Agricultural practices adjustments to policies aiming to decrease water pollution from agriculture

Shanxia Sun[1], Michael Delgado[2], Juan Sesmero[3]

[1] PhD Candidate, Agricultural Economics, Purdue University
[2] Assistant Professor, Agricultural Economics, Purdue University
[3] Assistant Professor, Agricultural Economics, Purdue University

Contact Information:

Shanxia Sun

Agricultural Economics, Purdue University

403 West State Street,

West Lafayette, IN 47907

sun217@purdue.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July27-29, 2014

Agricultural practices adjustments to policies aiming to decrease water pollution from agriculture

Abstract

Policies that aim to mitigate water pollution from fertilizer use in agriculture include input-based and output-based policies. Both cost-effectiveness and the speed for policies to take effect are important for policy assessment. In this study, we found that fertilizer price policies cannot decrease fertilizer use significantly due to the insignificant effect of fertilizer price on fertilizer use. Contrarily, the fertilizer use is elastic to output price, and policies that impose tax on corn production or subsidize soybean production or both are able to mitigate water pollution form fertilizer use significantly. Policies that can increase labor supply in planting season may also have strong effect on mitigation of water pollution. The slow adjustment rate of land allocation suggests that policies that affect fertilizer use through motivating farmers' land allocation adjustment from fertilizer-intensive crop to fertilizer-saving crop may be time costly.

Key words: water pollution, fertilizer use, policy assessment, land allocation adjustment

Introduction

Water pollution is an important water issue and concerns policymakers. It is widely acknowledged that some agricultural practice leads to high levels of water pollution (Hascic & Wu, 2006). Fertilizer (e.g., nitrogen and phosphorus) use and associated runoff is a main resource of water pollution in the surrounding watershed area (Baker 1992). Hence, most policies trying to mitigate agricultural pollution of water are directed deceasing fertilizer use. Policies being able to mitigate fertilizer use significantly are thought to have potential significant effect on water quality. Therefore, the first step in determining the effectiveness of policies on water quality is the effectiveness of policies on fertilizer use.

Policies that aim to mitigate water pollution from agriculture are shown as two different types: policies encouraging farmers to adjust agricultural management practice and policies regulating emission directly. Several studies have found that the former are more cost-effective (Diebel et al. 1992, Whittaker et al. 2003, Wu and Tanaka 2005, Langpap et al. 2008). These policies include input-based policies (i.e., taxing fertilizer use or subsidizing application reduction) and output-based policies (taxing fertilizer-intensive outputs or subsidizing fertilizer-saving outputs). The main objective of this study is to assess and compare these policy options on the basis of their cost-effectiveness to reduce pollution.

Input-based and output-based policies are likely to display different adjustment speed. Previous studies suggest that farmers' behavioral reactions to policies affecting crop choice may be slow due to crop rotation effects (Orazem and Miranowski 1994), and quasi-fixed capital and labor constraints (Arnberg and Hansen 2012). Menezes and Piketty (2012) also find evidence of slow adjustment.

The slow adjustment may cause problems for some policies because policymakers are interested not only in the cost-effectiveness, but also the speed at which policies induce the desirable water pollution mitigation. If a policy has a similar or maybe slightly higher cost effectiveness than other policies, but takes much longer to take effect, the policy may not be preferred by policymakers. However, previous literature has focused on the long term effects of policies precluding quantification of the time needed for policies to take effect. To find the trajectory of fertilizer use adjustment to different policies and track the amount of time each policy needs to take effect requires a dynamic analysis. Therefore, another main objective of this study is quantification of time trajectory of fertilizer application associated with input-based and output-based policies. Such quantification will also reveal potential tradeoffs (or complementarities as the case may be) between short and long term effectiveness of policies.

It has been found that the effectiveness of policies are affected by regional heterogeneity. Policies are found to be more cost-effective if they account for spatial heterogeneity (Bouzaher et al. 1990, Taylor et al. 1992). To avoid high regional heterogeneity in a large area, we focus our analysis on only one watershed, the Wabash River Watershed. The watershed covers 65 counties in Indiana, and 23 counties in Illinois. In this watershed, corn and soybean are two main crops produced and corn land adjustment will be the focus of this study.

Theoretical model

The model we cite in this study is the framework proposed by Lansink & Stefanou in 1997. One important reason we choose the model is that it is able to model asymmetric adjustment of quasi-fixed inputs. The adjustment cost of expanding and contracting may not be symmetric. Chang and Stefanou have found that symmetry adjustment is rejected in their study of Pennsylvania dairy farms. (Chang and Stefanou 1988) In this study, the adjustment of land allocation may also not be asymmetric since contracting production of one certain crop seems easier than expanding production of the crop due to the limit of farmers' total land and land availability in the market. Another point that deserves to mention is that the asymmetric model does not exclude the possibility of symmetry, which is nested in the asymmetry model and can be tested in the estimation. Another reason we choose this model is that currently this model has only been used in the context of quasi-fixed capital investment, not land allocation change. The land allocation adjustment has different characteristics from capital adjustment, such as crop rotation effect, soil productivity effect, land location constraint, etc. These special features of land allocation adjustment need to be put under consideration when farmers make their adjustment decisions and may cause different adjustment decision or adjustment trajectory compared to capital adjustment.

Lansink's model also model non-smooth adjustment of quasi-fixed inputs. When a study is built on farm level observations and the adjustment cost of the farmer is greater than the shadow value of the quasi-fixed input, there is no adjustment happened and the observed adjustment data show as zero. Zero values cause problem to estimation since a large number of adjustment data are truncated at zero. To solve the problem, he applied no-smooth adjustment in his model to capture the real meaning of zero adjustment, which is from the sluggishness of adjustment instead of zero shadow value of adjustment. Our study is built on county level observation and even if one single farmer's adjustment is sluggish and show as zero value in land change, the aggregation of land change of all farmers in one county is rarely zero unless all farmers in the county did not adjust their land allocation in that year. The higher level of data aggregation actually solves the problem of zero observations and transfers non-smooth adjustment of land allocation to smooth adjustment.[1] Hence, we exclude the non-smooth part of Lansink's model to meet the requirement of our study.

The model starts with the maximization of the discounted flow of profit for the producer producing multiple outputs using variable inputs and quasi-fixed inputs.

$$J(v, w, K, Z, t) = \max_{I} \int_{1}^{\propto} e^{-rs}\left[\pi(v, K(s), Z(s), s) - w'K - C\big(I(s)\big)\right]ds \qquad (1)$$

where K is a vector of quasi-fixed inputs and I is the corresponding quasi-fixed input adjustment; π is defined as vQ; v and w are (vectors of) market prices of netputs and quasi-fixed inputs, respectively; Q is a vector of netput quantities (positive for outputs, negative for inputs) and Z is a vector of fixed inputs; s reflects technological progress as a time trend; and $C(I)$ is the adjustment cost function.

The Hamilton-Jacobi equation of the optimization problem in equation (1) is as follow

$$rJ(v, w, K, Z, t) = \max_{I}\{\pi(v, K, Z, t) - w'K - C(I) + (I - \delta K)'J_k\} + J_t. \qquad (2)$$

The first-order condition of this optimization with the assumption of interior solution is

$$C_I = J_K \qquad (3)$$

, which means that the shadow value of the adjusted quasi-fixed input equals the marginal adjustment cost.

Differentiating (2) with respect to v, netputs equations can be derived as follow,

$$Q = rJ_v - J_{kv}\dot{K} - J_{kv} \qquad (4)$$

Differentiating (2) with respect to w, adjustment equations can be derived as

$$\dot{K} = J_{kw}^{-1}(rJ_w + K - J_{tw}) \qquad (5)$$

[1] However, we must stress that the adjustment is still sluggish even though we did not observe a large number of zero observations on land change. In our case, the sluggishness of land allocation adjustment show as the slow adjustment rate instead of no adjustment.

With the asymmetric adjustment cost function, the following optimal investment regimes will be realized,

$$\dot{K} = \begin{cases} \dot{K} < 0 \ \text{ if } J_k < q_1 \\ \\ \dot{K} > 0 \ \text{ if } J_k > q_2 \end{cases} \tag{6}$$

where q_1 and q_2 are the shadow price of the adjusted quasi-fixed input. When the shadow value of the adjusted quasi-fixed input J_k is smaller than shadow price of the adjusted quasi-fixed input, the adjustment is contracting. When the shadow value of the adjusted quasi-fixed input J_k is greater than shadow price of the adjusted quasi-fixed input, the investment is expanding.

Empirical model

Compared to the normalized quadratic specification, the symmetric normalized quadratic specification has the advantages that estimation results are invariant with respect to choice of the numeraire so it is used for the optimal value function. The value function is

$$J(v, w, z, K, t) = (a_1 a_2)\begin{pmatrix} v \\ w \end{pmatrix} + \frac{1}{2}(\theta' v)^{-1}(vw)\begin{bmatrix} A & C \\ C' & B \end{bmatrix}\begin{pmatrix} v \\ w \end{pmatrix} + \frac{1}{2}(\theta' v)(zKt)\begin{bmatrix} D & G & H \\ G' & E & L \\ H' & L' & F \end{bmatrix}\begin{bmatrix} z \\ K \\ t \end{bmatrix}$$

$$+ (vw)\begin{bmatrix} O & P & R \\ S & M^{-1} & U \end{bmatrix}\begin{bmatrix} z \\ K \\ t \end{bmatrix} \tag{7}$$

$$\sum_{i=1}^{\zeta} A_{ij}\,\bar{v}_i = 0 \qquad j = 1, \dots, \zeta$$

$$\sum_{i=1}^{\zeta} C_{ij}\,\bar{v}_i = 0 \qquad j = 1,2 \tag{8}$$

where θ represents a vector of average shares of netputs in total costs plus revenues and ζ is the number of netputs. Equation (8) are additional constraint imposed to equation (7) to identify all parameters in estimation.

Following equation (5), the adjustment equation for quasi-fixed inputs can be derived as

$$\dot{K} = (r + M)K + rM(a_2 + \theta v^{-1}(Bw + Cv) + Sz + Ut) - MU \qquad (9)$$

, which imply a multivariate linear accelerator mechanism

$$\dot{K}^* = (r + M)(K - K^*) \qquad (10)$$

where K^* is the optimal level of quasi-fixed input K.

$$K^* = rN(a_2 + \theta v^{-1}(Bw + Cv) + Sz + Ut) - NU \qquad (11)$$

$$N = -(r + M)^{-1}M. \qquad (12)$$

The shadow value of capital is

$$J_k = (\theta' v)(G'z + E'K + L't) + M^{-1\prime}w + P'v\ . \qquad (13)$$

If we have two quasi-fixed inputs, K_1 and K_2, and the asymmetric adjustment happens to K_2, the K_2 adjustment equations can be expressed as

$$\dot{K}_2^- = \gamma_2^- X + \epsilon_1$$

$$\dot{K}_2^+ = \gamma_2^+ X + \epsilon_2 \qquad (14)$$

where $X = (v, w, z, K, t)$ and ϵ_1 and ϵ_2 are disturbance terms.

The following netputs equations are also estimated:

$$Q^* = r\left(a_1 + (\theta' v)^{-1}(A'v + C'w) - \frac{1}{2}\theta(\theta' v)^{-2}(vw)\begin{bmatrix} A & C \\ C' & B \end{bmatrix}\binom{v}{w} + \frac{1}{2}\theta(zKt)\begin{bmatrix} D & G & H \\ G' & E & L \\ H' & L' & F \end{bmatrix}\begin{bmatrix} z \\ K \\ t \end{bmatrix} + O'z + P'K + R't\right) - (P' + \theta(G'z + E'K + L't)\dot{K} - R - \theta(HLF)\begin{bmatrix} z \\ K \\ t \end{bmatrix}.$$

(15)

Data

We focus our analysis on Wabash River Watershed, which includes 65 counties in Indiana, and 23 counties in Illinois. We include two outputs, corn and soybean; two variable inputs, fertilizer and labor; two quasi-fixed inputs, land allocated to each crop and capital; and one fixed input, total cropland.

Quantity and price data for all outputs and inputs are required for empirical implementation of model. Multiple sources of data are assembled to obtain the whole dataset. Quantity data of outputs, quantity and price data of land, price data of fertilizer and quantity data of capital are from the United States Department of Agricultural National Agricultural Statistics Service (USDA NASS). Price of corn and soybean are from GeoGrain. Quantity and price data of labor are from the United States Bureau of Labor Statistics. Quantity data of fertilizer are from the office of the Indiana State Chemist and the Office of the Illinois State Chemist.

Corn and soybean production in each county are used as output quantity and future corn and soybean price for each county are from Chicago Future Market price. County level data of employee and wage in crop production industry are used as labor quantity and wage. County level fertilizer quantity data are reported data from all fertilizer companies and sale agents to Fertilizer office in each state. Planting area data of corn and soybean in each county each year are used as land area allocated to each crop and their sum are used as total land. Only census data are available for land price from USDA NASS and these data only have observation for one year in every five year, so we used nonlinearly interpolation to recover annual land price data. For capital, number of tractor under use in the farm are used as capital quantity since tractors are the most typical capital investment in farms. Tractor quantity are also census data with observation in one year for every five year so we use nonlinearly interpolation to recover annual tractor quantity data.

To avoid high regional heterogeneity, this study only focus on one watershed and is built on county level analysis with county level data. It is desirable to obtain all data with county level. However, fertilizer and tractor price data cannot be obtained with county level due to the lack of variation across counties or even across states. Hence, national level fertilizer and tractor price data are chosen instead and these data only vary across different years not across different counties.

Results

Equation (15) are estimated to obtain price elasticities of inputs and outputs. To measure the effect of price policies on fertilizer use, we focus on the own price elasticity and cross price elasticities of fertilizer. Table 1 shows that the cross price elasticity of corn price on fertilizer is positive, which means that the increase of corn price will motivate fertilizer use. The cross price elasticity of soybean price on fertilizer use is negative, which indicates that the increase of soybean price will decline fertilizer use. The signs of the two elasticities are not surprising since corn is fertilizer-intensive crop and require more fertilizer use while soybean is fertilizer-saving crop. The result indicates that policies taxing corn production or subsidizing soybean production have significant effect on reduction of fertilizer use.

The cross price elasticity of labor on fertilizer is positive and it indicates the substitution relationship between fertilizer and labor. The substitution may come from the case that that when farmers have labor constraint in planting season, they tend to apply fertilizer in fall or winter to prepare for planting season and this cause the overuse of fertilizer. For this case, the increase of available labor in planting season can decrease fertilizer use in fall or winter. When we consider the mitigation of water pollution, the decrease of fertilizer use in fall or winter may have stronger effect on water quality than decrease of fertilize use in planting season because fertilizer applied in fall or winter can cause more fertilizer runoff through the long fallow season in winter than fertilizer applied in growing season.

Regression result shows that all coefficients of variables which include fertilizer price are not significant so we cannot get any implication from its own price elasticity. The insignificance of fertilizer price on fertilizer quantity indicates that farmers do not adjust their fertilizer use for the increase of fertilizer cost increase. Combined with positive effect of corn price increase, the result implies that fertilizer use are decided by the need of crop production more than by its own price change. Policies focusing on the increase of fertilizer cost of farmers may not be effective to decrease fertilizer use.

Table 1. Price elasticity of fertilizer

	Corn	Soybean	Fertilizer	Labor
Elasticity	0.92	-1.69	0.18	0.69

Equation (9) and equation (14) are estimated to obtain adjustment trajectories of capital and land allocated to corn respectively. Both symmetric and asymmetric adjustment of land allocated to corn are estimated. Table 2 shows that parameters of expanding and contracting functions are significantly different and support asymmetric adjustment of land allocation. The result also shows that the adjustment rate of contracting is higher than the adjustment rate of expanding, which means that it is faster for farmers to contract corn production than to expand corn production and it is consistent with Lansink and Stefanou's finding. (Lansink and Stefanou 1997)

Both in expanding and contracting adjustment of land allocation, the result shows slow adjustment rate. Expanding corn production requires eight years to achieve its adjustment goal. For contracting adjustment, even though it is faster than expanding, it still takes more than four years to achieve the optimal level. The result is consistent with the finding in previous literature (Menezes and Piketty, 2012) and indicates that policies which tend to decrease fertilizer use through affecting farmers' land allocation are time costly.

Table 2. Adjustment Rate

	Asymmetric Adjustment		Symmetric Adjustment
	Expanding	Contracting	
m11	0.12(2.65)	0.23(7.85)	0.39(11.12)
m12	0.01(0.75)	0.01(-1.89)	0.01(2.06)
m21	-0.13(-1.90)	0.14(2.35)	-0.05(-1.16)
m22	-0.03(-2.49)	0.02(1.85)	-0.01(-0.64)

Conclusion

Policies that aim to mitigate water pollution from fertilizer use in agriculture include input-based and output-based policies. Input-based policies take effect through taxing the use of fertilizer or inputs which are complementary to fertilizer or subsidizing the use of inputs which are substitutive to fertilizer. Output-based policies take effect through tax on fertilizer-intensive crop (i.e. corn) or subsidy on fertilizer-saving crop (i.e. soybean). Some policies are able to take effect on fertilizer use quickly by affecting fertilizer use directly in the current year while some policies affect fertilizer use indirectly through motivating farmers' adjustment of land allocation (i.e. moving land allocation from fertilizer-intensive crop to fertilizer-saving crop). Different policies are likely to display different speed to take effect and policies related to land allocation adjustment may require long time to take full effect due to farmers' sluggish behavioral reactions in land allocation adjustment.

In this study, we found that fertilizer price policies cannot decrease fertilizer use significantly due to the insignificant effect of fertilizer price on fertilizer use. Farmers seems hardly decrease their fertilizer use even with higher fertilizer price. Contrarily, the fertilizer use is elastic to output price, and output-based policies are much more effective to decrease fertilizer use. Hence, policies that impose tax on corn production or subsidize soybean production or both are able to mitigate water pollution form fertilizer use significantly. Policies that can increase labor supply in planting season may also have strong effect on mitigation of water pollution through decreasing fertilizer application in fall or winter.

The slow adjustment rate of land allocation suggests that policies that affect fertilizer use through motivating farmers' land allocation may be time costly. To decreasing fertilizer use through decreasing land allocated to corn requires four years to fully achieve its goal.

This study is limited since we only include the short term price elasticity of inputs and outputs on fertilizer. Adjustments rate of land allocation is slow and some effect of price change will continue until land allocation achieves its optimal level. Hence, the long term price elasticities are expected to be more elastic than short term elasticities since they can capture all effect of adjustments on quasi-fixed inputs. In future study, we would like to include long term elasticities in our study to capture the full effect of price changes on fertilizer use and measure the full effect of price policies on water pollution.

In future study we also would like to include price elasticities on all inputs and outputs since we only include price elasticities of variable inputs and outputs on fertilizer now. Elasticities among all inputs and outputs are able to capture the mutual effects of price policies completely. We also would like to include simulations to measure the magnitude and time required for different policies to achieve the same fertilizer use decrease goal. The simulations are able to show clear comparison among different policies on their cost-effectiveness and speed to take effect.

Reference

Arnberg, S. and Hansen, L. G., 2012. “Short-run and long-run dynamics of farm land allocation: panel data evidence from Denmark,” Agricultural Economics, 43, 179-190.

Baker, L. A., 1992. “Introduction to nonpoint source pollution in the United States and prospects for wetland use,” Ecological Engineering, 1, 1-26.

Bouzaher, A., Braden, J. A. and Johnson, G. V., 1990. “A dynamic programming approach to a class of nonpoint source pollution control problems,” Management Science, 36, 1-15.

Chang, C. C. and Stefanou, S. E., 1988. “Specification and estimation of asymmetric adjustment rates for quasi-fixed factors of production,” Journal of Economic Dynamics and Control, 12, 145-151.

Diebel, P. L., Taylor, D. B., Batie, S. S. and Heatwole, C. D., 1992. “Low-input agriculture as a ground water protection strategy,” Journal of the American Water Resources Association, 28, 755-761.

Hascic, I. and Wu, J., 2006. “Land use and watershed health in the United States,” Land Economics, 82, 214-239.

Langpap, C., Hascic, I. and Wu, J., 2008. “Protecting watershed ecosystems through targeted local land use policies,” American Journal of Agricultural Economics, 90, 684-700.

Lansink, A. O. and Stefanou, S. E., 1997. “Asymmetric adjustment of dynamic factors at the firm level,” American Journal of Agricultural Economics, 79, 1340-1351.

Menezes, T. A. and Piketty, M. G., 2012. “Towards a better estimation of agricultural supply elasticity: the case of soya beans in Brazil,” Applied Economics, 44, 4005-4018.

Orazem, P. F. and Miranowski, J. A., 1994. “A dynamic model of acreage allocation with general and crop-specific soil capital,” American Journal of Agricultural Economics, 76, 385-395.

Taylor, M. L., Adams, R. M. and Miller, S. F., 1992. “Farm-level response to agricultural effluent control strategies: the case of the Willamette Valley,” Journal of Agricultural and Resource Economics, 17, 173-185.

Whittaker, G., Fa¨re, R., Srinivasan, R. and Scott, D. W., 2003. “Spatial evaluation of alternative nonpoint nutrient regulatory instruments,” Water Resources Research, 39, 4.

Wu, J. and Tanaka, K., 2005. “Reducing nitrogen runoff from the Upper Mississippi River Basin to control hypoxia in the Gulf of Mexico: Easements or taxes?’’ Marine Resource Economics, 20, 121-144.