

Peer Effects and Farmer Heterogeneity in Tillage Choices

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1. Introduction

Increased demand for grain-fed meat as a result of rising incomes around the world has led to intensification of agricultural production in the past five decades (Correll (1998)). This trend combined with declining soil productivity has prompted farmers to apply an increasing amount of fertilizers (Tilman et al. (2002)), resulting in agricultural land use becoming one of the most important nonpoint sources of pollution. Phosphorus loadings from agricultural fields is of particular concern in freshwater systems because it causes eutrophication leading to algal blooms and hypoxia or anoxia, a state of low dissolved oxygen in water, causing deaths to aquatic animals and releasing various forms of phosphorus resulting in further eutrophication. Farmers' land management practices, including the timing, rate and placement of fertilizers, crop rotation and tillage choices have large impacts on the amount of nonpoint source pollution that is generated within a watershed. Voluntary adoption of management practices in response to incentives provided by existing policies have not resulted in socially desired level of ecosystem services indicating the presence of market failure. This calls for an improved understanding of farmer management practices, and both the pecuniary variables and non-pecuniary factors that determine decision making processes.

Previous literature has shown that adoption of best management practices depends not only on variables that influence economic profits, such as soil characteristics, cropping systems, scale of operation, but also on human capital variables like education, farming experience and health (Rahm and Huffman (1984)) and on non-pecuniary variables, like attitudinal and institutional variables (Ervin and Ervin (1982), Lynne et al. (1988)) as well as awareness of local environmental issues (Konar et al. (2012)). Social interactions have been shown to play an important role in adoption of agricultural technology (Bandiera and Rasul (2006), Munshi (2004), Conley and Udry (2001)) implying that farmers not only base their decisions on personal information but also pay attention to choices made by other farmers. This is particularly important in an environment of informational uncertainty. Social learning in adoption of agricultural technologies saves farmers the need for experimentation and could also lead to a multiplier effect when many farmers adopt, influenced by peer effects. Despite the evidence of impact of peer effects in psychology and economics, this is a relatively overlooked research question in the context of best management practices of farmers.

The purpose of this paper is to investigate the role of non-pecuniary factors, peer effects in particular, in farmers' management practices. This paper contends that there is an underlying farmer preference structure, unobserved by researchers, which is influenced by two major factors: (i) individual concerns for profitability, environmental stewardship, awareness of local environmental issues (Konar et al. (2012)) and (ii) peer effects, which takes

into account how a farmer responds to choices made by other farmers in their neighborhood or reference group. To test for the presence of peer effects, I borrow the methodology of analysis from Brock and Durlauf (2002) and employ it in a sample of farmers from the Maumee watershed counties in northwest Ohio. I find evidence that peer effects of farmers in a county is a crucial determinant for farmer tillage choices alongside other neighborhood level attributes. The presence of peer effects suggests the possibility of multiple equilibria in terms of farmers' tillage choices: as the number of farmers practicing no till (where farmers leave more than 90% organic residue on the ground in order to avoid disruption of soil) rather than conventional tillage practices increases, for example, the more likely a representative farmer is to also choose the no till option and vice versa. The implication is that heterogeneous groups of farmers may emerge that are characterized by differences in tillage choices explained, at least in part, by differences in the responsiveness to peer effects. This hypothesis is further tested in the sample by running a latent class analysis. Results indicate the presence of two classes of farmers with distinct parameter estimates confirming our assertions of the presence of farmer heterogeneity. Neighborhood level variables and impact of peer effects are important determinants to which class a farmer belongs, which in turn influences their tillage decisions. The results indicate that one class of farmers are more influenced by decisions made by others. It also indicates that farmers more aware about water quality outcomes are more likely to adopt conventional tillage over no till.

This paper makes multiple contributions to the literature on farmer land use and management decisions. First, it considers the role of peer effects of farmers in tillage choices, a relatively neglected topic in this literature, using the methodology of Brock and Durlauf (2002). Second, using latent class analysis this paper finds heterogeneity of farmers' tillage choices, part of which is attributable to impact of peer effects and neighborhood level (county in this study) variables. Third, this study finds that different classes of farmers exhibit distinct responsiveness to choices made by their other farmers or peers. Specifically, I find that farmers that are more likely to choose to practice no till are more influenced by what tillage choices made by their peers whereas farmers that are more likely to choose to practice conventional tillage are more aware of water quality issues. Fourth, this study focuses on field-level tillage decisions and controls for field specific characteristics including soil type, slope of field and crop which distinguishes it from others, because many policies focus on enrolling particular parcels of land rather than entire farms, hence a focus on field specific attributes is advantageous. Finally, this paper contributes to the literature by underscoring the importance of non-pecuniary variables, like peer effects and awareness of environmental issues, that are important for farmers' tillage choices. Taken together these results indicate that when socially suboptimal outcomes, like environmental degradation from farmers' land

management decisions, occur because of market failure it is useful for policymakers to account for non-pecuniary variables, particularly the role of peer effects, when relying solely on pecuniary variables is no longer adequate. The results suggest that policies that seek to promote reduced tillage could benefit by exploiting the role of peer effects among local communities of farmers.

The paper is divided as follows. Section 2 briefly summarizes some of the literature in farmer decision making processes in addition to social interactions literature in psychology and economics. Section 3 presents the theoretical model of peer effects (3.1), the empirical specification for peer effects (3.2) followed by the empirical specification of latent class analysis (3.3) to test the presence of farmer heterogeneity. Section 4 introduces the study region while section 5 discussed the survey and data used for the present analysis. Section 6 presents the results of the paper and section 7 discusses policy implications of the results. Section 8 discusses some robustness checks and finally section 9 concludes.

2. Literature

Voluntary incentive-based programs dominate U.S. policy approaches to securing ecosystem services from agricultural lands, and in most cases have not been sufficiently widespread to obtain the desired changes in ecosystem services. Existing literature on farmer decision making considers the problem in a profit maximizing framework (McConnell (1983)), taking into account the risk associated with alternative choices, the diffusion of new cropping and management practices, and programs that alter the profitability and riskiness of farmer choices (Wu et al. (2004)). While some researchers employed the profit maximizing framework, others extended the analysis to a utility maximizing problem (Rahm and Huffman (1984), Lynne et al. (1988)). Deleterious impacts of agricultural practices resulting from a failure to incorporate social costs by economic agents are expressions of market failure. Impact of land use on watershed health is an area of great concern. Watershed ecosystem involve a complex web of interactions between plants, animals and microbes. Existing studies have looked into the effects of land use on watershed health using indicators of water quality (Hascic and Wu (2006), Langpap et al. (2008)) as well as species habitat matrix (Langpap and Wu (2008)).

Rahm and Huffman (1984) find that the adoption of reduced tillage depends not only on soil characteristics, cropping systems and scale of operation but also on human capital variables like education, farming experience and health. They further find that human capital variables enhance the efficacy of adopted practices. Ervin and Ervin (1982) was one of the earliest papers to consider attitudinal and institutional variables in farmers' choices

of conservation tillage. Lynne et al. (1988) using a subjective utility maximizing framework found that attitudes favoring soil conservation lead to greater effort and enhance the efficacy of economic incentives provided for such adoption.

Alternative paradigms to a profit maximizing framework have been suggested and non-pecuniary variables, like attitudes towards conservation (Lynne et al. (1988)) or awareness of local environmental issues (Konar et al. (2012)), have been found to be important. The role of peer effects of farmers in the context of tillage choices have received little attention, despite the significant evidence of social interactions in psychology and economics.

Psychologists have explored the effect of choices made by others on individual behavior. They distinguish between descriptive norms (what is prevalent) and injunctive norms (what ought or should be). It has been found that public service announcements focusing on positive descriptive norms are more effective than when focused on negative descriptive norms (Cialdini (2003)). Goldstein et al. (2008) find evidence that appeals employing descriptive norms proved more effective than those invoking injunctive norms. This evidence suggest that, what individuals know (or think they know, perceive) about other people's choices have an important effect on individual choices. Early research in economics on social interactions goes as far back as Veblen (1899) who investigated the behavior of conspicuous consumption. Theoretical modeling in economics attempt to understand conformity behavior through social penalty (Akerlof (1980)), by positing that individuals get some intrinsic utility from conformity (Akerlof and Kranton (2000), Bernheim (1994), Becker (1974)), or by positing that individuals resort to 'herd behavior' when lacking information believing that others know better (Banerjee (1992)). The literature on conditional cooperation (Alpizar et al. (2008), Fishbacher et al. (2001)) point towards the fact that more people are willing to contribute to public goods when they observe unselfish behavior.

There is a significant amount of literature investigating social learning of farmers in technology adoption. Adoption of new technology entails risks to profitability and farmers do not have perfect information about the new technology. In a scenario of imperfect information and uncertainty, farmers typically learn from observing choices made by neighbors, otherwise called social learning. It is not the case that farmers are directly affected by the choices made by others, but those choices reveal important information to an observing farmer. Sometimes this might lead to suboptimal choices if agents ignore their private information and place too much weight on information gathered from others (Banerjee (1992)). Bandiera and Rasul (2006) find evidence for an increase in the probability of adoption of technology when the number of adopters are few while the probability declines when the number of adopters are many; one plausible explanation can be that farmers want to wait and find out about outcomes in order to free ride on information in the case of many early

adoptions. More informed farmers are found to be relatively less sensitive to other farmers' choices. Munshi (2004) finds that social learning gets weaker in a heterogeneous population especially when the technology is dependent on the unobserved characteristics of the neighbor who adopts. Conley and Udry (2001) have shown that information flows via complex networks formed through social interactions and not through the whole village or reference network. This provides us with enough reason to suspect that farmers might be influenced by peer effects to the extent that it might have a nontrivial impact on their chosen best management practices. Identification of the social interactions effect presents a formidable econometric challenge. Manski (Manski (1993), Manski (2000)) in his landmark work has highlighted some of the potential challenges in disentangling endogenous social interactions effect from contextual or correlated effects. Brock and Durlauf (2001a), Brock and Durlauf (2001b) and Brock and Durlauf (2002) analyzed the problem in a discrete choice framework and have established that under certain sufficient conditions social interactions effect can be econometrically identified.

3. Peer Effects

I assume that there is a latent underlying farmer preference structure, unobserved by the researcher, which is influenced by a farmer's beliefs about what other farmers in their neighborhood are doing. They have expectations not only about the choices made by other farmers in their reference group but also about other farmers' preferences defined over profitability, environmental stewardship and awareness of local environmental issues.

3.1. Theoretical Model

This paper follows the familiar modeling framework of social interactions literature in micro-econometrics (Brock and Durlauf (2002)). Consider individual farmers interacting within the same county. This is the case of local interactions, which posits that a farmer interacts only with other farmers in their own neighborhood or reference group (in our case county). We would presumably expect some interdependencies between the perceived average choice made by farmers in the county on the actual choice made by each farmer. This expectation for a given neighborhood is the same for all the farmers belonging in that reference group (in our case county).

Let us denote i to refer to a representative farmer from the neighborhood $n(i)$. Denote the choice made by farmer i as ω_i from a set of choices Ω_i . The vector ω is the collection of choices made by all I farmers in the neighborhood $n(i)$.

The indirect utility of farmers V have three components: the effect of observable private specific utility h_i of farmer i , the subjective belief μ_i^e of farmer i about the average behavior in the neighborhood (social utility) and unobserved random private specific utility ϵ_i . Hence farmers decide on individual tillage choices based on 1.

$$\omega_i = \underset{l \in \Omega_i}{\operatorname{argmax}} V(l, h_i, \mu_i^e(\omega), \epsilon_i) \quad (1)$$

where l is a representative alternative from the choice set Ω_i .

We impose a self consistency or rationality condition that the subjective belief of farmer i about average choices made in the neighborhood $n(i)$ will be equal to the conditional probability

$$\mu_i^e(\omega) = \mu(\omega | h_i, \mu_i^e(\omega) \forall i \in n(i)) \quad (2)$$

where $\mu(\cdot)$ is the probability measure generated by the model.

Farmers in our model are facing a choice set $\Omega_i = 1, 2, 3$, where 1 indicates conventional tillage (30% residue or less), 2 indicates conservation tillage (30 - 90% residue) and 3 indicates no till (more than 90 % residue)¹. Let us assume that choosing any alternative $l \in \Omega_i$ produces the indirect utility given by 3 for farmer i ,

$$V_{i,l} = h_{i,l} + Jp_{i,l}^e + \epsilon_{i,l} \quad (3)$$

where $h_{i,l}$ denotes observable private specific utility farmer i receives from choice l . $Jp_{i,l}^e$ is the subjective belief μ_i^e of farmer i about the average behavior in the neighborhood where J measures the strength of social utility derived from the farmer's expectation of the percentage ($p_{i,l}^e$) of farmers making the same choice l in the neighborhood $n(i)$. Finally $\epsilon_{i,l}$ denotes the unobserved random private specific utility, which are independent across i and are doubly exponentially distributed with index parameter β so that probability of alternative l , $\mu(\omega_i = l)$ for farmer i can be written as 4

$$\frac{\exp(\beta h_{i,l} + \beta J p_{i,l}^e)}{\sum_{j=0}^{l-1} \exp(\beta h_{i,j} + \beta J p_{i,j}^e)} \quad (4)$$

Imposing the self consistency or rationality assumption we get that the expectation of farmer i about the proportion of farmers choosing alternative l is same for all farmers and equal to the expected value of the proportion of the farmers choosing alternative l .

¹The variable tillage, described in the data section, is used where greater residue left on the ground (lower tillage level) is given a higher number

$$p_{i,l}^e = p_l \quad (5)$$

$$\Rightarrow p_{i,l}^e = \int \frac{\exp(\beta h_{i,l} + \beta J p_l)}{\sum_{j=1}^l \exp(\beta h_{i,j} + \beta J p_l)} dF_h \quad (6)$$

where F_h is the empirical probability distribution of $h_{i,j}$. Brouwer's fixed point theorem guarantees that there exists at least one value which solves 6. For a discussions on the conditions in which the presence of peer effects in a theoretical model presented above lead to the existence of multiple equilibria, see Brock and Durlauf (2002). The condition for the existence of multiple equilibria is $\frac{\beta J}{L} > 1$ where L is the number of alternatives, 3 in our case (conventional tillage, conservation tillage and no till). Intuitively this means that as the number of alternatives go up, the threshold level of βJ needed to sustain multiple equilibria goes up. As the number of alternatives go up, the percentage of people in the population whose utility is influenced by the random utility component go up and a smaller set of people are now influenced by peer effects.

3.2. *Econometric Specification*

The model defined as above can be estimated using standard econometrics. In this study, county is considered to be the relevant neighborhood or reference group for a representative farmer. Let us specify the deterministic observable private specific utility as

$$h_{i,l} = k_l + c_l' X_i + d_l' Y_{n(i)} \quad (7)$$

where X_i is the vector of individual characteristics for farmer i and $Y_{n(i)}$ is the vector of neighborhood characteristics. The likelihood function is then proportional to 8.

$$\prod_i \prod_l [\exp(\beta k_l + \beta c_l' X_i + \beta d_l' Y_{n(i)} + \beta J l p_{n(i),l}^e) 1(\omega_i = l)] \quad (8)$$

where $1(\omega_i = l)$ is an indicator function when the alternative l has been chosen, so that for each neighborhood $n(i)$ we have 9

$$p_{n(i),l}^e = E[1(\omega_j = l) | Y_{n(i)}, j \in n(i)] \quad (9)$$

Following the usual practice for multinomial logit models we impose some normalization assumptions because the complete set of parameters cannot be estimated (McFadden (1984)).

Let us assume $k_0 = 0, c_0 = 0, d_0 = 0, J_0 = 0$ and $\beta = 1$. For the technical conditions sufficient for identification, see Brock and Durlauf (2002). Intuitively this estimation technique avoids some of the pitfalls pointed out by Manski (Manski (1993), Manski (2000)) because the discrete choices are nonlinear in the peer effects. Identification requires that there be at least one neighborhood with sufficient variation within it, there be enough variation between neighborhoods in the neighborhood variables $Y_{n(i)}$ and there be no collinearity between the individual specific regressors X_i and neighborhood attributes $Y_{n(i)}$.

The presence of a strong impact of peer effects might indicate the presence of multiple equilibria, i.e. that farmers in different neighborhoods are practicing different tillage choices, influenced by choices made by their peers. This can be tested by employing the latent class model which investigates the presence of multiple classes of farmers, for example one class more likely to do no till than another, and estimates the number of classes in the sample, if any.

3.3. Farmer Heterogeneity: Latent Class Analysis

I assume the tillage choice for a particular field is the outcome of a utility maximization process in which the farmer decides how much residue to leave on a field after considering the attributes of the field, the crop chosen and his or her preference parameters. Residue levels map ordinally into particular styles of tillage with approaches that leave less than 30% of residue on the field considered conventional tillage, between 30 and 90% of residue on the field as conservation tillage and more than 90% of residue on the field called no-till.

I allow individual farmers to have heterogeneous preferences by estimating a finite-mixture or latent class model. The core assumption is that different classes of farmers exist and that farmers in each class have homogeneous preferences or decision processes for determining tillage practices but preferences of farmers vary across classes. The researcher is unable to observe which class a particular farmer belongs to or to observe the number of distinct classes. However, additional variables may be used to model class membership.

The outcome variable (y_i) for this model is the tillage choice (conventional tillage (0 - 30 % residue), conservation tillage (30 - 90 % residue) and no till (> 90 % residue)) made by an individual farmer i . I assume that there is only one nominal latent variable in our model. I posit that this latent nominal variable is the underlying preference variable of farmers which is affected by profitability, environmental stewardship, neighborhood level variables and peer effects of farmers. This latent variable, as the name suggests, is unobservable to the researcher.

There are two kinds of variables in a latent class model. The first set of variables are

known as predictors (z_i^{pred}) which affects the outcome variable (y_i) directly. The other variables are called covariates (z_i^{cov}) which determines the class membership of farmer i . Covariates affect the underlying latent preferences of farmers and hence determine their membership into different groups. Given class membership, predictors determine the outcome variable (y_i). Hence, for K -classes, the probability structure looks like 10

$$f(y_i|z_i^{pred}, z_i^{cov}) = \sum_{\alpha=1}^K P(\alpha|z_i^{cov})f(y_i|z_i^{pred}) \quad (10)$$

Peer effects of farmers do not determine tillage choices directly but if an increasing proportion of farmers in their neighborhood (county) is practicing no till, that might increase the likelihood of the representative farmer to belong to the class of farmers predominantly choosing no till. In other words the peer effects variable in this latent class model is a covariate and determines which class a farmer will belong to, which in turn determines their tillage choices. The complete model is estimated via maximum likelihood estimation in Latent Gold 4.5.

4. Study Region

The target population for this research was corn and soybean farmers in the Maumee watershed in northwest Ohio. The data consists of counties of Ohio in the Maumee watershed region. In figure 1, the Maumee watershed counties of Ohio are colored blue. The outline of the watershed region, which extends beyond Ohio, is also marked in the map. Land use in the Maumee, which drains into Lake Erie, is between 60% and 80% agricultural, with corn and soybean production making up the primary farming activities. Further, the environmental impacts from agricultural nonpoint source runoff have become a significant issue in Lake Erie due to phosphorus concentrations and subsequent large algal blooms. The Ohio Lake Erie Phosphorus Task Force Final Report (EPA (2010)) concludes that the majority of the phosphorus loading into Lake Erie is from agricultural sources, particularly from farms in the Maumee and Sandusky watersheds. 20.7% of the total phosphorus load in Lake Erie is from point sources while 60.8% is from nonpoint sources in the Maumee river watershed area. Consequently, results of this study have implications not only for residents in the Maumee watershed, but also for everyone who is impacted by the water quality in the Great Lakes. Finally, topological and soil conditions within the Maumee watershed are relatively homogenous, allowing analysis of heterogeneity to largely focus on preference heterogeneity rather than gross physical variation.



Fig. 1. The Study Region: Maumee Watershed Counties in Ohio

5. Survey and Data

A mail survey of 2000 farmers was conducted with postal addresses in counties within the Maumee watershed following a modified version of Dillman’s Tailored Design method (Dillman (2000)). Mailings included an announcement letter, a survey packet, a reminder letter and a replacement packet for non-respondents. Two key features of the survey include a question asking farmers the following:

If you had 100 points to assign to these five goals to demonstrate their relative importance when making farm management decisions, how would you do that?

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
Tillage Category		
Conventional	0.27	
Conservation	0.33	
No Till	0.40	
Crop Planted		
Corn	0.36	
Soybean	0.42	
Wheat	0.13	
Other	0.09	
Livestock on Farm		
	0.32	
Farm Gross Receipts		
<\$50k (=1)	35.5	
\$50 - 100k (=2)	17.8	
\$100 - 250k (=3)	13.3	
\$250 - 500k (=4)	9.9	
>\$500k (=5)	23.5	
Normalized Yield	1.12	0.67
Soil Type		
Clay	0.18	
Clay loam	0.51	
Silty loam	0.14	
Loam	0.04	
Sand	0.03	
Sandy loam	0.10	
Subjective Weighting of		
Profit	36.10	19.27
Environmental Stewardship	18.35	11.99
Crop Rotation		
Corn/Soybean	0.28	
Corn/Soybean/Wheat or Forage	0.34	
Other	0.29	
Not in a Rotation	0.09	
Awareness of Local Algae Bloom		
Not aware at all (=1)	0.13	
Somewhat aware (=2)	0.42	
Very aware (=3)	0.45	
Age	52.45	14.06
# Generations farm in family		
One (=1)	0.19	
Two (=2)	0.19	
Three (=3)	0.61	
Education		
<HS (=1)	0.02	
HS or equivalent (=2)	0.45	
Some College (=3)	0.20	
Associate's Degree (=4)	0.11	
Bachelor's Degree (=5)	0.15	
>Bachelor's Degree (=6)	0.07	

Table 2: Counties in the Sample

Counties	Frequency	% in Sample	Metropolitan Status
Allen	25	4.76	Small metro - Metropolitan
Auglaize	24	4.57	Micropolitan - Nonmetropolitan
Darke	52	9.90	Micropolitan - Nonmetropolitan
Defiance	22	4.19	Micropolitan - Nonmetropolitan
Fulton	30	5.71	Medium metro - Metropolitan
Hancock	19	3.62	Micropolitan - Nonmetropolitan
Hardin	20	3.81	Noncore - Nonmetropolitan
Henry	25	4.76	Noncore - Nonmetropolitan
Lucas	8	1.52	Medium metro - Metropolitan
Mercer	29	5.52	Micropolitan - Nonmetropolitan
Ottawa	12	2.29	Medium metro - Metropolitan
Paulding	19	3.62	Noncore - Nonmetropolitan
Putnam	47	8.95	Noncore - Nonmetropolitan
Sandusky	26	4.95	Micropolitan - Nonmetropolitan
Seneca	31	5.90	Micropolitan - Nonmetropolitan
Shelby	41	7.81	Micropolitan - Nonmetropolitan
Van Wert	28	5.33	Micropolitan - Nonmetropolitan
Williams	17	3.24	Noncore - Nonmetropolitan
Wood	32	6.10	Medium metro - Metropolitan
Wyandot	18	3.43	Noncore - Nonmetropolitan
Total	525	100	

For example, someone who places equal weight on making a profit and maintaining a farming lifestyle, but no weight on the remaining goals would assign 50 points to profit and 50 points to lifestyle, and 0 to the rest. Assign the points in the way that best reflects the importance of each goal to you. Be sure that the total points assigned add up to 100.

The five goals were (i) Making a Profit, (ii) Being an Environmental Steward, (iii) Protecting Human Health, (iv) Ensuring Farm Viability for My Children and (v) Maintaining a Farming Lifestyle.

The other unique aspect of the survey was that farmers were prompted to ‘Consider one of your fields where runoff is a potential problem’. For this field they were asked to report the type of tillage they employed last year with the options being conventional tillage (coded 1), conservation tillage (coded 2) or no-till (coded 3). Each option was denoted with the bounds of residue coverage associated with each type of tillage (30% residue or less, 30% - 90% residue, 90% residue or more). Other details collected about the field include the crop last planted, the yield for this last crop, the crop rotation maintained for the field rate

and the soil type (clay, clay loam, silty loam, loam, sand, sandy loam). Moreover farmers are asked whether they are aware about the algae issues in the Grand Lake St. Marys and Western Lake Erie Basin on a likert scale of 1 to 3. Key descriptive statistics appear in table 1. Table 2 presents a county break up of our data.

6. Results

The average variables represent the neighborhood level attributes for the particular variable. So average education for a neighborhood is the average education level of the county in question. Table 3 presents the marginal effects for the multinomial logit model of tillage practices with respect to the base category conventional tillage. The first column represents the likelihood of doing conservation tillage rather than conventional tillage, while the second column represents the likelihood of doing no till rather than conventional tillage. The variable percentage own till represents the impact of peer effects, and we see that it is positive and statistically significant (1.213) for no till. This means that as an increasing number of farmers in a county chooses to use no till, the probability that a representative farmer will use no till rather than conventional till goes up. Conversely if farmers in a particular county change from no till to conventional till, this makes a representative farmer more likely to choose conventional till rather than no till. This result indicates the possibility of multiple equilibria because if more people in a neighborhood use no till then that leads many others to also adopt the same tillage practice and we may have different counties with different tillage choices.

Crop choice is a significant determinant of tillage practices. Normalized yield is statistically significant but almost zero for conservation tillage. The column for conservative tillage further tells us that if in a reference group an increasing proportion of people give more points to profit out of 100, then a representative farmer is more likely to use conventional tillage than conservation tillage. A greater awareness about algal bloom in Grand Lake St Marys and Lake Erie makes farmers more likely to use conventional tillage. This can be reconciled with the recent findings that phosphorus runoff tends to be worse when more organic residue is left on the ground (conservation or no till) because of surface runoff. It is possible that a greater awareness about water quality outcomes make farmers more likely to adopt conventional tillage. Soil and slope of the field takes care, to an extent, of the potential endogeneity effects from the spatial variations and unobserved characteristics.

The above result of a strong impact of peer effect leads us to suspect that there may be multiple equilibria in tillage choices of farmers. We test this by carrying out a latent class analysis. Results from tables 4, 5 and 6 indicates the presence of a two latent class model

Table 3: Marginal Effects of MNL model for tillage choice

	Conservation	No till
Crop	-0.177*** (0.000360)	0.167*** (2.91e-05)
Normalized Yield	0.000980* (0.0894)	3.11e-05 (0.949)
Ann Gross Sales	0.00813 (0.708)	0.0289 (0.127)
Avg Profit	-0.0131** (0.0499)	0.00791 (0.178)
Avg Env	-0.0178 (0.229)	0.0157 (0.236)
Avg Edu	0.133 (0.176)	-0.123 (0.194)
Avg Gen	-0.408 (0.118)	0.0307 (0.898)
Avg Grand Lake St Marys	-0.200* (0.0677)	0.110 (0.269)
Avg Lake Erie	-0.501** (0.0336)	0.296 (0.155)
% Own Till (Peer Effects)	0.119 (0.732)	1.213*** (3.05e-05)
Rotation	0.0292 (0.562)	-0.0271 (0.557)
Soil	0.00499 (0.837)	-0.00538 (0.809)
Slope	-0.00246 (0.958)	-0.0174 (0.687)
Observations	324	

pvalues are presented in parentheses

*** p<0.01, ** p<0.05, * p<0.1

which is chosen to be appropriate for the sample at hand by using the Bayesian Information Criterion (BIC) statistic. Table 4 indicates that, 55% of the sample belongs to class 1 and 45% to class 2. In class 1, 60% do no till and 40% do conservation tillage, while in class 2, 56% do conventional tillage, 24% conservation tillage and 19% no till. Mean tillage presents the average numbers for the variable tillage which takes the values 1 (=conventional), 2 (=conservation) and 3 (=no till). A higher mean number indicates a greater amount of residue left on the ground on an average by the members of that class. Awareness of local algal blooms and the generations of farming are important determinants of class membership. The impact of peer effects is significant and is higher (0.48) in class 1 than in class 2 (0.281). This indicates that farmers in the two classes have different responsiveness to peer effects. Farmers in class 1 have on an average more people who are doing the same tillage that they are doing. Farmers in class 1 are slightly less aware about algal blooms in Lake Erie, and they belong to families who have been farming comparatively recently (lower average generation).

Table 4: Means of Attributes Across Estimated Classes

	Class 1	Class 2
% Sample in class	0.55	0.45
Tillage		
Conventional (=1)	0.001	0.564
Conservation (=2)	0.40	0.242
No Till (=3)	0.599	0.194
Mean Tillage of Class	2.60	1.63
Covariates		
Neighborhood Averages		
% Own Till (Peer Effects)***	0.491	0.281
Avg Profit	37.867	38.261
Avg Env	18.093	18.63
Avg Grand Lake St Marys**	1.394	1.393
Avg Lake Erie***	1.038	1.101
Avg Age	52.056	52.297
Avg Edu	3.106	3.121
Avg Gen**	2.469	2.512

*** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the model of latent class membership for class 1. A positive significant peer effects coefficient indicates that a greater impact of peer effect is more likely to place the farmer in class 1, and then given class membership that makes the farmer 60 % likely to do no till. A higher generation makes a farmer more likely to be in class 2. Farmers who

Table 5: Model of Latent Class Membership

	Prob (Latent Class 1)		
	Coefficient	Z-stat	Wald
Intercept	61.969*	1.745	3.058
Crop Rotation			
No Rotation	1.437*	0.204	0.1
Corn/Soybean	1.155*	0.172	-
Corn/Soybean/Forage	1.527*	0.234	-
Other	1.167*	0.166	
Neighborhood Averages			
% Own Till (Peer Effects)	102.926***	3.688	13.598
Avg Profit Pt	-0.269	-1.127	1.269
Avg Env Pt	-0.50	-1.201	1.443
Avg Grand Lake St. Marys	-12.623***	-2.503	6.263
Avg Lake Erie	-21.078***	-2.687	7.221
Avg Age	-0.554	-1.068	1.141
Avg Edu	7.854	1.592	2.534
Avg Gen	-0.554	-1.068	1.141
# Observations	317		

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Ordinal Model of Tillage Choice, 2-Latent Classes

	Class 1		Class 2		Wald Statistics
	Coefficient	Z-stat	Coefficient	Z-stat	Var Sig
Crop					
Corn	-	-	-	-	7.363
Soybean	0.408*	1.994	0.408*	1.994	
Wheat	0.625*	2.251	0.625*	2.251	
Other	-0.733*	-0.722	-0.733*	-0.722	
Livestock on Farm	-0.978*	-2.475	-0.196*	-0.859	6.97
Ann Gross Sales	0.493	1.713	0.493	1.713	0.029
Field's Fair Mkt Rent	0.0003	0.171	0.0003	0.171	0.029
Normalized Yield	-0.001	-0.736	-0.001	-0.736	0.541
Soil	Y		Y		
# Observations	317				

*** p<0.01, ** p<0.05, * p<0.1

are more aware about local algal blooms tend to be in class 2, 56% of whom do conventional tillage. Table 6 presents the coefficient of the predictors. Except for livestock, the difference in the coefficient values across classes were not statistically significant, so we imposed the restriction that they have the same value. Crop choice is an important determinant but there is no reason to expect that this would have different impacts on farmers belonging to

different classes.

7. Discussion

The results of this paper have important policy implications. If existing tillage choices are deemed socially suboptimal leading to harmful environmental impacts and policies based on incentives on pecuniary variables are inadequate to achieve socially desired outcomes, then policymakers need to take into account the impact of non-pecuniary variables on the behavior of agents. Policymakers make decisions based on the current stock of scientific knowledge and may have different objectives based on varying circumstances. The jury is divided on the environmental implications of reduced tillage. Reduced tillage is good for soil conservation and adoption of reduced tillage was promoted in the context when combating soil quality was a priority. Recent findings indicate that reduced tillage have a negative impact on water quality due to phosphorus loadings from surface runoff. This paper contends that no matter whether policymakers want to achieve the outcome associated with no till or conventional tillage, depending on the scientific consensus of the day, the knowledge of the impact of non-pecuniary variables can be useful to make policy recommendations more effective.

Supposing that a policymaker would want to induce more adoption of reduced tillage, they should keep in mind the impact of non-pecuniary variables, like impact of peer effects, on farmer choices. Our results suggest the possibility (table 3) of a multiplier effect. If a farmer in a particular neighborhood (county) is persuaded to switch to no till from conventional till, as a result increasing the proportion of farmers practicing no till in the neighborhood, it further leads to more farmers switching to no till from conventional till. Latent class results (table 4) also indicate that not everyone are impacted equally by what others around them are doing. Farmers more responsive to peer effects (class 1) tend to be more likely to practice no till. Farmers whose family have been in farming for fewer generations are more likely to be influenced by actions made by their peers because they are more likely to be in class 1. So a policymaker wanting to achieve more reduced tillage could design a publicity campaign to reach out to first generation farmers disseminating information about adoption of reduced tillage. Since they are more likely to belong to the class of farmers more readily influenced by decisions made by others, this could lead to a multiplier effect.

Results (tables 3, 5) also suggest that farmers who are more aware of local algal blooms are more likely to practice conventional tillage. Our environmental awareness variables only ask respondents about their awareness of local water quality outcomes. So it is plausible that farmers who are more concerned and hence aware about water quality are more likely to practice conventional tillage. This should not be extended to conclude that farmers using

conventional tillage are more environmentally conscious (or not). Farmers more concerned about soil quality and conservation may indicate a different result. If, as opposed to the previous case discussed, it is the goal of policymakers to induce adoption of conventional tillage over reduced tillage, then more effort should be invested in the dissemination of harmful effects on water quality outcomes of reduced tillage, because our results suggest that increased awareness about such outcomes make farmers less likely to adopt reduced tillage.

The results of this paper have a general applicability: that policymakers need to be cognizant of the impact of not only pecuniary variables, but also non-pecuniary variables, like impact of peer effects, on decision making processes of economic agents as it may add further insight into analyzing observed choices. No matter what the objective of the policymaker is, the knowledge of the impact of non-pecuniary variables and a willingness to make use of it alongside providing incentives through the use of pecuniary variables would only make their policy recommendations more effective.

8. Robustness

We have to make sure that the impact of peer effects is not driven because of the way we construct our variable. We run the same model in two situations to ensure that.

For the first robustness check we created two neighborhoods based on a county's metropolitan status (see table 2). We follow the National Center for Health Statistics' urban rural classification (Ingram and Franco (2012)) to assign counties to be either metropolitan (small, medium or large) or nonmetropolitan (micropolitan or noncore). The counties Auglaize, Darke, Defiance, Hancock, Hardin, Henry, Mercer, Paulding, Putnam, Sandusky, Seneca, Shelby, Van Wert, Williams and Wyandot are nonmetropolitan counties while Allen, Fulton, Lucas, Ottawa and Wood are metropolitan counties (see table 2). Running the multinomial logit model with peer effects variable we obtain the results in table 7, where Stata did not attain convergence but printed out results nonetheless. The pvalues are 1, suggesting the model fit is not good and several neighborhood average variables were automatically dropped because of collinearity.

Next, we utilized the soil classification of the Ohio Department of Natural Resources Division of Soil and Water Resources. The counties were divided into two broad groups. The first group contains the counties Williams, Fulton, Lucas, Ottawa, Defiance, Henry, Wood, Sandusky, Paulding and Putnam, while the second group contains Van Wert, Allen, Hancock, Seneca, Wyandot, Hardin, Auglaize, Mercer, Darke and Shelby. Results of the multinomial logit model with peer effects are presented in table 8. Convergence was not

Table 7: Coefficient of MNL model with Metro and Non metro counties

	Conservation	No till
Crop	0.0127 (1.000)	0.346 (1.000)
Ann Gross Sales	0.0756 (1.000)	0.165 (1.000)
% Own Till	863.2 (0.999)	2,796 (0.998)
Avg Profit	-57.02 (1.000)	-0.0346 (1.000)
Rotation	-0.145 (1.000)	-0.260 (1.000)
Soil	-0.197 (1.000)	-0.175 (1.000)
Slope	0.0885 (1.000)	-0.0584 (1.000)
Constant	1,897 (1.000)	-956.3
Observations	351	

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Coefficient of MNL model for Soil Regions

	Conservation	No till
Crop	-3.881	0.431
Ann Gross Sales	0.571	-0.366
% Own Till	1,976	4,146
Avg Profit	10.78	6.287
Avg Env	54.44	24.01
Rotation	-0.196	-3.169
Soil	-1.031	-0.458
Slope	-0.507	-0.814
Constant	-1,995	-2,067
Observations	357	

*** p<0.01, ** p<0.05, * p<0.1

reached and Stata could not compute standard errors, but nevertheless the results presented were produced by Stata. Like before, a bunch of variables were automatically dropped because of collinearity. These robustness checks confirm that a neighborhood created by any random combination of counties would not be driving the results.

9. Conclusion

This paper uses farmer survey data from the Maumee watershed counties in Ohio and contends that there is an underlying farmer preference structure which is influenced by peer effects. This includes not only the choices made by other farmers in the reference group but also beliefs of farmers about others in the group along with neighborhood characteristic variables. This paper utilizes the methodology of Brock and Durlauf (2002) to investigate the impact of peer effects on farmer tillage choices. A strong impact of peer effects indicate the possibility of the presence of multiple equilibria, i.e. farmers in different neighborhoods (counties) adopting distinct tillage choices significantly influenced by choices made by other farmers. To test the presence of heterogeneity of farmer tillage choices in our sample a latent class analysis is carried out. Results indicate that there are two classes of farmers, one more likely to practice no till, while the other conventional tillage. Results indicate that farmers have different responsiveness to peer effects. Farmers who tend to have higher responsiveness to peer effects are more to do no till. Awareness of harmful water quality outcomes make farmers more likely to adopt conventional tillage.

An improved understanding of farmer decision making processes is helpful to policymakers concerned about environmental outcomes associated with farmer land management practices. Policymakers need to be cognizant of not just of the impact of pecuniary variables but also non-pecuniary variables, like impact of peer effects and awareness of environmental issues, when designing policy prescriptions. The knowledge and willingness to put to use the information of the impact of non-pecuniary variables alongside incentives provided through pecuniary variables would potentially enhance the effectiveness of proposed policy recommendations.

References

- Akerlof, George A. (1980) “A Theory of Social Custom, of Which Unemployment May be one Consequence,” *The Quarterly Journal of Economics*.
- Akerlof, George A. and Rachel E. Kranton (2000) “Economics and Identity,” *The Quarterly Journal of Economics*.
- Alpizar, Francisco, Fredrik Carlson, and Olof Johansson-Stenman (2008) “Anonymity, reciprocity and conformity: Evidence from voluntary contributions to a national park in Costa Rica,” *Journal of Public Economics*.
- Bandiera, Oriana and Imran Rasul (2006) “Social Networks and Technology Adoption in Northern Mozambique,” *The Economic Journal*.
- Banerjee, Abhijit V. (1992) “A Simple Model of Herd Behavior,” *The Quarterly Journal of Economics*.
- Becker, Gary S. (1974) “A Theory of Social Interactions,” *National Bureau of Economic Research Working Paper Series*.
- Bernheim, B. Douglas (1994) “A theory of conformity,” *Journal of political Economy*.
- Brock, William A. and Steven N. Durlauf (2001a) “Discrete choice with social interactions,” *Review of Economic Studies*.
- (2001b) “Interactions-Based Models,” *Handbook of Econometrics 5*.
- (2002) “A Multinomial-Choice Model of Neighborhood Effects,” *American Economic Review*, Vol. 92, pp. 298–303.
- Cialdini, Robert B. (2003) “Crafting Normative Messages to Protect the Environment,” *Current Directions in Psychological Science*.
- Conley, Timothy and Christopher Udry (2001) “Social Learning through Networks: The Adoption of New Agricultural Technologies in Ghana,” *American Journal of Agricultural Economics*.
- Correll, David L. (1998) “The role of phosphorus in the eutrophication of receiving waters: A review,” *Journal of Environmental Quality*.
- Dillman, Don A. (2000) “The tailored design method,” *Mail and Internet Surveys*.

- EPA (2010) “Ohio Lake Erie Phosphorus Task Force Final Report,” *Environmental Protection Agency*.
- Ervin, Christine A. and David E. Ervin (1982) “Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications,” *Land Economics*.
- Fishbacher, Urs, Simon Gächter, and Ernst Fehr (2001) “Are people conditionally cooperative? Evidence from a public goods experiment,” *Economic Letters*.
- Goldstein, Noah J., Robert B. Cialdini, and Vladas Griskevicius (2008) “A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels,” *Journal of Consumer Research*.
- Hascic, I. and JunJie Wu (2006) “Land Use and Watershed Health in the United States,” *Land Economics*, Vol. 82, pp. 214–239.
- Ingram, Deborah D. and Sheila J. Franco (2012) “NCHS urban-rural classification scheme for counties,” *Vital and health statistics, Data evaluation and methods research*.
- Konar, Avishek, Brian E. Roe, and Elena G. Irwin (2012) “Do Farmers Have Heterogeneous Preferences for the Environment? A Latent-Class Approach to Tillage Choices.”
- Langpap, Christian, Ivan Hascic, and JunJie Wu (2008) “Protecting Watershed Ecosystems through Targeted Local Land Use Policies,” *American Journal of Agricultural Economics*, Vol. 90, pp. 684–700.
- Langpap, Christian and JunJie Wu (2008) “Predicting the Effect of Land-Use Policies on Wildlife Habitat Abundance,” *Canadian Journal of Agricultural Economics*, Vol. 56, pp. 195–217.
- Lynne, Gary D., John Scott Shonkwiler, and Leandro R. Rola (1988) “Attitudes and Farmer Conservation Behavior,” *American Journal of Agricultural Economics*.
- Manski, Charles F. (1993) “Identification of endogenous social effects: the reflection problem,” *Review of Economic Studies*.
- (2000) “Economic analysis of social interactions,” *Journal of Economic Perspectives*.
- McConnell, Kenneth E. (1983) “An Economic Model of Soil Conservation,” *American Journal of Agricultural Economics*.
- McFadden, Daniel L (1984) “Econometric analysis of qualitative response models,” *Handbook of econometrics 2*.

- Munshi, Kaivan (2004) "Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution," *Journal of Development Economics*.
- Rahm, Michael R. and Wallace E. Huffman (1984) "The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables," *American Journal of Agricultural Economics*.
- Tilman, David, Kenneth G. Cassman, Pamela A. Matson, Rosamond Naylor, and Stephen Polasky (2002) "Agricultural sustainability and intensive production practices," *Nature*.
- Veblen, T (1899) *The Theory of the Leisure Class*: Macmillan Company, Limited.
- Wu, JunJie, Richard M. Adams, Catherine L. Kling, and Katsuya Tanaka (2004) "From Micro-Level Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies," *American Journal of Agricultural Economics*, Vol. 86, pp. 26–41.