Global Growing Area Elasticities of Key Agricultural Commodities Estimated Using Dynamic Heterogeneous Panel Methods

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Abstract

We estimate the short- and long-run global response of corn, soybeans, wheat, and rice growing areas to international crop output price changes while controlling for the effects of price volatility and production costs. We allow responses to vary across countries by adopting methods from the panel time-series literature model. Our estimates of growing-area response are considerably lower than estimates obtained using traditional models. Previous findings appear biased due to the assumption of homogeneous response across countries. Our aggregate estimates of short- and long-run elasticities of four crop-growing areas, with respect to average price, are 0.024 and 0.143, respectively. Crop-specific results indicate that both corn and soybean growing areas are generally more responsive than wheat and rice. For corn and soybeans, the long-run own-price growing area elasticities are 0.210 and 0.631, respectively. The long-run own-price elasticities for wheat and rice are 0.372 and 0.047, respectively. The short-run own-price elasticities for corn and soybeans are 0.100 and 0.213, respectively, compared to wheat (0.035) and rice (0.001). Our findings also reveal that output price volatility acts as a disincentive for growing-area response in the long-run but not in the short-run.

Keywords: Crop price, price volatility, global growing-area response, elasticities, dynamic heterogeneous panel.

JEL codes: O13, Q11, Q13, Q15, Q18, Q24.

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Introduction

Estimates of short- and long-run agricultural crop-growing-area elasticities, with respect to crop output prices, are useful to policymakers and analysts who need to understand the effects of land use change on the environment, food production, and other policy related issues (Searchinger et al., 2008; Roberts and Schlenker, 2013; Haile et al., 2016). A long-running debate in the empirical literature over the magnitude of these elasticities continues. Askari and Cummings (1977), Rao (1989), and de Menezes and Piketty (2012) provide reviews of the literature. The estimates of elasticity vary depending on the theoretical and empirical model used, the method of estimation employed, as well as the sample of countries and crops included. In this paper, we provide consistent and updated estimates of the short- and long-run global agricultural growing area elasticities for four main agricultural commodities (corn, rice, wheat, and soybeans) using a dynamic heterogeneous panel model that accounts for heterogeneity in growing-area response. To the best of our knowledge, this is the first global study that addresses coefficient heterogeneity in a dynamic panel setting.

The elasticity of growing-area with respect to own-price depends on a country's share of global output, governmental domestic and trade policies, technology, random weather, input availability and use, the productivity of land, and price transmission of world prices to local prices, among other factors. Thus, there is no reason to expect that area elasticities are the same across crops and countries. For example, countries that produce a large share of world output tend to respond more in absolute terms than countries with a small share of world output, but likely less in relative terms. Similarly, countries that have higher productive land and more land available tend to respond more. This indicates potential for heterogeneity in the supply responses to prices across countries or groups of countries. Estimation of a worldwide aggregate supply model disregarding heterogeneous slope coefficients across countries leads to biased and inconsistent estimates in a dynamic model. Aggregation over countries can provide consistent estimates in a linear static model with heterogeneous coefficients if the proper theoretical framework of aggregation is adopted. However, our focus in this paper is the estimation of supply response in a dynamic panel model framework. The empirical agricultural supply response literature uses growing area (planted land), yield, or production as a proxy to denote supply. Our analysis focuses on estimating growing-area response to prices, so for the remainder of this paper, we use growing-area response to denote supply.[2]

The literature on estimating supply response to prices has mostly concentrated on one or a few countries (e.g., Binswanger et al., 1987; Lin and Dismukes, 2007; Barr et al., 2011; Yu et al., 2012; Hausman, 2012; de Menezes and Piketty, 2012; Miao et al., 2015; Haile et al., 2016). Recently, Roberts and Schlenker (2013), Haile et al. (2014), Hendricks et al. (2015), and Haile et al. (2015) provide estimates of supply response at the global level. In estimating global growing-area response, these authors either assume homogeneous response across countries, disregard time-series properties of the data, disregard aggregation bias by aggregating over countries in a dynamic supply framework, provide only a short-run response, or adopt a static model. Thus, the objective of this paper is to address these issues in modeling and estimating growing-area response functions.

Using a static supply model, Roberts and Schlenker (2013) and Hendricks et al. (2015) provide estimates of global aggregate growing-area response of four key crops (corn, soybeans, wheat, and rice) to average futures price while controlling for the endogeneity of futures price. One problem with a static model is that it ignores the dynamic nature of agricultural supply response. Haile et al. (2014) aggregate over countries to estimate their global crop-specific dynamic growing-area response model for corn, soybeans, wheat, and rice. In their dynamic model, they regress crop-specific growing area on a lagged growing area, own and competing-crop output prices, input prices, and a time trend. Pesaran and Smith (1995) show that aggregating over a group-specific linear dynamic model that includes a lagged dependent variable induces serial correlation in the residuals of the aggregate equation and produces biased and inconsistent estimates of the average coefficients on the lagged dependent variable as well as on the long-run parameters of interest. Haile et al. (2015) adopt a dynamic panel supply model to analyze global

[2]Planted land (growing area) is generally the best available method of gauging how cultivators translate their price expectations into action (Askari and Cummings, 1977). We use both growing-area response and supply response interchangeably throughout this paper.

growing-area response to price changes and price volatilities for the same four crops examined here. They estimate their model using pooled generalized instrumental variables or generalized methods of moments (GMM) estimators as developed by Arellano-Bond (1991) and Blundell and Bond (1998). Like other pooled panel estimators, GMM estimators address only intercept heterogeneity across panel units (countries). Pooled GMM estimators use past lagged levels as instrumental variables. However, when all the coefficients differ across countries, lagged levels are not valid instrumental variables in pooled GMM estimators. Therefore, the estimates from pooled GMM estimators are not consistent. It is important to examine the supply response to price changes using econometric methods that take care of both the heterogeneity in coefficients and nonstationary nature of the variables in a dynamic panel framework. Thus, we use the mean group (MG) estimator as developed by Pesaran and Smith (1995) to estimate our proposed dynamic heterogeneous panel model of global growing-area response. The MG estimator allows the intercepts, slope coefficients (short- and long-term), and error variances to vary across panel groups.

This article contributes to the study of global growing-area response in two ways. First, we analyze the global growing-area response to international crop output price changes for four key crops while controlling for the effects of price volatility and production costs by adopting an unrestricted dynamic heterogeneous panel model. We estimate the dynamic heterogeneous panel model using the MG estimator. Second, except for Haile et al. (2014), the existing empirical literature on global growing-area response to price changes only provides a short-run response. We provide both the short- and long-run own-price elasticities of growing area and show that they differ significantly but their difference is not as not as large as previously found.

Using country-specific yearly data on growing area, yield, futures prices, world spot prices, price volatilities, and world fertilizer prices from 1961 to 2014, we find that the estimates of short- and long-run elasticities of the aggregate growing area with respect to average price are about 0.024 and 0.143, respectively. With regard to crop-specific estimates, we show that in both the short- and long-run, corn and soybeans growing area are generally more responsive to own-price changes than wheat and rice. The highest response comes from soybeans and the lowest response is from rice. We estimate an own-price elasticity of 0.210 and 0.631 for corn and soybeans, respectively, in the long-run. The long-run responses of growing area with respect to an own-price for wheat and rice are 0.372 and 0.047, respectively. The short-run own-price elasticities for corn, soybeans, wheat, and rice are 0.100, 0.213, 0.035, and 0.001, respectively.

Along with the growing-area responses to prices, we also investigate the effects of price volatility shocks on growing-area allocations. Price volatility or instability acts as a disincentive for producers' resource allocation and investment decisions (Sandmo, 1971; Moschini and Hennessey, 2001) and can make producers worse off if relative risk aversion is not constant (Newbery and Stiglitz, 1982). In particular, smallholder farmers are less likely to invest in measures to raise productivity when price changes are unpredictable (FAO, 2011). Our findings reveal that crop output price volatility acts as a disincentive for growing-area response in the long-run but not in the short-run.

The rest of the paper is organized as follows. Section 2 provides an overview of the existing supply response model and discusses the proposed empirical model. Section 3 describes data. Section 4 presents the empirical findings and an interpretation of the findings. Section 5 concludes.

2 The Economic Model and Empirical Strategy

2.1 The Economic Model

Early work on supply response mainly focused on policy issues rather than the development and application of theoretical or econometric methods (e.g., Bean, 1929; Cassels, 1933). In the late 1950s and 1970s, two major approaches were developed to estimate supply response: the Nerlovian (1958) supply model and the supply function obtained from profit maximization using duality theory. The two basic ideas behind the formulation of Nerlovian supply model are adaptive expectations and partial adjustment. This model facilitates the analysis of both the speed and level of adjustment of growing area towards desired growing area. The duality approach is based on the theory of production and the firm and involves joint estimation of output supply and input demand functions. The weakness of the duality approach is that input prices are often difficult or impossible to obtain across countries. Thus, we base our analysis on the Nerlovian approach.

The popularity of the Nerlove approach (Askari and Cummings, 1977; Coleman, 1983; de Menezes and Piketty, 2012) owes to its simplicity and ease with which the parameters of interest can be interpreted. For example, a linear regression of log output quantity on log price and lagged log output produces estimates of both short- and long-run supply elasticities. In addition, there is often a delayed adjustment in agricultural markets due to a lack of availability of resources and consideration of crop rotations. Thus, it is essential to adopt a dynamic approach in modeling supply analysis that recognizes time lags in agricultural supply response (Yu et al., 2012). In its simplest version, Nerlove's structural supply model for a specific crop consists of the following three equations (Nerlove, 1979; Braulke, 1982)

$$A_t^* = \beta_0 + \beta_1 P_t^* + u_t \quad (1)$$

$$P_t^* = P_{t-1}^* + \pi \ (P_{t-1} - P_{t-1}^*) \quad (2)$$

$$A_t = A_{t-1} + \gamma \ (\mathrm{A}_t^* - A_{t-1}) \quad (3)$$

where A_t^* and A_t denote desired and realized planted area of a certain crop at time t, respectively, P_t^* and P_t refers to the vector of expected and actual own and competing crop prices at time t, u_t is the unobserved random factor with zero expected mean affecting area under planting, π and γ are the expectation and adjustment coefficients, respectively.

Two reduced-form variants of the above structural model can be derived either assuming adaptive price expectations (equation 2) or assuming partial adjustment (equation

3). When price expectations are adaptive and $A_t^* = A_t$, then the reduced form of the above structural model can be expressed as[3]

$$A_t = \beta_0 \pi + \beta_1 \pi P_{t-1} + (1-\pi) A_{t-1} + u_t \tag{4}$$

This states that growing-area supply is a function of its own lagged value and lagged price with the short-run price elasticity equal to $\beta_1 \pi$. Alternatively, when only the assumption of partial adjustment (equation 3) holds, the Nerlovian supply function takes the following form

$$A_t = \beta_0 \gamma + \beta_1 \gamma P_t^* + (1-\gamma) A_{t-1} + u_t \tag{5}$$

When both adaptive expectation and partial adjustment mechanisms are present, then by solving the systems (1)-(3) and including other exogenous non-price variables Z_t (input costs, technology shifters, weather shock, risk, expected yield etc.), we find the following reduced form of the Nerlovian supply equation

$$A_t = \mu + \delta_{10} P_{t-1} + \delta_{20} Z_t + \lambda_1 A_{t-1} + \lambda_2 A_{t-2} + \varepsilon_t \tag{6}$$

where $\mu = \beta_0 \pi \gamma$, $\delta_{10} = \beta_1 \pi \gamma$, $\lambda_1 = (1-\pi) + (1-\gamma)$, $\lambda_2 = -(1-\pi)(1-\gamma)$

and $\varepsilon_t = \gamma (u_t - (1-\pi) u_{t-1})$.

Equation (4) is not estimable because desired growing area is not observable unless $A_t^* = A_t$. Equation (5) is estimable as long as a suitable proxy for expected price is available. Identification of parameters in equation (6) is difficult because it is not possible to distinguish between π and γ when both adaptive expectations and partial adjustment are present (Nerlove, 1979; McKay et al., 1999). Among the three, most empirical estimations have been based on equation (5), which uses past-year realized price or futures price as the proxy of expected price. Thus, we rely mainly on the model specification (5) to estimate the global growing-area response.

[3] Nerlove (1956 pp. 502) derives this model by noting that any expected price can be written as a linear function of growing area. The Koyck transformation also provides the same specification.

2.2 Empirical Strategy

As the goal of this paper is to estimate the global growing-area response based on the country-specific variables that are observed in period t, country i (i=1,….,N), and crop c we express equation (5) in the following dynamic heterogeneous panel form

$$A_{ict} = \mu_{ic} + \sum_{k=1}^{4} \delta_{10ick} P_{ikt}^{e} + \sum_{k=1}^{4} \delta_{20ick} vol(\mathrm{P})_{ickt} + \delta_{30ic} FP_{ict} + \lambda_{ic} A_{ic,t-1} + \tau_{ic} t + \varepsilon_{ict} \qquad (7)$$

where A_{ict} denotes actual planted area of crop c (corn, soybeans, wheat, and rice) at time t, P_{ikt}^{e} refers to farmers' expected own and competing crop prices. Both are pre-planting time-observed prices or traded futures prices. $vol(\mathrm{P})$ is the measure of own and competing crop price risks that affect planting decisions, FP refers to prices of variable inputs (e.g., fertilizer price) and t is the time trend (a proxy for technology). All variables (except price volatilities) are in logarithmic forms, so the estimated coefficients can be interpreted as elasticities. For example, when $k = c$, the parameter δ_{10ick} can be interpreted as the own-price growing area elasticity. Otherwise for $k \neq c$ it can be interpreted as a cross-price elasticity.

In equation (7) we assume heterogeneous elasticities across countries and crops because our panel of countries is not similar in terms of development. Ignoring the heterogeneity in the dynamic panel can lead to inconsistent estimates of the parameters of interest in equation (7). One way to solve this problem is an estimation of N separate regressions. However, if the objective is to estimate the total mean of panel group elasticities, it is much more common to use pooling or aggregating. We now discuss potential bias of applying common estimation procedures—pooled and aggregate time-series—to the dynamic heterogeneous panel model (equation 7).

For simplicity, consider the following simple model, where the growing-area response equation of a certain crop for country i is expressed as a function of expected crop prices and lagged growing area

$$A_{it} = \delta_{10i} P_{it}^{e} + \lambda_i A_{i,t-1} + \varepsilon_{it}, i = 1, 2, ..., N, \; t = 1, 2, ..., T, \qquad (8)$$

with the short-run parameters δ_{10i} and λ_i as well as the long-run parameters $\theta_i = \delta_{10i} / (1-\lambda_i)$ and $\varphi_i = \lambda_i / (1-\lambda_i)$ varying across panel group i according to the following two random coefficients model:[4]

$$H_1 : \lambda_i = \lambda + \eta_{1i}, \quad \delta_{10i} = \delta_{10} + \eta_{2i} \tag{9}$$

and

$$H_2 : \varphi_i = \varphi + \xi_{1i}, \quad \theta_i = \theta + \xi_{2i} \tag{10}$$

First, consider the case where equation (8) is estimated using time-series data by aggregating across countries. In this case, aggregating (equation 8) over the panel group, utilizing equation (9), and including an intercept term, we can write the aggregate growing area of a certain crop at time t as

$$\overline{A}_t = \alpha + \delta_{10}\overline{P}_t^e + \lambda \overline{A}_{t-1} + \overline{\upsilon}_t \tag{11}$$

where $\overline{A}_t$ and $\overline{P}_t^e$ are sample means of A_{it} and P_{it}^e across i, and

$$\overline{\upsilon}_t = \overline{\varepsilon}_t + N^{-1}\sum_{i-1}^{N}(\eta_{1i}A_{i,t-1} + \eta_{2i}P_{it}^e) \tag{12}$$

In the aggregate equation (11), the macro disturbance $\overline{\upsilon}_t$ is correlated with crop price, as a result, the OLS estimators based on equation (11) will be biased and this bias does not disappear even if $N \to \infty$ *and* $T \to \infty$ (Pesaran and Smith, 1995). These authors show that the aggregated disturbance term will have a complicated pattern of serial correlation and the aggregate equation (11) will be misspecified such that it cannot be used to obtain consistent estimates of δ_{10} and λ. However, under two special cases, the OLS estimator will be consistent. Lewbel (1994) shows that if λ_i and δ_{10i} are independently distributed [$\mathrm{Cov}(\eta_{1i}, \eta_{2i}) = 0, \forall i$], then the aggregate short- and long-run growing-area elasticities can be estimated consistently using equation (11). The average long-run response of growing area to price changes will be consistent if equation (11) is estimated by allowing an infinite distributed lag specification between $\overline{A}_t$ and $\overline{P}_t^e$ (Pesaran and Smith, 1995).

[4] The results also hold in the case where the coefficients are fixed but differ across groups.

Second, consider the pooled estimates of equation (8). A pooled regression assumes homogeneous elasticities across countries. The pooled regression of the equation (8) including an intercept term can be expressed as

$$A_{it} = \alpha_i + \delta_{10} P_{it}^{e} + \lambda \ A_{i,t-1} + \upsilon_{it} \tag{13}$$

where

$$\upsilon_{it} = \varepsilon_{it} + \eta_{1i} A_{i,t-1} + \eta_{2i} P_{it}^{e} \tag{14}$$

In the empirical literature, four variants of the pooled estimator are used to estimate equation (13). They are pooled ordinary least squares (OLS), fixed effects (FE), random effects (RE), and GMM methods. Let's consider the extreme case where $\eta_{1i} = 0, \eta_{2i} = 0$ and $\alpha_i = \alpha$ (i.e., the heterogeneity of the coefficients is completely ignored). In this case, the OLS regression of current-year growing area on lagged growing area and other explanatory variables produces inconsistent estimates, because lagged growing area is correlated with the country fixed effects, α_i and therefore violates the strict exogeneity assumption. Anderson and Hsiao (1981) show that the pooled OLS regression estimates are inconsistent for small T and large N. However, they also show that for large T and small N the OLS estimates are consistent, which depends on the unrealistic assumptions about initial values of dependent variables. Next, consider the case where the heterogeneity of α_i are fixed but differ across countries. In this situation, for small T and large N, the estimates from FE estimator will suffer from dynamic panel bias because of the correlation between the lagged dependent variable and the mean random error, where the mean random error is the mean over the time period across each country (Nickell, 1981). As a result, the FE estimator will be inconsistent. The FE estimator will be consistent if the regressors (e.g., crop output prices) are not serially correlated and T is very large. We also note here that the RE estimator is inconsistent in dynamic panel regression because fixed effects are always correlated with the lagged dependent variable. This inconsistency does not disappear even when T goes to infinity. The fourth estimator is the instrumental variables estimator, or GMM estimator, as developed by Anderson and Hsiao (1982), Arellano and Bond (1991), and Blundell and Bond (1998). This estimator has been used in the recent literature to estimate dynamic panel models. The GMM estimator uses lagged levels of the dependent variables as the instrumental variables to remove dynamic panel bias. For small T and large N, where T/N tends to zero, it provides consistent estimates of short-run coefficients. However, with large T and N, where T/N tends to a positive constant, the GMM estimator has a negative asymptotic bias of order 1/N. When T < N, this asymptotic bias is always smaller than the fixed-effect bias. When T=N, the asymptotic bias of GMM and the fixed effect are the same. With T>=N the coefficients of the lagged dependent variable as estimated by GMM asymptotically coincide with the FE estimates (Alvarez and Arellano, 2003). Moreover, the GMM estimator is designed for micro datasets where N is large relative to T (Bond, 2002; Alvarez and Arellano, 2003; Roodman, 2009b). In our case, T is large relative to N.

In the more standard case (ours is similar to this) where $\eta_{1i} \neq 0, \eta_{2i} \neq 0$, and $\alpha_i = \alpha_i$, the estimates from all four pooled estimators as discussed above are biased and inconsistent because P_{it}^e and $A_{i,t-1}$ are correlated with υ_{it} (Pesaran and Smith, 1995). This bias does not go away even when N and T are very large. Pesaran and Smith (1995) note that this bias or inconsistency is different from that suffered by the FE estimator (assumes homogeneous slope) in small T panels as $N \to \infty$ (e.g., Nickell, 1981). When we use the FE estimator to estimate equation (8), the estimates of the long-run effect, θ, will be asymptotically biased, and overestimates the long-run effect if crop prices are positively autocorrelated, and underestimates it if prices are negatively autocorrelated. Even pooled GMM estimators such as Arellano-Bond (differenced GMM) or Blundell-Bond (system GMM) that use lagged values as instruments for endogenous explanatory variables are also inconsistent. Pooled GMM estimators are biased because the composite disturbances υ_{it} in equation (13) contains a lagged dependent variable. This means υ_{it} will be correlated with all variables that are correlated with P_{it}^e or $A_{i,t-1}$. Thus, lags of the endogenous explanatory variables are not valid instruments. Intuitively, only variables that are uncorrelated with lagged values of ε_{it} and P_{it}^e, have a zero correlation with υ_{it}, but such variables, assuming they exist, fail to yield a valid set of instruments, since they will also be uncorrelated with the regressors of equation (13) (Pesaran and Smith, 1995).

To summarize, estimating equation (7) or equation (8) by aggregating over countries and applying OLS, or traditional pooled panel regression methods, or GMM will generally result in biased and inconsistent estimates of growing-area elasticity. First, averaging the data over groups and estimating aggregate time-series data using the OLS method produces inconsistent estimates of parameters. Second, FE estimator produces biased and inconsistent estimates of the parameters of interest because of dynamic panel bias caused by the correlation between the lagged dependent variable and the unobserved country fixed effects. The GMM estimators are not consistent when the coefficient on the lagged dependent variable and autocorrelated regressors are heterogeneous. This is because lags of the dependent variable are not valid instruments as used by GMM estimators. Moreover, GMM estimators overfit long T panels (usually for $T>10$), assumes cross-section independence among panel members, and requires stationarity of the variables. Therefore, we need an estimator that accounts for all of these issues and provides consistent estimates of the growing-area elasticity.

We propose to use the mean group (MG) estimator as developed by Pesaran and Smith (1995)[5]. The MG estimator allows the intercepts, elasticities (short- and long-term), and error variances to vary across groups. Given the characteristics of the data that we have, the MG estimator is the most suitable method to estimate global crop growing-area response. We have data on crop area, yield, prices, price volatilities, and yield shock for four major crops for many countries. The countries differ from each other in terms of production culture, technology, economic development, institution, and so on. Therefore, it is likely that the response of the crop growing area will differ across countries—both in the short- and long-run. Thus, we rely on the MG estimator to estimate our dynamic heterogeneous panel growing-area response model. The MG estimator involves estimating separate regressions for each panel group and averaging the coefficients over groups. This estimator provides both the short- and long-run estimates of parameters of interest.

[5] Appendix A shows mathematical details of the consistency of MG estimator.

Given the autoregressive lag relation in equation (7), we hypothesize that the growing-area response model has the following general autoregressive distributed lag (ARDL) (1, 1, 1, 1, 1) dynamic panel form[6]

$$\begin{aligned} A_{ict} = \mu_{ic} + \sum_{k=1}^{4}\delta_{10ick}P_{ikt}^{e} + \sum_{k=1}^{4}\delta_{20ick}vol(\mathrm{P})_{ikt} + \delta_{30ic}FP_{ict} + \sum_{k=1}^{4}\delta_{11ick}P_{ik,t-1}^{e} + \\ \sum_{k=1}^{4}\delta_{21ick}vol(\mathrm{P})_{ik,t-1} + \delta_{31ic}FP_{ict-1} + \lambda_{ic}A_{ic,t-1} + \tau_{ic}t + \varepsilon_{ict} \end{aligned} \tag{15}$$

This ARDL specification improves on the usual autoregressive lag (ADL) model equation (7) in several ways. First, the assumption that the disturbances ε_{ict} are distributed independently across countries is not necessary and the assumption of its independence across time can be satisfied as long as we add additional lags of both dependent and explanatory variables in the ARDL model (Pesaran et al., 1999). Second, it is not necessary to have the variables be integrated of the same order. Third, and most important, it is easy to reparametrize the model into error correction form from which we can easily distinguish the estimates of the short- and long-run elasticities. Moreover, contrary to the assumption of stationary expectations usually made for the partial adjustment model, the error correction model (ECM) incorporates forward-looking behavior by agricultural producers as it can be derived from the minimization of an inter-temporal quadratic loss function (Nickell, 1985). We can also test for co-integration in the ECM by closer investigation of the statistical significance of the error correction term. Thus, we work with the following error correction (EC) reparametrization of equation (15) in estimating global growing-area response

$$\begin{aligned} \Delta A_{ict} = \phi_{ic}(A_{ic,t-1} - \theta_{0ic} - \sum_{k=1}^{4}\theta_{1ick}P_{ikt}^{e} - \sum_{k=1}^{4}\theta_{2ick}vol(\mathrm{P})_{ikt} - \theta_{3ic}FP_{ict}) + \sum_{k=1}^{4}\delta_{11ick}\Delta P_{ikt}^{e} + \\ \sum_{k=1}^{4}\delta_{21ick}\Delta vol(\mathrm{P})_{ickt} + \delta_{31ic}\Delta FP_{ict-1} + \varepsilon_{ict} \end{aligned} \tag{16}$$

[6] Griliches (1967) discusses adding lags of explanatory variables as additional controls in the Nerlove's partial adjustment model.

where Δ denotes first difference, $\theta_{0ic} = \dfrac{\mu_i}{1-\lambda_{ic}}$, $\theta_{jic} = \dfrac{\delta_{j0ic} + \delta_{j1ic}}{1-\lambda_{ic}}$, and $\phi_{ic} = -(1-\lambda_{ic})$,

$k = 1, 2, \ldots, 4$.

Equation (16) is our main empirical model. The objectives of this paper are to estimate the short-run own-price growing-area elasticity, δ_{11ic}, and its mean; the long-run own-price growing-area elasticity, θ_{1ic}, and its mean; and the error correction speed of adjustment parameter, ϕ_{ic}, and its mean. As long as the adjustment parameter, λ_{ic} is less than unity, the long-run growing-area elasticity will always be greater than the short-run elasticity. Thus, we can express both the short- and long-run country-specific and global growing-area elasticities as follows:

The short-run change in growing area with respect to own-price changes for country i and global elasticities are

$$\left.\frac{\partial \Delta A_{ict}}{\partial \Delta P^e_{ict}}\right|_{short-run} = \delta_{11ic},\ \bar{\delta}_{11} = \sum_{i=1}^{N} \delta_{11ic} / N \tag{17}$$

The long-run growing-area response to own-price for country i and global elasticities are

$$\left.\frac{\partial A_{ict}}{\partial P^e_{ict}}\right|_{long-run} = \theta_{1ic} = \frac{(\delta_{10ic} + \delta_{11ic})}{1-\lambda_{ic}},\ \bar{\theta}_1 = \sum_{i=1}^{N} \theta_{1ic} / N \text{ or } \bar{\theta}_1 = (\bar{\delta}_{10} + \bar{\delta}_{11}) / (1-\bar{\lambda}) \tag{18}$$

We estimate the total mean of each parameter of equation (16) by running separate OLS regressions for each country and taking the weighted average of the country-specific estimates, which is known as estimates from the MG estimator. Because of the non-linear nature of the parameters in equation (16), we apply Stata's nonlinear combinations of estimators (nlcom command) to estimate the mean parameters.

The central assumption for the validity of the MG estimator is the assumption of exogeneity of explanatory variables. The key variables in our dynamic panel model are expected crop price. For the expected price, we use pre-planting time futures or spot price. We assume that the pre-planting time price is exogenous to growing area. The standard assumption of no omitted variables holds as long as growing area is not affected by expected yield shocks and unobserved factors that affect growing area are unknown prior to planting. As a result, the pre-planting futures prices are exogenous to growing area (Hendricks et al., 2014). Our exogeneity assumption of expected price is also supported by findings of existing empirical literature. Choi and Helmberger (1993) find almost no difference between OLS and three-stage least square estimates of the U.S. soybean growing-area response to price changes. Hendricks et al. (2015) find only a very small bias in regressions with the global growing-area response to the futures price.

Suppose our exogeneity assumption fails and anticipated yield or demand shocks affect futures prices. Pesaran (1997) show that in the mean group estimation, it relatively straightforward to allow for the possible correlation between explanatory variables and the disturbances when estimating the long-run coefficients, as long as the explanatory variables have finite-order autoregressive representations. Moreover, to assess the robustness of our original regression results to our exogeneity assumption, we include current-year realized yield shock as a control variable for the proxy of the anticipated production shocks. This is similar to the approach of Roberts and Schlenker (2013) and Hendricks et al. (2015). These authors use current-year realized yield shock as a control variable in their empirical supply model to account for the endogeneity of futures prices that may arise from the anticipation of production shocks.

3 Data and Variables

We use a comprehensive database covering country-level data from 1961 to 2014. The data include area planted, area harvested, yields, futures prices, and spot prices for each of the four main crops. In addition, the data include fertilizer prices indices that are used as proxies for production costs.

We obtain data on area planted from country-specific statistical sources wherever data were available. In the case where data on planted area were not available, we use area harvested as a proxy for planted land. Data on area harvested and yields for each country are obtained from the FAOSTAT database by the Food and Agricultural Organization (FAO), United Nations. Crop futures prices traded in Chicago Board of Trade (CBOT) are obtained from the Quandl database. The international spot prices and fertilizer price indices are obtained from the database Global Economic Monitor (GEM) Commodities, World Bank Group. All prices are converted in real terms using the U.S. urban Consumer Price Index (CPI). We obtain CPI from the U.S. Bureau of labor Statistics (BLS).

We construct a panel dataset for a group of 31 countries (or regions) based on the country-specific caloric share in global aggregate (four crops) caloric production. A country that produces greater than equal to 0.5% of the total global caloric production is considered as single panel unit. The remaining countries are aggregated and denoted as the rest of southern hemisphere and northern hemisphere depending on the planting date of each crop.

Farmers around the world are assumed to make their planting decision based on the prices they expect to receive at harvest time. In modeling their expectation, we use two price series: (*a*) the U.S. crop futures prices measured during the pre-planting period on contracts for harvest-time delivery; and, (*b*) the pre-planting time international spot prices. As the crop planting dates in each country differ, the futures and spot prices vary across countries. Planting and harvesting calendar for corn, soybeans, wheat, and rice are reported in tables B1, B2, B3, and B4 of appendix B.[7] For countries in the southern and northern hemisphere, we use the planting times of Brazil and the U.S., respectively. The futures price for each crop is pre-planting harvest time price traded in CBOT. The spot price is pre-planting time observed or actual price. Haile et al. (2015) and Miao et al. (2015) model the farmers' price expectation in a similar fashion. Haile et al. (2015) model for countries around the world and Miao et al. (2015) model for the states of the U.S. Examples of other studies that use the price of harvest-time contract traded prior to planting are Orazem and Miranowski (1994), Roberts and Schlenker (2013), and Hendricks et al. (2015).

We include price volatility as a control to measure the impact of price risk on growing-area decision. We construct the price risk (a measure of price volatility) by calculating the standard deviation of pre-planting 12-month price return. Price return is defined as the ratio of current month log prices to past month log prices (i.e., $\ln P_t \ / \ln P_{t-1}$). Price risk is also

[7] Crop calendar for each crop is from http://www.amis-outlook.org/amis-about/calendars/en/ and Haile et al. (2015).

country specific because we calculate the 12-month standard deviation for each country based on the varying planting dates. We include current-year realized yield shocks in our empirical model as a proxy for anticipated weather or other anticipated supply shocks that may affect growing area decisions as a robustness check. We assume that farmers take into account these expected yield shocks, defined as the actual yield deviation to predicted yield, while allocating land across crops. Following Roberts and Schlenker (2013), we model yield of each country-crop pair as a flexible time trend to construct yield shock. Flexible trends are approximated by a restricted cubic spline, which places knots at a specific interval of time. A restricted cubic spline produces a continuous smooth function for a variable that is linear before the first knot, a piecewise cubic polynomial between adjacent knots, and linear again after the last knot (StataCorp, 2013).

We estimate global aggregate as well as crop-specific responses for the four main agricultural crops. In estimating aggregate response to price changes, we sum up the growing area of four crops for each panel group. The average price is the caloric-weighted average of either the harvest time futures prices or the international spot prices of corn, soybeans, wheat, and rice. Price risk is the simple average of crop-specific standard deviation. Country-specific yield shock is constructed by taking the log of the weighted average of crop-specific yield shocks. In estimating crop-specific growing-area response, we use the variables as defined above. Fertilizer price indices are common to all of our empirical models and are also crop- and country-specific.

Figure 1 shows global growing area changes from 1961 to 2014. While calculating both absolute and percentage changes, we take 4-year averages so that bias from year-on-year fluctuations caused by random shocks is minimized. Several findings are noteworthy: first, growing area of all crops increased substantially and similarly in both the 1981–1984 and 2011–2014 periods. Growing area increases were low from the late 1980s to early 2000s. Second, absolute changes of corn and soybeans growing area are greater compared to wheat and rice area in the 2011–2014 period. Third, overall, soybeans exhibit the largest percentage change, while wheat exhibits the smallest change. Corn and rice are in the middle and exhibit similar percentage changes. Given these patterns of changes, it would make sense if the growing-area response to crop prices is highest for soybeans followed by corn, rice, and wheat if proportional changes in prices are the same for all crops.

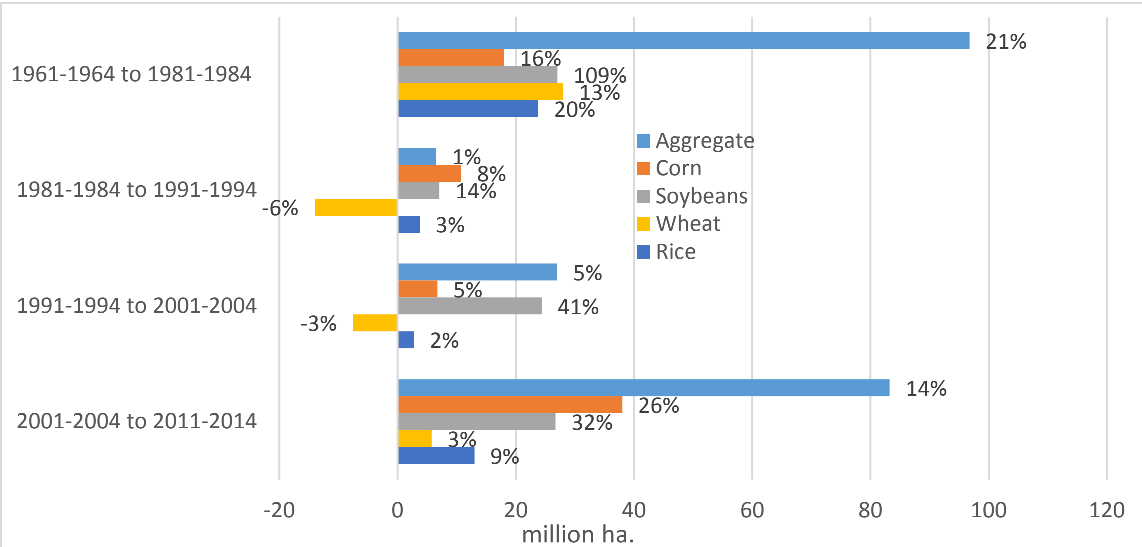

Figure 1. Changes in global growing area from 1961 to 2014.

4 Empirical Results and Discussions

For large T and N, it is likely that the variables will have unit roots. Hence, this section starts by presenting the unit root tests that are shown in Table 1. We employ the Maddala and Wu (1999) Fisher-type, lm-Pesaran-Shin (2003), and Pesaran (2007) panel unit root tests. In all approaches, we conduct the test with no trend. The number of lags for each series is chosen in such a way that the Akaike information criteria (AIC) for the regression is minimized. The null hypothesis for all approaches is all panels contain unit roots.

The results show that most of the variables are nonstationary in levels form but their first difference is stationary. As expected, the yield shock is stationary. The presence of nonstationary variables in level imply that the pooled or standard fixed-effect regression model would not constitute a co-integrating regression and the parameter estimates would be inconsistent (Pesaran and Smith, 1995). The empirical model of equation (16) takes care of such problem by introducing the error correction adjustment parameter ϕ_i .

Table 1. Unit Root Test Results

	Fisher (ADF)-Inverse Chi Square		lm-Pesaran-Shin (2003)		Pesaran (2007)	
	H0: No Unit Root		H0: No Unit Root		H0: No Unit Root	
Variables	Level: p value	Difference: p value	Difference: p value	Difference: p value	Level: p value	Difference: p value
Aggregate area	0.516	0.000	0.710	0.000	0.048	0.000
Maize area	0.021	0.000	0.567	0.000	0.010	0.000
Soybeans area	0.051	0.000	0.000	0.000	0.914	0.000
Wheat area	0.004	0.000	0.000	0.000	0.011	0.000
Rice area	0.190	0.000	0.516	0.000	0.980	0.000
Aggregate price	0.971	0.000	0.160	0.000	0.000	0.000
Maize price	0.910	0.000	0.162	0.000	0.981	0.000
Soybeans price	0.847	0.000	0.545	0.000	0.974	0.000
Wheat price	0.932	0.000	0.150	0.000	0.003	0.000
Rice price	0.025	0.000	0.000	0.000	0.084	0.000
Aggregate shock	0.000	0.000	0.000	0.000	0.000	0.000
Maize shock	0.000	0.000	0.000	0.000	0.000	0.000
Soybeans shock	0.000	0.000	0.000	0.000	0.000	0.000
Wheat shock	0.000	0.000	0.000	0.000	0.000	0.000
Rice shock	0.000	0.000	0.000	0.000	0.000	0.000
Fertilizer price	0.919	0.000	0.938	0.000	0.994	0.000

Note: Lag for each unit root test is chosen based on Akaike information criteria (AIC)

The primary parameters of interest are the short- and long-run global growing-area elasticities with respect to crop prices. We report both in terms of aggregate growing-area response of four crops and in terms of crop-specific growing-area response. In estimating aggregate growing-area response, we assume land and other input requirements are identical for each crop. A practical reason for aggregation is that prices for all four crops are highly correlated, which seriously impedes identification of multiple cross-price elasticities. Furthermore, separating cross-price elasticities from own-price elasticities is quite difficult with correlated prices (Roberts and Schlenker, 2013). When estimating crop-specific growing-area response, we relax this assumption and instead assume producers reallocate their cropland across crops based on the relative crop prices. This means the area expansion of a particular crop can come from its competing crops rather than from new land.

Table 2 presents the aggregate estimates of growing-area response to prices derived from the ECM specification (equation 16). Columns of the table differ from each other by the estimation methods as well as by the type of the price variables. The MG estimator allows heterogeneity in intercepts, coefficients, and error variances. The dynamic fixed-effect (DFE) method allows only fixed but heterogeneous intercepts. Columns (1)–(2) of table 2 reports estimates of the growing-area response assuming each country faces the same global futures price, whereas columns (3)–(4) report the response assuming each country faces a country-specific price.

In each model, we focus on the short- and long-run estimates as well as the coefficient (adjustment) on the error correction term to investigate the evidence for a long-run relationship (table 2). The error correction parameter also allows adjustment from short-run to long-run. In all MG and DFE models, the error correction terms are negative and significant—strong evidence for the long-run impact of price on the aggregate growing area. The results show that the growing-area response to price changes are positive and significant across all models—both in the short- and long-run. In general, the long-run response is higher when we use the DFE estimator, especially with country-specific prices. However, as mentioned earlier, fixed-effects estimates of long-run response are asymptotically biased and overestimate the long-run effect when positive autocorrelation is present in the explanatory variables. A simple pooled fixed-effects regression of current year price on lagged price with time trend provides strong evidence of positive autocorrelation in prices where the autocorrelation coefficient equals to 0.826 (the result is not reported here). The short-run response of growing area to price changes are almost the same across all price specifications. The results show that higher crop prices induce farmers to increase planted area both in the short- and long-run. These estimates also implicitly imply that in the short-run, the area expansion of the four key crops mainly comes through substitution within these crops, whereas in the long-run, the expansion comes either from the rest of the crop area or from non-agricultural land.

Table 2. Estimates of Global Aggregate Growing-Area Response to Price

	ln(area)	ln(area)	ln(area)	ln(area)
	MG	DFE	MG	DFE
	global price[a]	global price	country price[b]	country price
	(1)	(2)	(3)	(4)
Long-Run				
Supply Elast.	0.144*	0.188*	0.143+	0.239*
	(0.032)	(0.083)	(0.033)	(0.093)
Trend	0.006**	0.006**	0.006**	0.008**
	(0.002)	(0.002)	(0.002)	(0.003)
Short-Run				
Error Correction	-0.314**	-0.066**	-0.313**	-0.068**
	(0.038)	(0.014)	(0.037)	(0.013)
Supply Elast.	0.027*	0.029**	0.024*	0.021**
	(0.007)	(0.007)	(0.007)	(0.007)
*N(31*53)*	1643	1643	1643	1643
Test of parameter constancy:				
chi-square		480.86		487.74
(p-value)		(0.00)		(0.00)

Note: [a]Global price means same international price for each county. [b]Country price means country-specific international price. Estimates are obtained using STATA's xtpmg command. The MG elasticity estimates are a weighted average. The weights are $\sum_t \sum_c A_{ict} / \sum_i \sum_t \sum_c A_{ict}$. For each model, we use futures price weighted by crop-specific caloric share. Standard errors are in parentheses. Asterisks **, *, and + denote significance at the 1 %, 5%, and 10% levels, respectively.

Our estimates of short-run growing area elasticities in table 2 are much lower than the estimates of Roberts and Schlenker (2013) and Hendricks et al. (2015) as reported in table 6. These authors use a static supply model and aggregate over countries to investigate the response of an aggregated four crops growing area to price. Recall that the MG estimator assumes all the parameters are heterogeneous across countries whereas the DFE estimator assumes homogeneous slope coefficients. We report the chi-square and p-value for the test of parameters constancy.[8] The p-value (bottom row in table 2) indicates that we do not support the assumption of parameter constancy, which means MG estimators are preferable to the DFE. We hypothesize that these will also hold for the crop-specific regression. Hence, for the crop-specific regressions, we only report results based on the MG estimator.

[8] Swamy (1970) random-coefficients model programmed in STATA as xtrc command provides the results of parameter constancy with regression output.

In estimating crop-specific growing-area response, we make several assumptions regarding the effects of competing crop prices. First, we assume that corn and soybeans compete for the same land around the world, especially in top producing countries, so we expect a negative cross-price elasticity. This assumption seems reasonable as planting-time of both crops are almost the same as shown in appendix tables B1 and B2. Second, the prices of wheat and rice do not affect corn and soybeans growing-area decisions. The planting-time of wheat is different from that of corn and soybeans, so it less likely that corn and soybeans will compete with wheat for the same land. Land used for rice planting is not suitable for corn and soybeans, at least in the short-run. Third, wheat and rice prices do affect each other's land allocation even though, in general, planting time for the two crops is different as shown in appendix tables B3 and B4.

Suppose we assume for a moment that we find a negative estimate of the coefficient on the wheat price when we run a simple linear regression of soybeans growing area on soybean price, wheat price, and a time trend. We argue here that this negative cross-price elasticity is the result of endogeneity of wheat price to soybeans growing-area decisions caused by different planting time. For example, Argentina plants wheat in May-August in year t and plants soybeans mostly in November-December at year t-1. Both are reported as time t growing area in the FAO database because they are both harvested in the same year. The most recent pre-planting wheat supply price is February-April average futures price at time t, whereas for soybeans the price is July-October pre-planting average futures price at time t-1. Using this data when we regress soybeans growing area on its own price and wheat price, we are likely to get a negative cross-price elasticity between soybeans and wheat. This is not because wheat price affects soybeans planting decision but rather the higher (lower) growing area in soybeans increases (decreases) its production, thereby the supply of soybeans increases (decreases) and its price goes down (up). This lower (higher) price of soybeans also forces spot price of wheat to go down (up) because both prices move together—this creates a negative correlation between wheat price and soybeans growing area and makes wheat price endogenous to soybeans growing area. We think the negative cross-price elasticity as found in the literature is not because wheat price affects soybeans acreage decision—rather, a higher growing area in soybeans increases its production and makes less land available for wheat. For example, in their global annual growing area regression, Haile et al. (2015) find a negative cross-price elasticity between soybeans and wheat.[9]

We start with the crop-specific results where we assume corn and soybeans are substitutable in production (table 3). The results show that the responses of corn and soybeans growing area to own-price are positive and statistically significant both in the short- and long-run, which is consistent with economic theory. As expected, the short-run responses are smaller than the long-run responses. This happens as land is mostly a fixed input and it requires time to prepare new land for crop cultivation when price increases. The results also show that soybeans have very high long-run growing-area response to its price. This is not unexpected as during the sample period soybeans went through the largest percentage increase in growing area compared to other crops (see figure 1) and two of the largest producers of soybeans, Argentina and Brazil, were dramatically expanding production during this time period. The results suggest that holding everything else constant, in the short-run, a 10% increase in corn and soybeans prices tend to increase corn and soybeans planting area by about 1.2% and 1.7%, respectively. The corresponding long-term growing-area responses for corn and soybeans are about 2.7% and 8.3%, respectively.

Both corn and soybeans cross-price elasticities are negative and statistically significant (table 3), which implies corn and soybeans compete for the same land at the global level. The results show that the negative response of soybeans growing area to an increase in corn price is stronger than the effect of a change in corn area to a change in soybeans price. These cross-price responses are higher in the long-run. The soybeans price effect on corn growing area is almost similar in magnitude in the short- and long-run.

The effects of own-price volatilities are positive in the short-run and negative in the long-run (columns 1a and 2a in table 3). The results suggest that an increase in price

[9] We are not sure whether they used expected wheat price before the soybeans planting time to account for endogeneity of wheat price, perhaps they did. However, it will be interesting to see the effect of period t-1 wheat supply price on soybeans planting decisions.

volatilities of corn and soybeans tends to increase land allocation in both crops in the short-run but not in the long-run. The findings of short-run positive effects are consistent with previous global-level studies as well as national-level studies, which find similar results (Haile et al., 2015; de Menezes and Piketty, 2012). If mean prices are high with high price volatilities, then producers respond by producing more through increasing growing area.

Table 3. Estimates Corn and Soybeans Growing-Area Response to Price Using MG Estimator

	Corn (1a)	Corn (1b)	Soybeans (2a)	Soybeans (2b)
Long-run				
Corn Price	0.235**	0.302**	-0.596**	-0.538**
	(0.063)	(0.076)	(0.093)	(0.093)
Soybeans Price	-0.059*	-0.042	0.825**	0.842**
	(0.029)	(0.028)	(0.036)	(0.035)
Corn Price volatility	-1.699+	0.418	0.352	-0.180
	(0.995)	(0.990)	(3.625)	(2.494)
Soybeans Price volatility	-0.708	0.036	-2.223**	0.353
	(0.734)	(0.677)	(0.641)	(0.743)
Fertilizer Price		-0.185**		-0.152*
		(0.052)		(0.062)
Short-Run				
Error Correction	-0.404**	-0.441**	-0.346**	-0.372**
	(0.054)	(0.056)	(0.043)	(0.043)
Corn Price	0.118**	0.115**	-0.244**	-0.155**
	(0.027)	(0.026)	(0.037)	(0.036)
Soybeans Price	-0.068**	-0.073**	0.166**	0.167*
	(0.016)	(0.016)	(0.046)	(0.043)
Corn Price volatility	0.767**	0.750**	-0.453+	0.500*
	(0.235)	(0.242)	(0.233)	(0.255)
Soybeans Price volatility	0.003	-0.254+	0.194	-0.055
	(0.106)	(0.138)	(0.118)	(0.132)
Fertilizer Price		0.020		-0.087**
		(0.013)		(0.015)
N	1423	1423	1423	1423

Note: Estimates are obtained using STATA's xtpmg command. The own-price elasticity estimates of each crop are a weighted average. The weights are $\sum_t A_{ict} / \sum_t \sum_i A_{ict}$. For each model, we use pre-planting futures price for the proxy of expected price. Standard errors are in parentheses. Asterisks **, *, and + denote significance at the 1%, 5%, and 10% levels, respectively.

In addition to output price and its volatility, input price affects land use decisions. Fertilizer price has a negative effect on both corn and soybeans growing-area in the long-run (table 3). A higher fertilizer price means a higher cost of production, and therefore farmers tend to produce less by lowering growing area. In the short-run, the effect of fertilizer price on soybeans is negative and statistically significant, whereas it is not negative and significant for corn. From table 3, we also find that when fertilizer price (input cost) is not included as a control (columns a and b) in the supply equations of corn and soybeans, we find relatively lower long-run growing-area elasticities. This is probably because of the negative correlation between input costs and random error term.

Table 4 reports results for the wheat and rice growing area elasticities. It also reports corn and soybeans growing area elasticities where we include only own-price of both crops. Except for rice, all own-price elasticities are found to be positive and statistically significant. Averaging columns 1a and 1b in table 4 shows that in the short-run, a 10% increase in the price of wheat leads to a 0.35% increase in wheat growing area, everything else held constant. In the long-run, an equivalent increase in the price of wheat leads to a 3.72% increase in wheat area.

Columns 2a and 2b of table 4 report rice growing area elasticities. The results in both columns show that rice growing area does not respond to changes in price, as indicated by insignificant statistical results. These are evident both in the short- and long-run. We explain these low or insignificant responses using two facts. First, the top rice producing countries in the world are either developing countries or least-developed countries, where rice is the staple food and where government intervention (price subsidy or other supports) is a common case whenever a production shock occurs. For example, in late 2007, the Indian government took protectionist measures, banning the export of non-basmati rice and imposing an export tariff on basmati rice to increase domestic supply and lower domestic price. This action resulted in a reduction in rice supply in global markets and price hike in the world rice price that was not reflected in the domestic market. Therefore, supply did not respond with respect to higher world prices. China and Bangladesh, the first- and fifth-ranked rice producers in the world, respectively, hardly participate in the international rice export market. Therefore, the growing-area response of rice in these two countries are likely to depend on domestic producer price rather than the international price.

The growing-area elasticities of corn and soybeans are positive and significant (columns 3a–4b in table 4). We find that, in the short-run, a 10% increase in the price of corn leads to a 1% increase in corn growing area, everything else held constant. In the long-run, an equivalent increase in the price of corn leads to a 2.10% increase in corn area. The short-and long-run responses of soybeans growing area to own-price are higher than the corresponding responses of corn growing area.

Table 4. Estimates of Crop-Specific Growing-area response to Price Using MG Estimator

	Wheat		Rice		Corn		Soybeans	
	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Long-Run								
Supply Elast.	0.345**	0.398**	0.033	0.060	0.193**	0.229**	0.539**	0.722**
	(0.134)	(0.163)	(0.106)	(0.115)	(0.046)	(0.063)	(0.076)	(0.065)
Price Volatility	-4.974**	-3.716**	0.610	0.365	-5.113**	-1.113	-6.866**	0.716
	(1.403)	(1.315)	(2.491)	(2.153)	(1.537)	(1.121)	(1.971)	(0.909)
Fertilizer price		-0.129		0.032		-0.210**		-0.634**
		(0.109)		(0.128)		(0.058)		(0.079)
Short-Run								
Error Correction	-0.333**	-0.390**	-0.326**	-0.348**	-0.345**	-0.380**	-0.185**	-0.287**
	(0.040)	(0.045)	(0.031)	(0.035)	(0.047)	(0.046)	(0.014)	(0.022)
Supply Elast.	0.038**	0.032+	0.001	-0.005	0.089**	0.109**	0.221**	0.205**
	(0.029)	(0.034)	(0.021)	(0.023)	(0.028)	(0.028)	(0.045)	(0.037)
Price Volatility	0.207	0.130	-0.001	-0.001	0.958**	0.888**	0.333*	-0.024
	(0.257)	(0.212)	(0.213)	(0.202)	(0.260)	(0.237)	(0.133)	(0.108)
Fertilizer price		0.008		-0.012		-0.011		-0.073**
		(0.017)		(0.019)		(0.010)		(0.016)
N	1440	1440	1456	1456	1560	1560	1423	1423
Test of parameter constancy: Chi-square (p-value)	657.31 (0.000)		465.47 (0.000)		1602.73 (0.000)		3224.71 (0.000)	

Note: Estimates are obtained using STATA's xtpmg command. The elasticity estimates of each crop are a weighted average. The weights are $\sum_t A_{ict} / \sum_t \sum_i A_{ict}$. Except for rice, we use pre-planting futures price for the proxy of expected price. For rice, we use pre-planting international spot price. Standard errors in parentheses. Asterisks **, *, and + denote significance at the 1%, 5%, and 10% levels, respectively.

In general, the effects of price volatilities on growing area are positive in the short-run and negative in the long-run (columns 1a, 2a, 3a, and 4a of table 4). In the short-run, the effects are statistically significant for corn and soybeans; whereas in the long-run, the effects are significant for wheat, corn, and soybeans. These findings are consistent with producers being well-informed about the price risks, and absorbing risk in the short-run through several risk management tools such as insurance, hedging, options, and so on. In the long-run, producers focus more on wealth accumulation than absorbing price risks. Larger commercial farms increasingly accounted for the bulk of the production of U.S. grains and oilseeds and these larger commercial farms perhaps place more focus on net wealth accumulation in the long-run and less in avoiding production and market risks in the short-run (Lin and Dismukes, 2007). An alternative explanation is, of course, that price volatility does not belong in the model, and we are picking up a spurious correlation.

The effects of fertilizer price indices on growing area are negative across all four crops, with the long-run effect being stronger than the short-run effect (table 4). This is consistent with the economic theory that predicts that production cost increases will lead to reductions in planted acres. Another explanation of the negative coefficients on the fertilizer prices is that a higher fertilizer price may induce farmers to adopt high yielding but less fertilizer-intensive seeds—which, perhaps, provide higher production for a given or lower amount of land.

The error correction speed of adjustment parameters ϕ_i is negative across all crops and statistically significant. This provides evidence of a long-run relationship and implies that the long-run coefficients are consistently estimated (table 4). The estimates of adjustment parameters indicate the slow speed of adjustment towards the long-run equilibrium. In the last row of table 4, we also report the results for parameter constancy. In all crop cases, we reject the null hypothesis of parameter constancy across countries. These results provide justification for using MG estimators in estimating crop growing-area response.

Robustness Check

We check the robustness of our original regression results by including the current-year realized yield shocks as an additional control variable in the supply equation. The observed yield shocks will proxy for anticipated yield shocks if there is any predictability about growing season weather at planting time. If there is, then futures prices will be correlated with the error term in the supply model. Results are reported in appendix tables C1, C2, C3, and C4 of appendix C, which are analogous to tables 2, 3, 4, and 5 of this article. Estimated elasticities that control for predicted yield shocks are quite similar to the results without control. Therefore, endogeneity of futures prices does not seem to be an issue of concern in our supply response model.

Results with Alternative Estimators

Estimating a dynamic heterogeneous panel-data model disregarding heterogeneity in coefficients can lead to biased and inconsistent estimates. Estimates of growing-area responses to prices using several alternative estimators are given in table 5. The estimates in column 1 are from pooled OLS, which assume all coefficients are the same across the panel group. The estimates in columns 2–4 are from alternative pooled estimators, which assume panel-specific intercepts but same slope coefficients for each panel group. The estimates in column 5 are from a random-coefficient estimator in which separate regressions are estimated for each panel group by treating all the parameters as a realization (in each panel) of a stochastic process. Results in columns 1–3 and 5 are derived from a Nerlovian partial adjustment model and results in column 4 are derived from the dynamic specification of equation (16). Results of table 5 are comparable with the results (which do not include fertilizer price) of tables 2 and 4.

The pooled OLS estimates in column 1 indicate that the long-run growing area elasticities are quite high and are not consistent with simple observations of the data. For example, the results show that the OLS estimate of aggregate growing-area response to price is negative and the estimate of wheat growing-area response is quite low. These estimates are biased because the lagged dependent variable (growing area) is correlated with the panel group heterogeneity. The pooled FE in column 2 and DFE in column 4 overestimate the long-run responses because prices are autocorrelated and incorrectly ignoring heterogeneity in coefficients induces serial correlation in the disturbances. By similar logic, the Blundell-Bond GMM estimates in column 3 are biased and inconsistent. Moreover, lagged levels are not valid instruments when heterogeneity in coefficients are present.

Table 5. Estimates of Growing-Area Response with Alternative Estimators

	Pooled OLS	FE	GMM	DFE	Random Coefficients
	(1)	(2)	(3)	(4)	(5)
Long-run					
Aggregate	-504.1	0.294**	0.199**	0.239*	0.043**
Corn	1.79*	0.794**	0.361*	0.638**	0.315**
Soybeans	1.21**	0.957**	1.13**	1.023**	0..894**
Wheat	0.628	0.635**	0.449**	0.516**	0.323**
Rice	38.30	0.315**	0.745**	0.259*	0.084
Short-run					
Aggregate	0.019**	0.020**	0.043**	0.021**	0.011
Corn	0.021*	0.121*	0.095*	0.463**	0.117**
Soybeans	0.062*	0.533**	0.233**	0.752**	0.450**
Wheat	0.005	0.076**	0.087**	0.169**	0.097**
Rice	0.013	0.033*	0.100**	0.043	0.022

Notes: Right-hand side variables in columns 1–3 and 5 are a lagged dependent variable, expected own-crop price, own-crop price volatility, a trend, and country-specific intercepts. Column 4 uses the similar specification as shown in equation (16). Elasticity estimates in column 3 are from the two-step system-GMM estimator that use two-years lagged dep. var. and treat lagged dependent variable and price as endogenous. Results in column 3 also use robust standard errors with Windmeijer (2005) finite sample correction. The results in column 3 are estimated using XTABOND2 in STATA and a collapsed instrument matrix as suggested by Roodman (2009a). The lags used for instruments vary by crop—usually from 3 lags to 5 lags. The results in column 5 are from Swamy (1970) random coefficient estimator and are estimated using XTRC in STATA. Asterisks **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% levels, respectively.

The random coefficients estimates in column 5 reveal that in general, the responses of growing area are larger in magnitude than the MG estimates. The estimates from random coefficients estimator are consistent, but the estimator is applicable only when coefficients are random across groups. Our proposed MG estimator is applicable irrespective of whether the slope coefficients are random or fixed, in the sense that the diversity in the slope coefficients across cross-sectional units cannot be captured by means of a finite parameter probability distribution (Pesaran, 2015 pp. 718) Moreover, the MG estimator is more efficient than random coefficients estimator in random- and fixed-coefficients models.

Table 6 reports a summary of the global growing-area elasticities estimated by recent studies. Our estimate of short-run aggregate elasticity is lower than estimates of Roberts and Schlenker (2013) and Hendricks et al. (2015). Studies that provide crop-specific short-run elasticities generally have higher estimates than ours. For example, the long-run growing-area response of soybeans as found in previous work is more than double relative to our estimate. A comparison of our results in table 5 with the table 4 results indicates that these differences are likely due to the use of a static model or a lack of accounting for coefficient heterogeneity in the dynamic panel data model.

Table 6. Estimates of Global Growing-Area Response in Different Studies

Study	Crop	Price Used	Elasticity: Short-run	Elasticity: Long-run	Model/Estimator
Roberts and Schlenker (2013)	Aggregate four crops	Futures	0.078	N/A	Static (Aggregate) /IV
Hendricks et al. (2015)	Aggregate four crops	Futures	0.064	N/A	Static (Aggregate or Country-Specific) /OLS or IV
Haile et al. (2014)	Corn	Spot	0.18	0.23	Dynamic (Aggregate) /OLS
	Soybeans	Spot	0.37	1.15	
	Wheat	Spot	0.09	0.20	
	Rice	Spot	0.02	0.06	
Haile et al. (2016b)	Corn	Spot	0.23	N/A	Dynamic Panel (Fixed Effect: homogenous slope) /GMM
	Soybeans	Spot	0.37	N/A	
	Wheat	Spot	0.11	N/A	
	Rice	Spot	0.06	N/A	
FAPRI*	Corn	Domestic	0.14		N/A
	Soybeans	Domestic	0.31		
	Wheat	Domestic	0.18		
	Rice	Domestic	0.07		
This article**	Aggregate	Futures	0.024	0.144	Dynamic Panel (Heterogeneous coefficients) /MG
	Corn	Futures	0.089	0.193	
	Soybeans	Futures	0.229	0.539	
	Wheat	Futures	0.038	0.345	
	Rice	Spot	0.001	0.033	

Note: *From Haile et al. (2016b). ** Aggregate estimates are with respect to average price and crop-specific estimates are with respect to own prices and its volatilities.

5 Conclusions

This paper makes two contributions. First, it demonstrates that use of a dynamic heterogeneous panel data model to account for heterogeneous (country-specific) growing-area response to price provides consistent estimates of global growing area supply elasticities. Second, by applying the MG estimator to the dynamic model, we demonstrate that it results in more inelastic elasticities than estimators that have been used previously. In contrast to previous studies, which attribute more inelastic response to the price being endogenous, we demonstrate that more elastic estimates are the result of a misspecified model.

Using annual data for the period 1961 to 2014, this paper provides both long- and short-run elasticities of growing area with respect to price. As expected, long-run elasticities are much higher than short-run elasticities, which is consistent with Nerlove's partial adjustment theory and with the existing empirical literature (Roberts and Schlenker, 2013; Haile et al., 2014; Haile et al., 2015). However, our results differ from previous global-level estimates in terms of magnitude as well as differences between short- and long-run responses because we account for parameter heterogeneity across crop-producing countries.

We find that the short- and long-run elasticities estimates of the aggregate growing area with respect to own prices are about 0.024 and 0.143, respectively. The existing short-run aggregate estimates are much higher than our estimate. With regard to crop-specific estimates, we find that corn and soybeans growing area are more responsive to price changes than rice and wheat area. Soybeans exhibits the highest response, whereas rice shows the lowest response. These are evident both in the short- and long-run. The short-run own-price elasticities for corn and soybeans are 0.100 and 0.213, respectively, compared to wheat (0.035) and rice (0.001). The long-run response of growing area for corn and soybeans with respect to price changes are 0.210 and 0.631, respectively, compared to wheat (0.372) and rice (0.047). Price transmission from the international rice market to domestic producer markets is perhaps very low because of government intervention (input price support or some sort of subsidy), which may lead to these low rice growing-area response to international price changes. For example, in late 2007, India, the top exporter of rice (as of 2015/16), imposed an export ban on all non-basmati rice exports in an effort to ensure sufficient supplies for their population. This intervention causes a spike in international rice price but that price hike perhaps was not transmitted to the domestic market and thereby producers did not get the actual price signal to plant more rice.

Economic theory shows that in a competitive market situation, higher price volatilities act as a disincentive for production expansion if a producer is risk averse (Sandmo, 1971). However, our empirical findings in the short-run are not in line with the theory. Except for wheat, the own-price volatilities impact on growing-area decisions are, in general, positive in the short-run. These may happen because the leading producers of these crops (particularly corn and soybeans) adopt several risk management tools such as insurance products, hedging, and options to absorb price risk in the short-run. Therefore, in the long-run, producers lower their effort (growing area) with respect to higher price volatilities. The impact of wheat price volatilities on the wheat growing area is negative in the short-run but statistically insignificant.

References

Alvarez, J., Arellano, M., 2003. The time series and cross-section asymptotics of dynamic panel data estimators. Econometrica 71(4), 1121–1159.

Anderson, T. W., Hsiao, C., 1981. Estimation of dynamic models with error components. J. Am. Stat. Assoc. 76, 598–606.

Anderson, T. W., Hsiao, C., 1982. Formulation and estimation of dynamic models using panel data. J. Econometrics 18 (1), 47–82.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte-Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58(2), 277–297.

Askari, H., Cummings, J. T., 1977. Estimating agricultural supply response with the Nerlove model: A survey. Int. Econ. Rev. 18(2), 257–292.

Barr, K. J., Babcock, B. A., Carriquiry, M. A., Nassar, A. M., Harfuch, L., 2011. Agricultural land elasticities in the United States and Brazil. Appl. Econ. Pers. Pol. 33(3), 449–462.

Bean, L. H., 1929. The farmers' response to price. J. Farm Econ. 11(3), 368–385.

Binswanger, H., Yang, M.-C., Bowers, A., Mundlak, Y., 1987. On the determinants of cross-country aggregate agricultural supply. J. Econometrics 36(1), 111–131.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econometrics 87(1), 115–143.

Bond, S. R., 2002. Dynamic panel data models: A guide to micro data methods and practice. Portuguese Econ. J. 1(2), 141–162.

Braulke, M., 1982. A note on the Nerlove model of agricultural supply response. Int. Econ. Rev. 23(1), 241–244.

Cassels, J. M., 1933. The nature of statistical supply curves. J. Farm Econ. 15(2), 378–387.

Choi, J.-S., Helmberger, P. G., 1993. Acreage response, expected price functions, and endogenous price expectations. J. Agric. Res. Econ. 18(1), 37–46.

Colman, D., et al., 1983. A review of the arts of supply response analysis. Rev. Mark. Agric. Econ. 51(3), 201–23.

de Menezes, T. A., Piketty, M.-G., 2012. Towards a better estimation of agricultural supply elasticity: the case of soya beans in Brazil. Appl. Econ. 44(31), 4005– 4018.

Food and Agriculture Organization (FAO), 2011. The State of Food Insecurity in the World: How does international price volatility affect domestic economies and food security? FAO, Rome.

Griliches, Z., 1967. Distributed lags: A survey. Econometrica 35(1), 16–49.

Haile, M. G., Brockhaus, J., Kalkuhl, M., 2016a. Short-term acreage forecasting and supply elasticities for staple food commodities in major producer countries. Agric. Food Econ. 4(1), 17.

Haile, M. G., Kalkuhl, M., Braun, J., 2014. Inter-and intra-seasonal crop acreage response to international food prices and implications of volatility. Agric. Econ. 45(6), 693–710.

Haile, M. G., Kalkuhl, M., Von Braun, J., 2016b. Worldwide acreage and yield response to international price change and volatility: A dynamic panel data analysis for wheat, rice, corn, and soybeans. Am. J. Agric. Econ. 98(1), 172–190.

Hausman, C., 2012. Biofuels and land use change: sugarcane and soybean acreage response in Brazil. Env. Res. Econ. 51(2), 163–187.

Hendricks, N. P., Janzen, J. P., Smith, A., 2015. Futures prices in supply analysis: Are instrumental variables necessary? Am. J. Agric. Econ. 97(1), 22–39.

Hendricks, N. P., Sinnathamby, S., Douglas-Mankin, K., Smith, A., Sumner, D. A., Earnhart, D. H., 2014. The environmental effects of crop price increases: Nitrogen losses in the US corn belt. J. Env. Econ. Manag. 68(3), 507–526.

Im, K. S., Pesaran, M. H., Shin, Y., 2003. Testing for unit roots in heterogeneous panel. J. Econometrics 115(1), 53–74.

Lewbel, A., 1994. Aggregation and simple dynamics. Am. Econ. Rev. 84(4), 905–918.

Lin, W., Dismukes, R., 2007. Supply response under risk: Implications for counter-cyclical payments' production impact. Appl. Econ. Pers. Pol. 29(1), 64–86.

Maddala, G. S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxf. Bull. Econ. Stat. 61(S1), 631–652.

McKay, A., Morrissey, O., Vaillant, C., 1999. Aggregate supply response in Tanzanian agriculture. J. Intl. Trade Econ. Dev. 8(1), 107–123.

Miao, R., Khanna, M., Huang, H., 2016. Responsiveness of crop yield and acreage to prices and climate. Am. J. Agric. Econ. 98(1), 191–211.

Moschini, G., Hennessy, D. A., 2001. Uncertainty, risk aversion, and risk management for agricultural producers. Handb. Agric. Econ. 1, 87–153.

Nerlove, M., 1956. Estimates of the elasticities of supply of selected agricultural commodities. J. Farm Econ. 38(2), 496–509.

Nerlove, M., 1958. The Dynamics of Supply: Estimation of Farm Supply Response to Price. John Hopkins University Press, Baltimore.

Nerlove, M., 1979. The dynamics of supply: retrospect and prospect. Am. J. Agric. Econ. 61(5), 874–888.

Newbery, D. M., Stiglitz, J. E., 1982. Risk aversion, supply response, and the optimality of random prices: A diagrammatic analysis. Q. J. Econ. 97 (1), 1–26.

Nickell, S., 1985. Error correction, partial adjustment and all that: An expository note. Oxf. Bull. Econ. Stat. 47(2), 119–129.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49(6) 1417–1426.

Pesaran, M. H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econometrics 22(2), 265–312.

Pesaran, M. H., 2015. Time Series and Panel Data Econometrics. Oxford University Press.

Pesaran, M. H., Shin, Y., Smith, R. P., 1997. Pooled estimation of long-run relationships in dynamic heterogeneous panels. University of Cambridge, Department of Applied Economics.

Pesaran, M. H., Shin, Y., Smith, R. P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. J. Am. Stat. Assoc. 94(446), 621–634.

Pesaran, M. H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. J. of Econometrics 68(1), 79–113.

Rao, J. M., 1989. Agricultural supply response: A survey. Agric. Econ. 3(1), 1–22.

Roberts, M. J., Schlenker, W., 2009. World supply and demand of food commodity calories. Am. J. Agric. Econ. 91 (5), 1235–42.

Roberts, M. J., Schlenker, W., 2013. Identifying supply and demand elasticities of agricultural commodities: implications for the US ethanol mandate. Am. Econ. Rev. 103(6), 2265–2295.

Roodman, D., 2009a. A note on the theme of too many instruments. Oxford Bulletin of Econ. and Statis. 71(1), 135–158.

Roodman, D., 2009b. How to do xtabond2: An introduction to difference and system GMM in Stata. Stata J. 9 (1), 86–136.

Sandmo, A., 1971. On the theory of the competitive firm under price uncertainty. Am. Econ. Rev. 61 (1), 65–73.

Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., Yu, T. H., 2008. Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. Science 319 (5867), 1238–1240.

StataCorp, 2013. Stata 13 Base Reference Manual. Stata Press, College Station, TX.

Swamy, P. A. V. B., 1970. Efficient inference in a random coefficient regression model. Econometrica 38, 311–323.

Yu, B., Liu, F., You, L., 2012. Dynamic agricultural supply response under economic transformation: A case study of Henan, China. Am. J. Agric. Econ. 94(2), 370-376.

Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. J. Econometrics 126, 25–51.

Appendix A Derivation of the Consistency of MG Estimator

We show the consistency of MG estimator following Pesaran et al. (1996). For simplicity, we work with the model specification as shown in equation (8). Let's write the model (8) more compactly as

$$A_{it} = \gamma_i x_{it} + \varepsilon_{it}, \;\; \varepsilon_{it} \sim \text{i.i.d. } (0, \sigma_i^2), \;\; i = 1, 2, ..., N, \; t = 1, 2, ..., T, \tag{A1}$$

where $x_{it} = (P_{it}^{\prime e}, A_{i,t-1})'$ and $\gamma_i = (\delta_{10i}, \lambda_i)$. The disturbance ε_{it} is assumed to be distributed independently of the parameters and regressors. We also assume that the between group disturbances covariances are zero, i.e., $E(\varepsilon_{it}\varepsilon_{jt'}) = 0$ for all t and t', $i \neq j$. Now, the estimator of γ_i for each group i given by

$$\hat{\gamma}_i = (X_i' H_T X_i)^{-1} X_i' H_T A_i, \;\; i = 1, 2, ..., N \tag{A2}$$

where X_i and A_i are the $T \times 2$ and $T \times 1$ observation matrices for the explanatory variables and the dependent variable for the ith country. $H_T = I_T - l_T (l_T' l_T)^{-1} l_T'$, where I_T is identity matrix of order T and I_T is a $T \times 1$ unit vector. We compute the MG estimator of γ_i as

$$\hat{\gamma}_{MG} = \sum_{i=1}^{N} \hat{\gamma}_i \; / \; N \tag{A3}$$

which can be expressed as

$$\hat{\gamma}_{MG} = \bar{\gamma} + \frac{1}{N} \sum_{i=1}^{N} (X_i' H_T X_i)^{-1} X_i' H_T \varepsilon_i \tag{A4}$$

where $\bar{\gamma} = N^{-1} \sum_{i=1}^{N} \gamma_i$. For a fixed N , as $T \to \infty$ we have

$$\text{plim}_{T\to\infty}(\hat{\gamma}_{MG}) = \bar{\gamma} + \frac{1}{N} \sum_{i=1}^{N} \left(\frac{X_i' H_T X_i}{T} \right)^{-1} + \text{plim}_{T\to\infty} \left(\frac{X_i' H_T \varepsilon_i}{T} \right) = \bar{\gamma} \tag{A5}$$

where $\text{plim}_{T\to\infty} \left(\frac{X_i' H_T \varepsilon_i}{T} \right) = 0$, given the assumptions that we made about the disturbances.

Now let's assume that $\gamma_i^{'s}$ are independently distributed across groups. Then by the law of large numbers (as $N \to \infty$) we have $\bar{\gamma} \xrightarrow{p} \gamma$. This confirms the consistency of the MG estimator $\hat{\gamma}_{MG}$.

Appendix B Planting and Harvesting Calendar

Table B1. Corn Planting and Harvesting Calendar for the Sample Countries

Country	Year t												Year t+1											
	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Argentina																								
Australia																								
Bangladesh																								
Brazil																								
Canada																								
China																								
Egypt																								
India																								
Indonesia																								
Iran																								
Japan																								
Mexico																								
Myanmar																								
Pakistan																								
Philippines																								
South Africa																								
Thailand																								
Turkey																								
U.S.																								
Vietnam																								
F. USSR																								
F. Yugoslav																								
France																								
Germany																								
Hungary																								
Italy																								
Rest of North																								
Rest of South																								
Romania																								
Spain																								
UK																								

	Planting		Harvesting		Both Plant. And Harvest.

Table B2. Soybeans Planting and Harvesting Calendar for the Sample Countries

	Year t												Year t+1											
	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Argentina																								
Australia																								
Brazil																								
Canada																								
China																								
India																								
Indonesia																								
Iran																								
Japan																								
Mexico																								
Myanmar																								
Pakistan																								
Philippines																								
South Africa																								
Thailand																								
Turkey																								
U.S.																								
Vietnam																								
Bangladesh																								
Egypt																								
Former USSR																								
F Yugoslav																								
France																								
Germany																								
Hungary																								
Italy																								
R. of North																								
R. of South																								
Romania																								
Spain																								
UK																								

	Planting		Harvesting		Both Plant. And Harvest

Table B3. Wheat Planting and Harvesting Calendar for the Sample Countries

	Year t												Year t+1											
Country	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D
Argentina																								
Australia																								
Bangladesh																								
Brazil																								
Canada																								
China																								
Egypt																								
India																								
Iran																								
Japan																								
Mexico																								
Myanmar																								
Pakistan																								
South Africa																								
Turkey																								
U.S.																								
FUSSR																								
F Yugoslav																								
France																								
Germany																								
Hungary																								
Indonesia																								
Italy																								
Philippines																								
Rest of North																								
Rest of South																								
Romania																								
Spain																								
Thailand																								
UK																								
Vietnam																								

	Planting		Harvesting		Both Plant. And Harvest

Table B4. Rice Planting and Harvesting Calendar for the Sample Countries

	Year t												Year t+1											
country	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
Argentina			H	H	H	H			P	P	P	P			H	H	H	H			P	P	P	P
Australia			H	H	H					P	P	P			H	H	H					P	P	P
Bangladesh			P	P	P	P	B	B			H	H			P	P	P	P	B	B			H	H
Brazil	P	P	B	B	B	H	H	H		P	P	P	P	P	B	B	B	H	H	H		P	P	P
China		P	P	P	P	B	B	H	H	H	H			P	P	P	P	B	B	H	H	H	H	
Egypt				P	P	P	P			H	H					P	P	P	P			H	H	
India	H		H	H	B	P		P	H	H	B	B	H		H	H	B	P		P	H	H	B	B
Indonesia	P		H	H	H	H	P	P		B	B	B	P		H	H	H	H	P	P		B	B	B
Iran					P	P		H	H								P	P		H	H			
Japan				P	P				H	H	H					P	P				H	H	H	
Mexico	H				P	P	P	P	P	H	H	H	H				P	P	P	P	P	H	H	H
Myanmar					P	P				H	H	H					P	P				H	H	H
Pakistan					P	P	P	P	H	H	H	H					P	P	P	P	H	H	H	H
Philippines			P	P	P	P	P	P	H	H	H	H			P	P	P	P	P	P	H	H	H	H
South Africa				H	H	H			P	P	P	P				H	H	H			P	P	P	P
Thailand	B	B	P	H	B	B	P	P		H	H	H	B	B	P	H	B	B	P	P		H	H	H
Turkey				P	P	P			H	H						P	P	P			H	H		
U.S.				P	P	P		H	H	H						P	P	P		H	H	H		
Vietnam	P	P	B	B	B	B	B	B	B	B	B	B	P	P	B	B	B	B	B	B	B	B	B	B
Canada				P	P	P		H	H	H						P	P	P		H	H	H		
Former USSR				P	P			H	H							P	P			H	H			
Former Yugoslav SFR		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
France		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
Germany		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
Hungary		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
Italy		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
Rest of North				P	P	P		H	H	H						P	P	P		H	H	H		
Rest of South	P	P	B	B	B	H	H	H		P	P	P	P	P	B	B	B	H	H	H		P	P	P
Romania		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
Spain		P	P	P				H	H	H	H			P	P	P				H	H	H	H	
UK		P	P	P				H	H	H	H			P	P	P				H	H	H	H	

P	Planting	H	Harvesting	B	Both Plant. And Harvest

Appendix C Further Empirical Results

Table C1. Estimates of Global Aggregate Growing-Area Response to Price

	ln(area)	ln(area)	ln(area)	ln(area)
	MG	DFE	MG	DFE
	Global price and shock	Global price and shock	County price and shock	County price and shock
	(1)	(2)	(5)	(6)
Long-Run				
Supply Elast.	0.142^{+}	0.158^{+}	0.146**	0.227*
	(0.038)	(0.089)	(0.039)	(0.096)
Shock	0.027	-0.449	0.138	0.060
	(0.399)	(1.180)	(0.149)	(0.309)
Trend	0.006**	0.006*	0.006**	0.007**
	(0.002)	(0.002)	(0.002)	(0.003)
Short-Run				
Error Correction	-0.313**	-0.065**	-0.307**	-0.065**
	(0.038)	(0.013)	(0.037)	(0.013)
Supply Elast.	0.025*	0.027**	0.024*	0.018**
	(0.007)	(0.007)	(0.007)	(0.007)
Shock	0.089	0.135^{+}	0.066*	0.084**
	(0.057)	(0.069)	(0.029)	(0.014)
*N (31*53)*	1643	1643	1643	1643
Test of parameter constancy : chi-square				534.637
(p-value)				(0.000)

Note: Estimates are obtained using STATA's xtpmg command. The MG elasticity estimates are a weighted average. The weights are $\sum_t \sum_c A_{ict} / \sum_i \sum_t \sum_c A_{ict}$. For each model, we use futures price weighted by crop-specific caloric share. Standard errors in parentheses. Asterisks **, *, and $^{+}$ denote significance at the 1 %, 5%, and 10% levels, respectively.

Table C2. Estimates Corn and Soybeans Growing-Area Response to Price Using MG Estimator

	Corn (1a)	Corn (1b)	Soybeans (2a)	Soybeans (2b)
Long-run				
Corn Price	0.218**	0.325**	-0.533**	-0.496**
	(0.059)	(0.072)	(0.091)	(0.093)
Soybeans Price	-0.071*	-0.074*	0.821**	0.822**
	(0.028)	(0.031)	(0.041)	(0.035)
Corn Price volatility	-0.986	0.969	-2.563^{+}	-2.366
	(1.093)	(1.239)	(1.545)	(1.551)
Soybeans Price volatility	-0.975	-0.309	-1.449**	0.865
	(0.830)	(0.785)	(0.537)	(0.695)
Fertilizer Price		-0.179**		-0.151*
		(0.061)		(0.065)
Short-Run				
Error Correction	-0.410**	-0.436**	-0.366**	-0.385**
	(0.050)	(0.053)	(0.048)	(0.048)
Corn Price	0.111**	0.110**	-0.249**	-0.155**
	(0.026)	(0.026)	(0.040)	(0.037)
Soybeans Price	-0.067**	-0.073**	0.143**	0.156**
	(0.016)	(0.016)	(0.047)	(0.045)
Corn Price volatility	0.716*	0.634*	-0.552*	0.388^{+}
	(0.291)	(0.277)	(0.277)	(0.228)
Soybeans Price volatility	0.048	-0.237	0.239^{+}	0.054
	(0.102)	(0.145)	(0.143)	(0.163)
Fertilizer Price		0.023^{+}		-0.093**
		(0.012)		(0.016)
*N (28*T)*	1423	1423	1423	1423

Note: Estimates are obtained using STATA's xtpmg command. The MG elasticity estimates of each crop are a weighted average. The weights are $\sum_t A_{ict} / \sum_t \sum_i A_{ict}$. For each model, we use pre-planting futures price for the proxy of expected price. Standard errors in parentheses. Asterisks **, *, and $^{+}$ denote significance at the 1 %, 5%, and 10% levels, respectively.

Table C3. Estimates of Crop-Specific Growing-Area Response to Price Using MG Estimator

	Wheat		Rice		Corn		Soybeans	
	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)	ln(area)
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Long-Run								
Supply Elast.	0.336**	0.394**	0.021	0.048	0.194**	0.234**	0.544**	0.733**
	(0.118)	(0.160)	(0.114)	(0.125)	(0.049)	(0.065)	(0.101)	(0.048)
Price Volatility	-4.803**	-3.395**	0.886	0.476	-5.479**	-1.541	-7.272**	1.413
	(1.322)	(1.279)	(2.513)	(2.157)	(1.748)	(1.411)	(1.466)	(1.231)
Fertilizer price		-0.125		-0.004		-0.212**		-0.647**
		(0.112)		(0.104)		(0.057)		(0.103)
Short-Run								
Error Correction	-0.323**	-0.377**	-0.329**	-0.345**	-0.356**	-0.389**	-0.183**	-0.289**
	(0.038)	(0.043)	(0.033)	(0.036)	(0.048)	(0.047)	(0.014)	(0.023)
Supply Elast.	0.051**	0.038**	0.002	-0.006	0.088**	0.108**	0.228**	0.207**
	(0.024)	(0.026)	(0.021)	(0.022)	(0.027)	(0.027)	(0.045)	(0.038)
Price Volatility	-0.146	-0.114	0.028	0.031	0.946**	0.903**	0.334**	-0.074
	(0.188)	(0.176)	(0.220)	(0.204)	(0.261)	(0.252)	(0.129)	(0.114)
Fertilizer price		-0.014		-0.002		-0.013		-0.072**
		(0.016)		(0.018)		(0.010)		(0.017)
N	1432	1432	1459	1458	1560	1560	1423	1423
Test of parameter constancy: Chi-square (p-value)	776.274 (0.000)		835.417 (0.000)		1533.622 (0.000)		3236.142 (0.000)	

Note: Estimates are obtained using STATA's xtpmg command. The elasticity estimates of each crop are a weighted average. The weights are $\sum_t A_{ict} / \sum_t \sum_i A_{ict}$. Except for rice, we use pre-planting futures price for the proxy of expected price. For rice, we use pre-planting international spot price. Standard errors in parentheses. Asterisks **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% levels, respectively.

Table C4. Estimates of Growing-Area Response with Alternative Estimators

	Pooled OLS	FE	GMM	DFE	Random Coefficients
	(1)	(2)	(3)	(4)	(5)
Long-run					
Aggregate	-295.1	0.302**	0.125*	0.227*	0.045**
Corn	1.80*	0.795**	0.369+	0.639**	0.307**
Soybeans	1.21**	0.957**	1.04**	1.024**	0..891**
Wheat	0.617	0.630**	0.451**	0.494**	0.318**
Rice	39.86	0.317**	4.74	0.255*	0.091
Short-run					
Aggregate	0.019**	0.021**	0.031*	0.018**	0.012
Corn	0.021*	0.121*	0.083*	0.467**	0.119**
Soybeans	0.062*	0.447**	0.294*	0.752**	0.450**
Wheat	0.005	0.075**	0.065*	0.202**	0.095**
Rice	0.013	0.033*	0.055*	0.044	0.024

Notes: Right-hand side variables in columns (1)-(3) and (5) are a lagged dependent variable, expected own-crop price, own-crop price volatility, a trend, and country-specific intercepts. Column (4) uses the similar specification as shown in equation (16). Elasticity estimates in column (3) are from the two-step system-GMM estimator that treat the lagged dependent variable as predetermined and the price as endogenous. Results in column (3) also use robust standard errors with Windmeijer (2005) finite sample correction. The results in column (3) are estimated using XTABOND2 in STATA and a collapsed instrument matrix as suggested by Roodman (2009a). The lags used for instruments vary by crop—usually from 3 lags to 5 lags. The results in column (5) are from Swamy (1970) random coefficient estimator and are estimated using XTRC in STATA. Asterisks **, *, and + denote significance at the 1%, 5%, and 10% levels, respectively.