The Dynamics of Supply: U.S. Corn and Soybeans in the Biofuel Era

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ABSTRACT *We estimate U.S. corn and soybean supply responses by exploiting the large exogenous price variations associated with implementation of the Renewable Fuel Standard. We focus on recent years and on the 12 U.S. midwestern states and estimate a system of dynamic equations that is consistent with the role of crop rotation. Corn and soybean acreages respond more in the short run than in the long run. Cross-price elasticities of acreage responses are negative and fairly large in absolute value such that, when corn and soybean prices move together, the response of total acreage allocated to these two crops is extremely inelastic.* (JEL Q11)

1. Introduction

The Renewable Fuel Standard (RFS), initially established by the 2005 Energy Policy Act and considerably extended by the 2007 Energy Independence Security Act, has introduced a sizable new source of demand for corn and soybeans to produce ethanol and biodiesel. Ceteris paribus, such an exogenous demand shock would be expected to increase the price of corn and soybeans (Fabiosa et al. 2010; Cui et al. 2011). Indeed, the RFS is credited with being one of the main causes of the commodity price increases in the last decade (Mallory, Hayes, and Babcock 2011; Hochman et al. 2012; Roberts and Schlenker 2013; Wright 2014). These price effects are traceable to a largely exogenous demand shock—the biofuel boom driven by RFS mandates—and thus provide an ideal opportunity to revisit the econometric analysis of supply response, an object of considerable interest in agricultural economics.

Land Economics • November 2018 • 94 (4): 593–613
ISSN 0023-7639; E-ISSN 1543-8325

The resurgence of interest in the U.S. agricultural supply response is also motivated by the policy implications of the RFS. The massive expansion of biofuel production in the United States has put considerable upward pressure on commodity prices. A major concern is that, if the U.S. supply response cannot accommodate such an expanded demand, then land elsewhere in the world may be converted to the production of these commodities. This possible indirect land use effect is crucial to evaluate the consequence of the RFS on greenhouse gas emissions (e.g., Searchinger et al. 2008; Barr et al. 2011; Berry 2011; Berry and Schlenker 2011; Roberts and Schlenker 2013; Gohin 2014; Babcock 2015; Haile, Kalkuhl, and von Braun 2016). Hence, major economic policy conclusions hinge on the extent to which the U.S. supply response is (in)elastic. As discussed in more detail below, existing studies are less than conclusive on this matter.

The study of agricultural supply response has traditionally decomposed it in terms of separate acreage and yield responses. Studies of acreage responsiveness have relied on a variety of model specifications. Given suitable aggregation conditions, profit maximization has been relied on to derive theory-consistent parameterizations (Chambers and Just 1989; Moore and Negri 1992; Moore, Gollehon, and Carey 1994; Arnade and Kelch 2007; Fezzi and Bateman 2011; Lacroix and Thomas 2011; Laukkanen and Nauges 2014). In these studies, estimation equations are derived from flexible functional forms such as translog or normalized quadratic, and standard restrictions from optimization (homogeneity in prices, symmetry, and adding up) are maintained. Another approach that represents supply response in terms of acreage

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shares is the linear logit specification based on Theil's (1969) multinomial extension of the linear logit model (e.g., Bewley, Young, and Colman 1987; Wu and Segerson 1995; Miller and Plantinga 1999; Carpentier and Letort 2014). Alternatively, acreage responsiveness has been approached with more ad hoc models, including plain linear specifications (e.g., Morzuch, Weaver, and Helmberger 1980; Lee and Helmberger 1985; Shideed and White 1989; Goodwin and Mishra 2006; Arnberg and Hansen 2012; Hausman 2012; de Menezes and Piketty 2012; Miao, Khanna, and Huang 2016). Some of these studies also differentiate between short- and long-run behavior, an element of interest in this setting at least since Nerlove (1956) (e.g., Arnberg and Hansen 2012; Hausman 2012; de Menezes and Piketty 2012). The dynamics of supply can be complex once one explicitly accounts for crop rotational effects (Eckstein 1984, 1985), with results that depart form the canonical findings of traditional Nerlovian models (Hendricks, Smith, and Sumner 2014).

In this paper, we study the acreage and yield response for U.S. corn and soybeans. The presumption is that farmers maximize expected profit, and that their aggregate decisions at the county level (our unit of observation) can be thought of as that of a representative expected profit maximizer. That is, similar to most of the aforementioned studies, there is an implicit assumption that the aggregation conditions that justify this simplification hold, at least approximately.[1] We explicitly model three land uses: corn, soybeans, and everything else. We assume that the acreage shares, which are a function of the per acre revenue vector, can be parameterized by a linear function, an assumption that makes the specification of dynamic adjustment tractable and permits the use of standard instrumental variable estimation procedures. Our parameterization maintains the symmetry restrictions of profit maximizations (at the mean), in addition to the homogeneity property and the adding-up condition. Additionally, we maintain symmetry for the dynamic adjustment coefficients.

Our analysis focuses on the rainfed producing regions of the Midwest. We use panel data at the county level, specifically counties in the 12 states that comprise the Midwest region of the U.S. Census Bureau: Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Michigan (MI), Minnesota (MN), Missouri (MO), Nebraska (NE), North Dakota (ND), Ohio (OH), South Dakota (SD), and Wisconsin (WI). This region accounts for the vast majority of U.S. production: over the 11 years of 2005–2015 that we use for the analysis of acreage response, the Midwest accounted for 87% of U.S. corn and 84% of U.S. soybean production.[2] The period 2005–2015 fully exploits the price changes that we presumed are influenced by the exogenous biofuel expansion. Furthermore, focusing on recent data reduces the impact of unmodeled factors that may not hold constant over a longer period. In particular, a thorny issue in modeling agricultural supply response to price concerns the role that (changing) agricultural price and income support policies may have played (Lee and Helmberger 1985; McIntosh and Shideed 1989). Such factors are approximately constant for the period of our analysis.[3]

The dynamic specification of acreage allocation that we adopt permits us to accommodate the implications of crop rotation. Most dynamic representations of agricultural supply have been rooted in Nerlove's (1956, 1958) seminal models. Whether rationalized in terms of adaptive expectations or partial adjustment, such models imply that the long-run supply response to a sustained price shock is larger in the long run than in the short run.

[1] Note that our research question is not related to the distinct "disaggregation" problem, considered by some land allocation studies (e.g., Miller and Plantinga 1999; Chakir 2009), that arises when, for example, county land use estimates are used to impute subcounty parameters. The task of inferring individual behavior from aggregate data has been termed the "ecological inference" problem by King (1997).

[2] Because the counties that enter our sample mostly produce both corn and soybeans, we do not need to address the corner solution issue, which is one of the main concerns in some studies (Moore and Negri 1992; Fezzi and Bateman 2011; Lacroix and Thomas 2011).

[3] In particular, price-support payments have been nearly zero since 2005 for soybeans and since 2006 for corn, and direct payments have been quite stable since 2005 for both corn and soybeans (see, e.g., charts provided by the Environmental Working Group at https://farm.ewg.org/index.php).

Eckstein (1984) questioned this premise as being inconsistent with crop rotation. The practice of alternating growing corn and soybeans on a given plot, widespread in the U.S. Midwest, has been shown to increase profit by increasing yields, reducing fertilizer needs, and improving weed control (e.g., Bullock 1992). When these considerations outweigh those associated with possible adjustment costs, the short-run response to price can exceed the long-run response. Hendricks, Smith, and Sumner (2014) find empirical support for the underlying role of crop rotation by estimating a Markov transition probability model for field-level crop data from satellite imagery—the Cropland Data Layer (CDL) made available by the U.S. Department of Agriculture (USDA)[4] —for three central midwestern states.

Uncovering the effects of crop rotation is best pursued with data at the plot level, as done by Hendricks, Smith, and Sumner (2014). Still, there remains scope for studying supply response with aggregate data because the underlying research question (as in our case) often pertains to this level, and because such data are typically more easily available and/or more reliable. For example, the use of CDL data to track land use changes over time is open to pitfalls (Lark et al. 2017). Hence, our model relies on a traditional panel regression estimated with county-level data. In order to be consistent with the implications of crop rotation, however, our dynamic specification includes the vector of lagged dependent variables as explanatory variables. A dynamic panel generalized method of moments (GMM) estimator is used to avoid the possible bias due to the presence of lagged dependent variables.

The results from our analysis suggest that, due to significant cross-crop dynamics between corn and soybeans, the U.S. supply responses for corn and soybeans are indeed larger in the short run than in the long run. Our baseline model estimates the own-price supply elasticities, at the mean point of the data, to be 0.50 for corn and 0.38 for soybeans in the short run (the long-run counterparts are 0.39 and 0.26, respectively). Most of this responsiveness is due to acreage allocation decisions, as we find that the yield supply response to price is essentially nil. The model also identifies cross-price effects between corn and soybeans, which are emerging as important parameters because of the RFS: as conventional ethanol mandates have reached their statutory maximum, increasing amounts of biodiesel have been mandated (which increases the demand for vegetable oil and, consequently, oilseeds) (Moschini, Lapan, and Kim 2017). Cross-price elasticities are found to be relatively large: the cross-price elasticity between corn and soybeans at the mean is estimated to be –0.31, and that between soybeans and corn to be –0.50 in the short run (the long-run counterparts are –0.23 and –0.32, respectively). This also implies that, when both corn and soybean prices increase—a likely implication of the full implementation of the RFS—the response of total acreage allocated to these two key crops is very small. We estimate this total elasticity, at the mean point, to be equal to 0.04 in the short run and 0.06 in the long run, which suggests that the ability of the U.S. corn and soybean production sector to accommodate the demand shock due to the RFS is limited.

2. The Model

Our unit of observation is a county-year. Land allocations are presumed to be consistent with the choices of a representative farmer who maximizes expected profit. We posit that cropland can be devoted to three alternative uses: corn, soybeans, and "all other" uses. The latter category includes crops other than corn and soybeans, as well other land uses typically included in cropland measures.[5] Because these three allocation choices exhaust the

[4] See https://www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php.

[5] In particular, as explained in the data section, this encompasses cultivated summer fallow, cropland used for pasture, and idle cropland (which includes land diverted to conservation uses, such as the federal Conservation Reserve Program) (Bigelow and Borchers 2017). Hence, both the decision problem discussed in this section, and the empirical analysis that follows, are consistent with the possibility that previously uncultivated land may contribute to corn and/or soybean acreage.

set of possible land allocations, total county cropland A is assumed to be fixed. Hence, the decision problem can be stated as that of choosing acreage shares $s_k \equiv A_k/A$, where A_k is the acreage allocated to the kth crop ($k=1$ for corn, $k=2$ for soybeans, and $k=3$ for all other uses). Therefore, the problem of the representative agent can be stated as

$$\max_{s_1,s_2,s_3} \; (s_1\tilde{r}_1 + s_2\tilde{r}_2 + s_3\tilde{r}_3)A - \tilde{C}(s_1,s_2,s_3;A,w,\mathbf{z})$$
$$s.t. \quad \sum_{k=1}^{3} s_k = 1, \qquad [1]$$

where $\tilde{r}_k$ denote expected per acre revenues, w is an index of all input prices (other than land), and $\mathbf{z}$ is a vector of quasi-fixed factors (or environmental conditions) that constrains land allocation choices. The cost function $\tilde{C}(s_1,s_2,s_3;A,w,\mathbf{z})$ is assumed to be increasing and convex in the individual shares s_k, thereby capturing in a simple fashion the motives for acreage diversification (Carpentier and Letort 2014).[6] This cost function is also increasing in total cropland A, and also increasing, concave, and homogeneous of degree one in the input price w.

Considerable simplification, without much loss of generality, is obtained by assuming that the cost function $\tilde{C}$ is homogeneous of degree one in total cropland A, that is, $\tilde{C}(s_1,s_2,s_3;A,w,\mathbf{z}) = A \times \tilde{C}(s_1,s_2,s_3;1,w,\mathbf{z})$. Essentially, this permits the land allocation problem, all else equal, to be independent of the size of the county. Furthermore, because of the price homogeneity property of the cost function $\tilde{C}(s_1,s_2,s_3;A,w,\mathbf{z})$, the objective function in [1] is homogeneous of degree one in $\tilde{r}_1$, $\tilde{r}_2$, $\tilde{r}_3$, and w, implying optimal allocations are homogeneous of degree zero in $\tilde{r}_1$, $\tilde{r}_2$, $\tilde{r}_3$, and w. This homogeneity property can be maintained at the outset by expressing expected per acre revenues in real terms (i.e., $r_k \equiv \tilde{r}_k/w$ for $k=1,2,3$). Given all that, and explicitly maintaining the land constraint $s_1+s_2+s_3=1$, the land allocation problem in [1] can be restated as

$$\max_{s_1,s_2} \; [(r_1-r_3)s_1 + (r_2-r_3)s_2 + r_3] - C(s_1,s_2;\mathbf{z}), \qquad [2]$$

where the relevant cost function in equation [2] satisfies $C(s_1,s_2;\mathbf{z}) \equiv \tilde{C}(s_1,s_2,1-s_1-s_2;1,1,\mathbf{z})$. Solving the optimality conditions for this (unconstrained) problem, optimal acreage allocations can be written as

$$s_k^* = f_k((r_1-r_3),(r_2-r_3),\mathbf{z}) \quad \text{for } k=1,2, \qquad [3]$$

and, of course, $s_3^* = 1 - s_1^* + s_2^*$.

Acreage Response Equations

For the purpose of specifying the econometric model, observed acreage shares in county i at time t can be written as $s_{kit} = s_{kit}^* + \varepsilon_{kit}$. The land allocation model sketched out in [2] is inherently static. To capture the dynamic effects on acreage allocation implied by crop rotation in a simple way, we permit the vector of conditioning variables $\mathbf{z}_{it}$ to include own- and cross-lagged shares, s_{1it-1} and s_{2it-1}. The set of conditioning variables also includes environmental variables such as spring water stress (Palmer Z indices in March, April, and May), denoted $\tilde{\mathbf{z}}_{it}$, which may directly affect planting decisions. Hence, we are implicitly defining $\mathbf{z}_{it} \equiv (\tilde{\mathbf{z}}_{it}, s_{1it-1}, s_{2it-1})$. By postulating a linear functional form for the optimal share functions in [3], and by imposing symmetry in the response to per acre expected revenues,[7] and symmetry in the response to lagged shares, the acreage allocation equations for corn and soybeans are expressed as

$$s_{1it} = \tilde{\alpha}_{1i} + \beta_{11}(r_{1it}-r_{3it}) + \beta_{12}(r_{2it}-r_{3it}) + \gamma_{11}s_{1it-1} + \gamma_{12}s_{2it-1} + \boldsymbol{\zeta}_1'\tilde{\mathbf{z}}_{it} + \varepsilon_{1it}, \qquad [4]$$

$$s_{2it} = \tilde{\alpha}_{2i} + \beta_{12}(r_{1it}-r_{3it}) + \beta_{22}(r_{2it}-r_{3it}) + \gamma_{12}s_{1it-1} + \gamma_{22}s_{2it-1} + \boldsymbol{\zeta}_2'\tilde{\mathbf{z}}_{it} + \varepsilon_{2it}. \qquad [5]$$

[6] Because in this setting A is fixed, increased land allocation to any one use is equivalent to an increase in its share s_k. The maintained assumption that the cost function in equation [1] is increasing and convex in the vector of shares, therefore, implies that increased land allocation to a given crop (corn, say) entails increasing marginal cost.

[7] The price symmetry property of supply equations is inherited by acreage equations if yields are independent of prices, a property supported by the empirical results reported below and that we maintain in estimation.

Our formulation of the land allocation problem intuitively presumes that the driving factors are expected per acre revenues associated with alternative uses. These per acre returns reflect the impact of both prices and yields, and their covariance. To make equations [4] and [5] actually estimable, we further assume that the (normalized) expected per acre revenue can be expressed as follows:

$$r_{kit} = p_{kit} y_{kit} + v_{ki} \quad \text{for} \quad k = 1,2,3, \qquad [6]$$

where p_{kit} is the expected output price, y_{kit} is the expected yield, and v_{ki} is the covariance of realized price and yield, all for crop k in county i. (Recall that, for two random variables v_1 and v_2, $\mathrm{E}[v_1 v_2] = \mathrm{E}[v_1]\mathrm{E}[v_2] + \mathrm{cov}(v_1, v_2)$.) Note that the covariance term in [6] is assumed to be county specific but time invariant. Furthermore, the expected local (county-specific) price is not observed. Following standard practice, this expected local price can be decomposed as $p_{kit} \equiv \overline{p}_{kt} + \delta_{ki}$, where $\overline{p}_{kt}$ is a national reference expected price (which, as explained later, we measure by the futures price) and δ_{ki} is the expected local "basis."

As defined in this context, the basis captures both temporal and spatial factors affecting (1) the differences between cash and futures prices at the delivery point for the futures contract, and (2) the difference between contemporaneous cash prices between location k and the futures delivery point. A number of factors affect these temporal and spatial price relationships, including returns to storage and transportation costs (Jiang and Hayenga 1997). Whereas component (1) is common to all counties in a given year, the spatial component in (2) differs across counties. Reliable information about cash prices is available at only a very few locations, and hence a structural representation of the basis relationship for each county is not feasible. For tractability, therefore, we assume that the local basis δ_{ki} is time invariant, although this basis is permitted to be crop specific (i.e., to differ between corn and soybeans). Denoting the product of the national expected reference price and the local expected yield as $\overline{r}_{kit} \equiv \overline{p}_{kt} y_{kit}$, the expected per acre revenues in equation [6] are as follows:

$$r_{kit} = \overline{r}_{kit} + \delta_{ki} y_{kit} + v_{ki} \quad \text{for} \ \ k = 1,2,3. \qquad [7]$$

A stylized fact of agricultural productivity is that expected crop yields have steadily trended upward since the mid-1930s, a reflection of technical progress ultimately due to public and private investments in research and development activities (Alston et al. 2010). Our analytical framework thus permits us to capture the effect of trending yields on crop allocation decisions. As discussed in more detail later, expected yields have a common linear trend and county-specific intercepts, and the estimated expected yields will be fully reflected in the $\overline{r}_{kit}$ regressors. But, given the structure of equation [7], trending yields should also interact with the basis term δ_{ki} , implying the presence of county-specific trend effects. The fact that the terms δ_{ki} are unobserved makes it difficult to identify these local effects. Still, to capture at least the mean of these implied trends, we include a common time trend in each estimating share equation. In conclusion, therefore, we end up with the following two estimating equations:

$$s_{1it} = \alpha_{1i} + \beta_{11}\pi_{1it} + \beta_{12}\pi_{2it} + \gamma_{11}s_{1it-1} + \gamma_{12}s_{2it-1} + \boldsymbol{\zeta}_1' \tilde{\mathbf{z}}_{it} + \tau_1 T_t \varepsilon_{1it}, \qquad [8]$$

$$s_{2it} = \alpha_{2i} + \beta_{12}\pi_{1it} + \beta_{22}\pi_{2it} + \gamma_{12}s_{1it-1} + \gamma_{22}s_{2it-1} + \boldsymbol{\zeta}_2' \tilde{\mathbf{z}}_{it} + \tau_2 T_t \varepsilon_{2it}. \qquad [9]$$

where $\pi_{kit} \equiv (\overline{r}_{kit} - \overline{r}_{3it})$, for $k = 1,2$, represents relative expected per acre revenues, and T_t is a linear trend variable. The county-specific fixed components of the basis, and the covariance between price and yields, are absorbed by the county-specific intercepts α_{ki}.

The system of equations [8] and [9] can be expressed in a vector notation as follows:

$$\mathbf{s}_{it} = \boldsymbol{\alpha}_i + \mathbf{B}\boldsymbol{\pi}_{it} + \boldsymbol{\Gamma}\mathbf{s}_{it-1} + \boldsymbol{\psi}'\mathbf{x}_{it} + \boldsymbol{\varepsilon}_{it}, \qquad [10]$$

where $\mathbf{s}_{it}$ is the 2 × 1 vector of shares; $\boldsymbol{\alpha}_i$ is the 2 × 1 vector of constants; $\boldsymbol{\pi}_{it}$ is the 2 × 1 vector of relative per acre revenues; $\mathbf{x}_{it}$ is the 4 × 1 vector of Palmer Z indices in March, April, and May, and time trend; and $\mathbf{B} = [\beta_{kj}]$ and $\boldsymbol{\Gamma} = [\gamma_{kj}]$ are (symmetric) 2 × 2 matrices of coefficients. We note at this juncture that, whereas the parameters in $\mathbf{B}$ characterize the short-run supply responses to expected revenues (prices), long-run supply responses are defined by $\mathbf{B}^{LR} \equiv (\mathbf{I}-\mathbf{\Gamma})^{-1}\mathbf{B}$. For the system of supply response equations to be dynamically stable it is necessary that the eigenvalues of the matrix of lagged-dependent coefficients $\mathbf{\Gamma}$ be less than one in absolute value.

Yield Response Equations

For the purpose of computing expected per acre revenues, in addition to expected prices, we need expected yields. We postulate simple linear equations for yield response, following the literature reviewed earlier. Specifically, the expected yield for crop k, county i, at time t is modeled as

$$y_{kit} = \alpha_{ki}^{y} + \beta_{k}^{y} p_{kit} + \boldsymbol{\xi}_{k}^{'} \boldsymbol{\omega}_{it} + \gamma_{k}^{y} T_{t}, \qquad [11]$$

where the vector $\boldsymbol{\omega}_{it}$ includes weather variables (heat and water stress) that are all county and time specific, and T_t is the trend variable defined earlier, which captures exogenous technological progress. The presence of the own expected output price (deflated by general input price) in equation [11] also permits us to investigate whether, and to what extent, expected output prices influence expected yields.

Endogeneity Issues

A standard concern in the econometric estimation of supply equations involves identification and the potential problem of endogenous prices. Given the presumption that the large price increases experienced in the period under consideration were triggered by exogenous demand shifts, including the major role played by the implementation of the RFS, we believe that the potential endogeneity problem is not a major concern in our analysis. The remaining subtle issue concerns the futures prices. Since Gardner (1976) suggested using the futures price as a measure of the expected price, the endogeneity issue has been raised (e.g., Choi and Helmberger 1993). The (subtle) rationale of such endogeneity is predicated on the possibility that farmers may be partially aware of forthcoming supply shocks at decision time, thereby changing their planting area accordingly, which in turn may affect futures prices. When the predictable supply shocks are (usually negatively) correlated with decision-time futures prices, omitting such predictable components from the estimating equation induces correlations between the price variable and the error term and thereby causes endogeneity bias.

There have been efforts to deal with the foregoing endogeneity problem. The crux of the matter concerns how predictable weather shocks affect planting decisions and thereby affect expected price. In the context of an aggregate global caloric supply, it is shown that such endogeneity can be treated by instrumenting price with past weather shocks (Roberts and Schlenker 2013), or simply by including current realized shocks as a proxy for predictable shocks (Hendricks, Janzen, and Smith 2015). In this paper, however, our focus is local (U.S. county-level) supply behavior. Hence, similar to Hendricks, Smith, and Sumner (2014), we assume that the national expected prices (i.e., futures prices) are exogenous.

Estimation

When estimating the equation system of [10], applying simple ordinary least-squares (OLS) estimators, which ignores the individual fixed effects, is known to be problematic because unobserved county-specific heterogeneity tends to be correlated with lagged dependent variables. For example, a severe negative county-specific random shock resulting in a low corn acreage share—given the short time frame of our panel data—may be confounded with the estimated county-specific intercept. Hence, including last year's low corn shares in the current period corn equation may cause positive correlation between the lagged dependent variable and the county-specific heterogeneity in the error term. As a result, the coefficient of the own-lagged dependent variable is overestimated (upward bias). Thus, we need to control the unobserved county-specific heterogeneity to deal with the endogeneity from the omitted variable bias.

To control for the time-invariant, county-specific unobserved heterogeneity, an immediate option is to use the within-groups estimator (i.e., individual fixed effects estimator) by demeaning variables (e.g., by introducing county-specific dummy variables). When using the within-groups estimator, however, the coefficient estimates of own-lagged dependent variables tend to be biased downward because the error term contains the information of demeaned lagged shares (Nickell 1981). Another way to control the unobserved heterogeneity is to take first differences, which, from equation [10], yields following system:

$$\Delta \mathbf{s}_{it} = \mathbf{B}\Delta \boldsymbol{\pi}_{it} + \boldsymbol{\Gamma}\Delta \mathbf{s}_{it-1} + \boldsymbol{\psi}'\Delta \mathbf{x}_{it} + \Delta \boldsymbol{\varepsilon}_{it}. \quad [12]$$

Although the county-specific heterogeneity is eliminated without causing the bias identified by Nickell (1981), equation [12] is still subject to correlation between lagged shares and error terms because both have $t-1$ terms: $s_{ki,t-1}$ in $\Delta s_{ki,t-1}$ and $-\varepsilon_{mi,t-1}$ in $\Delta\varepsilon_{mit}$ for $k=1,2$ and $m=1,2$. Because the own-lagged shares are negatively correlated with corresponding error terms (the case of $k=m$), OLS estimates on the own-lagged share coefficients in equation [12] are biased downward.

To account for endogeneity in the differenced equations, we use the difference GMM estimator as suggested by Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991). Although the foregoing differenced equation estimators have been developed for single-equation models, we can extend them to the two-equation system of interest here (Arnberg and Hansen 2012). To implement this estimator, we use two types of moment-weighting matrices. The first matrix reflects the MA(1) feature of differenced errors and assumes homoskedasticity and no cross-equation correlation, resulting in the one-step GMM estimator. The other matrix allows heteroskedasticity and cross-equation correlation by utilizing residuals from the one-step estimator, resulting in the two-step GMM estimator. Whereas the two-step estimator improves efficiency over the one-step estimator in the case of a complicated error structure, it is subject to downward bias in the computed standard errors, especially in small samples (Arellano and Bond 1991).[8] For comparison purposes, we report both results.

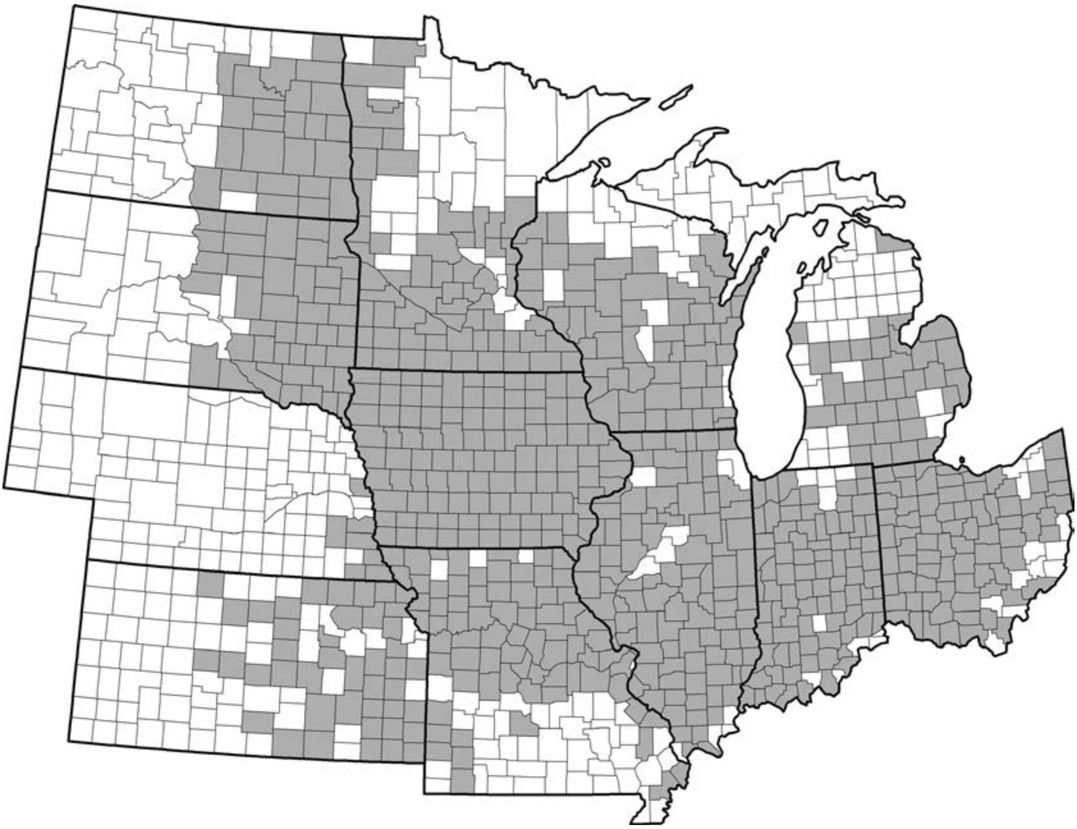
The remaining issue is the choice of instruments. Basically, any lagged level is valid for constructing an instrument, as long as it is lagged sufficiently to handle the existing serial correlation in the error term. However, this proliferation of possible instruments is unattractive because too many instruments overfit the endogenous variables and in turn preserve the bias (Roodman 2009a). The possible remedies are twofold (Roodman 2009b): (1) collapsing the instrument matrix so that each lag generates only one instrument per endogenous variable, and (2) excluding longer lags from instruments. We use both treatments for our instruments. To delimit valid lags, we check the serial correlation on the error term by regressing residuals on each of their lags, as discussed by Wooldridge (2010, 319–20) (see Drukker 2003 for the test performance). Because the equation is first-differenced, the residuals tend to display properties of an MA(1) process. Hence, we expect negative correlation in the first-lagged residual, and so to uncover correlation in the levels it is most meaningful to check twice-lagged residuals. For example, if the estimated coefficient of a twice-lagged residual is significant, we can infer that there is first-order serial correlation in levels, and then for share variables third and higher lagged levels are valid for instruments.

3. Data

For the analysis, we construct two datasets: an acreage dataset for 2005–2015, and a yield dataset for 1971–2015. Restricting the analysis of acreage decisions to 2005–2015 is based on our desire to focus on supply response in the period of the RFS implementation, as discussed in the introduction. The purpose of estimating the yield response model, on the other hand, is to account for anticipated yield increases in computing expected per acre returns. Because the underlying technical progress responsible for yield increases is inherently a long-term phenomenon, observations over a sufficiently long period are desirable. Hence, we estimated the yield model over the much longer period of 1971–2015. In what follows, we explain how we construct each variable in these datasets. The actual analyzed

[8] Windmeijer (2005) proposes a correction procedure for this bias.

Figure 1
Geographic Scope of the Analysis: 686 Counties in 12 Midwestern States



counties in the 12 midwestern states are displayed in Figure 1, and summary statistics are described in Table 1. All monetary values in Table 1 are expressed in their nominal values. For the actual estimation, by construction we consider relative terms normalized by the general input price, as discussed earlier.

Acreage Shares

County-level acreage values for corn and soybeans are from the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA).[9] The 12 midwestern states consist of 1,055 counties with 11,605 data points over the examined 11 years. Focusing on counties that are nonirrigated (i.e., less than 10% irrigation rate, as defined by Xu et al. 2013) and in the traditionally delimited rainfed area (i.e., east of the 100th meridian) yields 832 counties with 9,152 data points. Because NASS/USDA data have missing values, we chose to drop counties with more than one-third of values missing over the 11-year period, resulting in 686 counties with 7,546 data points. After dropping missing data points, we obtain 6,961 observations, still over 686 counties.[10] Note that during the estimation taking the first lag on shares causes loss in observations (besides first differencing). To reduce such data loss, we constructed first-lagged shares by filling in 2004 values.

[9] See https://quickstats.nass.usda.gov/.

[10] To be precise, we have 120 data points out of 7,546 that are missing both corn and soybean acreage values. We drop 277 additional data points because either the corn or soybean acreage value is missing. Finally, 188 observations were dropped because of missing previous year acreage values.

Table 1
Summary Statistics (686 Counties)

	Mean	Std. Dev.	Min.	Max.
Data for Acreage Equations: 2005–2015 (6,961 Observations)				
Acreage share for corn	0.35	0.15	0.005	0.77
Acreage share for soybeans	0.32	0.12	0.004	0.65
Acreage share for other crop	0.33	0.22	0.0005	0.98
Expected revenue for corn ($1,000/acre)[a]	0.63	0.20	0.16	1.07
Expected revenue for soybeans ($1,000/acre)[a]	0.43	0.14	0.14	0.74
Expected revenue for other crop ($1,000/acre)[a]	0.42	0.15	0.10	1.05
Input price index (2010 = 1)	1.03	0.18	0.73	1.23
Palmer *Z* index in Mar	–0.21	1.71	–4.25	7.08
Palmer *Z* index in Apr	0.80	2.18	–4.00	9.04
Palmer *Z* index in May	0.37	2.14	–4.09	8.76
Data for Yield Equations: 1971–2015 (29,494 Observations)				
Yield for corn (bu/acre)	116	36	7	236
Yield for soybeans (bu/acre)	36	10	4	73
Expected price for corn ($/bu)	2.97	1.06	1.26	5.89
Expected price for soybeans ($/bu)	6.91	2.40	2.87	13.31
Input price index (2010 = 1)	0.64	0.26	0.21	1.23
GDD in growing season	2,432	324	1,168	3,418
EDD in growing season	37	50	0	494
Palmer *Z* index in May	0.40	2.21	–4.78	9.35
Palmer *Z* index in Jun	0.24	2.22	–6.51	9.05
Palmer *Z* index in Jul	0.47	2.37	–5.69	15.21
Palmer *Z* index in Aug	0.36	2.19	–5.72	11.69
Palmer *Z* index in Sep	0.16	2.20	-4.94	15.63

[a] The "expected revenues" are the reduced values ($\overline{p}_k \cdot y_k$), without basis and own covariance terms.

Hence, level equation models based on equation [10] have 6,961 observations, while differenced equation models based on equation [12] have 6,149 observations.

In our context, the third category "all other uses" is meant to capture all acres that could conceivably have been planted to corn or soybeans but were not. Hence, we compute it as the difference between total "cropland" and the sum of acres planted to corn and soybeans, as discussed in the previous paragraph. County-level cropland acres are taken from the USDA Census of Agriculture,[11] the main source of land use data in the United States. Total cropland includes five components: cropland harvested, crop failure, cultivated summer fallow, cropland used for pasture, and idle cropland (for a full definition, see Bigelow and Borchers 2017, appendix 1). Census data are available only at five-year intervals, and some imputation for year-specific cropland measures would be necessary. Consistent with the presumption that, within a given county, total available cropland is unlikely to have varied over the last decade, we postulated a constant county-level total cropland area, and we measure it by the maximum among census values recorded over the most recent three censuses (2002, 2007, and 2012). Somewhat oddly, it turns out that for a few cases (113 observations out of 6,961) the sum of corn and soybean acreages from the NASS/USDA is greater than the aforementioned total cropland measure from the U.S. Census of Agriculture, which would imply negative acreage for the "other crops" aggregate. To resolve this issue, for the aforementioned 113 observations, the acreage for cropland allocated to uses other than corn and soybeans is obtained directly from CDL data (see the Appendix for details).

[11] See https://www.agcensus.usda.gov/.

Expected per Acre Revenues

In order to construct the reduced per acre revenue variables used in equations [8] and [9] (i.e., $\overline{r}_{kit} \equiv \overline{p}_{kt} y_{kit}$), we construct expected output prices ($\overline{p}_{kt}$) and expected yields (y_{kit})

for corn and soybeans (while constructing an index of expected per acre revenue for the other crop, as explained later). Expected national prices are constructed from futures prices. Specifically, for crop $k=1$, 2 in year t we set $\overline{p}_{kt} = p_{kt}^{f,\tau}$, where $p_{kt}^{f,\tau}$ denotes the futures price for the first delivery month after harvest, quoted at decision time τ. Daily futures price data were obtained from Quandl.[12] We use futures prices with a delivery month of December for corn and with a delivery month of November for soybeans. We average daily closing futures prices over January to March (i.e., before the planting season). The general input price index is approximated by the national price index for all agricultural intermediate goods from the USDA Economic Research Service.[13] Because the input price index is updated only up to 2013, we keep the 2013 value for 2014 and 2015.

Expected yield values for corn and soybeans are based on the estimated parameters of equation [11]. Given that including or excluding the own-expected price provides virtually identical predicted yields (as shown in the results section), we use the model without output prices. Furthermore, to obtain the expected yield that is relevant at farmers' decision times, we use unconditional mean values for the weather variables over 1971–2015. As for the "other crops" aggregate, this is heterogeneous across counties, both in terms of the types of land uses (other than corn and soybeans) that might be considered by farmers, and the acreage extent of these other crops. To proceed, we proxy per acre revenue for "other crops" with an index of expected revenues for wheat, alfalfa, and sorghum. Appendix Table A1 documents that wheat, alfalfa, and sorghum are in fact the major crops other than corn and soybeans for the states considered in this study. The expected wheat price is constructed similarly to the procedure used for corn and soybeans: it uses the wheat futures price (for the December delivery month, quoted at the decision time). As for the expected alfalfa and sorghum prices, these are measured by averaging state-level received prices for the months of January to March (as done by Hendricks, Smith, and Sumner 2014). Expected yield is the predicted value from county-specific regressions on a linear time trend using NASS/USDA wheat, alfalfa, and sorghum yield data.[14] Now, the expected revenues for wheat, alfalfa, and sorghum are aggregated in the county-specific index by using 2010 acreages as weights. Due to the presence of considerable missing values in NASS/USDA acreage data, we use CDL data to obtain wheat and alfalfa acreage information used in this weighting procedure.[15]

Yield and Weather Variables

County-level yield values for corn and soybeans are obtained from NASS/USDA for 1971–2015. We collect yield values for the 686 counties used in the acreage estimation. To run the seemingly unrelated regression (SUR) model we drop data points for which at least one of either corn or soybean yield is missing. After dropping missing data points, over the 45 years of the sample we eventually have 29,494 observations for yield estimation.

We consider seven weather variables. Two of them are heat variables: growing degree days (GDD) and excess heat degree days (EDD) in the growing season (June to September); and five are water stress variables: monthly Palmer Z indices for May, June, July, August, and September. The definition of these weather variables, and the way they are assembled, follows closely the procedure described by Xu et al. (2013). Briefly, GDD accounts for additional beneficial degrees within 10 °C and 30 °C, while EDD captures additional harmful degrees over 32.2 °C. For 1971–2014 we used the compiled daily temperature data from United States Historical Climatology Network (USHCN) of the

[12] See https://www.quandl.com.

[13] See https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/.

[14] Because of missing values for price and yield in other crops, values for alfalfa in IL are also used for IN, and values for sorghum in IL, KS, and MO are used for IL, IN, IA, KS, MO, NE, and SD.

[15] The base year is chosen as 2010 in order to strike a balance between the accuracy of the CDL, which began using a 30 m subgrid (replacing 56 m) for the entire United States in 2010, and the accuracy of predicted wheat yield (wheat yield data is available only up to 2007 from NASS/USDA).

Table 2
Estimation Results for Corn and Soybean Yields, Seemingly Unrelated Regression Model

	Without Price		With Price	
Variable	Corn Yield (1)	Soy Yield (2)	Corn Yield (3)	Soy Yield (4)
Corn price			0.233* (0.120)	
Soy price				–0.001 (0.016)
Growing degree days	0.008*** (0.001)	0.007*** (<0.001)	0.008*** (0.001)	0.007*** (<0.001)
Excess degree days	–0.299*** (0.004)	–0.069*** (0.001)	–0.299*** (0.004)	–0.069*** (0.001)
Palmer *Z* index in May	–1.054*** (0.048)	–0.375*** (0.013)	–1.053*** (0.052)	–0.375*** (0.013)
Palmer *Z* index in Jun	–0.484*** (0.051)	–0.181*** (0.014)	–0.503*** (0.052)	–0.180*** (0.015)
Palmer *Z* index in Jul	1.636*** (0.051)	0.188*** (0.014)	1.653*** (0.052)	0.187*** (0.014)
Palmer *Z* index in Aug	0.772*** (0.050)	0.693*** (0.014)	0.770*** (0.050)	0.693*** (0.014)
Palmer *Z* index in Sep	–0.382*** (0.050)	–0.017 (0.014)	–0.375*** (0.050)	–0.017 (0.014)
Trend	1.666*** (0.008)	0.431*** (0.002)	1.682*** (0.012)	0.431*** (0.003)
Constant	77.771*** (3.202)	12.452*** (0.893)	75.728*** (3.371)	12.477*** (0.937)
R^2	0.76	0.76	0.76	0.76
Cross correlation of residuals	0.56		0.56	
Own price elasticity			0.010* (0.005)	–0.0004 (0.005)

Note: Standard errors are in parentheses. For elasticities, standard errors are obtained by the delta method.
*, *** Significance at the 10% and 1% levels, respectively.

National Oceanic and Atmospheric Administration (NOAA), which is provided by the Carbon Dioxide Information Analysis Center (CDIAC).[16] However, the CDIAC no longer provides annual updates as of 2014, thus we collected temperature data from the Parameter-Elevation Regressions on Independent Slopes Model database for 2015.[17] Palmer *Z* index data were collected using the daily index data from NOAA's National Centers for Environmental Information.[18] The index measures the deviation from normal water stress, represented by 0, where –2 or less indicates drought and +5 or more indicates flood conditions. All weather variables have no missing values for the 686 counties over 45 years.

4. Results

Because the estimated yield response equations are used to compute per acre expected revenues that feed into the acreage response equations, as discussed earlier, we present these results first.

Yield Response

The estimation results for the yield equations, based on equation [11], are displayed in Table 2. We consider two specifications, with and without the inclusion of the own-expected output price. For both cases, the two yield equations are estimated with the SUR model, although for the case where prices are omitted, the estimated results are identical to those of OLS. The estimated coefficient of the linear trend variable, for the model without inclusion of the own price, shows that exogenous technological change is responsible for a gain of 1.666 bu/acre/year for corn, and 0.431 bu/acre/year for soybeans, a result consistent with recent estimates (e.g., Xu et al. 2013). The weather variables are strongly significant for both corn and soybean yield and across all specifications. Growing season GDD and EDD show the expected signs (positive and negative, respectively). The deviation of water stress is bad for yield during the early and late growing season (that is, planting time and harvesting time) but beneficial during the middle of the growing season (July and August). When including own price, as in columns (3) and (4) of Table 2, the explanatory power of weather and trend variables remains essentially the same. The coefficients of the price variable are not statistically significant

[16] See http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html.
[17] See http://prism.oregonstate.edu/.
[18] See https://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers/.

Table 3
Estimated Coefficients under Dynamic and Static Models

	Dynamic Model 1: One-Step Difference GMM		Dynamic Model 2: Two-Step Difference GMM		Static Model: Two-Step Difference GMM	
Variable	Corn (1)	Soy (2)	Corn (3)	Soy (4)	Corn (5)	Soy (6)
Corn revenue	0.29***	–0.27***	0.29***	–0.26***	0.36***	–0.34***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)
Soy revenue	–0.27***	0.29***	–0.26***	0.29***	–0.34***	0.37***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.008)
Other revenue	–0.03***	–0.03***	–0.03***	–0.03***	–0.02***	–0.03***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.003)	(0.003)
Lagged corn share	–0.10	0.26*	–0.03	0.32**		
	(0.164)	(0.151)	(0.145)	(0.135)		
Lagged soy share	0.26*	–0.19	0.32**	–0.13		
	(0.151)	(0.141)	(0.135)	(0.129)		
Palmer *Z* index in Mar	–0.002***	0.001***	–0.002***	0.001***	–0.003***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Palmer *Z* index in Apr	–0.002***	0.001***	–0.002***	0.001***	–0.002***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Palmer *Z* index in May	–0.002***	–0.001**	–0.003***	–0.001***	–0.003***	<–0.001
	(0.0004)	(0.0003)	(0.0003)	(0.003)	(0.0001)	(0.0001)
Trend	<0.001	0.003***	<–0.001	0.003***	<0.001	0.004***
	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0002)	(0.0002)
Cross correlation in residuals	–0.17		–0.13		–0.28	
p-Value of Hansen's *J* statistic			0.40		0.54	

Note: Standard errors are in parentheses and clustered by counties. GMM, generalized method of moments.
*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

at the customary 5% level. Perhaps most important, their magnitude is economically insignificant: the calculated elasticities of yield response with respect to own-expected output price, at the mean point of the data, are very small: 0.01 for corn and –0.0004 for soybeans. Hence, for the purpose of computing the expected per acre revenue variables for the acreage response equations, we rely on the estimated model of the first two columns of Table 2.

Acreage Response

The estimation results under the acreage models are displayed in Table 3. All dynamic models are based on first differencing as in equation [12]. The results under the heading "Dynamic Model 1" are based on a one-step GMM estimator, while those under the heading "Dynamic Model 2" are based on the two-step GMM estimator. Table 3 also includes results for the static model that omits all lagged dependent variables, with estimation relying on the two-step GMM estimator. All standard errors of estimates are clustered by counties to account for the possible correlated behavior within each county. For comparison purposes, we also estimate three additional models—level-equation OLS, within-groups (fixed effects) OLS, and differenced equation OLS estimators—which are reported in Appendix Table A2.

The assumption underlying our estimation strategy is that the futures price and anticipated yields are exogenous, and thus we treat the constructed per acre return variables as exogenous, along with the spring Palmer *Z* indices. Except for acreage shares, therefore, we use regressors in differences as instruments without lagging. Note that the time trend effect is estimated by constant term in differenced equations, and constant terms are used as instruments too. We find evidence of third-order serial correlations in the error terms for both corn and soybean equations. Hence, we use fifth or longer lagged levels for endogenous variables—corn and soybean shares—for both equations. By collapsing the instrument matrix, we have one instrument per lag per variable, and we choose to use only fifth lagged share levels as instruments, yielding two instruments. Given that there is a trade-off between bias and efficiency in terms of number of instruments in the dynamic panel model (e.g., Hendricks, Janzen, and Dhuyvetter 2012), we sacrifice some efficiency by choosing a small number of instruments. This is mainly because adding more share instruments (such as sixth lag of corn share and sixth lag of soybean share) weakens the orthogonality of instruments to error terms, resulting in high Hansen's J statistics. Admittedly, because each of our estimation equations includes two lagged dependent variables, and there are serial correlations in the level-equation error terms, results may be sensitive to the choice of instruments.[19]

We find that the coefficients for all per acre revenue variables are significant for both corn and soybean equations, under all models in Table 3 (and under all models in Appendix Table A2). In particular, the magnitudes of these coefficients are almost the same under all dynamic models that control the individual fixed effects (that is, the dynamic Models 1 and 2 in Table 3, and the dynamic Models 4 and 5 in Appendix Table A2). This supports the assumption of exogeneity of per acre revenue variables to the idiosyncratic error terms. We also find that those estimates under the static model are larger in absolute terms than those under the dynamic models.

Under dynamic Models 1 and 2, the coefficients of own-lagged shares are not significant, while those of cross-lagged shares are significant. One way to check the validity of those estimates is to compare them with biased estimates. It turns out that the GMM estimates on own-lagged shares are lower than the level equation OLS estimates and higher than the differenced equation OLS estimates. The GMM estimates on cross-lagged shares are similar to those of the within-groups estimates. Therefore, we conclude that the difference GMM estimates are not suffering significantly from finite sample bias. Note that the eigenvalues of the estimated **A** matrix (the coefficients of own and cross-lagged shares) are (0.113, –0.406) for dynamic Model 1, and (0.241, –0.408) for dynamic Model 2, implying that both are dynamically stable.

Severe rainfall in March and April (as captured by the Palmer Z indices) is significantly associated with less corn share but with more soybean share, while in May it explains less shares for both. The cross correlation of residuals between corn and soybean equations are –0.13 to –0.28. For both dynamic and static two-step estimators, the overidentification test statistics (Hansen's J statistics) indicate that the null hypothesis of valid instruments is not rejected.

Elasticities

The properties of the acreage response functions are best illustrated by supply elasticities. If q_k denotes output supply of crop k, then $q_k \equiv A_k y_k = s_k A y_k$. Given that expected yield y_k is independent of prices, the supply elasticity with respect to any explanatory variable is equivalent to the elasticity of the corresponding acreage share. Hence, recalling the construction of per acre expected revenue variables discussed earlier, their estimated coefficients (the **B** matrix) permits the direct calculation of four short-run elasticities $\eta_{kj} \equiv (\partial q_k / \partial p_j)(p_j / q_k)$, $k, j = 1,2$. The remaining short-run elasticities are computed by exploiting the theoretical restrictions for adding-up, symmetry, and homogeneity, as follows:

$$\eta_{3k} = -\eta_{1k}\frac{s_1}{s_3} - \eta_{2k}\frac{s_2}{s_3}, \text{ for } k = 1,2,3 \text{ (adding-up); } \quad [13]$$

$$\eta_{k3} = \eta_{3k}\frac{s_3}{\bar{r}_k}\frac{\bar{r}_3}{s_k}, \qquad \text{for } k = 1,2 \text{ (symmetry); } \quad [14]$$

$$\eta_{kw} = -\sum_{\ell=1}^{3}\eta_{k\ell}, \qquad \text{for } k = 1,2,3 \text{ (homogeneity), } \quad [15]$$

where η_{kw} means the acreage elasticity for crop k with respect to the input price index.

The elasticities are reported in Table 4. All elasticities are evaluated at the mean of

[19] As many applications do, introducing year dummies might reduce the correlation between instruments and errors by controlling any common shocks for all counties in a given year. However, it would distort the explanatory power of per acre revenues that include the futures prices, which are common for all counties.

Table 4
Elasticities at Overall Means

	Corn Price	Soy Price	Other Price	Input Price	η_T
Dynamic: Short Run					
Corn acreage	0.50*** (0.013)	–0.31*** (0.009)	–0.03*** (0.006)	–0.16*** (0.004)	0.04*** (0.007)
Soybean acreage	–0.50*** (0.014)	0.38*** (0.012)	–0.03*** (0.007)	0.16*** (0.004)	
Other acreage	–0.05*** (0.009)	–0.03*** (0.007)	0.07*** (0.011)	0.02*** (0.003)	—
Dynamic: Long Run					
Corn acreage	0.39*** (0.034)	–0.23*** (0.011)	–0.07* (0.038)	–0.09*** (0.010)	0.06* (0.031)
Soybean acreage	–0.32*** (0.032)	0.26*** (0.014)	–0.01 (0.015)	0.07** (0.030)	
Other acreage	–0.12* (0.061)	–0.01 (0.015)	0.09* (0.045)	0.04* (0.020)	—
Static					
Corn acreage	0.61*** (0.010)	–0.40*** (0.008)	–0.02*** (0.004)	–0.19*** (0.003)	0.03*** (0.003)
Soybean acreage	–0.65*** (0.013)	0.48*** (0.010)	–0.04*** (0.004)	0.20*** (0.004)	
Other acreage	–0.03*** (0.006)	–0.04*** (0.004)	0.06*** (0.005)	0.01*** (0.002)	—

Note: Standard errors are in parentheses and obtained by the delta method. η_T is the responsiveness of total acreage allocated to corn and soybeans with respect to same scaling changes in both prices.
*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

the relevant variables, and the corresponding standard error is calculated with the delta method.[20] Given the small difference in the magnitude between one-step and two-step estimates, our baseline dynamic model is based on the two-step GMM estimator because it might improve efficiency to some degree from the one-step estimator when the error structure is not simple. (A caveat is that the robust standard errors might be biased downward for the two-step estimator.) For the dynamic model, calculation of long-run elasticities is analogous to calculation of the short-run elasticities, except that the parameter matrix $\mathbf{B}$ is replaced by $(\mathbf{I}-\mathbf{\Gamma})^{-1}\mathbf{B}$.

Most elasticity values turn out to be statistically significant at the 1% significance level. Under all three cases, all signs accord with expectations. The sign of acreage response with respect to the input price turns out to be positive for soybean acreage and other acreage, which might seem counterintuitive at first blush. It is important, however, to recall that the adding-up condition applies: input price changes do affect acreage, but, because acreage allocations must add up to the given total county cropland, it is not possible for all acreage responses to input price to have the same sign. Based on the baseline dynamic model, the corn and soybean own- and cross-elasticities, which are our main interest, show that both crops have a more elastic response in the short run than in the long run. This is because of the structure of the estimated matrix $\mathbf{\Gamma}$ in the dynamic models, shown in Table 3, which displays strong cross-acreage dynamics between corn and soybeans. Note that corn elasticities are larger than those of soybeans in absolute terms. The cross-price elasticities are fairly large in absolute value, relative to the own-price elasticities, indicating that an expansion of corn acreage largely comes at the expense of soybean acreage (and vice versa). The short-run elasticities for corn and soybeans under the static model are larger than their counterparts under the dynamic model.

Given the relatively large magnitude of cross-price elasticities, an interesting question concerns the responsiveness of total acreage allocated to the two crops, corn and soybeans, resulting from a generalized increase in their prices (a likely outcome from the implementation of the RFS). To best illustrate this concept, therefore, we compute a "total" elasticity η_T defined as follows. Consider scaling the price of both corn and soybeans by a constant $\kappa > 0$, and represent total acreage share allocated to these two crops as

[20] The obvious evaluation point for these elasticities is the mean point of the local per acre revenues r_{kit}. Because of the unobserved component of the basis and price-yield covariance, however, we evaluate the elasticities at the mean point of the variables $\bar{r}_{kit}$ defined earlier.

$s_T \equiv s_1(\kappa r_1, \kappa r_2) + s_2(\kappa r_1, \kappa r_2)$. The total elasticity η_T can then be defined as

$$\eta_T \equiv \frac{\partial s_T}{\partial \kappa} \frac{\kappa}{s_T}\bigg|_{\kappa=1}. \quad [16]$$

By taking derivative with respect to κ of the individual crop shares, and evaluating at $\kappa = 1$, this total elasticity can be expressed in terms of the individual elasticities as follows:

$$\eta_T = \frac{s_1}{s_T}(\eta_{11} + \eta_{12}) + \frac{s_2}{s_T}(\eta_{21} + \eta_{22}). \quad [17]$$

The total elasticity, computed from the reported individual price elasticities, is also reported in Table 4. The elasticity η_T turns out to be equal to 0.04 and 0.06 for the short- and long-run cases, respectively, under the baseline dynamic model, and equal to 0.03 under the static model. This shows an extremely inelastic response of acreage allocated to corn and soybeans: for instance, a doubling of the real price of both of these crops would result in an expansion of the cropland allocated to corn and soybeans of only 4% in the short run (6% in the long run). Although such a response is very inelastic, it is actually somewhat more elastic than the total elasticity implied by the estimate reported by Hendricks, Smith, and Sumner (2014). Although they do not report the total elasticity defined here, it is easily computed based on their individual elasticity estimates. For example, for their long-run elasticity values, the implied total elasticity is equal to 0.0025. The fact that Hendricks, Smith, and Sumner (2014) implied total acreage response is even more inelastic than our estimates, of course, is consistent with the fact that their study uses data for only the three main midwestern states (IL, IN, and IA), where these two crops already account for the vast majority of cropland devoted to annual crops.

Given the estimates of the dynamic parameters $\mathbf{\Gamma}$ and the short-run response parameters $\mathbf{B}$, we can project cumulated values of response parameters $\mathbf{B}_t$ for each year of t as follows:

$$\mathbf{B}_t = \mathbf{B} \times \left(\sum_{\ell=1}^{t} \mathbf{\Gamma}^{(\ell-1)} \right) \quad \text{for } t = 1, 2, \ldots, \quad [18]$$

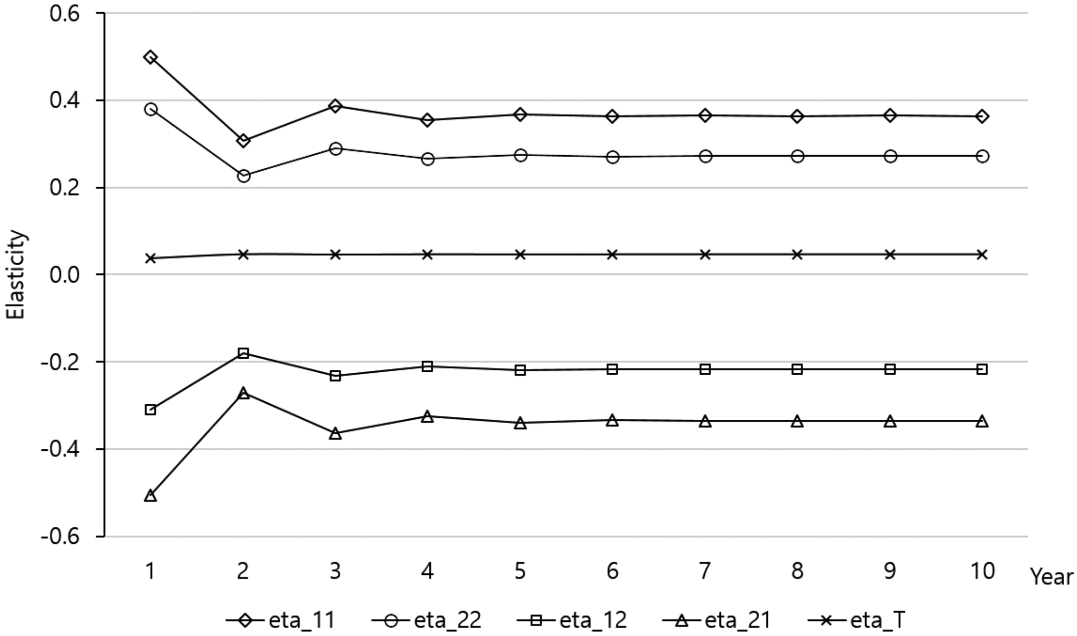
where we assume that the (permanent) changes in per acre revenues occur at $t = 1$. Figure 2 describes the adjustment of elasticities calculated from the projected parameters based on equation [18]. All own- and cross-elasticities show a large adjustment in the first period. The adjustment path displays the oscillating pattern implied by crop rotation effects, discussed by Eckstein (1984). These values converge to the long-run values quickly (most of the adjustment is completed after just three periods). The resulting total elasticity is low and quite stable in all periods, another illustration of the implications of crop rotation.

Robustness

Because the parameters of the expected yields in equation [11] are estimated from a longer time series than for the acreage equation, as discussed earlier, the question arises as to whether the presumption of a linear time trend with the same coefficient for the entire period is appropriate. As noted by a reviewer, the widespread adoption of genetically engineered (GE) corn and soybean varieties since the late 1990s might suggest the possibility of structural changes. As a robustness check, therefore, we also consider a more flexible representation of the trend variable; specifically, we let T_t be represent by a linear spline with two knots (Greene 2012, 159–60), yielding separate trend coefficients for three subperiods: 1971–1985, 1986–2000, and 2001–2015. Results are reported in Appendix Table A3. For corn we find that yield gains per year have indeed trended up, with the largest expected annual yield gain realized in the last subperiod. For soybeans, on the other hand, the first and last subperiods exhibit essentially identical estimated trend coefficients, whereas the middle period, 1986–2000, displays significantly lower yield gains. For both corn and soybeans, these results are consistent with the results of Xu et al. (2013), who find that adoption of GE varieties increased expected yields for corn but not for soybeans.

In the context of our acreage response model, in any event, trending yields matter because they enter into the determination of expected per acre revenues. To investigate

Figure 2
Adjustment of Acreage Responses to Changes in per Acre Revenues



how acreage response is affected by the more flexible specification of yield response, Appendix Table A4 reports the analog of Table 3, and Appendix Table A5 reports the analog of Table 4. It is verified that the results reported here are quite robust to a more flexible representation of the yield response.

5. Comparison with the Literature

Table 5 puts our results for acreage response in the context of findings from previous studies. This table focuses on studies that estimated both own- and cross-price elasticities; as noted earlier, several studies did not do that. Only two of the referenced studies estimated both short- and long-run elasticities, and the latter are denoted with "[LR]." Notwithstanding the difficulty of comparing estimates from studies that differ in scope, data, and methods, four observations appear in order. First, in most cases, corn and soybeans turn out to be substitutes, in accordance with what one should expect when the jointness arises because of an allocatable fixed input (land). Second, in studies conducted before 2000, roughly speaking, the own- and cross-price elasticities for corn tend to be smaller than (or equal to) those of soybeans, in absolute value, while this feature seems absent in more recent studies. Third, the absolute magnitudes of elasticities are larger after 2000. Fourth, our short- and long-run values are very similar to those presented by Hendricks, Smith, and Sumner (2014), except for somewhat increased acreage responses for corn in both the short and long run.

The magnitude of the estimate response of yields to crop prices has been somewhat controversial. Berry and Schlenker (2011), using U.S. state-level data from 1961 to 2009, argue that the yield price elasticities of U.S. crops are no higher than 0.1. Analyzing years from 1980, Scott (2013) obtains the upper bounds of U.S. corn and soybean yield elasticities as 0.04 and 0.11, respectively, based on his indirect approach. Meanwhile, Goodwin et al. (2012) estimate the yield response with respect to their interseasonal price (the average harvest-time futures prices in February) to be in the range 0.19 to 0.27 (for IN, IL, and IA over 1996–2010). They also find small but significant intraseasonal yield response (i.e., yield response in the early growing season).

Table 5
Selected Studies on U.S. Corn and Soybean Acreage Elasticities

					With Respect To	
	Region	Unit	Period	Elasticity Of	Corn Price (or Revenue)	Soy Price (or Revenue)
Lee and Helmberger 1985[a]	IL, IN, IA, OH	State	1948–1980	Corn acres	0.12	–0.17
				Soy acres	–0.23	0.35
Shideed and White 1989[b,c]	United States	Nation	1951–1986	Corn acres	0.19	–0.10
				Soy acres	–0.18	0.41
				Corn acres	0.26 [LR]	–0.15 [LR]
				Soy acres	–0.69 [LR]	1.58 [LR]
Chavas and Holt 1990[d]	United States	Nation	1954–1985	Corn acres	0.07	–0.11
				Soy acres	–0.16	0.06
Orazem and Miranowski 1994[e]	IA	County	1952–1991	Corn acres	0.10	0.02
				Soy acres	0.01	0.33
Miller and Plantinga 1999[f]	IA	County	1981–1994	Corn acres	0.93, 2.35	–1.05, –0.50
				Soy acres	–1.59, 0.55	0.53, 1.76
Arnade and Kelch 2007	IA	County	1960–1999	Corn acres	0.01	–0.04
				Soy acres	–0.03	0.05
Hendricks, Smith, and Sumner 2014[c]	IL, IN, IA	Field	1999–2010	Corn acres	0.40	–0.31
				Soy acres	–0.46	0.36
				Corn acres	0.29 [LR]	–0.22 [LR]
				Soy acres	–0.33 [LR]	0.26 [LR]
This paper[c]	12 midwestern states	County	2005–2015	Corn acres	0.50	–0.31
				Soy acres	–0.50	0.38
				Corn acres	0.39 [LR]	–0.23 [LR]
				Soy acres	–0.32 [LR]	0.26 [LR]

[a] Values are based on their free-market regime.
[b] Values are based on the results using futures price.
[c] [LR] denotes long-run values.
[d] Values are with respect to own and cross revenues instead of prices.
[e] Values are based on the results under rational expectations.
[f] Numbers are paired with smallest and largest values across values for three counties under their unconditional model.

Miao, Khanna, and Huang (2016), focusing on rainfed counties (east of the 100th meridian) over 1977–2007, obtain a relatively large and statistically significant corn yield price elasticity of 0.23, while the elasticity of soybean yield response at the mean was found to be statistically not significantly different from zero. Our results, discussed earlier, agree with those of Miao, Khanna, and Huang (2016) for soybeans (for which we find a zero price elasticity), whereas for corn we find a positive but small yield price elasticity (0.01), corroborating results reported by Berry and Schlenker (2011).

6. Conclusion

The RFS is widely credited with contributing significantly to commodity price increases. This exogenous source of new demand for agricultural products provides an ideal setting to estimate the supply response for corn and soybeans, the major agricultural commodities produced in the United States. This paper estimates the U.S. corn and soybean supply responses by focusing on the most recent 11 years (2005–2015), which have been most directly affected by the implementation of the RFS. In addition, in this period the impact of traditional government support programs has been minimal, making it easier to econometrically identify farmers' supply responses to price signals. One of the main motives of interest in our analysis is to assess the dynamic supply substitutability between corn and soybeans. Hence, the analysis focused on the 12 midwestern states of the traditional corn belt, where most counties are typically observed to produce both crops. Acreage and yield responses are modeled separately. Acreage share equations maintain the standard theoretical properties of homogeneity, adding-up, and symmetry.

Our results, under the dynamic models that we consider, indicate that the U.S. supply responses for corn and soybeans are larger in the short run than in the long run, and that they are quite inelastic. This outcome is attributed to the strong cross-acreage dynamics related to crop rotation behavior. Given that the yield response is nearly zero, we obtain an estimated own-price supply response (at the mean) of 0.50 for corn and 0.38 for soybeans in the short run (and 0.39 and 0.26 in the long run). Our estimated elasticities are quite similar to the short-run and long-run elasticities reported by Hendricks, Smith, and Sumner (2014), and support their conclusions on the impact of crop rotation conjectured by Eckstein (1984).

Cross-price elasticities between corn and soybeans turn out to be negative, as expected, and relatively large in magnitude in the short run and long run. This means that, when both corn and soybean prices move together, the total acreage allocated to these two crops is very inelastic: the relevant total elasticity is 0.04 in the short run and 0.06 in the long run. These results have implications for the future prospects of the RFS. The initial ambitious RFS mandate targets for total biofuel use have had to be scaled back because of the failure of commercial cellulosic biofuel production. Meanwhile, expansion of corn-based ethanol use is at present limited by the so-called blend wall. Hence, given the unfeasibility of scaling up cellulosic biofuel production, a possible avenue for expanding total biofuel consumption is to promote use of biodiesel, which is not constrained by the blend wall (Irwin and Good 2016). Insofar as soybean oil is the marginal fuel for biodiesel production, as analyzed by Moschini, Lapan, and Kim (2017), expanding biodiesel production will require more soybeans. Because of the strong negative cross-elasticity of acreage response, as characterized in this paper, expanded demand for soybeans will put upward pressure on both soybean and corn prices. Indeed, given the extremely inelastic response of total acreage allocated to these two crops, as estimated in this paper, we conclude that the ability of the U.S. corn and soybean production sector to accommodate the demand shock due to the RFS is quite limited. These results are consistent with the observation that, while world production has grown in response to commodity price increases over the 11 years of our study, the U.S. share of world production of both corn and soybeans has been declining.

Acknowledgments

This project was partly supported by NIFA grant, contract number 20146702321804. The authors thank two anonymous reviewers for their constructive comments.

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