Fe_Indiana	-0.309**	0.165	9.845***	3.902	-2.413	1.838	11.21***	8.14***
Fe_Michigan	0.272	0.229	16.688***	6.121	-28.739***	8.137	21.34***	19.98***
Fe_Ohio	-0.163	0.130	17.582***	6.125	-8.588***	2.764	19.22***	17.81***
Intercept								
0-will never adopt	1.185	1.007	68.688***	26.635	188.210***	53.635	356.751***	31.654***
1-unlikely to adopt	2.132***	0.523	78.113***	24.857	107.043***	30.283		
2-likely to adopt	1.716***	0.102	30.69***	9.589	6.654***	1.886		
3-will definitely adopt	-1.270***	0.508	-49.71***	16.154	-97.838***	27.748		
4-already adopted	-3.763***	1.026	-127.77***	41.491	-204.069***	57.951		
Number of observations			1885					
Class size	61.3%		21.1%		17.6%			
R^2	0.4353		0.5949		0.9577			
			0.7131					
Log-likelihood			-2104.54					
AIC			4457.08					
BIC			5144.25					

[a]The first Wald statistic indicates the overall significance of the predictor in driving adoption likelihood across the classes, and the second statistic (Wald(=)) indicates a statistical difference in the coefficients across the three distinct classes respectively

Table 6. Results of 3-Class Latent Class Model for the Adoption of Avoiding Fall Application

Predictors	**Class1**	**s.e.**	**Class2**	**s.e.**	**Class3**	**s.e.**	**Wald[a]**	**Wald(=)[a]**
Socio-psychological variables: Individual characteristics								
eff_avoidfall	0.683***	0.068	1.572***	0.346	-2.184***	0.739	203.38***	21.69***
risk_farmer	-0.006	0.018	-0.459***	0.142	1.196***	0.381	20.10***	19.59***
identity_farmer	0.186***	0.054	-0.148	0.214	1.710***	0.676	20.65***	7.69***
concern	-0.070	0.044	0.715***	0.226	0.495*	0.279	15.50***	14.80***
Socio-psychological variables: Town-level averages								
fam_4r_avg	0.305***	0.127	-1.617***	0.536	-3.716**	1.952	17.83***	15.16***
iden_farm_avg	-0.053	0.092	1.191***	0.431	0.785	0.822	8.59***	8.49***
eff_fall_avg	-0.075	0.150	-0.605	0.525	1.833	1.822	2.88	2.32
Field (spatial) characteristics								
corn_2013	0.258***	0.093	-0.162	0.404	4.400***	1.744	14.78***	6.75*
field_acre	-0.001	0.001	0.000	0.004	-0.008	0.005	3.33	1.93
plant_acre	0.000	0.000	0.000	0.000	0.001	0.001	8.89***	0.97
dist_town	0.011	0.004	-0.013	0.009	-0.178***	0.060	20.56***	16.50***
soil_top	-0.072	0.083	-0.332	0.315	-0.339	0.602	3.10	0.69
slope 0-2%	-0.278	0.093	-0.036	0.328	2.622***	0.981	33.07	20.98
slope 2-5%	-0.132	0.095	-0.997***	0.442	2.310***	1.029		
slope 5-10%	-0.076	0.128	0.731	0.467	2.676***	1.241		
slope > 10%	0.389	0.270	1.088	1.000	-3.934***	1.786		
slope not sure	0.097	0.123	-0.786**	0.381	-3.673***	1.374		
soil_clay	-0.349***	0.101	-0.297	0.385	6.613***	2.206	28.03***	10.12***
soil_sand	-0.113	0.303	5.097***	1.511	1.822	1.434	13.19***	12.74***
Farm enterprise characteristics								
field_rent	0.053	0.081	-0.620	0.427	3.600***	1.116	12.76***	12.54***
crop_insurance	0.058	0.095	0.011	0.346	-4.694***	1.456	10.74***	10.57***
livestock	0.019	0.081	-0.259	0.336	-4.736***	1.961	6.10	6.06*

num_field	-0.001	0.002	-0.008**	0.004	-0.092***	0.044	7.90**	6.14*
harvester_hpw	-0.158**	0.078	-0.169	0.305	0.400	0.632	5.56	0.76
p_custom	0.000	0.000	0.000	0.000	-0.001*	0.000	4.94	4.19
cost_variable	-0.001	0.000	0.001	0.002	0.005	0.004	3.94	3.21
Crop reporting district fixed effects								
Fe_Indiana	-0.192	0.138	-0.564	0.572	4.521***	1.563	12.28***	9.45***
Fe_Michigan	0.658***	0.230	-0.155	0.592	6.244***	2.502	16.95***	6.97***
Fe_Ohio	0.043	0.109	-0.583	0.534	5.272***	1.651	11.27***	11.25***
Intercept								
0-will never adopt	1.105	0.811	-4.830*	2.700	-3.270	7.133	416.66***	42.60***
1-unlikely to adopt	2.535***	0.426	-0.035	1.320	3.092	3.288		
2-likely to adopt	0.848***	0.116	3.019***	0.631	3.778***	1.030		
3-will definitely adopt	-1.989***	0.433	2.439*	1.429	0.571	3.518		
4-already adopted	-2.499***	0.829	-0.593	2.497	-4.171	6.685		
Number of observations			1862					
Class size	64.9%		22.2%		12.9%			
R^2	0.4815		0.6685		0.9076			
			0.6621					
Log-likelihood			-2277.3					
AIC			4814.59					
BIC			5533.42					

[a]The first Wald statistic indicates the overall significance of the predictor in driving adoption likelihood across the classes, and the second statistic (Wald(=)) indicates a statistical difference in the coefficients across the three distinct classes respectively.

Table 7. Results of 3-Class Latent Class Model for the Adoption of Avoiding Winter Application

Predictors	**Class1**	**s.e.**	**Class2**	**s.e.**	**Class3**	**s.e.**	**Wald[a]**	**Wald(=)[a]**
Socio-psychological variables: Individual characteristics								
eff_avoidwinter	0.931***	0.081	-0.588***	0.149	7.218***	2.235	178.81***	103.64***
risk_farmer	-0.060***	0.020	0.074***	0.035	0.807***	0.330	16.57***	15.15***
identity_farmer	0.129***	0.059	0.391***	0.125	-10.846***	3.427	27.86***	13.41***
concern	0.059	0.044	0.179***	0.076	-2.631***	1.028	15.69***	8.68***
Socio-psychological variables: Town-level averages								
fam_4r_avg	0.036	0.166	-0.200	0.246	-6.146***	2.365	7.48***	7.22***
iden_farm_avg	0.109	0.106	0.078	0.179	-12.235***	4.214	9.82***	8.58***
eff_winter_avg	0.289	0.177	0.323	0.341	-6.296***	2.689	9.59***	6.00***
Field (spatial) characteristics								
corn_2013	0.153	0.110	0.236	0.185	-23.649***	7.918	13.30***	9.20***
field_acre	0.001	0.001	0.002	0.001	0.011	0.013	3.17	1.06
plant_acre	0.000	0.000	0.000	0.000	0.012	0.004	10.69***	9.56***
dist_town	-0.006*	0.004	0.020**	0.010	-0.105	0.076	7.71***	6.94***
soil_top	-0.037	0.095	0.052	0.164	3.613	1.899	3.78	3.78
slope 0-2%	0.174**	0.089	0.121	0.156	6.729	2.416	32.44***	11.16
slope 2-5%	0.176*	0.098	0.119	0.167	0.414	1.035		
slope 5-10%	0.212	0.138	0.476	0.305	13.897	4.740		
slope > 10%	-0.410*	0.244	-0.271	0.361	-21.055	6.714		
slope not sure	-0.151	0.108	-0.445***	0.202	0.015	1.392		
soil_clay	0.021	0.103	0.094	0.206	-11.323***	3.552	10.47***	10.31***
soil_sand	0.388	0.288	0.716	0.643	28.724***	10.198	11.40***	7.88***
Farm enterprise characteristics								
field_rent	0.061	0.092	-0.388**	0.199	-9.439***	3.126	12.65***	12.37***
crop_insurance	0.044	0.096	0.032	0.160	4.563***	1.864	6.31***	5.87***
livestock	-0.518***	0.098	0.509***	0.226	5.155***	2.231	36.71***	22.17***

num_field	-0.002	0.002	0.023***	0.009	-0.635***	0.208	16.60***	16.55***
harvester_hpw	0.105	0.087	0.203	0.155	-10.505***	3.689	11.94***	8.56***
p_custom	0.000	0.000	-0.0002**	0.000	-0.002**	0.001	12.52***	11.54***
cost_variable	0.001	0.000	0.000	0.001	-0.005	0.008	1.69	1.39
Crop reporting district fixed effects								
Fe_Indiana	0.072	0.157	0.190	0.287	-12.152***	4.232	8.97***	8.48***
Fe_Michigan	0.554***	0.238	0.001	0.349	13.017***	4.795	13.11***	8.40***
Fe_Ohio	0.218	0.127	0.284	0.231	-16.967***	5.589	14.75***	9.53***
Intercept								
0-will never adopt	4.219***	1.427	-0.320	1.957	-192.566***	60.637	230.097***	45.583***
1-unlikely to adopt	4.225***	1.054	-0.331	1.213	-85.511***	27.011		
2-likely to adopt	2.742***	0.855	-3.932	3.211	15.573***	4.787		
3-will definitely adopt	-7.112***	3.425	2.458**	1.242	104.537***	32.880		
4-already adopted	-4.073***	1.479	2.125	1.941	157.966***	50.176		
Number of observations			1877					
Class size	59.8%		30.1%		10.1%			
R^2	0.4481		0.9735		0.9799			
			0.7958					
Log-likelihood			-1891.77					
AIC			4026.88					
BIC			4713.52					

[a]The first Wald statistic indicates the overall significance of the predictor in driving adoption likelihood across the classes, and the second statistic (Wald(=)) indicates a statistical difference in the coefficients across the three distinct classes respectively

Figure Captions

Figure 1. Map of the study region: the Maumee River watershed in the western Lake Erie basin

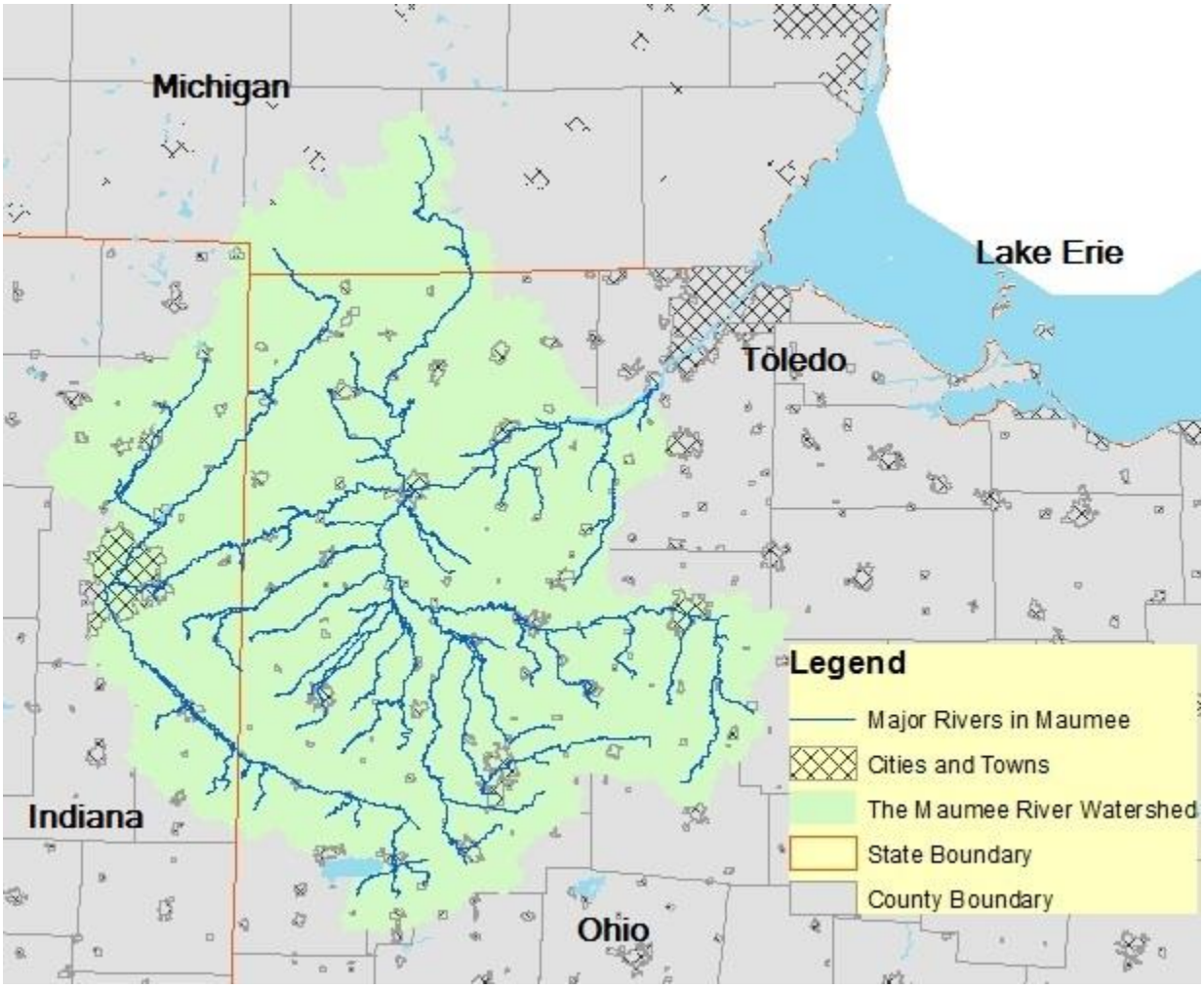
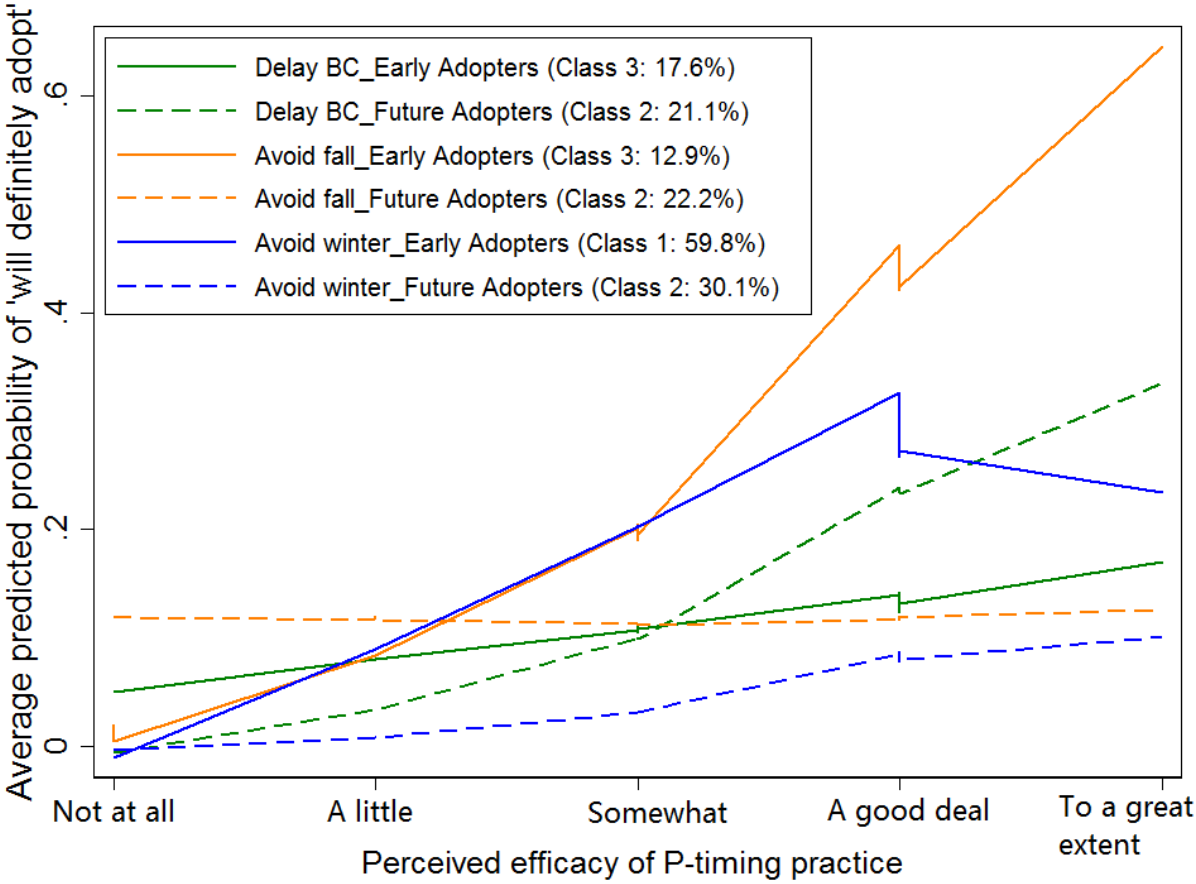


Figure 2. The effects of perceived efficacy on the predicted probability of "will definitely adopt" the practice for "early adopter" class vs. "likely future adopter" class



Note: The solid lines refer to the "early adopter" class, which is class 3, class 3 and class 1 for delaying broadcast, avoiding fall and avoiding winter application respectively; and the dashed lines refer to the "likely future adopter" class that is class 2 for all three timing-related conservation practices.