The Environmental Effects of Crop Price Increases: Nitrogen Losses in the U.S. Corn Belt

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Abstract

High corn prices cause more land to be planted to corn, which increases the use of nitrogen fertilizer. Some of this nitrogen flows into waterways and causes serious environmental damage. We estimate that nitrogen losses are highly inelastic with respect to crop prices, but that the absolute losses can still be large. Our results suggest that changes in corn and soybean prices due to the U.S. ethanol mandate have expanded the size of the hypoxic zone in the Gulf of Mexico by roughly 288 square miles on average. To obtain these estimates, we use a panel of field-level crop data derived from satellite imagery. We merge these data with predictions from the Soil and Water Assessment Tool (SWAT) to estimate nitrogen losses by field. Our econometric model allows for substantial spatial heterogeneity, which is important for reducing bias in dynamic panel estimates and accounting for possible correlation between acreage response to price and nitrogen losses.

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Agricultural production generates externalities through its effects on environmental goods such as water quality, wildlife habitat, and carbon sequestration. As crop prices change, farmers change their planted acreage, which in turn changes the generation of these externalities. For example, it has been argued that higher crop prices due to the production of ethanol has increased nutrient losses from the Corn Belt into surface water (e.g., Donner and Kucharik 2008; Secchi et al. 2011; Langpap and Wu 2011), increased monoculture production systems that are associated with losses of biocontrol services (Landis et al. 2008), and increased greenhouse gases from agricultural land use expansion (e.g., Searchinger et al. 2008).

The magnitude of these external effects depends not just on the amount of land allocated to crop production, but also on where that production takes place. Increased corn acreage on sandy or highly erodible soils may lead to greater nitrogen losses than increased production on other soil types. The temporal dynamics of crop production also matter—nitrogen losses from growing corn on a particular field may be greater if corn was grown on that same field the prior year than if soybeans were grown the prior year. Thus, estimating the environmental effects of crop production accurately requires a model that incorporates spatial heterogeneity and production dynamics.

In this article, we use the model of Hendricks, Smith, and Sumner (2012) to estimate the response of nitrogen losses in Iowa, Illinois, and Indiana to a change in crop prices. These three states alone produce roughly 15% of the world's corn and soybeans,[1] and yet this region's losses of nitrogen and phosphorus from crop production are cited as a leading cause of the "dead zone" in the Gulf of Mexico (Dale et al. 2010). *The Economist* (2012) calls the dead zone an "ecological disaster" that results in losses valued at roughly $2.8 billion per year to fisheries and also notes that nutrient losses cause algal blooms in waters within the Corn Belt that make these waters dangerous for humans, pets, and fish.

[1]This statistic is calculated from Food and Agriculture Organization (FAO) data on world production and National Agricultural Statistics Service (NASS) state-level production data for the period 2000–2010.

We estimate that the long-run nitrogen loss elasticity with respect to the price of corn is 0.103 and the long-run nitrogen loss elasticity with respect to the price of soybeans is -0.030 for most of Iowa, Illinois, and Indiana. These estimates are important for understanding the effect of government policies on nitrogen losses from the Corn Belt. For example, we use these elasticity parameters to estimate the effect of the ethanol mandate in the United States on the size of the hypoxic zone in the Gulf of Mexico. Our elasticity parameters are also important inputs for estimating the effect of U.S. farm subsidy programs on nitrogen losses.

The United States produced 13.9 billion gallons of ethanol in 2011, which corresponds to 40 percent of U.S. corn production.[2] Based on the estimates obtained by Roberts and Schlenker (forthcoming) and Carter, Rausser, and Smith (2012), we assume that the U.S. ethanol mandate has increased the price of corn by 30 percent and the price of soybeans by 15 percent. With this assumption, our elasticity parameters imply that the U.S. ethanol mandate has increased nitrogen losses from this region by 2.64 percent. Our estimate of the effect of the ethanol mandate on nitrogen losses is smaller than previous estimates, but not trivial. Using estimates from Obenour et al. (2012) that relate nitrogen exports from the Mississippi River to the size of the hypoxic zone in the Gulf of Mexico, our results suggest that the U.S. ethanol mandate has increased the size of the hypoxic zone by 288 mi^2. For perspective, this 288 mi^2 is 5.5 percent of the 13,600 km^2 average hypoxic zone size from 1985 to 2010 (Turner, Rabalais, and Justić 2012) and 15 percent of the 5,000 km^2 target hypoxic zone size (Dale et al. 2007).[3] Furthermore, the effect of the ethanol mandate on water quality is not limited to the hypoxic zone in the Gulf of Mexico.[4]

[2]For every bushel of corn that is used in ethanol production, one-third returns to the food system in the form of distiller's grains. This by-product is used for animal feed and it implies that, although 40 percent of US corn was used in ethanol production, the net loss to the food system was 27 percent.

[3]The target size of the hypoxic zone was set by the Mississippi River/Gulf of Mexico Task Force, which consists of several federal and state agencies.

[4]For example, the U.S. ethanol mandate likely results in land use changes around the world that may also have water quality implications for different regions of the world.

Our estimate of the effect of the ethanol mandate on nitrogen losses is significantly smaller than estimates from Donner and Kucharik (2008). They estimate that producing 15 billion gallons of ethanol by 2022 increases nitrogen losses by 10–18 percent. However, they assume that all of the corn required to meet the mandate (using 2004–2006 U.S. corn production as a baseline) is produced in the United States. This assumption likely overstates the effect of the mandate because demand for corn for other uses will decrease and production will increase globally as corn demand shifts due to the mandate.

The parameters in our econometric model vary spatially. We estimate the parameters separately for 108 soil-climatic regimes, which are defined using soil taxonomy classifications within Major Land Resource Areas as identified by the Natural Resources Conservation Service. Our results illustrate the importance of spatially modeling land use change. Modeling the spatial heterogeneity of coefficients is important because (i) estimates of dynamic models can be severely biased if coefficient heterogeneity is ignored (Robertson and Symons 1992; Pesaran and Smith 1995) and (ii) changes in nitrogen losses due to changes in crop production depend on local climates and soils. We find that fields that exhibit relatively larger nitrogen losses from growing corn in consecutive years are relatively more likely to respond to a price increase by growing corn in consecutive years. However, we find in our application that reducing the bias from coefficient heterogeneity in a dynamic production system is the primary benefit of modeling the coefficient heterogeneity.

Several previous articles that link land use change to environmental outcomes do not allow spatial heterogeneity of the coefficients in the econometric model (Wu et al. 2004; Langpap, Hascic, and Wu 2008; Lacroix and Thomas 2011; Fezzi and Bateman 2011). In these models, the predicted land use varies spatially only due to the inclusion of explanatory variables derived from disaggregated soils and climatic data—the parameters of these models do not vary across space. The most common approach of other studies is to allow spatial heterogeneity of land use change through the use of spatial regimes, i.e., dividing

space into multiple sub-regions and estimating different parameters for each sub-region.[5] Langpap and Wu (2011) estimate separate land use models for two groups of U.S. states. Newburn and Berck (2006) allow coefficients to differ by four regions and model the remaining heterogeneity within regions using a random parameters logit model. Several articles use land capability classifications (LCC) as spatial regimes (Lichtenberg 1989; Plantinga 1996; Lubowski, Plantinga, and Stavins 2008; Nelson et al. 2008). In Iowa, Illinois, and Indiana, 94 percent of the cropland is in three LCC's, so this classification would allow very little spatial heterogeneity if applied to our sample.

In addition to spatial heterogeneity, we show that temporal dynamics also matter because nitrogen losses depend not just on total corn acreage, but also on crop rotation patterns. We find that, in response to a price shock, changes in nitrogen losses are smaller in the short run than in the long run. This result arises because corn after corn acreage responds to a price shock *less* in the short run than in the long run, and nitrogen losses are largest from fields with consecutive years of corn.[6] For example, if the price of corn increases permanently, some land switches from a corn-soybean rotation to continuous corn. Of the land that switches to continuous corn, roughly half is planted to corn after soybeans in the first year since roughly half of the land in a corn-soybean rotation is planted to soybeans in a given year. In the subsequent year, acreage of corn after corn increases. These dynamics stand in contrast to the dynamics of aggregate corn acreage. Hendricks, Smith, and Sumner (2012) show that aggregate corn acreage responds to price shocks *more* in the short run than in the long run because some fields that change crops in response to a price shock have an incentive to switch back to the previous crop in subsequent years due to the benefits of crop rotation.

We estimate the econometric model of crop rotation response to price using crop data derived from satellite imagery—the Cropland Data Layer from USDA—that provides a comprehensive accounting of crops in Iowa, Illinois, and Indiana from 2000 to 2010. Field bound-

[5] Another approach for allowing coefficients to vary spatially is through locally weighted regression (e.g., Cho, Bowker, and Park 2006).

[6] Corn after corn results in greater nitrogen losses than corn after soybeans partly because more fertilizer is applied to corn after corn.

aries are approximated with Common Land Unit boundaries as defined by the Farm Service Agency. The effective expected crop price is the sum of a futures price, an expected loan deficiency payment, and an expected basis. Our field-level dataset for the econometric analysis contains roughly 8.75 million observations.

For the econometric model, we specify corn and soybean crop rotations as first-order Markov transition probabilities (the rotational margin). We then use these Markov transition probabilities to calculate the probability of a corn after corn sequence, a corn-soybean rotation, and a soybeans after soybeans sequence—as well as the short-run and long-run marginal effects of price changes on these sequences. We also estimate first-order Markov transition probabilities for transitions between corn or soybeans and other crops (the extensive margin).

We use the Soil and Water Assessment Tool (SWAT) to estimate how changes in land use affect nitrogen losses from each field. The SWAT model is a continuous-time, distributed-parameter, hydrologic and water quality model developed by USDA ARS (Arnold et al. 1998). It has been widely used to assess the impacts of landcover and management practices on water and nutrients at the field and watershed scale (Gassman et al. 2007; Douglas-Mankin, Srinivasan, and Arnold 2010; Tuppad et al. 2011). In this study, we merge spatially-explicit SWAT results for nitrogen losses at the edge-of-the-field with spatially-explicit results from the econometric model. We then calculate the average change in nitrogen losses across the region due to a change in expected price.

1 Model of Crop Rotation Response to Price

We separately estimate price responses along the "rotational margin" (transitions between corn and soybeans) and the "extensive margin" (transitions between corn or soybeans and other crops). This model setup implies that farmers make sequential decisions, first deciding whether or not to plant one of the two main crops (corn and soybeans) and then deciding which of corn or soybeans to plant. We find very small price responses at the extensive

margin, so modeling the two margins independently is likely to negligibly influence our results.

1.1 Econometric Model

Hendricks, Smith, and Sumner (2012) formulate a conceptual model similar to that of Hennessy (2006) for a farmer's dynamic optimization of crop rotations. Assuming that prices beyond the current year are expected to remain constant and assuming one-year memory of the crop rotation—that is, only the crop from the previous year affects returns in the current year—Hendricks, Smith, and Sumner (2012) show that the optimal planting decision is conditional on the previous crop. From this conceptual model, we can derive an econometric model of first-order Markov transition probabilities. We write the set of reduced-form Markov transition probabilities as follows:

$$\Phi_{it}^{cc} = Prob\left(c_{it} = 1 | c_{i,t-1} = 1\right) = F\left(\lambda_{1i} + \beta_{1i}^{c} p_{it}^{c} + \beta_{1i}^{s} p_{it}^{s} + \theta_{1i}' soil_i + \delta_{1i} pre_{it} + \kappa_{1i} t\right), \quad (1)$$

$$\Phi_{it}^{sc} = Prob\left(c_{it} = 1 | c_{i,t-1} = 0\right) = F\left(\lambda_{2i} + \beta_{2i}^{c} p_{it}^{c} + \beta_{2i}^{s} p_{it}^{s} + \theta_{2i}' soil_i + \delta_{2i} pre_{it} + \kappa_{2i} t\right), \quad (2)$$

where Φ_{it}^{cc} denotes the probability of a transition from corn to corn on field i in year t, Φ_{it}^{sc} denotes the probability of a transition from soybeans to corn, p_{it}^{c} is the expected effective price of corn including government payments, p_{it}^{s} is the expected effective price of soybeans including government payments, $soil_i$ is a vector of soil characteristics (percent clay, percent silt, and slope), pre_{it} is the cumulative April–May precipitation above average for the region, and t is a time trend.[7] Above average April–May precipitation is included as a regressor because heavy spring rains may delay corn planting and cause some farmers to switch to soybeans. $F(\cdot)$ denotes the cumulative distribution function, which we specify as logistic.

[7] We omit prices for inputs that differ between corn and soybean production (e.g., the price of fertilizer) because of the challenge of identifying the effect of the price of fertilizer separately from crop prices with only 11 years of data. However, using crop budgets, Hendricks, Smith, and Sumner (2012) show that changes in crop prices have much larger effects on crop rotation returns than proportional changes in fertilizer prices, so we expect the bias from this omission to be small.

Note that the probability of planting soybeans given that the previous crop was corn is $\Phi_{it}^{cs} = 1 - \Phi_{it}^{cc}$, and the probability of planting soybeans given that the previous crop was soybeans is $\Phi_{it}^{ss} = 1 - \Phi_{it}^{sc}$. We write coefficients with an i subscript to denote heterogeneity across fields.

The econometric specification in equations (1) and (2) only accounts for one-year memory of the crop rotation. Hendricks, Smith, and Sumner (2012) develop an econometric model that accounts for two-year memory, but they report that specifying one-year memory or two-year memory makes little difference to their estimates of aggregate elasticities. There are two reasons that we only account for one-year memory in this paper. First, we integrate our econometric model with a water quality model in this paper and we have nitrogen loss estimates for two year crop sequences, but not three year crop sequences.[8] Second, we choose a one-year memory specification because it requires estimation of fewer parameters. By including fewer parameters, we are able to estimate the model for more spatial regimes to give as much spatial heterogeneity as is reasonable with our data. In contrast, Hendricks, Smith, and Sumner (2012) are concerned primarily with estimating aggregate supply elasticities.

Another difference is that Hendricks, Smith, and Sumner (2012) specify a single equation linear probability model with lagged dependent variables, whereas we specify Markov transition probabilities with logit models in this paper. By estimating transition probabilities—or interactions of the lag and prices—we allow the price response to differ depending on the crop that was previously planted. This difference in specification makes a negligible difference to estimates of aggregate supply elasticities. The more flexibile transition probability specification could be important in this paper because we need estimates of the change in the probability of planting corn after corn in response to prices since nitrogen losses depend on the sequence of crops. The choice of logit or linear probability is largely superficial

[8]The one-year memory econometric model gives the probability of corn after corn versus corn after soybeans, which we link to the nitrogen loss estimates. A two-year memory econometric model also gives, for example, estimates of the probability of corn-corn-corn versus corn-corn-soybeans, but we have no corresponding nitrogen loss estimates.

for marginal effects in our application. Logit, however, constrains predicted probabilities between 0 and 1, which is convenient when predicting land use scenarios.

The probability of planting corn, denoted Π_i^c, is the probability of planting corn given that corn was previously planted multiplied by the long-run probability of planting corn plus the probability of planting corn given that soybeans were previously planted multiplied by the long-run probability of planting soybeans:

$$\Pi_{it}^c = \Phi_{it}^{cc}\Pi_{it-1}^c + \Phi_{it}^{sc}\left(1 - \Pi_{it-1}^c\right). \tag{3}$$

In the long run (i.e., steady-state) $\Pi_{itLR}^c = \Pi_{it}^c = \Pi_{i,t-1}^c$. Rearranging (3) gives the long-run probability in terms of estimated transition probabilities:[9]

$$\Pi_{it}^c|_{LR} = \frac{\Phi_{it}^{sc}}{\Phi_{it}^{sc} + (1 - \Phi_{it}^{cc})}. \tag{4}$$

The short-run change in the probability of planting corn with respect to a change in price is obtained by taking the derivative of the transition probabilities in (3) and evaluating at the long-run probabilities:

$$\left.\frac{\partial \Pi_{it}^c}{\partial p_{it}^j}\right|_{SR} = \frac{\partial \Phi_{it}^{cc}}{\partial p_{it}^j}\,\Pi_{it}^c|_{LR} + \frac{\partial \Phi_{it}^{sc}}{\partial p_{it}^j}\left(1 - \Pi_{it}^c|_{LR}\right), \tag{5}$$

where p_{it}^j is the expected price of crop j. In other words, the short-run marginal effect of price is the weighted average of the marginal effects of the transition probabilities, where the weights correspond to the long-run probability of planting corn and the long-run probability of planting soybeans. The long-run marginal effect of price is obtained by taking the derivative of (4):

$$\left.\frac{\partial \Pi_{it}^c}{\partial p_{it}^j}\right|_{LR} = \frac{\frac{\partial \Phi_{it}^{sc}}{\partial p_{it}^j}\left(1 - \Phi_{it}^{cc}\right) + \frac{\partial \Phi_{it}^{cc}}{\partial p_{it}^j}\Phi_{it}^{sc}}{\left[\Phi_{it}^{sc} + (1 - \Phi_{it}^{cc})\right]^2}. \tag{6}$$

[9] See Hamilton (1994, p. 683) for an alternative derivation.

In the case where the probability of planting corn is a linear probability model with a single lagged dependent variable, equation (6) simplifies to the usual result of the the short-run coefficient divided by one minus the coefficient on the lagged dependent variable.

The probability of planting corn two years in a row, denoted Π_{it}^{cc}, is the probability of planting corn given that corn was previously planted multiplied by the probability of planting corn:

$$\Pi_{it}^{cc} = \Phi_{it}^{cc} \Pi_{it-1}^{c}. \tag{7}$$

The long-run probability of planting corn two years in a row is obtained by substituting (4) into (7). Similarly, we can write the probability of planting a corn-soybean rotation ($\Pi_{it}^{c\text{-}s}$) and soybeans after soybeans Π_{it}^{ss} as follows:

$$\Pi_{it}^{c\text{-}s} = \frac{1}{2}\left[\Phi_{it}^{sc}\left(1 - \Pi_{it-1}^{c}\right) + \left(1 - \Phi_{it}^{cc}\right)\Pi_{it-1}^{c}\right], \tag{8}$$

$$\Pi_{it}^{ss} = \left(1 - \Phi_{it}^{sc}\right)\left(1 - \Pi_{it-1}^{c}\right), \tag{9}$$

where the probability of a corn-soybean rotation is the average of the probability of corn after soybeans and the probability of soybeans after corn. Equations (7)–(9) give the probability of observing a particular sequence of crops at a given price level, without conditioning on what was actually planted in a particular year.

The short-run marginal effect of price on the probability of planting corn after corn is

$$\left.\frac{\partial \Pi_{it}^{cc}}{\partial p_{it}^{j}}\right|_{SR} = \frac{\partial \Phi_{it}^{cc}}{\partial p_{it}^{j}} \left.\Pi_{it}^{c}\right|_{LR}. \tag{10}$$

The short-run marginal effect of price on the probability of planting corn after corn is the change in the probability of corn after corn, holding constant the probability of having previously planted corn. The long-run marginal effect is as follows:

$$\left.\frac{\partial \Pi_{it}^{cc}}{\partial p_{it}^{j}}\right|_{LR} = \frac{\partial \Phi_{it}^{cc}}{\partial p_{it}^{j}} \left.\Pi_{it}^{c}\right|_{LR} + \Phi_{it}^{cc} \left.\frac{\partial \Pi_{it}^{c}}{\partial p_{it}^{j}}\right|_{LR}, \tag{11}$$

where the long-run marginal effect of price accounts for changes in the probability that corn was previously planted.

The marginal effects of price on corn-soybeans and soybeans after soybeans sequences are defined similarly. Note, however, that theory does not give an expected sign for the effect of a change in the price of corn on the probability of a corn-soybean rotation. If an increase in the expected price of corn causes a larger reduction in soybeans after soybeans than an increase in corn after corn, then the probability of a corn-soybean rotation could increase on average due to an increase in the price of corn.

Hendricks, Smith, and Sumner (2012) show that aggregate corn acreage response to a price shock is larger in the short run than in the long run. For example, if the price of corn increases permanently, some land previously planted to continuous soybeans switches to a corn-soybean rotation. This land is planted to corn first, then is rotated to soybeans in the second year—causing aggregate corn acreage to decrease in the second year. From equations (10) and (11), corn after corn acreage responds to a price shock less in the short run than in the long run. This result is also intuitive. For example, if the price of corn increases permanently, some land switches from a corn-soybean rotation to continuous corn. Of the land that switches to continuous corn, roughly half is planted to corn after soybeans in the first year, since roughly half of the land in a corn-soybean rotation is planted to soybeans. In the second year, acreage of corn after corn increases.

Our method of estimating the probability of different crop rotations differs from Wu et al. (2004). Using our notation, Wu et al. (2004) estimate the probability of planting continuous corn as $\Phi_{it}^{cc} Prob\,(c_{it-1} = 1 | c_{i,t-2})$. In other words, they predict that the probability of planting corn in two consecutive years conditional on the crop that was planted in some initial year. Marginal effects in their model are conditional on the initial distribution of crops and cannot be interpreted as either short-run or long-run marginal effects. In contrast, our predicted probability of planting each rotation in equations (7)-(9) conditions on the

long-run probability of planting corn for a particular price level. We can, therefore, estimate short-run and long-run marginal effects from any initial price level.

At the extensive margin, we also estimate first-order Markov transition probabilities:

$$Prob\left(cb_{it}=1|cb_{i,t-1}=1\right)=F\left(\lambda_{3i}+\beta_{3i}^{cb}p_{it}^{cb}+\beta_{3i}^{o}p_{it}^{o}+\theta_{3i}'soil_i+\kappa_{3i}t\right), \tag{12}$$

$$Prob\left(cb_{it}=1|cb_{i,t-1}=0\right)=F\left(\lambda_{4i}+\beta_{4i}^{cb}p_{it}^{cb}+\beta_{4i}^{o}p_{it}^{o}+\theta_{4i}'soil_i+\kappa_{4i}t\right), \tag{13}$$

where cb_{it} equals one if corn or soybeans were planted and equals zero if another crop was planted, p_{it}^{cb} is an index of expected corn and soybean prices, and p_{it}^{o} is an index of expected wheat and alfalfa prices. We do not estimate transitions with land uses other than crops due to limitations of the Cropland Data Layer. This choice is likely to have negligible effects on our results, however, because aggregate data indicate minimal changes in the acreage of other land uses in this region [see the appendix in Hendricks, Smith, and Sumner (2012)]. The long-run probability of planting corn or soybeans is denoted Π_{it}^{cb} and is defined similarly to equation (4).

The total probability of planting corn is the probability of planting corn given that corn or soybeans were planted multiplied by the probability of planting corn or soybeans:

$$Prob\left(c_{it}=1\right)=\Pi_{it}^{c}\Pi_{it}^{cb}. \tag{14}$$

From this relationship, we derive the total marginal effect of price on field i as follows:

$$\frac{\partial Prob\left(c_{it}=1\right)}{\partial p_{it}^{j}}=\underbrace{\frac{\partial\Pi_{it}^{c}}{\partial p_{it}^{j}}\Pi_{it}^{cb}}_{Rotational\,Margin}+\underbrace{\Pi_{it}^{c}\frac{\partial\Pi_{it}^{cb}}{\partial p_{it}^{j}}}_{Extensive\,Margin}, \tag{15}$$

where we can define either short-run or long-run marginal effects. We calculate the aggregate price elasticity by averaging marginal effects of price across all fields—weighted by field size—and converting into elasticity form.

1.2 Estimation

There are two reasons it is important to model the coefficient heterogeneity: (i) estimates can be severely biased if coefficient heterogeneity is ignored, and (ii) we are inherently interested in the distribution of coefficients. In dynamic panels with a heterogeneous intercept, pooled logit or probit estimates of the coefficient on the lagged dependent capture unobserved heterogeneity rather than true state dependence (Heckman 1981b). Furthermore, when the coefficients are heterogeneous, estimating a single coefficient for all fields (i.e., pooling) leads to biased estimates (Robertson and Symons 1992; Pesaran and Smith 1995). For example, suppose the true coefficient on the price of corn varies across fields. By forcing all fields to have the same coefficient β_1^c on price, the coefficient heterogeneity $(\beta_{1i}^c - \beta_1^c)p_{it}^c$ is forced into the error term. Then, because prices are autocorrelated, the error term is also autocorrelated, which causes the coefficient on the lagged dependent variable to partly capture the autocorrelation of prices. If we had a panel with large T, then we could estimate separate coefficients for each field. But with small T, field-specific estimates of a dynamic model suffer from small-sample bias.

We manage the trade-off between heterogeneity bias and small sample bias by forming groups of similar fields and estimating separate coefficients for each group of fields. We refer to our estimator as a "conditional grouped coefficients" estimator. It is a grouped coefficients estimator because the coefficients differ across 108×2 groups of similar fields as defined by 108 soil-climatic regimes and 2 transition groups. We describe construction of the soil-climatic regimes in section 2.3. It is a conditional estimator because, within each soil-climatic regime, we estimate the model separately for two sets of fields at the rotational margin: (i) fields that were never planted in monoculture (i.e., corn after corn or soybean after soybeans were never observed) and (ii) fields that were planted in monoculture at least once. At the extensive margin, we estimate the model separately, within each soil-climatic

regime, for (i) fields that transitioned between corn or soybeans and other crops and (ii) fields that always planted corn or soybeans.[10]

We assume that the Markov chains are reducible for those fields where certain transitions were never observed. At the rotational margin, for fields that were never planted in monoculture we impose the identifying restrictions $\Phi_{it}^{cc} = 0$ and $\Phi_{it}^{sc} = 1$. At the extensive margin, for fields that were always planted to corn or soybeans we impose the identifying restrictions $Prob\,(cb_{it} = 1|cb_{i,t-1} = 1) = 1$ and $Prob\,(cb_{it} = 1|cb_{i,t-1} = 0) = 1$. Thus, the short-run and long-run marginal effects of price are zero for these fields. This conditional estimation approach is like the conditional likelihood approach used in discrete-choice models in that the parameters are only identified for fields that changed states (Heckman 1981a). A similar estimation strategy is used by Bernard and Jensen (2004), who estimate the probability of a firm exporting as a function of whether the firm exported in the previous period.[11]

Standard errors are cluster-robust bootstrap standard errors with 500 replications, where we cluster by counties.[12] Bester, Conley, and Hansen (2011) propose clustering by large spatial blocks as a method to account for spatial autocorrelation. Intuitively, if spatial blocks have a large number of observations and if the spatial blocks are well-shaped, then there are few observations at the borders that are correlated with observations in other blocks.[13]

[10]Fields that always planted other crops are not included in our econometric analysis—that is, we assume that the response to price is zero for fields that always planted other crops during our sample period.

[11] Hendricks, Smith, and Sumner (2012) argue that the bias induced by this conditioning is likely to be small.

[12]Hendricks, Smith, and Sumner (2012) cluster standard errors by crop-reporting districts, which are blocks of counties. In this study, we estimate the model separately for 108 soil-climatic regimes, whereas Hendricks, Smith, and Sumner (2012) estimate the model separately for 24 regimes. The model can fail for some bootstrap replications if the clusters include large blocks of observations and the model is estimated for a large number of groups. We choose smaller clusters for this analysis because we have a larger number of soil-climatic regimes.

[13]"Well-shaped" essentially rules out long, narrow spatial blocks.

2 Data for Econometric Model

We report summary statistics of our data in table 1 and provide descriptions of the data sources and construction of the variables in this section. The rotational margin sample includes observations (field-year pairs) that were classified as corn or soybeans in two consecutive years. The extensive margin sample includes observations that were classified as a crop in two consecutive years and where the field was classified as corn or soybeans at least once during the sample period. We use the same crop, price, soil, and weather data as Hendricks, Smith, and Sumner (2012), which provides a more detailed description of the data than we provide here.

2.1 Crop Data and Field Boundaries

Our data come from the Cropland Data Layer (CDL),[14] which is produced by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). NASS describes the Cropland Data Layer as a "Census by Satellite." The CDL is an image of an entire state with a crop or land use classification code corresponding to each pixel, where pixels are less than one acre in size. NASS classifies pixels using data from satellite sensors and performs extensive validation exercises to "ground truth" the data. Our analysis uses the CDL in Illinois for the period 1999–2010 and Iowa and Indiana for the period 2000–2010.

Our empirical analysis uses three crop classifications: corn, soybeans, and other crops (primarily alfalfa and wheat). According to accuracy assessments conducted by NASS, the probability that the CDL correctly classifies corn or soybeans is roughly 95% on average in these three states. The CDL is less accurate at distinguishing between other crops, so we merge them all into a single category. The CDL is also less accurate at classifying noncrop land uses. Fortunately, noncrop land use, say for grazing livestock, is a very small part of

[14] The Cropland Data Layer can be viewed and downloaded at `http://nassgeodata.gmu.edu/CropScape/`. For details on the methodology of constructing the Cropland Data Layer, see Boryan et al. (2011).

land mix that is ever planted to crops in the central Corn Belt. For these two reasons, we do not estimate changes in corn and soybean acres from transitions with noncrop land uses.

We do not use each pixel from the Cropland Data Layer as a separate unit of analysis for the econometric model for three main reasons: (i) a farmer's crop decision is made at the field level not the pixel level, (ii) pixels are more likely to be misclassified at field boundaries, and (iii) estimating econometric models with every pixel is computationally burdensome (see Rashford, Albeke, and Lewis 2013). Rather, we use Common Land Unit (CLU) boundaries from the Farm Service Agency to approximate "field" boundaries and choose a point near the centroid of the CLU as our unit of analysis. We use points that are diagonally offset from the centroid of the CLU because CLUs are often split into two fields, so the centroid may not be classified from the same field each year. We choose the distance that the point is offset from the centroid to be proportional to the size of the CLU and we choose the direction randomly. Many of the CLUs that are extremely small are likely to be gullies, waterways, or farmsteads, so the empirical analysis includes only points corresponding to CLUs larger than 15 acres.

2.2 Expected Crop Prices

In our econometric model, a right-hand side regressor is the expected effective price prior to planting including per-unit government payments—for which we use the shorthand "expected price." Expected crop prices are the sum of a futures price, an expected basis, and an expected government-set loan deficiency payment. For corn, the futures price is the average price in January–March of a December futures contract. For soybeans, the futures price is the average price in January–March of a November futures contract. Futures price data are obtained from the Commodity Research Bureau.

We use the basis in March, prior to planting, as the expectation for the harvest basis. The basis in March provides a reasonable expected basis prior to planting because storage bounds arbitrage opportunities. To measure the basis, we use spot prices in March for 93

market locations in the three states for corn and 90 locations for soybeans from GeoGrain. Each of the locations had at least one cash price recorded in March for every year in our crop dataset. We estimate the expected basis for each location as the average difference between the March spot price and the nearby May futures contract. We then interpolate to every point in the crop dataset using inverse distance weighting.[15]

Throughout the data period, the U.S. government provided a subsidy for corn and soybeans when market prices are low—called loan deficiency payments. The loan deficiency payment equals the positive difference between a county-specific loan rate and the posted county price—the government's measure of the local market price—times the farmer's production. This program provided a payment to growers but did not create a floor price for buyers and the government acquires no commodities, so we assume the loan rate truncates the price distribution from below. Assuming that the harvest-price has a lognormal conditional distribution, we use the formula for a truncated mean to estimate an expected price that incorporates the possibility of a loan deficiency payment. The truncation of the distribution occurs at the average county loan rate for the three states. The mean of the distribution is the log futures price (adjusted for the average difference between the futures price and average posted county price across the three states) and for the standard deviation we use the average implied volatility in January–March of December options for corn and November options for soybeans, adjusted for time until contract expiration.[16] Data on the implied volatility are from the Commodity Research Bureau.

For use in our extensive margin models, we construct a Laspeyres index of expected corn and soybean prices and a Laspeyres index of expected alfalfa and wheat prices for the analysis of changes between corn and soybeans and other crops. We construct these indexes at the county level using the expected crop yield times the crop acreage in 2000 as the weights

[15]Inverse distance weighting gives a weighted average of the q nearest neighbors. The weights are $1/\left(distance^k\right)$, where k is a smoothing parameter, thus greater weight is given to closer markets. Parameter values for interpolation were set at $q = 4$ and $k = 2$. Lo and Yeung (2002, p. 326) state that $k = 2$ is typically used for inverse distance weighting.

[16]The difference between the posted county price and the loan rate in each year differs little between counties for 2004–2010.

for expected prices. Expected yield is the prediction from county-specific regressions with a linear trend using NASS county-level data from 1980 to 2010. The expected alfalfa price, for which no futures market exists, is the average January–March price in Iowa.[17] The expected wheat price is the sum of a futures price and an expected loan deficiency payment.

2.3 Soil-Climatic Regimes

Construction of the soil-climatic regimes is as follows. First, we use Major Land Resource Areas (MLRAs) from the Natural Resources Conservation Service (NRCS) to define groups of fields. NRCS defines Major Land Resource Areas as areas with similar soils, climate, and land uses. There are 33 MLRAs in the three states, but some of these MLRAs are near the state borders and contain little area in our study region. We combine small MLRAs with neighboring MLRAs with similar characteristics to create 24 groups. We further divide these groups according to soil taxonomy classifications, which are available in the Soil Survey Geographic (SSURGO) database from NRCS. Soil taxonomy classifies soils by general characteristics of the soil with six classification hierarchies: order, sub-order, great-group, sub-group, family, and series. There are over 1,000 unique classifications in the region, but we do not have enough data to estimate separate coefficients for this many classifications. Instead, we divide MLRAs by the soil taxonomy order only if there are greater than 25,000 observations in the order and greater than 25,000 observations in the remaining orders. We continue in a similar fashion to divide orders by sub-orders, great-groups, and sub-groups while ensuring 25,000 observations in each of our soil-climatic regimes.[18] This procedure results in 108 soil-climatic regimes.

Hendricks, Smith, and Sumner (2012) perform their analysis using the 24 spatial regimes from the Major Land Resource Areas. They do not further divide the groups using soil taxonomy classifications as we do in this paper. We include as many spatial regimes as

[17] Monthly price data for our sample period are only available for Iowa. We obtain these data from NASS.

[18] We complete this process with the dataset used to estimate the extensive margin response, so fields in the extensive and rotational margin datasets belong to the same soil-climatic regimes.

seems feasible with our data because we wish to allow flexibility in the potential correlation between price response and nitrogen loss sensitivity. In part, our model can accommodate this additional flexibility because we impose one-year memory on the temporal dynamics. Hendricks, Smith, and Sumner (2012) use fewer regimes because they estimate a model with two-year memory, in which coefficients on two lags are identified with relatively few observations if the model is estimated across too many groups.

2.4 Other Soil and Weather Data

Data on soil texture (percent clay, percent silt, and percent sand) and slope are from the SSURGO database. Precipitation in April and May for each year are from PRISM (Parameter-elevation Regressions on Independent Slopes Model). PRISM interpolates precipitation data to create a grid of monthly precipitation with a resolution of about 2.5 miles x 2.5 miles. PRISM data are USDA's official climatological data.

3 SWAT Model Description and Data Used

The SWAT model is a continuous-time, distributed-parameter, hydrologic and water quality model developed by USDA ARS (Arnold et al. 1998). It has been widely used to assess the impacts of landcover and management practices on water and nutrients at the field and watershed scale (Gassman et al. 2007; Douglas-Mankin, Srinivasan, and Arnold 2010; Tuppad et al. 2011). Weather, topography, soil properties, landcover and land management inputs are used by SWAT to simulate hydrologic, soil erosion, sediment, nutrient, pesticides, and bacteria yield responses; this study focused on the hydrologic and nutrient model components. SWAT delineates a watershed into subwatersheds, which are further divided into hydrologic response units (HRUs) that represent areas within a subwatershed having similar landcover, soil, and slope (Gassman et al. 2007; Daggupati et al. 2011). SWAT simulates field-scale processes at the HRU scale, aggregates HRU outputs at the subwatershed scale, and routes the surface runoff along with dissolved and suspended constituents via channels

to the watershed outlet. In this study, we use SWAT results for nitrogen losses at the edge-of-the-field in order to merge spatially-explicit results from SWAT with the results from the econometric model.

A beta version of SWAT 2010 was used for this study; this version included model components that were later released in SWAT 2012 (Arnold et al. 2013). SWAT models were developed for four watersheds that cover most of Iowa, Illinois, and Indiana, including 89 subwatersheds (figure 1a) and 45,363 HRUs (figure 1b). Precipitation, air temperature and other meteorological inputs were developed using the automatic climate generator included in SWAT (Richardson and Nicks 1990; Neitsch et al. 2011). USGS hydrologic unit codes (HUCs) at the 4-digit scale (Seaber, Kapinos, and Knapp 1987), the National Hydrography Dataset (NHD) stream network, and a 90-m (3 arc second) resolution digital elevation model (DEM) (Gesch et al. 2002; Gesch 2007) were used in watershed configuration and topographic parameterization. State Soil Geographic (STATSGO) data were used to define spatial soil input parameters. Landcover data—for the purpose of defining HRUs in SWAT—were obtained by combining two geospatial data layers similar to Srinivasan, Zhang, and Arnold (2010). Land areas that were classified as each major crop (corn, soybeans, wheat, alfalfa and oats) by the 2010 NASS Cropland Data Layer (CDL) and also classified as agricultural by the 2006 National Land Cover Data (NLCD) were assigned the crop type designated by the NASS CDL. Land areas classified as agricultural land by NLCD but not NASS were assigned as general row-crop agriculture in SWAT. All other land areas (non-agricultural land) were classified according to the NLCD designation.

State-level planting and harvest dates were used. State-level fertilizer use data for each crop were obtained from the NASS Agricultural Chemical Usage Survey. Average usage of nitrogen, phosphate, and potash for each crop was calculated as the 2000-2005 average application on acres receiving the fertilizer multiplied by the percent of acres that received the fertilizer. The NASS fertilizer data do not differentiate fertilizer use by crop rotation; we used different levels of nitrogen fertilizer depending on the crop and year in rotation use

for corn after corn and corn after soybeans. The 2000-2005 average nitrogen use for corn is used as the nitrogen use for corn after soybeans. We do not use more recent data on corn nitrogen use because there has been a large increase in the acreage devoted to corn after corn in recent years. For Iowa and Illinois, we estimate the difference in nitrogen use on corn after corn compared to corn after soybeans using the Corn Nitrogen Rate Calculator developed by Sawyer et al. (2006). For Indiana, we use the difference reported in Camberato et al. (2012).

Identification of cropland with tile drainage is critical for accurate modeling of nitrogen losses in the Midwest U.S. In a recent science update on Northern Gulf of Mexico hypoxia, Dale et al. (2007, p. 62) state: "It is clear that agricultural drainage in the Corn Belt is extensive, the general distributions of drainage and cropland are correlated, and nitrate concentrations are correlated with patterns of cropland and drainage." Tile drainage (figure 2) was assumed to be located in areas with less than 2 percent slope and poorly, somewhat poorly or very poorly drained soils, similar to Srinivasan, Zhang, and Arnold (2010) and Dale et al. (2007). Tile drainage parameters were input consistent with previous studies (Green et al. 2006; Hu et al. 2007; Sui and Frankenberger 2008).

The SWAT model was run using the detailed climate, soils, topography, land use, and land management data and methods described above without hydrologic calibration, as demonstrated by Srinivasan, Zhang, and Arnold (2010) in the same region with reasonable results. HRU-level results were obtained by running the SWAT model for a 10-year period with a 3-year "warm-up" period (Jan 1999 to Dec 2011) separately for each of the following crop rotations on all cropland: continuous corn, continuous soybeans, corn-soybean rotation, wheat, oats, and alfalfa. These runs produced the nutrient losses that would result by growing each crop type or crop rotation on each land parcel. The corn-soybean rotation was simulated twice—with corn in even years and with corn in odd years. Ten-year average annual nitrogen losses from each HRU across the entire modeled area were determined for the following land uses: corn after corn, corn after soybeans, soybeans after corn, soybeans

after soybeans, wheat, oats, and alfalfa. Nitrogen losses from corn after soybeans represent the average nitrogen losses during years of corn production in the corn-soybean rotation, and similarly for soybeans after corn. The HRU-level results were used to represent field-level total nitrogen loss for each soil, slope, and land use. The field-level nitrogen loss results for each land use throughout the study area were georeferenced for economic analyses.

4 Results

First, we report results from the econometric model that is estimated using all of the crop data in Iowa, Illinois, and Indiana. Next, we report results from the SWAT model, which is run for watersheds that cover most of the area in the three states. Last, we integrate the econometric and SWAT results to estimate the effect of crop prices on nitrogen losses for the region that includes results from both models.

4.1 Crop Rotation Response to Price

Table 2 reports aggregate price elasticities for corn and soybean acreage response to price. Aggregate price elasticities are the average marginal effects of price across all fields—weighted by the size of each field—converted into elasticity form. The rotational, extensive, and total marginal effects of price are calculated using equation (15). All marginal effects of price are evaluated at average prices and the trend corresponding to 2010. The bottom row of table 2 reports the relative difference in the short-run (ε_{SR}) and long-run (ε_{LR}) elasticities, which is analogous to the coefficient on a single lagged dependent variable in a linear regression.

Panel A of table 2 reports corn acreage price elasticities. The response at the extensive margin is minimal—that is, very little change in corn and soybean acres occurs through changes with other crops in response to changes in expected prices. A 10% increase in the expected price of corn results in a 4.1% increase in corn acreage in the short run and a 3.1% increase in the long run. The cross-price elasticity for corn acreage is negative and large relative to the own-price elasticity. Panel B of table 2 reports soybean acreage price

elasticities. In the short run, a 10% increase in the expected price of soybeans results in a 4.0% increase in soybean acreage and a 3.0% increase in the long run. The magnitude of the cross-price elasticity for soybean acreage is actually larger than the own-price elasticity. Corn and soybean acreage may be more responsive to changes in corn prices than soybean prices because soybeans are grown largely to capture rotational benefits. The response to a price shock is 32% larger in the short run than in the long run (bottom row of table 2) because some fields that changed crop rotations due to a price shock switch back to the previous crop in order to continue the new rotation. We use a different econometric specification here than in Hendricks, Smith, and Sumner (2012) because we are linking the results to an environmental model. The difference in specification, however, makes little difference to estimates of the aggregate elasticities—the elasticities in table 2 are very similar to those in table 2 of Hendricks, Smith, and Sumner (2012).

Table 3 reports aggregate elasticities of crop rotation responses to expected crop prices. We report crop rotation price elasticities conditional on corn or soybeans being planted since the extensive margin response is negligible. The short-run and long-run marginal effects of price on corn after corn are calculated as in equations (10) and (11) and marginal effects of price for the corn-soybean rotation and soybeans after soybeans are calculated similarly from derivatives of (8) and (9).

An increase in the expected price of corn increases the probability of planting corn after corn and decreases the probability of planting a corn-soybean rotation and planting soybeans after soybeans (table 3). The effect of an increase in the expected price of soybeans is the opposite sign for all rotations. Although theory does not give an expected sign for the marginal effect of price on a corn-soybean rotation, it is not surprising that increases in the expected price of corn decrease the probability of a corn-soybean rotation since corn after corn is more prominent than soybeans after soybeans.

Elasticities of a corn-soybean rotation are substantially smaller than elasticities for corn after corn and soybeans after soybeans (table 3) for two reasons. First, there is a larger

probability of planting a corn-soybean rotation on average, so relative changes are smaller. Second, a decrease in the probability of a corn-soybean rotation from switching to corn after corn is partly offset by an increase in the probability of a corn-soybean rotation by switching from soybeans after soybeans.

Although the corn acreage response to a price shock is *larger* in the short run than in the long run (bottom row of table 2), the crop rotation response to a price shock is *smaller* in the short run than in the long run (bottom row of table 3). For example, when the expected price of corn increases some fields switch from a corn-soybean rotation to continuous corn. Of the land that switches to continuous corn, roughly half is planted to corn after soybeans in the first year, since roughly half of the land in a corn-soybean rotation is planted to soybeans. In the second year, acreage of corn after corn increases.[19]

Figure 3 shows maps of the observed crop transitions and results from the econometric model. The maps only show results where results from the SWAT model intersect the results from the econometric model. Panel A of figure 3 shows the crop transitions that were observed from 2009 to 2010. In the first map, red indicates fields that were corn in 2009 and corn in 2010 and green indicates fields with any other crop transition. Corn after corn is planted more in northern Illinois, west-central Illinois, northeastern Iowa, and northwest Indiana. In the second map, purple indicates fields that were either corn in 2009 and soybeans in 2010 or soybeans in 2009 and corn in 2010. In the third map, blue indicates fields that were soybeans in 2009 and soybeans in 2010. Soybeans after soybeans are planted more in southern Illinois and eastern Indiana.

Panel B of figure 3 shows the long-run probability of planting each crop rotation predicted from the econometric model using equations (7)-(9) at average prices and the trend corresponding to 2010. In the first map, darker orange corresponds to a greater probabil-

[19]The difference between the short-run and long-run response may depend on the direction of the price change. For example, when the expected price of corn decreases some fields switch from continuous corn to a corn-soybean rotation. Of the fields that switch to a corn-soybean rotation, we would expect all of them to plant soybeans after corn in the first year, so we would not expect any difference between the short-run and long-run response of corn after corn to a decrease in the expected price of corn. We leave the possibility of asymmetric price response dynamics for future research.

ity of planting corn after corn. In the second map, darker purple corresponds to a greater probability of a corn-soybean rotation. In the third map, darker blue corresponds to a greater probability of planting soybeans after soybeans. The predicted probabilities in panel B correspond well to the spatial concentration of observed transitions in panel A.

Panel C of figure 3 shows the long-run marginal effects of an increase in the price of corn. Our estimates of the marginal effects of price vary spatially because we estimate the econometric model separately for soil-climatic regimes. In the first map, darker green corresponds to areas with a greater increase in the probability of corn after corn from an increase in the price of corn. A marginal effect of 0.2 indicates an increase in the long-run probability of planting corn after corn by 0.2 from a $1 per bushel increase in the expected price of corn. Corn after corn is more likely to increase in Iowa, north and central Illinois, and northwest Indiana from an increase in the price of corn.

In the second map of panel C, darker blue indicates a larger increase in the long-run probability of planting a corn-soybean rotation and darker red indicates a larger decrease in the long-run probability of planting a corn-soybean rotation from an increase in the price of corn. In other words, blue regions are those where an increase in the price of corn primarily causes a shift from soybeans after soybeans to a corn-soybean rotation and red regions are those where an increase in the price of corn primarily causes a shift from a corn-soybean rotation to corn after corn. In the third map of panel C, darker green indicates a larger decrease in the probability of planting soybeans after soybeans from an increase in the price of corn. The maps give a rich form of spatial heterogeneity of crop rotation response to price that would not likely be captured by differences in marginal effects from the logistic functional form, spatial regimes from a few land capability classifications, or by a spatial process where the researcher defines a spatial weights matrix.

4.2 Nitrogen Losses from Land Use Change

Table 4 gives the average nitrogen losses from the edge of fields as predicted by the SWAT model for different land uses. Nitrogen losses are the sum of nitrate and organic nitrogen losses. Corn after corn generates the largest nitrogen losses, primarily because more fertilizer is applied to corn after corn since there is no nitrogen carry-over from a previous soybean crop. We find a negligible difference in nitrogen losses between a corn-soybean rotation (average nitrogen losses of corn after soybeans and soybeans after corn) and a continuous soybean rotation. Soybean cultivation generates large nitrogen losses relative to wheat, oats, and alfalfa likely due to greater nitrogen availability as well as other factors, such as the timing of storms relative to surface cover. Our estimates indicate that there are slightly larger nitrogen losses during the production of soybeans after corn than corn after soybeans, perhaps because soybeans produce less residue to protect the soil from water runoff. The standard deviations of nitrogen losses are relatively large, indicating substantial variation among fields across the region.

It is difficult to compare our estimates of nitrogen losses with results from field experiments since nitrogen losses depend on a large number of factors including weather, fertilizer application rates, presence of tile drainage, and soils. Still, our estimates of nitrogen losses are generally consistent with those reported by Sawyer and Randall (2008), who survey a number of results from field experiments. We also found our estimates to fall within the range of other modeling studies in the region. For example, Gowda, Mulla, and Jaynes (2008) report annual average measured (26.0 kg/ha) and modeled (24.2 kg/ha) nitrate-N losses in a central-Iowa watershed with 90 percent of the cropland planted to a corn-soybean rotation close to our values for corn after soybeans and soybeans after corn. Sogbedji and McIsaac (2006) report annual average measured (42.5 kg/ha) and modeled (42.2 kg/ha) riverine nitrate-N in an Illinois watershed with 85 percent of the cropland planted to a corn-soybean rotation close to our values for corn after corn.

Figure 4 shows the relative difference in nitrogen losses if corn after corn is planted rather than a corn-soybean rotation, where we calculate the annual nitrogen loss from a corn-soybean rotation as the average of the nitrogen losses from planting corn after soybeans and soybeans after corn. Darker red areas indicate areas where conversion from a corn-soybean rotation to corn after corn would result in greater increases in nitrogen losses—in other words, areas of greater environmental sensitivity to land use change. For example, a value of 0.5 indicates that corn after corn results in 50 percent more nitrogen losses than a corn-soybean rotation. The spatial concentration of environmental sensitivity to land use change indicates there may be value in estimating the spatial heterogeneity of land use response to price.

4.3 Integrated Economic and Environmental Models

Table 5 reports elasticities of nitrogen losses with respect to changes in corn and soybean prices. We calculate average nitrogen losses from the edge of fields $\left(\bar{NL}\right)$ as

$$\bar{NL} = \sum_i \frac{a_i}{A} \sum_m \Pi_i^m NL_i^m, \tag{16}$$

where a_i is the acres of field i, A is the total acreage of all fields in our sample, Π_i^m is the predicted probability of land use m from the econometric model, and NL_i^m is the nitrogen loss of land use m from the SWAT model. We consider the following land uses: corn after corn, corn after soybeans, soybeans after corn, soybeans after soybeans, wheat, oats, and alfalfa. The SWAT model gives nitrogen losses for each of these land uses. Our econometric model gives the probability of each transition between corn and soybeans and the probability of other crops. To estimate the probability of wheat for field i, we multiply the probability of "other crops" by the proportion of observations classified as wheat on field i for those observations classified as "other crops"—and similarly for oats and alfalfa. If the crop data indicate an "other crop" besides wheat, oats, or alfalfa, then we use the average nitrogen

loss of wheat, oats, and alfalfa. These observations represents less than 0.5% of land use in our sample.

The elasticity of nitrogen losses with respect to the price of crop j is calculated as

$$\frac{\partial \bar{NL}}{\partial p^j}\frac{\bar{p}^j}{\bar{NL}} = \sum_i \frac{a_i}{A}\sum_m \frac{\partial \Pi_i^m}{\partial p^j} NL_i^m \frac{\bar{p}^j}{\bar{NL}}, \tag{17}$$

where all probabilities and marginal effects are calculated at average prices and the trend corresponding to 2010. Short-run nitrogen loss elasticities are obtained by using short-run land use marginal effects of price in (17), and similarly for long-run price elasticities. We do not estimate standard errors for the nitrogen loss elasticities. We could estimate standard errors by estimating the average nitrogen loss elasticity for each bootstrap replication of the econometric model. However, this approach would ignore uncertainty in our estimates from the SWAT model and overestimate the precision of our estimates.

Column (1) of table 5 reports nitrogen loss elasticities generated by combining our econometric results with output from the SWAT model. A 10% increase in the expected price of corn results in a 0.52% increase in nitrogen losses from fields in the short run and a 1.03% increase in nitrogen losses from fields in the long run. Nitrogen losses are positively related to the expected price of corn and negatively related to the expected price of soybeans primarily due to changes in corn after corn acreage. We tested the robustness of our elasticity estimates by only using the 24 Major Land Resource Areas (MLRAs) as spatial regimes rather than the 108 soil-climatic regimes and obtained the same nitrogen loss elasticities after rounding to three decimal places (results not reported separately).

The nitrogen loss response to a price shock is 50% smaller in the short run than in the long run (bottom row of table 5). The short-run response is smaller primarily because the response of corn after corn to a price shock is smaller in the short run and corn after corn results in larger nitrogen losses than corn after soybeans. Another reason for this difference is that the long-run response exceeds the short-run response at the extensive margin for corn and

soybean acreage. Extensive margin changes give greater changes in nitrogen losses because the difference in nitrogen losses from corn or soybeans versus other crops is large. However, even if we estimate the nitrogen loss elasticities using only rotational margin responses, the short-run response is still 49% smaller than the long-run response (results not reported). Thus, the dynamics of corn after corn acreage response to price is the main driver of the dynamics of nitrogen losses.

Modeling the spatial heterogeneity of coefficients is important because (i) estimates of dynamic models can be severely biased if coefficient heterogeneity is ignored and (ii) changes in nitrogen losses from changes in crop production depend on local climates and soils. Column (2) of table 5 illustrates the effect of second reason by reporting nitrogen loss elasticities calculated by imposing the same price response on all fields rather than allowing spatially heterogeneous responses. The econometric model is the same in column (2) as column (1), but we only use average crop acreage response to price in column (2). Nitrogen loss elasticities are smaller using the average response to price because corn after corn acreage tends to have a greater response to price on land where nitrogen losses are more sensitive to conversions from corn-soybeans to corn after corn. The correlation coefficient is 0.24 between the long-run marginal effect of corn after corn with respect to the price of corn and nitrogen losses from corn after corn instead of a corn-soybean rotation.

To show the effect of the first reason, column (3) of table 5 reports nitrogen loss elasticities if we impose common coefficients for all fields (i.e., pooling) in the econometric estimation. For the pooled estimator, we estimate Markov transition probabilities with logit models but estimate a single model for all fields. Pooled estimates are biased because unobserved heterogeneity is confounded with the dynamics and because heterogeneous responses to autocorrelated prices are confounded with dynamics (see Hendricks, Smith, and Sumner 2012). Short-run marginal effects of price are smaller for the pooled estimator so nitrogen loss elasticities are smaller in column (3) than column (1). The difference between the short-

run and long-run price elasticities is also slightly smaller with the pooled estimator (bottom row of table 5).

In summary, the results in table 5 indicate that the first reason for modeling spatial heterogeneity is especially important in our application because the difference between the heterogeneous and average estimators (columns 1 and 2) is smaller than the difference between the average and pooled estimators (columns 2 and 3).

4.4 The U.S. Ethanol Mandate and Hypoxia in the Gulf

We illustrate the usefulness of our nitrogen loss elasticities by utilizing them to estimate the effect of the U.S. ethanol mandate on hypoxia in the Gulf of Mexico. The solid line in figure 5 shows the size of the hypoxic zone in the Gulf of Mexico from 1985 to 2012. From 1995 to 2012 the size of the hypoxic zone averaged roughly 6,000 square miles, but varied year to year, in large part due to weather. For example, the hypoxic zone was small in 1988 and 2012 due to severe droughts in the Corn Belt, which led to relatively low nutrient exports to the Gulf of Mexico. The dashed line in figure 5 shows nitrogen exports from the Mississippi River into the Gulf of Mexico from 1985 to 2011. Nitrogen exports also vary largely due to weather. The large variability of the size of the hypoxic zone and nitrogen exports makes it difficult to distinguish whether or not the hypoxic zone and nitrogen exports have increased in recent years when corn prices have been relatively high.

We assume that the U.S. ethanol mandate has increased the price of corn by 30 percent. This assumption is consistent with some recent studies. For example, Roberts and Schlenker (forthcoming) estimate that the 2009 Renewable Fuel Standard has increased the price of grains by 20 percent and Carter, Rausser, and Smith (2012) estimate that the 2007 expansion of the Renewable Fuel Standard in the United States increased the price of corn by 30 percent. Neither of these articles gives an estimate of the increase in the price of soybeans. We assume that the price of soybeans has increased 15 percent due to the ethanol mandate. However,

our results are not highly sensitive to different assumptions about the change in the price of soybeans.[20]

Using the nitrogen loss elasticities shown in column (1) of table 5, a 30 percent increase in the price of corn and 15 percent increase in the price of soybeans leads to a 2.64 percent increase in nitrogen losses from Iowa, Illinois, and Indiana in the long run. We estimate the effect of the U.S. ethanol mandate on the size of the hypoxic zone in the Gulf of Mexico using estimates from Obenour et al. (2012). They develop a regression model that relates the size of the hypoxic zone (measured midsummer) to a normalized metric of water column stratification and the normalized May nitrogen concentration (see equation 13 of Obenour et al. 2012). We obtain data from the USGS on the May nitrogen loads and stream flow from the Mississippi and Atchafalaya River outlets. The nitrogen concentration is calculated as the load divided by the stream flow. A 2.64 percent increase in nitrogen concentration translates to a 288 mi^2 (746 km^2) increase in the size of the hypoxic zone according to the regression estimates of Obenour et al. (2012). To provide a point of reference, the average county size in the three states in our sample is 515 mi^2.

Our estimates of the effect of the U.S. ethanol mandate on hypoxia in the Gulf improve upon previous estimates. Donner and Kucharik (2008) report much larger effects. They estimate that producing 15 billion gallons of ethanol by 2022 would increase nitrogen exports by 10–18 percent. Their 15 billion gallon scenario assumes that all of the increase in corn production to meet the mandate occurs in the United States. Therefore, Donner and Kucharik (2008) likely overstate the effect of the ethanol mandate on nitrogen exports.

Secchi et al. (2011) simulate nitrogen exports under different price scenarios using a programming model of cropping decisions and the SWAT model for water quality outcomes. In order to estimate implied nitrogen loss elasticities from their results, we examine two of their scenarios that have a similar price of soybeans. Between scenarios 2 and 3 in Secchi

[20] If we assume that the price of corn increased by 30 percent but the price of soybeans increased by only 5 percent, then nitrogen losses increase by 2.94 percent. If the price of soybeans increased by 25 percent, then nitrogen losses increase by 2.34 percent.

et al. (2011), the price of corn increases from \$5.00 per bushel to \$5.20 per bushel (4.0 percent increase) while the price of soybeans decreases from \$12.50 per bushel to \$12.48 per bushel (0.2 percent decrease). Their simulations suggest that total nitrogen losses increase 1.4 percent between these two scenarios, implying a nitrogen loss elasticity with respect to the price of corn of roughly 0.35 compared to our estimate of 0.103 in the long run. Their nitrogen loss elasticity is substantially larger than our estimate primarily because they estimate a much larger corn acreage response to price. Their results indicate that corn acreage increases 6.7 percent between these two scenarios, implying a corn acreage elasticity with respect to the price of corn of roughly 1.68 compared to our estimate of 0.31 in the long run.

Langpap and Wu (2011) estimate a corn acreage elasticity with respect to the price of corn of 0.246, similar to our estimate. However, they estimate substantial conversions from non-cropland to cropland in response to changes in the price of corn; they estimate an elasticity of cropland acreage with respect to the price of corn of 0.059 for the Corn Belt. One potential explanation for their estimate of substantial conversions between non-cropland and cropland is that they use crop data from 1979–1997, a period when cropland acreage in the U.S. was heavily distorted by government set-aside programs. Langpap and Wu (2011) simulate several price scenarios that indicate increases in nitrogen losses of roughly 11–30 percent. None of their scenarios, however, represent the effect of a particular policy.[21]

While our estimates represent an improvement, several caveats to our calculations are warranted. First, the effect of the ethanol mandate on prices is highly debated among economists. However, it is straightforward to use our results to estimate the effect of the ethanol mandate on the hypoxic zone using different price changes. Second, we estimate losses from the states of Iowa, Illinois, and Indiana only. Extensive margin changes in land use may be larger in other regions within the Mississippi River Basin, which would produce a larger effect on the hypoxic zone. Wright and Wimberly (2013), for example, provide

[21] Langpap and Wu (2011, p. 158) recognize this limitation of their scenarios.

evidence of substantial conversions of grassland to corn production in the eastern Dakotas. Third, our econometric model only accounts for changes in land use with respect to changes in crop prices. Due to data limitations, we do not account for changes in fertilizer application rates and management practices. Fourth, our estimates of the effect on hypoxia in the Gulf do not represent the full extent of water quality effects from the ethanol mandate. The shift in demand due to the ethanol mandate increases corn production around the world, not just in the Corn Belt. Ethanol production in the Corn Belt may, for example, cause more algal blooms in upland reservoirs as well as hypoxic zones around the world.

5 Conclusion

We estimate that the long-run nitrogen loss elasticity with respect to the price of corn is 0.103 and the long-run nitrogen loss elasticity with respect to the price of soybeans is -0.030 for most of Iowa, Illinois, and Indiana. Our nitrogen loss elasticity estimates are smaller than those implied by the results of Secchi et al. (2011) and Langpap and Wu (2011). The difference occurs primarily because we estimate different corn acreage response to price at the rotational and extensive margins.

Our elasticity estimates suggests that the U.S. ethanol mandate has increased nitrogen losses from this region by 2.64 percent—assuming that the ethanol mandate has increased the price of corn by 30 percent and the price of soybeans by 15 percent. Using parameters from Obenour et al. (2012) that relate nitrogen exports to the size of the hypoxic zone in the Gulf of Mexico, we estimate that the U.S. ethanol mandate has increased the size of the hypoxic zone by 288 mi^2 on average.

We contribute to the literature that integrates spatially heterogeneous agricultural production models with environmental models. One reason to model the spatial heterogeneity of acreage response to price is the possibility that the response of acreage to price may be correlated with the environmental sensitivity to land use change. We find, however, that the primary reason to model coefficient heterogeneity in dynamic production systems is to

obtain unbiased estimates of acreage response parameters. In other applications, there may be a stronger correlation between acreage response parameters and environmental sensitivity to land use change, giving further motivation to account for spatial heterogeneity in econometric models.

Although aggregate corn acreage responds to price shocks *more* in the short run than in the long run (Hendricks, Smith, and Sumner 2012), we show that nitrogen losses respond to price shocks *less* in the short run than in the long run. The dynamics of nitrogen losses result primarily from the dynamics of corn after corn acreage. Corn after corn acreage increases less in the short run because some fields that switch from a corn-soybean rotation to continuous corn must plant corn after soybeans in the first year that they switch. These dynamics have water quality implications because corn after corn results in larger nitrogen losses than corn after soybeans.

There are, however, several limitations in this study that need addressed by future research. One limitation is the lack of accurate data on conversions of land not planted to crops. State-level data from the Farm Service Agency indicates that Conservation Reserve Program (CRP) acreage decreased 524,000 acres in Iowa, Illinois, and Indiana from 2006 to 2012. Assuming all of this land was converted to cropland, it would represent less than a 1 percent increase in cropland. However, these conversions are especially important for environmental outcomes. A challenge of estimating this margin of adjustment is that CRP payments are endogenously determined by the government. As another limitation, this study does not estimate the response of fertilizer use or management practices to expected crop prices due to data limitations. We may underestimate the change in nitrogen losses if higher crop prices increase fertilizer use. On the other hand, we may overestimate the change in nitrogen losses if higher crop prices lead to increased adoption of conservation practices (Miranowski 1984).

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Figure 1: Distribution of (a) Watersheds, Subwatersheds and (b) Hydrologic Response Units (HRUs) used in the SWAT Model

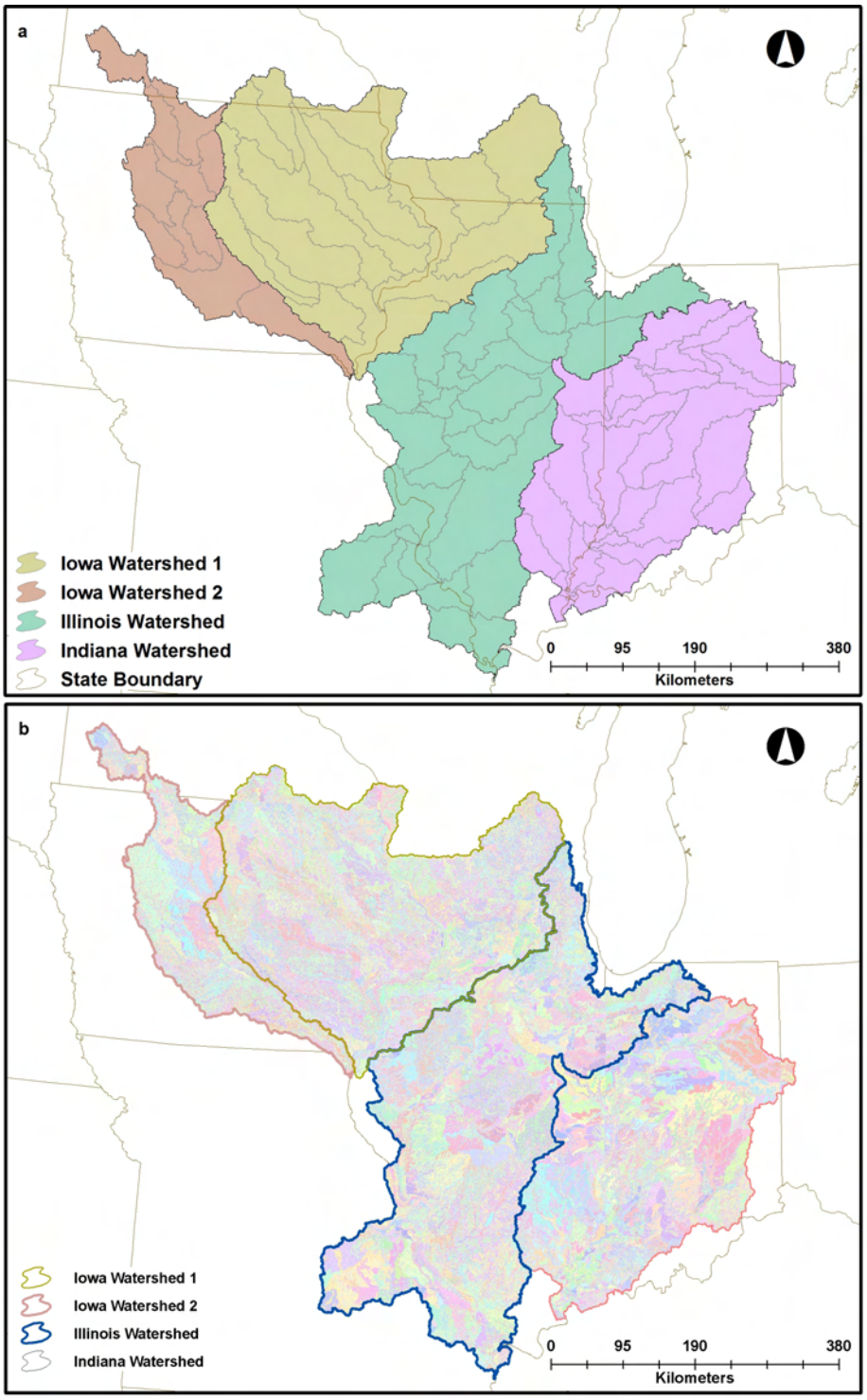
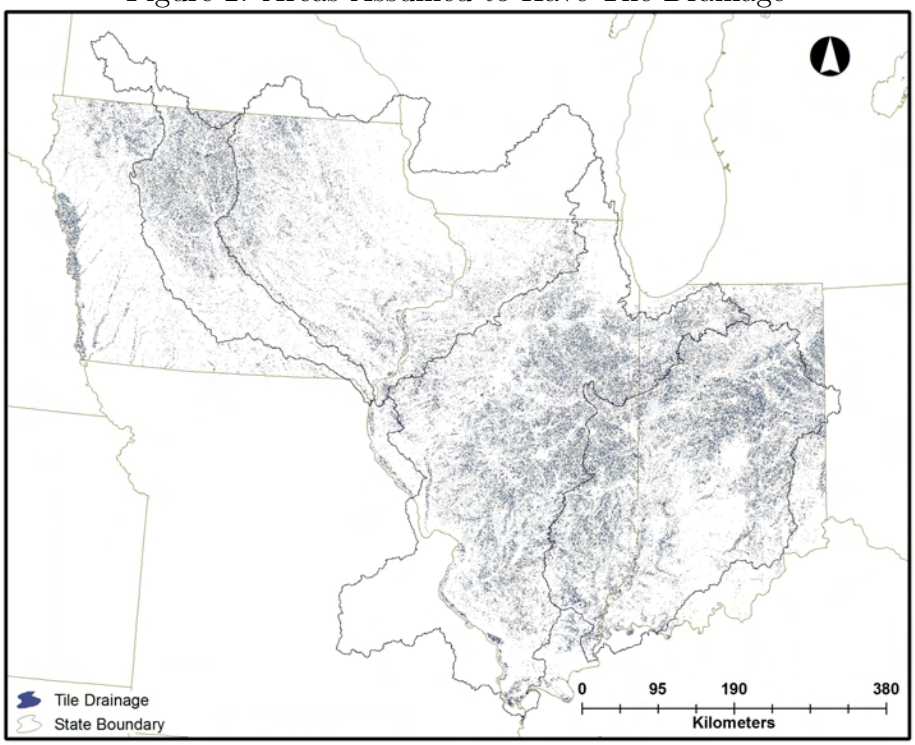


Figure 2: Areas Assumed to Have Tile Drainage



Notes: Tile drainage was assumed to be located in areas with less than 2 percent slope and poorly, somewhat poorly or very poorly drained soils.

Figure 3: Maps of Observed Crop Transitions and Crop Rotation Results from Econometric Model

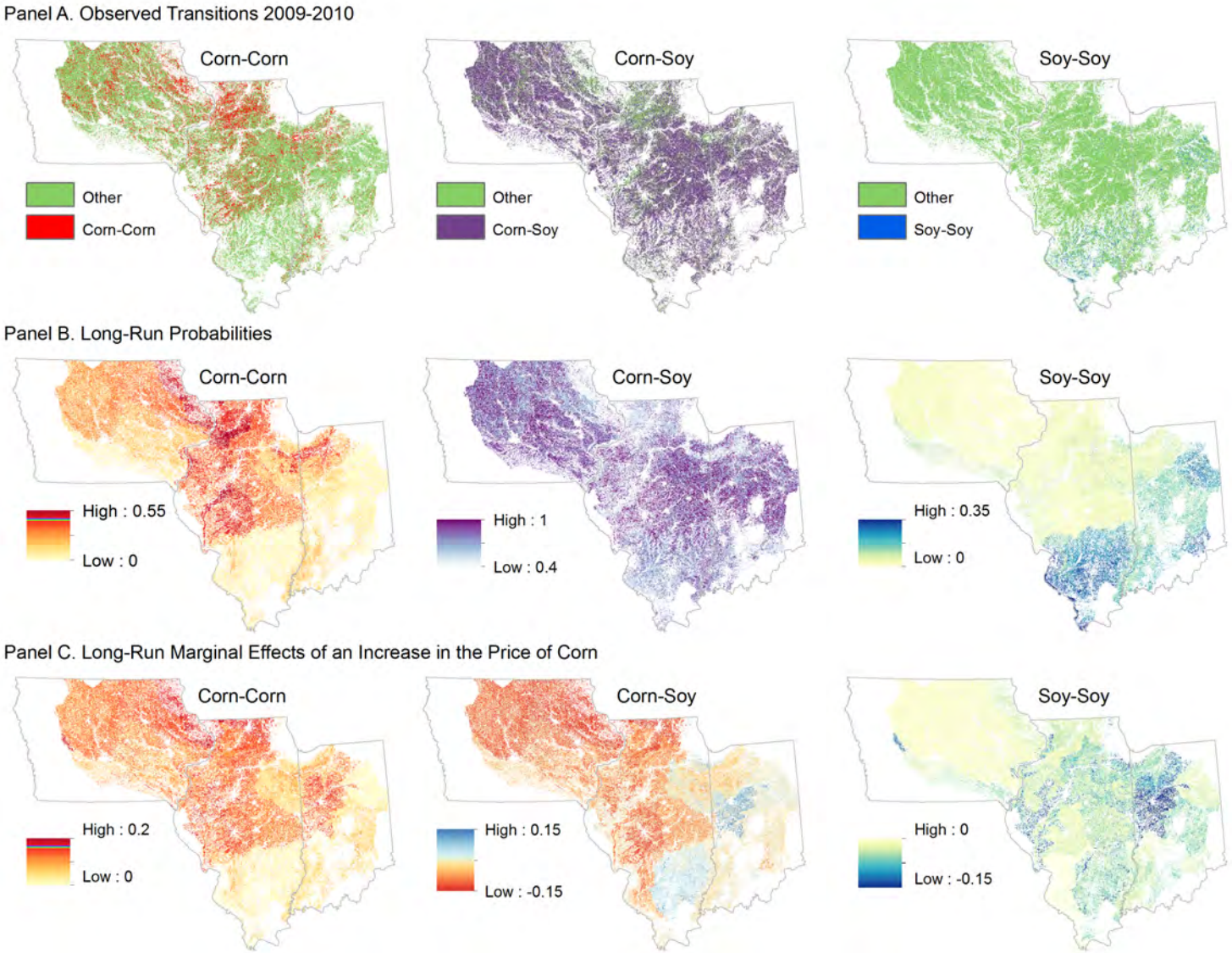


Figure 4: Relative Difference in Nitrogen Loss from Corn after Corn Instead of a Corn-Soybean Rotation

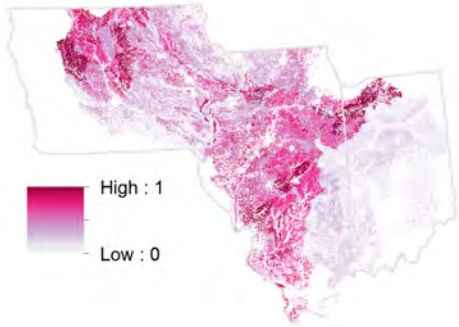
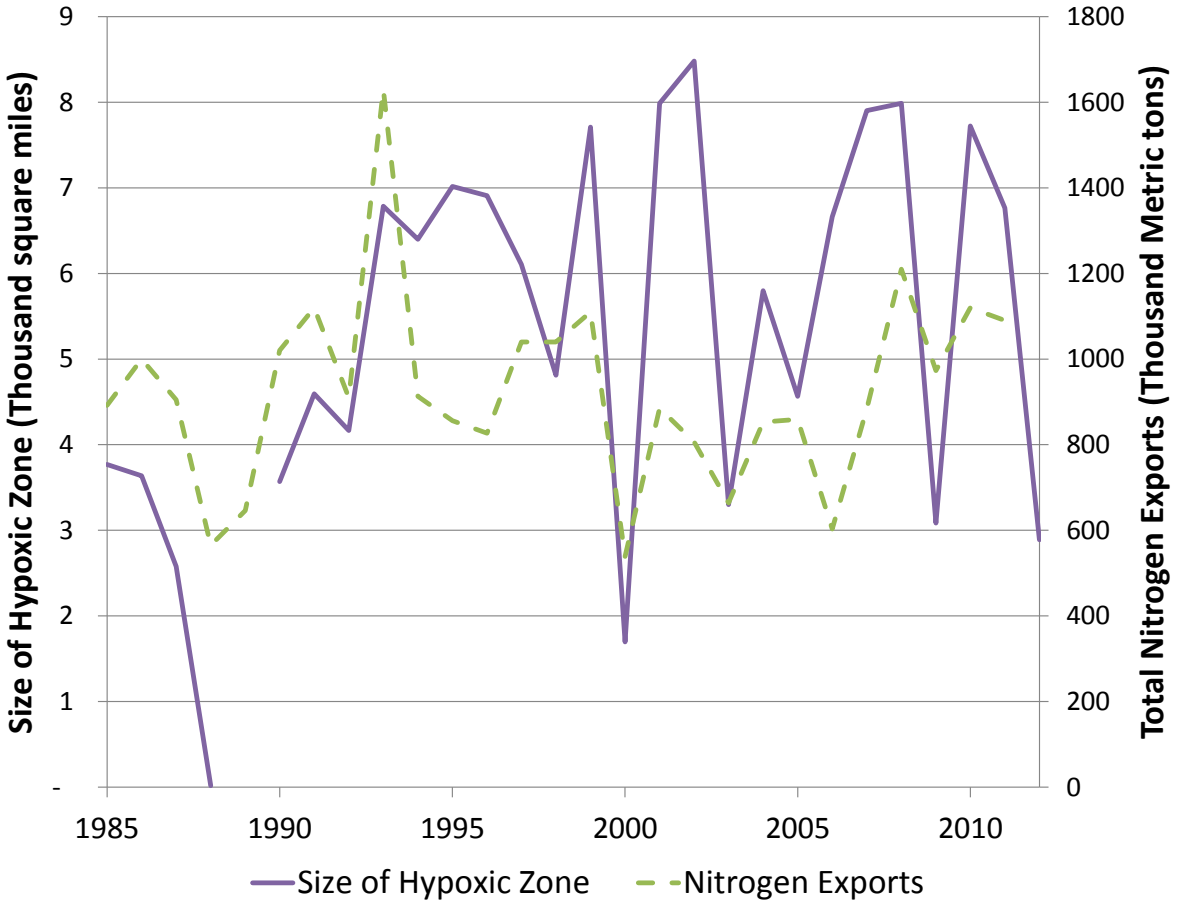


Figure 5: Size of the Hypoxic Zone in the Gulf of Mexico and Nitrogen Exports to the Gulf of Mexico from the Mississippi-Atchafalaya River Basin



Notes: The size of the hypoxic zone is measured annually by the Louisiana Universities Marine Consortium. Data on the size of the hypoxic zone are available at `http://www.gulfhypoxia.net/`. No data are available for 1989. Nitrogen exports are the total Mississippi-Atchafalaya River Basin loads of nitrogen (N02+N03). U.S. Geological Survey estimates of nitrogen loads are available at `http://toxics.usgs.gov/hypoxia/mississippi/flux_ests/delivery/index.html`.

Table 1: Descriptive Statistics of the Samples for Econometric Estimates

	Mean	Std. Dev.
Panel A. Rotational Margin Sample (N=7,025,089)		
Corn	0.55	0.50
Soybeans	0.45	0.50
Corn after Corn	0.16	0.37
Corn after Soybeans	0.39	0.49
Soybeans after Corn	0.39	0.49
Soybeans after Soybeans	0.07	0.25
Never Monoculture	0.36	0.48
Monoculture at Least Once	0.64	0.48
Expected Price of Corn ($/bu)	3.27	0.87
Expected Price of Soybeans ($/bu)	7.72	1.89
April-May Precip Above Average (inches)	0.92	1.65
Percent Clay	0.27	0.07
Percent Silt	0.51	0.14
Slope	2.89	3.23
Panel B. Extensive Margin Sample (N=8,753,451)		
Corn or Soybeans	0.98	0.14
Other Crops	0.02	0.14
Always Corn or Soybeans	0.89	0.32
Other Crops at Least Once	0.11	0.32
Index of Corn and Soybean Prices	1.21	0.31
Index of Alfalfa and Wheat Prices	1.27	0.29
Percent Clay	0.27	0.07
Percent Silt	0.51	0.15
Slope	2.99	3.40

Notes: Panel A gives descriptive statistics for the rotational margin sample—observations (field-year pairs) that were classified as corn or soybeans in two consecutive years. Panel B gives descriptive statistics for the extensive margin sample—observations that were classified as a crop but where the field was classified as corn or soybeans at least once during the sample period and for which there is a crop observed in two consecutive years.

Table 2: Aggregate Corn and Soybean Acreage Elasticities for all Fields in Iowa, Illinois, and Indiana

	Rotational (1)	Extensive (2)	Total (3)
Panel A. Corn Acreage Elasticities			
Expected Price of Corn			
Short-run	0.41*	0.001	0.41*
	(0.018)	(0.001)	(0.018)
Long-run	0.31*	0.004*	0.31*
	(0.015)	(0.001)	(0.015)
Expected Price of Soybeans			
Short-run	-0.32*	0.001	-0.32*
	(0.017)	(0.000)	(0.017)
Long-run	-0.24*	0.002*	-0.24*
	(0.014)	(0.000)	(0.014)
Panel B. Soybean Acreage Elasticities			
Expected Price of Soybeans			
Short-run	0.40*	0.001	0.40*
	(0.022)	(0.001)	(0.022)
Long-run	0.30*	0.002*	0.30*
	(0.017)	(0.001)	(0.017)
Expected Price of Corn			
Short-run	-0.52*	0.001	-0.51*
	(0.022)	(0.001)	(0.022)
Long-run	-0.39*	0.003*	-0.38*
	(0.019)	(0.001)	(0.019)
$\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$	-0.33*	0.69	-0.32*
	(0.012)	(0.404)	(0.012)

Notes: Aggregate elasticities are calculated as the elasticity of the average marginal effect of price across all fields, weighted by the size of the fields. Results in column (1) are from logit models of equations (1)-(2). The transition probabilities are estimated separately for soil-climatic regimes. Within each soil-climatic regime, the model is estimated for fields that planted monoculture at least once and the price response is assumed to be zero for those fields that never planted monoculture. Results in column (2) are from logit models of equations (12)-(13). The transition probabilities are estimated separately for soil-climatic regimes. Within each soil-climatic regime, the model is estimated for those fields that transitioned between corn or soybeans and other crops and the price response is assumed to be zero for fields that always planted corn or soybeans. The last row gives the relative difference in the long-run (ε_{LR}) and short-run (ε_{SR}) elasticities that is analogous to the coefficient on a single lagged dependent variable. Standard errors are clustered by counties and estimated with bootstrap replications.

*Significant at the 5 percent level.

Table 3: Aggregate Crop Rotation Elasticities for all Fields in Iowa, Illinois, and Indiana

	Corn after Corn (1)	Corn-Soybeans (2)	Soybeans after Soybeans (3)
Expected Price of Corn			
Short-run	0.84*	-0.12*	-1.14*
	(0.038)	(0.015)	(0.129)
Long-run	1.28*	-0.18*	-1.69*
	(0.060)	(0.018)	(0.171)
Expected Price of Soybeans			
Short-run	-0.72*	0.13*	0.69*
	(0.045)	(0.015)	(0.098)
Long-run	-1.07*	0.18*	1.10*
	(0.067)	(0.019)	(0.125)
$\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$	0.34*	0.36*	0.32*
	(0.010)	(0.028)	(0.011)

Notes: Aggregate elasticities are calculated as the elasticity of the average marginal effect of price across all fields, weighted by the size of the fields. These elasticities represent results from the same regressions as column 1 of table 2. The short-run and long-run marginal effects of corn after corn are calculated as in equations (10) and (11) and marginal effects for a corn-soybean rotation and soybeans after soybeans are calculated similarly from derivatives of (8) and (9). Standard errors are clustered by counties and estimated with bootstrap replications.

*Significant at the 5 percent level.

Table 4: Average Nitrogen Losses (lbs/acre) at the Edge of Field for Different Land Uses

	Mean	Std. Dev.
Corn after Corn	41.2	24.1
Corn after Soy	27.8	16.0
Soy after Corn	31.1	21.5
Soy after Soy	29.3	17.0
Wheat	7.8	5.8
Oats	9.5	5.5
Alfalfa	12.6	8.2

Notes: This table gives results from the Soil and Water Assessment Tool (SWAT). Results give average and standard deviation—weighted by size of fields—of total nitrogen losses at the edge of field. Total nitrogen is the sum of nitrates and organic nitrogen.

Table 5: Elasticities of Nitrogen Losses

	Response to Price		
	Heterogeneous	Average	Pooled
	(1)	(2)	(3)
Expected Price of Corn			
Short-run	0.052	0.045	0.036
Long-run	0.103	0.088	0.060
Expected Price of Soybeans			
Short-run	-0.015	-0.014	-0.006
Long-run	-0.030	-0.027	-0.010
$\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$	0.50	0.49	0.40

Notes: Elasticities in this table give the percent change in average nitrogen losses from a 1 percent change in corn or soybean prices calculated using equation (17). Column (1) reports elasticities using econometric results that are estimated separately for soil-climatic regimes and transition groups as in tables 2 and 3. Column (2) reports elasticities using the average marginal effects of land use response to prices rather than spatially heterogeneous responses, but the same econometric model as in column (1). Column (3) reports elasticities imposing common coefficients for all fields (i.e., pooling) in the econometric estimation.