AJAE appendix: "Crop Supply Dynamics and the Illusion of Partial Adjustment"

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Note: The material contained herein is supplementary to the article named in the title and published in the *American Journal of Agricultural Economics* (*AJAE*).

A1 Additional Details on Data Construction

A1.1 Crop Data and Field Boundaries

We do not use each pixel from the Cropland Data Layer as a separate unit of analysis for the econometric model for two main reasons: (i) a farmer's crop decision is at the field level, not the pixel level, and (ii) pixels are more likely to be misclassified at field boundaries. 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. The Farm Service Agency states that the CLU data contain digitized field boundaries, where fields are defined as "agricultural land that is delineated by natural and man-made boundaries such as road ways, tree lines, waterways, fence lines, etc." (Farm Service Agency 2007). Many of the CLUs that are extremely small are likely to be gullies, waterways, or farmsteads, so we include only points corresponding to CLUs larger than 15 acres in the empirical 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. The distance that the point is offset is 15% of the square root of the area of the CLU. Small CLUs are unlikely to be split into two fields so staying near the centroid improves the likelihood of being within the CLU. Large CLUs are more likely to be split into separate fields so it is preferable to move further from the centroid to avoid a field boundary. Moving diagonally avoids field boundaries since boundaries in the Corn Belt are more likely to be north-south or east-west. Of the CLUs greater than 15 acres, 90.9% of our points fall within the corresponding Common Land Unit.

A1.2 Expected Crop Prices

For spot price data, 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. The basis is interpolated using inverse distance weighting. 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.

When constructing expected loan deficiency payments, we assume that the truncation of the distribution of anticipated prices 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 posted county price in 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. In our regressions, we use the level of expected prices rather than log expected prices.

Using data on daily posted county prices and loan rates for 2004–2010 from the Farm Service Agency, we find that the posted county price of corn in these three states is on average \$0.33 below the nearby futures price while the county loan rate of corn is on average \$0.02 above the national loan rate. Using a futures price as the mean of the distribution and the national loan rate as the truncation would underestimate the expected loan deficiency payments for corn (and similarly for soybeans). The difference between the posted county price and the loan rate in each year differs little between counties for 2004–2010. Because we do not have data for 1999-2003, we assume the expected loan deficiency payment is constant across counties and varies only by year.

A2 Aggregate Acreage Dynamics with Two-Year Memory

Evidence from agronomy experiment plots indicates that rotation incentives are primarily obtained from the crop in the previous year, but the crop from two years previous has some effect (Hennessy 2006). Iowa State University and the University of Illinois release crop budgets for a corn-corn-soybean rotation, indicating that there is a demand for information on these rotations in these key states. If corn and soybean rotations have two-year memory, then—for a given set of prices—the optimal rotation can be restricted to rotations that repeat after three years. In other words, the set of optimal rotations is $< cc >$, $< ss >$, $< cs >$, $< ccs >$, and $< ssc >$.

One possible distribution of optimal crop rotations with two-year memory is illustrated in figure A1. When rotations are in long-run equilibrium, all of the land in continuous corn is planted to corn, two-thirds of the land in corn-corn-soybeans is planted to corn, etc. The long-run aggregate share of corn acres is

$$\text{(A1)}\quad \bar{C}^{LR} = 1 \cdot G\left(\theta^1\right) + \frac{2}{3} \cdot \left(G\left(\theta^2\right) - G\left(\theta^1\right)\right) + \frac{1}{2} \cdot \left(G\left(\theta^3\right) - G\left(\theta^2\right)\right) + \frac{1}{3} \cdot \left(G\left(\theta^4\right) - G\left(\theta^3\right)\right).$$

The differential of the long-run share of corn acres is

$$\text{(A2)}\quad d\bar{C}^{LR} = \frac{1}{3} g\left(\theta^1\right) \frac{\partial \theta^1}{\partial p} dp + \frac{1}{6} g\left(\theta^2\right) \frac{\partial \theta^2}{\partial p} dp + \frac{1}{6} g\left(\theta^3\right) \frac{\partial \theta^3}{\partial p} dp + \frac{1}{3} g\left(\theta^4\right) \frac{\partial \theta^4}{\partial p} dp.$$

Now consider the short-run change in corn acres from an increase in the relative price. All of the fields that switch from corn-corn-soybeans to continuous corn plant corn in the short run, so 1/3 of these fields plant corn that otherwise would have planted soybeans. All of the fields that switch from corn-soybeans to corn-corn-soybeans plant corn in the short run, so 1/2 of these fields plant corn that otherwise would have planted soybeans. Two-thirds of the fields that switch from soybeans-soybeans-corn to corn-soybeans plant corn in the short run, so 1/3 of these fields plant corn that otherwise would have planted soybeans. All of the fields that switch from continuous soybeans to soybeans-soybeans-corn plant corn in the short run, so all of these fields change to corn. The short-run change in the share of corn acres for an increase in the relative price is

$$\text{(A3)}\ \ d\bar{C}^{SR} = \frac{1}{3}g\left(\theta^1\right)\frac{\partial\theta^1}{\partial p}dp + \frac{1}{2}g\left(\theta^2\right)\frac{\partial\theta^2}{\partial p}dp + \frac{1}{3}g\left(\theta^3\right)\frac{\partial\theta^3}{\partial p}dp + g\left(\theta^4\right)\frac{\partial\theta^4}{\partial p}dp \quad if\ dp > 0.$$

Using similar reasoning, the short-run response to a decrease in the relative price is

$$\text{(A4)}\ \ d\bar{C}^{SR} = g\left(\theta^1\right)\frac{\partial\theta^1}{\partial p}dp + \frac{1}{3}g\left(\theta^2\right)\frac{\partial\theta^2}{\partial p}dp + \frac{1}{2}g\left(\theta^3\right)\frac{\partial\theta^3}{\partial p}dp + \frac{1}{3}g\left(\theta^4\right)\frac{\partial\theta^4}{\partial p}dp \quad if\ dp < 0.$$

Subtracting the long-run response from (A3) and (A4) gives

$$\text{(A5)}\ \ d\bar{C}^{SR} - d\bar{C}^{LR} = \begin{cases} \frac{1}{3}g\left(\theta^2\right)\frac{\partial\theta^2}{\partial p}dp + \frac{1}{6}g\left(\theta^3\right)\frac{\partial\theta^3}{\partial p}dp + \frac{2}{3}g\left(\theta^4\right)\frac{\partial\theta^4}{\partial p}dp & if\ dp > 0 \\ \frac{2}{3}g\left(\theta^1\right)\frac{\partial\theta^1}{\partial p}dp + \frac{1}{6}g\left(\theta^2\right)\frac{\partial\theta^2}{\partial p}dp + \frac{1}{3}g\left(\theta^3\right)\frac{\partial\theta^3}{\partial p}dp & if\ dp < 0 \end{cases}.$$

Again, the short-run response to price is larger in absolute value than the long-run response. As in the case of one-year memory, the difference between the short-run and long-run response occurs from the conversion of continuous cropping to a crop rotation. But in the case of two-year memory there is also a difference in the short-run and long-run response from conversions between crop rotations. For example, when the relative price increases, all of the fields that switch from corn-soybeans to corn-corn-soybeans are planted to corn in the short run, but in the long run only 2/3 of these fields are planted to corn.

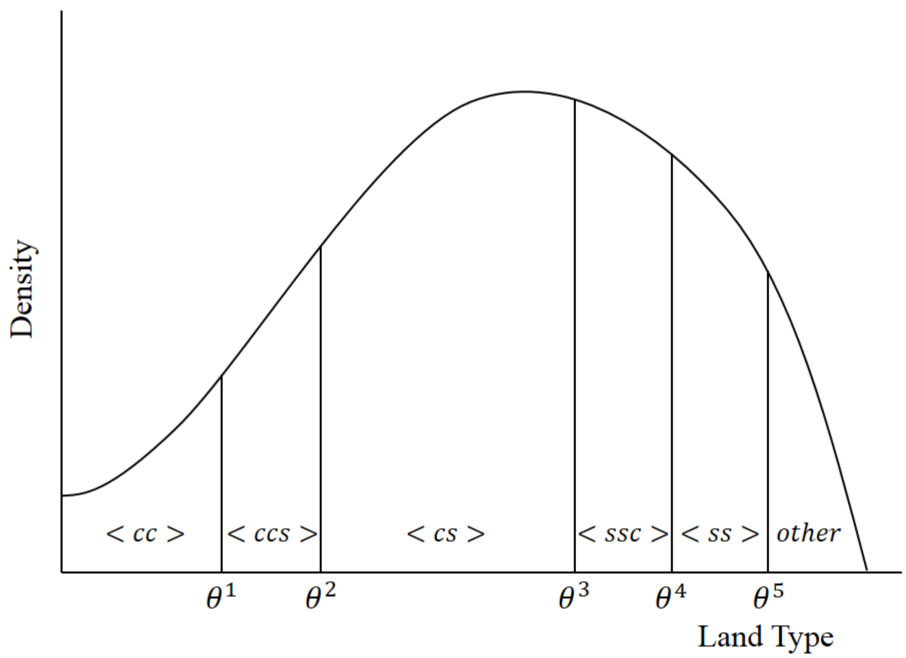


Figure A1: Illustration of Land Heterogeneity and Crop Rotations with Two-Year Memory

A3 Regression Results with Two-year Memory

The conceptual model in the article indicates that the planting decision at the rotational margin depends on the previous crop (see equations (7) and (8)). For two-year memory, the probability that corn is planted on a particular field this year depends on the previous two crops on that field, which implies second-order Markov dependence. We set up a second-order Markov model by defining each two-year sequence as belonging to one of four states: (1) $c_{i,t} = 1, c_{i,t-1} = 1$; (2) $c_{i,t} = 0, c_{i,t-1} = 1$; (3) $c_{i,t} = 1, c_{i,t-1} = 0$; or (4) $c_{i,t} = 0, c_{i,t-1} = 0$.

It is sufficient to specify the following model for the transitions between the four states:

(A6)

$$\Phi_{it}^{11} = Pr\left(c_{it} = 1 | c_{i,t-1} = 1, c_{i,t-2} = 1\right) = \lambda_{1i} + \beta_{1i}^{c} p_{it}^{c} + \beta_{1i}^{s} p_{it}^{s} + \boldsymbol{\theta}'_{1i}\mathbf{x}_i + \kappa_{1i}t,$$

(A7)

$$\Phi_{it}^{23} = Pr\left(c_{it} = 1 | c_{i,t-1} = 0, c_{i,t-2} = 1\right) = \lambda_{2i} + \beta_{2i}^{c} p_{it}^{c} + \beta_{2i}^{s} p_{it}^{s} + \boldsymbol{\theta}'_{2i}\mathbf{x}_i + \kappa_{2i}t,$$

(A8)

$$\Phi_{it}^{31} = Pr\left(c_{it} = 1 | c_{i,t-1} = 1, c_{i,t-2} = 0\right) = \lambda_{3i} + \beta_{3i}^{c} p_{it}^{c} + \beta_{3i}^{s} p_{it}^{s} + \boldsymbol{\theta}'_{3i}\mathbf{x}_i + \kappa_{3i}t,$$

(A9)

$$\Phi_{it}^{43} = Pr\left(c_{it} = 1 | c_{i,t-1} = 0, c_{i,t-2} = 0\right) = \lambda_{4i} + \beta_{4i}^{c} p_{it}^{c} + \beta_{4i}^{s} p_{it}^{s} + \boldsymbol{\theta}'_{4i}\mathbf{x}_i + \kappa_{4i}t,$$

where Φ_{it}^{mj} denotes the probability of a transition from state m to state j on field i in year t and other variables are defined as in the article. These four equations are sufficient to describe the system because $\Phi_{it}^{m2} = 1 - \Phi_{it}^{m1}$, $\Phi_{it}^{m4} = 1 - \Phi_{it}^{m3}$, and all other transitions have zero probability.

Many of the fields in our sample visit only some of the four transition states during the sample period. For example, about a third of our fields never plant monoculture; they alternate between corn and soybeans throughout the sample period. Such fields alternate between states 2 ($c_{i,t} = 0, c_{i,t-1} = 1$) and 3 ($c_{i,t} = 1, c_{i,t-1} = 0$) and are unresponsive to prices in our short sample period. To the extent that such fields are less responsive to price (i.e., have smaller β_{mi}) than other fields in the same MLRA, including them in a group-level regression induces a heterogeneity bias. Thus, we divide the fields in each MLRA into four groups depending on the observed transitions, and we estimate separate regressions for each group. The four groups are: fields that never planted either of the monoculture possibilities (i.e., corn after corn and soybean after soybeans were never observed), fields that never planted soybeans after soybeans (but did plant corn after corn), fields that never planted corn after corn (but did plant soybeans after soybeans), and fields with all states observed.

These four sets of fields comprise 98% of the acres in our dataset that planted corn or soybeans—we exclude the remaining 2% of fields from the analysis. Only 12% of the acres in the sample for our rotational margin regressions exhibited all four states during the sample period. A slightly larger proportion (17%) visited all states except consecutive corn, whereas 37% visited all states except consecutive soybeans.

We assume that the Markov chains are reducible for those fields where certain states were never observed. For the fields that never planted monoculture, we impose the restriction $\Phi_{it}^{11} = 0$, $\Phi_{it}^{23} = 1$, $\Phi_{it}^{31} = 0$, and $\Phi_{it}^{43} = 1$, which implies that the short-run and the long-run marginal effects are zero for these fields. For the fields that never planted soybeans after soybeans, we impose the identifying restriction $\Phi_{it}^{43} = 1$. For the fields that never planted corn after corn, we impose the identifying restriction $\Phi_{it}^{11} = 0$.

The matrix of transition probabilities, analogous to equation (16) in the article, is a 4x4 matrix for second-order Markov transition probabilities. We can then calculate the long-run probability of the states from the system of equations in (18) and (19). Because states 1 and 3 imply that corn is planted in the current year, we can write the long-run probability of corn as $\Pi_{it}^{c} = \boldsymbol{e}'\boldsymbol{\Pi}_{it}$, where $\boldsymbol{e}' = [\ 1 \quad 0 \quad 1 \quad 0\ ]$.

Table A1 reports aggregate corn acreage elasticities at the rotational margin from second-order Markov transition probabilities as described above. We cluster standard errors by year using a wild bootstrap. Estimating second-order Markov transitions requires the estimation of substantially more parameters than first-order Markov transitions, which decreases precision and causes the long-run marginal effects to explode in some bootstrap replications. The bootstrap replications of the parameter $\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$ indicate that most replications give an estimate between -0.5 and 0, but a few replications give estimates near 1 or even exceeding 1. In table A1, we report the standard error on the elasticities as the standard deviation of bootstrap replications after trimming replications with estimates of $\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$ less than -0.95 or greater than 0.5. Our estimates of the standard errors on the short-run elasticities are similar whether we trim the bootstrap replications or not.

The results in table A1 are comparable to column (1) of table 2 in the article. Our main results in the article are robust to allowing for two-year memory of crop rotations. Long-run elasticity estimates are the same with second-order Markov transition probabilities, and the short-run elasticities are only slightly smaller.

Table A1: Estimates of Corn Acreage Elasticities at the Rotational Margin with Second-order Markov Transition Probabilities

Own-Price Elasticity	
Short-run	0.37**
	(0.114)
Long-run	0.29**
	(0.098)
Cross-Price Elasticity	
Short-run	-0.27*
	(0.130)
Long-run	-0.22
	(0.128)
$\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$	-0.27**
	(0.089)

Notes: The results in this table show aggregate elasticity estimates from second-order Markov transition probabilities. The transition probability models are estimated separately for each Major Land Resource Area (MLRA). Within each MLRA, the model is estimated separately for fields that never planted soybeans after soybeans, fields that never planted corn after corn, and fields with all states observed. The price response is assumed to be zero for those fields that never planted monoculture. Standard errors are clustered by year and estimated with a wild bootstrap.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

A4 Additional Evidence of a Small Extensive Margin Response to Price

Table A2 gives perspective on the amount of land that could enter corn or soybean production from different land use categories in Iowa, Illinois, and Indiana. The table reports the total acres of major land use categories in 2007—the most recent data available—reported by Economic Research Service (ERS) of the USDA as well as state-level data for individual crops reported by NASS summed across all three states. The ERS data only report acres of cropland used for crops and do not split those acres by crop planted, so we supplement the ERS data with the NASS data for crop-specific acreage.

Land planted to other crops is the most likely source of new corn or soybean acreage. But land planted to other crops is only 8 percent of the total land planted to corn or soybeans (table A2). To give perspective, 33.9 million acres of corn were planted in 2007—a 19 percent increase from corn acreage in 2006. This increase in corn acreage was larger than the total acres that are planted to other crops. Another likely source of new corn or soybean acreage is cropland that is idled or used for pasture. This land use is only 8 percent of the total land planted to corn or soybeans (table A2). Most of the cropland idled and used for pasture is land that is idled by the Conservation Reserve Program (CRP).[1] The amount of CRP conversion to corn or soybeans depends on the expiration of CRP contracts and the government's willingness to increase CRP payments to maintain CRP acreage. There is more land in pasture or forest, but it seems likely that land in other crops or idled cropland would be converted to corn or soybean production before pasture or forest.

Figure A2 shows acreage deviations of land use categories from their 2000–2010 mean. Panel A shows changes in corn and soybean acres separately—reflecting changes at the rotational margin. Panel B shows changes in the total acres planted to corn or soybeans, changes in acres of other crops, and changes in CRP acres—reflecting changes at the extensive margin. Figure A2 clearly shows that acreage transitions between corn and soybeans are much larger than changes in total corn or soybean acres. Acres of CRP changed little

[1] The Farm Service Agency reports 3.4 million acres in CRP in these three states.

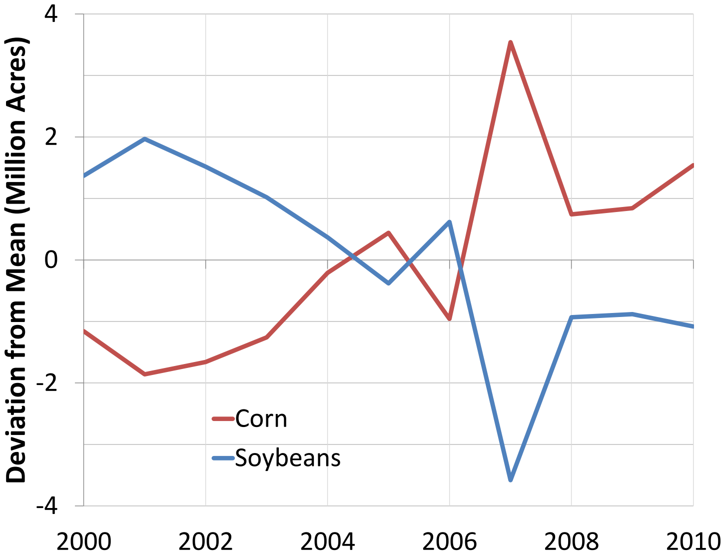
during the period. Acreage of other crops did decrease slightly from 2008 to 2010 with a corresponding increase in total corn and soybean acreage. Our regressions at the extensive margin only consider changes with other crops, and figure A2 indicates that transitions with other crops should capture the majority of any extensive margin response. The figure also indicates that the extensive margin response is likely to be small for these three states.

Table A2: Major Land Uses in Iowa, Illinois, and Indiana in 2007

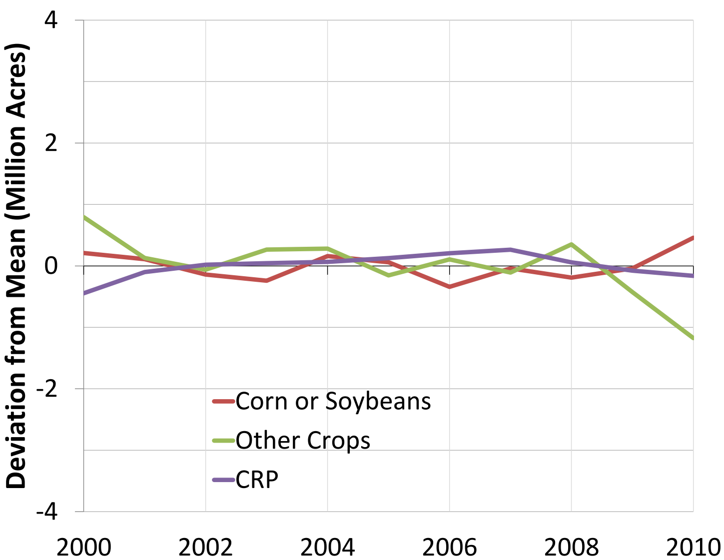
Land Use	Million Acres	Acres of Land Use Relative to Acres of Corn or Soybeans
Corn	33.9	0.61
Soybeans	21.8	0.39
Other Crops	4.4	0.08
Cropland Idle or Used for Pasture	4.3	0.08
Pasture and Range	6.0	0.11
Forest Grazed	1.6	0.03
Forest not Grazed	10.2	0.18

Note: Area of major land uses are from ERS. Data are available at `http://www.ers.usda.gov/data-products/major-land-uses.aspx` and descriptions of land use categories are available at `http://www.ers.usda.gov/data-products/major-land-uses/glossary.aspx`. We do not report acres of "special uses" which includes urban areas and parks or miscellaneous land which include industrial sites, marshes, etc. Corn, soybeans, and "other crop" acreage are from NASS state-level data.

Figure A2: Acreage of Land Use Categories in
Iowa, Illinois, and Indiana as Deviations from 2000-2010 Means



Panel A. Changes in Acres of Corn and Soybean



Panel B. Changes in Acres of Extensive Margin Land Use Categories

Note: Crop acreage data are from NASS state-level data. Conservation Reserve Program (CRP) data are from the Farm Service Agency and are available at `http://www.fsa.usda.gov/FSA/webapp?area=home&subject=copr&topic=crp-st`.

A5 Robustness to Including the Price of Fertilizer

We use University of Illinois crop budgets to give a rough idea of the importance of changes in fertilizer prices versus crop prices in the crop rotation decision.[2] The University of Illinois releases budgets each year prior to planting for corn after soybeans, soybeans after corn, corn after corn, soybeans after two years of corn, and wheat. They report separate budgets for different regions, but here we use the budget for Northern Illinois. We define the annual returns from rotating corn and soybeans as the average returns of corn after soybeans and soybeans after corn. We define the annual returns from continuous corn as the returns of corn after corn.

Using the 2012 expected prices that are used in the Illinois crop budget, rotating corn and soybeans has a higher return than continuous corn by $38 per acre per year. If the price of corn increases 25% and all other prices remain constant, then rotating corn and soybeans has a *lower* return than continuous corn by $71 per acre per year. In contrast, if the price of fertilizer decreases 25% and all other prices remain constant, then rotating corn and soybeans still has a *higher* return than continuous corn by $22 per acre per year. Clearly, changes in crop prices have a much larger effect on crop rotation decisions than changes in fertilizer prices of a similar magnitude.

In table A3, we report elasticities from conditional grouped coefficients OLS that also include the price of fertilizer as a regressor. We construct an index for the price of fertilizer using information on the use of three different fertilizers and their prices. Schnitkey (2010) states that application rates typical of high-productivity land in Illinois are 180 pounds of anhydrous ammonia, 170 pounds of DAP, and 85 pounds of potash. These application rates are used as weights for their respective prices each year. While the application rates are

[2] The 2012 crop budgets are available at `http://farmdoc.illinois.edu/manage/2012_crop_budgets.pdf`.

likely to vary across space, we do not have data on this variation. Annual prices of each type of fertilizer in April are obtained from ERS.[3]

The price of fertilizer is endogenous. We observe the price of fertilizer in the spring when it is typically applied before planting, thus more acres planted to corn may increase the price of fertilizer since the Corn Belt is a large consumer of fertilizer. A suitable instrument would affect the price of fertilizer, but not the planting decision between corn and soybeans. We consider the price of natural gas as an instrument since natural gas comprises 70–90% of the production cost of ammonia (Kramer 2004), which is key to producing anhydrous ammonia and DAP. Since natural gas prices are highly correlated with other energy prices, the exclusion restriction could be violated. However, substantial energy costs are incurred for both corn and soybean production and University of Illinois crop budgets indicate a small difference ($3/acre) in fuel costs for rotating corn and soybeans versus continuous corn. The price of natural gas is the average October–March industrial price obtained from the U.S. Energy Information Administration.[4]

The elasticities in table A3 indicate that the results in our article are robust to including the price of fertilizer as an additional regressor. Results in column (1) report estimates without instrumenting the price of fertilizer. The short-run own-price elasticity is slightly larger than our preferred estimate in the article (0.42 versus 0.40). The short-run cross-price elasticity is slightly smaller than our preferred estimate in the article (-0.28 versus -0.31). The short-run elasticity with respect to the price of fertilizer seems plausible (-0.04), but should be viewed with skepticism since the price of fertilizer is likely endogenous. Results in column (2) report estimates that use the price of natural gas as an instrument for the price of fertilizer. The own-price and cross-price elasticities in column (2) are also very similar to the preferred estimates reported in the article and the price elasticity with respect to the price of fertilizer is small with an unexpected positive sign.

[3]Fertilizer price data are available at `http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx`.

[4]Natural gas price data are available at `http://www.eia.gov/dnav/ng/ng_pri_sum_dcu_nus_m.htm`.

Table A3: Estimates of Corn Acreage Elasticities
at the Rotational Margin that Include the Price of Fertilizer

	Model	
	(1)	(2)
Own-Price Elasticity		
Short-run	0.42**	0.38**
	(0.086)	(0.090)
Long-run	0.30**	0.27**
	(0.063)	(0.066)
Cross-Price Elasticity		
Short-run	-0.28**	-0.30**
	(0.091)	(0.122)
Long-run	-0.20**	-0.22**
	(0.066)	(0.090)
Fertilizer Price Elasticity		
Short-run	-0.04	0.02
	(0.031)	(0.029)
Long-run	-0.03	0.01
	(0.023)	(0.022)
$\frac{\varepsilon_{LR}-\varepsilon_{SR}}{\varepsilon_{LR}}$	-0.39**	-0.38**
	(0.010)	(0.011)
Price of Fertilizer Instrumented	N	Y

Notes: The results in this table show estimates of the conditional grouped coefficients model at the rotational margin that include the price of fertilizer as a regressor. The only difference from the results in column 1 of table 2 in the article is that we also include the price of fertilizer in the regressions. In column (1) of this table we include the price of fertilizer without instrumenting and in column (2) we use the price of natural gas as an instrument for the price of fertilizer. Standard errors are clustered by year.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

A6 The Effect of Aggregation on Heterogeneity Bias

In this section, we formalize our discussion in the article about the effect of aggregation on the bias of dynamic panel estimates using the bias formulas from Pesaran and Smith (1995). Consider a linear dynamic model with a heterogeneous coefficient on an autocorrelated regressor,

(A10)

$$\begin{aligned}
y_{it} &= \gamma y_{i,t-1} + \beta_i x_{it} + \alpha_i + \varepsilon_{it}, \\
x_{it} &= \mu(1-\rho) + \rho x_{i,t-1} + w_t + \eta_{it} \\
w_t &\sim N\left(0, (1-\phi)\,\sigma_x^2\right), \quad \eta_{it} \sim N\left(0, \phi\sigma_x^2\right) \\
\beta_i &= \beta + u_g + v_i \\
u_g &\sim N\left(0, (1-\omega)\,\sigma_\beta^2\right), \quad u_i \sim N\left(0, \omega\sigma_\beta^2\right) \\
\varepsilon_{it} &\sim N\left(0, \sigma_\varepsilon^2\right),
\end{aligned}$$

where ρ is the autocorrelation coefficient of x_{it}, w_t is a component of the variation in x_{it} that is common to all individuals, η_{it} is idiosyncratic variation of x_{it}, and ϕ is the proportion of the variance of x_{it} that is due to idiosyncratic variation. The econometric literature typically refers to a common factor as the special case where none of the variation is idiosyncratic, $\phi = 0$. The coefficient β_i has mean β and a component that is common to groups, u_g, and a component that varies within groups, v_i. The proportion of the variance of β_i that is within groups (i.e., the intra-class correlation coefficient) is ω.

Although we are concerned with the case of small T in our article, it is instructive to examine the bias of fixed effects as $T \to \infty$ since this will isolate the bias that is due to the heterogeneous coefficient.[5] Denote the fixed effects estimates with individual data (e.g., field-level data) as $\hat{\gamma}^{ind}$ and $\hat{\beta}^{ind}$. Pesaran and Smith (1995) show that the bias of pooled

[5]With small T there is also the well-known negative bias of the coefficient on the lagged dependent variable.

fixed effects when $N \to \infty$ and $T \to \infty$ is

(A11)

$$\underset{N\to\infty,T\to\infty}{plim}\left(\hat{\gamma}^{ind}\right)-\gamma=\frac{\rho\left(1-\gamma\rho\right)\left(1-\gamma^{2}\right)\sigma_{\beta}^{2}}{\Psi_{1}},$$

(A12)

$$\underset{N\to\infty,T\to\infty}{plim}\left(\hat{\beta}^{ind}\right)-\beta=-\frac{\beta\rho^{2}\left(1-\gamma^{2}\right)\sigma_{\beta}^{2}}{\Psi_{1}},$$

where

$$\text{(A13)}\quad \Psi_{1}=\frac{\sigma_{\varepsilon}^{2}}{\sigma_{x}^{2}}\left(1-\rho^{2}\right)\left(1-\gamma\rho\right)^{2}+\left(1-\gamma^{2}\rho^{2}\right)\sigma_{\beta}^{2}+\left(1-\rho^{2}\right)\beta.$$

The bias of $\hat{\gamma}^{ind}$ is positive and the bias of $\hat{\beta}^{ind}$ is negative. The bias is increasing in the variance of β_i, and increasing in the signal-to-noise ratio ${\sigma_x^2}/{\sigma_\varepsilon^2}$.

Next, consider the bias of fixed effects when aggregate data are used instead of individual data. Let the aggregation occur over groups denoted by the subscript g. Since the dynamics are not heterogeneous in (A10), aggregating will not deform the dynamics in this simply case. Denote the average group-level coefficient as $\bar{\beta}_g = \frac{1}{N_g}\sum_{i\in g}\left(\beta+u_g+v_i\right)$, where N_g is the number of individuals in group g. Assuming independence between the group and individual-level components, the variance of the group-level coefficients is $Var\left(\bar{\beta}_g\right) = \left(1-\omega\right)\sigma_\beta^2 + \frac{\omega\sigma_\beta^2}{N_g}$. The variance of the aggregate x_{it} is $Var\left(\bar{x}_{gt}\right) = \left(1-\phi\right)\sigma_x^2 + \frac{\phi\sigma_x^2}{N_g}$. The variance of the aggregate idiosyncratic errors is $Var\left(\bar{\varepsilon}_{gt}\right) = \frac{\sigma_\varepsilon^2}{N_g}$.

Substituting the variance of the parameters with aggregate data into equations (A11) and (A12), the bias of fixed effects with aggregate panel data is

(A14)

$$\underset{N\to\infty,T\to\infty}{plim}\left(\hat{\gamma}^{agg}\right)-\gamma=\frac{\rho\left(1-\gamma\rho\right)\left(1-\gamma^{2}\right)\left(\left(1-\omega\right)\sigma_{\beta}^{2}+\frac{\omega\sigma_{\beta}^{2}}{N_{g}}\right)}{\Psi_{2}},$$

(A15)

$$\underset{N\to\infty,T\to\infty}{plim}\left(\hat{\beta}^{agg}\right)-\beta=-\frac{\beta\rho^{2}\left(1-\gamma^{2}\right)\left(\left(1-\omega\right)\sigma_{\beta}^{2}+\frac{\omega\sigma_{\beta}^{2}}{N_{g}}\right)}{\Psi_{2}},$$

where

(A16)

$$\Psi_{2}=\frac{\sigma_{\varepsilon}^{2}/N_{g}}{\left(1-\phi\right)\sigma_{x}^{2}+\frac{\phi\sigma_{x}^{2}}{N_{g}}}\left(1-\rho^{2}\right)\left(1-\gamma\rho\right)^{2}+\left(1-\gamma^{2}\rho^{2}\right)\left(\left(1-\omega\right)\sigma_{\beta}^{2}+\frac{\omega\sigma_{\beta}^{2}}{N_{g}}\right)+\left(1-\rho^{2}\right)\beta.$$

Aggregation decreases σ_{β}^{2}, which decreases the bias of fixed effects. Aggregating also increases the signal-to-noise ratio, which increases the bias of fixed effects.

In the case where all the parameter variation is within groups (i.e., $\omega=1$), then using aggregate data reduces the parameter heterogeneity and the fixed effects estimator converges to the true mean parameter values as the number of individuals in each group increases (for large T). When all of the parameter variation is between groups (i.e., $\omega=0$), then the variation in β_i is not reduced by aggregation. But the signal-to-noise ratio increases, and the bias of fixed effects is larger with aggregate data than with individual data. In summary, using aggregate data decreases the bias of fixed effects when most of the parameter variation is within groups. However, using aggregate data increases the bias of fixed effects when a substantial portion of the parameter heterogeneity is between groups that are aggregated and the variation in x_{it} has a component that is common to all individuals.

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