Estimating Short- and Long-run Global Growing Area Elasticities of Key Agricultural Commodities from Dynamic Heterogeneous Panels

Abstract

We investigate the short- and long-run global growing area response of corn, soybeans, wheat, and rice to international crop output price changes while controlling for the effects of price volatility and production costs. We model the global growing area response as heterogeneous across countries by adopting a dynamic heterogeneous panel and examine it by employing new methods and diagnostics that we use from the panel time-series literature. We obtain the estimates of short- and long-run global growing area response to price changes that are significantly lower than the estimates obtained by traditionally used models. Previous findings appear biased upward several folds, possibly due to the assumption of homogeneous slope coefficients across countries. The results show that the estimates of short- and long-run elasticities of aggregate (four crops) growing area with respect to average price are about 0.024 and 0.143, respectively. The crop-specific results show that both in the short- and long-run, corn and soybeans growing area are more responsive to own-price changes than wheat and rice. For corn and soybean, the long-run estimates of own-price elasticities are 0.210 and 0.631, respectively. The long-run responses of growing area with respect to price changes 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.

Introduction

Estimates of short- and long-run agricultural crops growing area elasticities with respect to crop output prices are important quantities to policy makers and researchers for understanding land use dynamics, the effects of land use change on environment, food production and other policy related issues (Searchinger et al. 2008; Roberts and Schlenker 2013; Haile, Brockhaus and Kalkuhl 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 review 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 account 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 effects of crop prices on world production decisions of a particular crop vary depending on the country-specific share of output in total global output, government policies, technology, random weather, input use, the productivity of land, price transmission of world prices to local prices, among other factors. Thus the effects of price changes are not 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 perhaps less in relative terms. Similarly, countries that have higher productive land tend to respond more than others. This indicates potential for heterogeneity in the supply responses to prices across countries or groups. 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 on 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[1].

The literature on estimating supply response to prices has mostly concentrated on one or a few countries (e.g., Binswanger, Yang, and Mundlak 1987; Lin and Dismukes 2007; Barr et al. 2009; Yu, Liu, and You 2012; Hausman 2012; de Menezes and Piketty 2012; Miao, Khanna, and Huang 2015; Haile, Brockhaus, and Kalkuhl 2016). Recently, Roberts and Schlenker (2013), Haile, Kalkuhl, and von Braun (2014), Hendricks, Janzen, and Smith (2015), and Haile, Kalkuhl, and von Braun (2015) provide estimates of supply response at the global level. In estimating global growing area response, these authors either assume homogeneous slopes across countries, or disregard time-series properties of the data, or disregard aggregation bias by aggregating over countries in a dynamic supply framework, or provide only a short-run response, or adopt a static model. Thus, the scope of this paper is to address these issues in modeling and estimating growing area response function.

Using a static supply model, Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (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. A problem with a static model is that it ignores the dynamic nature of agricultural supply response. Haile, Kalkuhl, and von Braun (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 dependent variable, 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

[1]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.

estimates of the average coefficients on the lagged dependent variable as well as on the long-run parameters of interest. Haile, Kalkuhl, and von Braun (2015) adopt a dynamic panel supply model to analyze global 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. But, 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 recently developed 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, Kalkuhl, and von Braun (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 covering the period 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 both in the short- and long-run, corn and soybeans growing area are 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 own price changes 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 as 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 producers' 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

The supply function is defined as the response of output to price. Early work on supply response mainly focused on policy issues rather 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 the supply response: Nerlovian (1958) supply model and the supply function in a profit maximization framework based on the 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 second approach is based on the theory of production and the firm and it involves joint estimation of output supply and input demand functions. The weakness of this approach is that input prices are difficult to obtain across countries. We have limited or almost no information on input prices. Thus, we base our analysis on the model specification of Nerlove.

The popularity of the Nerlove approach (Askari and Cummings 1977; Coleman 1983; de Menezes and Piketty 2012) is its simple specification and interpretation of the parameters of interest. For example, a simple linear regression of logged output quantity on logged price and lagged log output produces estimates of both short- and long-run supply elasticities. Second, usually there is a delayed adjustment in agricultural markets due to the availability of resources and the cycle of agricultural production. Thus, it is essential to adopt a dynamic approach in modeling supply analysis that recognizes the time lags in agricultural supply response (Yu, Liu, and You 2012). In its simplest version Nerlove's structural supply model for a specific crop consists of the following three equations (Nerlove 1979; Braulke 1982)

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

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

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

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[2]

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

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

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

When both adaptive expectation and partial adjustment mechanism 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

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

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 but it is if $A_t^* = A_t$. Equation (5) is estimable as long as a suitable proxy for the expected price is available. The 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, Morrisey, and Vaillant 1999). Among the three, most empirical estimations have been based on the equation (5), which uses past-year realized price or futures price traded in the futures market as the proxy of expected price. Thus, we mainly rely on the model specification of equation (5) to estimate the global growing area response.

[2] Nerlove (1956) derive this model by noting that any expected price can be written as a linear function of growing area (p 502). The Koyck transformation also provide 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 which are observed over period t, for country i (i=1,….,N) and crop c we express the equation (5) in the following dynamic heterogeneous panel form

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

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 the 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 cross-price elasticity.

In equation (7) we assume heterogeneous slope coefficients across countries and crops as our panel group is not similar in nature 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. But, if the objective is to estimate the total mean of panel group slope coefficients it is much more common to use pooling or aggregating. We now discuss potential bias of using commonly used estimation procedures—pooled and aggregate time-series—to the dynamic heterogeneous panel model (equation 7).

For simplicity, let's 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

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

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[3]:

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

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

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

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

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

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

In the aggregate equation (11), the macro disturbance $\bar{\upsilon}_t$ 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 and it cannot be used to obtain consistent estimates of δ_{10} and λ. However, with two special cases, the OLS estimator will be consistent. First, 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). Second, 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 $\bar{A}_t$ and $\bar{P}_t^e$ (Pesaran and Smith 1995).

[3] 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 assume homogeneous slope coefficients across countries. The pooled regression of the equation (8) including an intercept term can be expressed as

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

where

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

In the empirical literature, four variants of the pooled estimator are used to estimate equation (13). They are pooled ordinary least squares (OLS), fixed-effect, random-effect, 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 (1982) show that the pooled OLS regression estimates, in this case, are biased unless unrealistic assumptions are made on the initial conditions. 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 fixed-effects estimator will suffer from dynamic panel bias because of the correlation between lagged dependent variable and the mean random error, where the mean random error is the mean over time period across each country (Nickell 1981). As a result, fixed effects estimator will be inconsistent. Fixed effect 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 random-effects estimator is inconsistent in dynamic panel regression, because fixed effects are always correlated with the lagged dependent variable. This inconsistent doses 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), 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

(IVs) to remove dynamic panel bias. For small T and large N, where T/N tends to zero, it provides consistent estimates of short-run slope 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 fixed effect are the same. With T>=N the coefficients of the lagged dependent variable as estimated by GMM asymptotically coincide with the fixed effect 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 fixed effects estimator (assumes homogeneous slope) in small T panels as $N \rightarrow \infty$ (e.g. Nickell 1981). When we use fixed effects estimator to estimate equation (8), the fixed effects estimator 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 estimator such as Arellano-Bond (differenced GMM) or Blundell (system GMM) that uses 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 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).

In short, we summarize the above discussion as follows. Estimating equation (7) or equation (8) by aggregating over countries and applying OLS, or using traditional pooled panel regression methods, or GMM may yield biased and inconsistent estimates of growing area elasticity. First, averaging the data over groups and estimating aggregate time-series data using OLS method produces inconsistent estimates of parameters. Second, fixed effects or within group 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 incorporate all these issues and provide consistent estimates of the growing area elasticity.

We propose to use the mean group (MG) estimator as developed by Pesaran and Smith (1995). The MG estimator allows the intercepts, slope coefficients (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 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.

Now, given the autoregressive lag relation in the equation (7), we hypothesize that the growing area response model of equation (7) has the following general autoregressive distributed lag (ARDL) (1, 1, 1, 1, 1) dynamic panel form[4]

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

This ARDL specification has the advantages over 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, Shin and Smith 1999). Second, it is not necessary to have the variables to be integrated of the same order. Third and the most important, it is easy to reparametrize the above model into the error correction form. From the error correction form, 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 inter-temporal quadratic loss function (Nickell 1985). We can also test for cointegration 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

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

[4] 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 $\phi_{ic} = -(1-\lambda_{ic})$, $k = 1, 2, \ldots, 4$.

The 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 as well as 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 are

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

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

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

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 parameter 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 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. As long as growing area is not affected by expected yield shocks and unobserved factors that affect growing area are unknown prior to planting, the standard assumption of no omitted variables holds—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 the OLS and three-stage least square estimates of the U.S. soybean growing area response to price changes. Hendricks, Janzen, and Smith (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, Janzen, and Smith (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 for the period 1961 to 2014. The data mainly include area planted, area harvested, yields, futures prices, and spot prices for each of the four main crops. The data also include fertilizer prices indices that are used as proxies for production costs.

We obtain data on area planted from the country-specific statistical sources wherever data were available. In the case where data on planted area were not available, we use area harvested for the proxy of 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, the World Bank. 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 or 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 expected prices that they expect at harvest time. In modeling their expectation, we use two price series: i) the U.S. crop futures prices measured during the pre-planting period on contracts for harvest-time delivery ii) 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 of corn, soybeans, wheat, and rice are reported in tables A1, A2, A3, and A4 of the appendix[5]. For countries in the southern and northern hemisphere, we use the planting time 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, Kalkuhl, and von Braun et al (2015) and Miao, Khanna, and Huang (2015) model the farmers' price expectation in a similar fashion. Haile, Kalkuhl, and von Braun (2015) model for countries around the world and Miao, Khanna, and Huang (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, Smith, and Sumner (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

[5] Crop calendar for each crop is from http://www.amis-outlook.org/amis-about/calendars/en/ and Haile, Kalkuhl, and von Braun (2015).

standard deviation of pre-planting 12 months 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 country-specific because we calculate the 12 months standard deviation for each country based the varying planting dates. When we check the robustness of our results, we include current-year realized yield shocks in our empirical model as a proxy for weather or other supply shocks that may affect growing area decisions. We assume that farmers' take into account these expected yield shocks while allocating land across crops. It is defined as the actual yield deviation to predicted yield. Following Roberts and Schlenker (2013), we model yield of each country-crop pair on 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. 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 growing area response for the four main agricultural crops. In estimating global aggregate growing area 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 **y**ield 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 over the period 1961 to 2014. While calculating both absolute and percentage changes, we take 4-year average so that bias from year-on-year fluctuations caused by random shocks is minimized. Several findings are noteworthy: first, growing area of all crops has climbed up in a similar fashion during the 1981-1984 and 2011-2014 compared to their immediate previous period. In general, changes has slowed down starting from the late 80s to the beginning of 2000s. Second, the absolute changes of corn and soybeans growing area are higher relative to wheat and rice area in 2011-2014 compared to changes that have occurred from the period 1961-1964 to 1980-1981. Third, overall, soybeans exhibits 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 percentage changes, we roughly guess that the growing area response to crop prices will be higher for soybeans followed by corn, rice, and wheat if proportional changes in prices are the same for all crops.

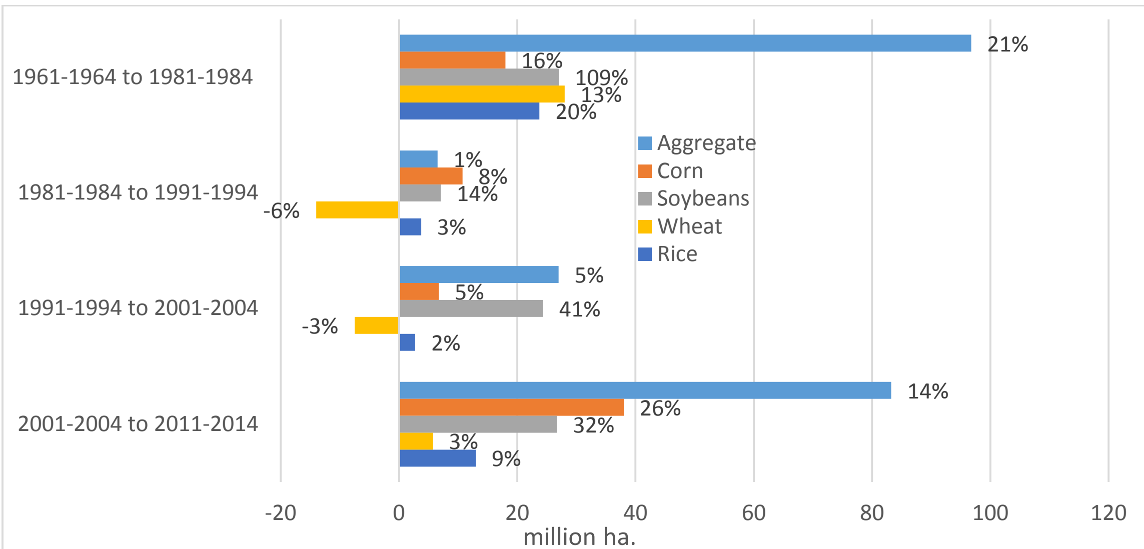

Figure 1. Changes in global growing area over the period 1961 to 2014

Empirical Results and Discussions

For large T and N, it is most likely that the variables will have unit roots, that is, the variables might be nonstationary. Hence, this section starts by presenting the unit root estimates of variables. Table 1 presents the statistics of the unit root tests. 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 of Table 1 show that except for yield shock, most of the variables are nonstationary at the level form but their first difference is stationary. The presence of nonstationary variables in level form imply that the pooled or standard fixed effect regression model would not constitute a cointegrating regression and the parameter estimates would be inconsistent (Pesaran and Smith, 1995). The empirical model of equation (12) 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 requirement are identical for each crop. A practical reason for aggregation is that prices for all four crops tend to vary synchronously, which seriously impedes identification of multiple cross-price elasticities and separating cross-price elasticities from own-price elasticities (Roberts and Schlenker 2013). While estimating crop-specific growing area response, we relax our assumption—instead, we assume producers' may 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. Crop-specific growing area response to prices are valuable inputs to adopt crop-specific policies.

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 (DFF) method allows only fixed but heterogeneous intercepts. Columns (1)-(2) of the table 2 report estimates of the growing area response assuming each country faces same global futures price whereas columns (3)-(4) report the response assuming each country faces 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—a 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 DFE estimator, especially with country-specific prices. But 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 the strong evidence of positive autocorrelation in prices where 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 specification. The results suggest 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	global price	country price	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)
Constant	4.905**	0.979**	4.886**	0.987**
	(0.615)	(0.216)	(0.598)	(0.210)
*N(31*53)*	1643	1643	1643	1643
Test of parameter constancy (Swamy 1970) :				
chi-square		480.86		487.74
(p-value)		(0.00)		(0.00)

Note: 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, Janzen, and Smith (2015) [see table 6]. These authors use a static supply model and aggregate over countries to investigate the response of aggregate 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[6]. 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 than 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.

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 at the same time (tables A1 and A2 in the appendix). 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. Third, wheat and rice prices do affect each other's land allocation as in general, the planting time for both crops are distinct from each other (tables A3 and A4 in the appendix). Suppose, one of our assumptions does not hold. Let's 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 soybeans and wheat prices 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 at year t and plants soybeans mostly in November-December at time t-1. Both are reported as time t growing area in FAO database. 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 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

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

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 of wheat price affect soybeans acreage decision rather a higher growing area in soybeans increases its production. For example, in their global annual growing area regression, Haile, Kalkuhl, and von Braun (2015) find a negative cross-price elasticity between soybeans and wheat[7].

Now, 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 are 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 ready for the crop cultivation with the changes in prices. 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 (Figure 1). The results suggest that given everything else constant, in the short-run a 10 % increase in corn and soybeans prices tend to raise corn and soybeans planting area by about 1.2 % and 1.7 % respectively. The corresponding long-term growing area responses are about 2.7 % and 8.3 % respectively.

Both corn and soybeans cross-price elasticities are negative and statistically significant (table 3), which imply corn and soybeans compete for the same land at the global level. The results show that the negative response of soybeans growing area with an increase in corn price is stronger than vice versa. These responses are relatively larger in the long-run, especially, the corn price long-run effect is much stronger than its short-run effect. The

[7] 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.

soybeans price effect on corn growing area is almost similar in magnitude in the short- and long-run.

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)
Constant	5.616**	6.104**	4.385**	4.809**
	(0.819)	(0.832)	(0.585)	(0.588)
N	1423	1423	1423	1423

Note: 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.

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 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 who find similar results

(Haile, Kalkuhl, and von Braun 2015 and 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 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. Columns (1a) and (1b) show 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.

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 term	-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)
Constant	4.489^{**}	5.332^{**}	4.143^{**}	4.469^{**}	4.701^{**}	5.192^{**}	1.940^{**}	3.400^{**}
	(0.639)	(0.678)	(0.505)	(0.546)	(0.729)	(0.713)	(0.173)	(0.262)
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: 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.

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 occur. 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, which were 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 producer 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 its domestic producer price rather than 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 run responses of soybeans growing area to own-price are higher than the corresponding responses of corn growing area.

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). Or, price volatility does not belong in the model.

The effects of fertilizer price indices on growing area are negative across all four crops—the long run effect is stronger than the short run (table 4). These are consistent with the economic theory that an increase in fertilizer prices means an increase in production costs—as a result, producers' expected net return go down and they respond by planting less. 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 parameters 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 account for the predicted yield shocks that may affect the futures prices and therefore futures prices turn out to be endogenous to supply analysis. Results are reported in tables B1, B2, B3, and B4 of appendix B, which are analogous to tables 2, 3, 4, and 5 of this article. The estimated results which control for predicted yield shocks are very 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

As we discussed earlier, estimating dynamic heterogeneous panel data model disregarding heterogeneity in slope 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 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 random-coefficient estimator—that is, 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 Nerlovian partial adjustment model and result 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.

Table 5. Estimates of Growing Area Response with Alternative Estimators

	Pooled OLS	Fixed Effect	GMM	Dynamic Fixed Effect	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 (12). 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 in (3) 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 pooled OLS estimates in column (1) indicate that the long-run growing area elasticities are quite high and are not consistent with the economic theory and/or reality. 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 fixed effects in column (2) and dynamic fixed effect 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.

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, p. 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 literature. Our estimate of short-run aggregate elasticity differs compared to the estimates of Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015). Studies that provide crop-specific short-run elasticity, in general, overestimate the growing area response as compared to our estimates. The long-run growing area response of soybeans as found in the previous work is more than double relative to our estimate. We think all of these differences are either due to the use of a static model or disregarding coefficients 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, Janzen, and Smith (2015)	Aggregate four crops	Futures	0.064	N/A	Static (Aggregate or Country-Specific) /OLS or IV
Haile, Kalkuhl, and Braun (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, Kalkuhl, and Braun (2015)	Corn	Spot	0.23	N/A	Dynamic (Panel Fixed Effect) /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	0.025	0.144	Dynamic (Heterogeneous Panel) /MG
	Corn	Futures	0.09	0.193	
	Soybeans	Futures	0.22	0.539	
	Wheat	Futures	0.04	0.345	
	Rice	Spot	0.001	0.033	

Note: Our results are only with respect to own price and its volatility. *From Haile, Kalkuhl, and Braun (2015)

5 Conclusions

By examining global growing area responses of key agricultural crops with respect to price changes and volatilities, this paper makes two major contributions to the existing literature. First, it proposes a dynamic heterogeneous panel data supply model to allow for heterogeneous growing area responses across countries. Ours is the first dynamic panel study on global growing response to international crop price changes and price volatilities to address parameter heterogeneity across countries. Second, by applying MG estimator to the dynamic model, this paper provides consistent estimates of short- and long-run elasticities of the global growing area for aggregate four crops as well as for corn, soybeans, wheat, and rice separately. These growing area elasticities are important for understating global land supply dynamics and the environmental effects of land use change.

Using annual data for the period 1961 to 2014, this paper shows that both aggregate growing area of four crops and crop-specific growing area responds to crop price changes more in the long-run than in the short-run. These findings are consistent with Nerlove's partial adjustment theory and are in line with the findings of existing empirical literature (Roberts and Schlenker 2013; Haile, Kalkuhl, and von Braun 2014; Haile, Kalkuhl, and von Braun 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 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). But 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.

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Appendix A

Table A1. Corn Planting and Harvesting Calendar for the Sample Countries

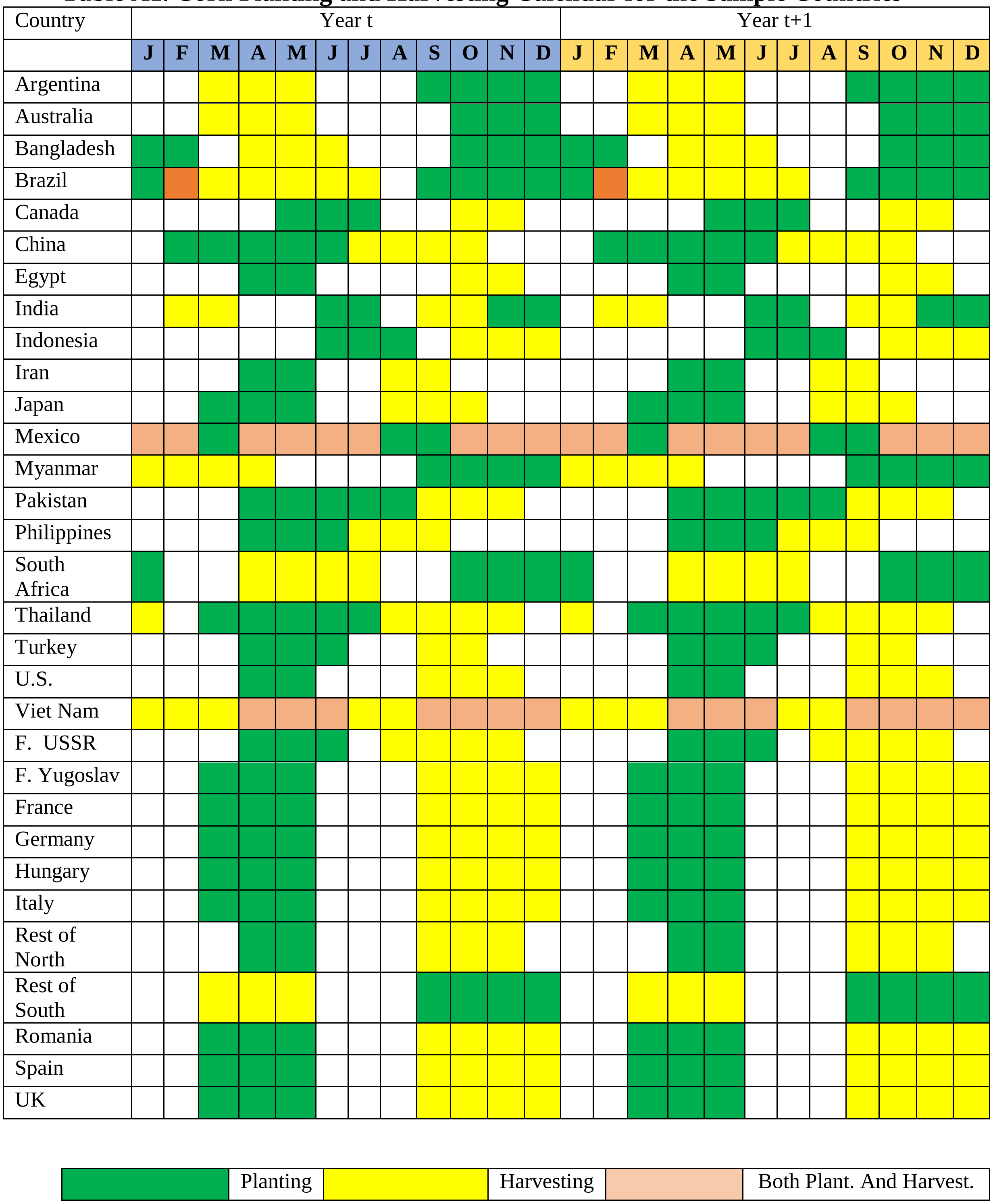

Table A2. Soybeans Planting and Harvesting Calendar for the Sample Countries

	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	P		H	H	H	H					P	P	P		H	H	H	H					P	P
Australia			H	H	H						P	P			H	H	H						P	P
Brazil	H	H	H	H	H				P	P	P	P	H	H	H	H	H				P	P	P	P
Canada					P	P			H	H	H						P	P			H	H	H	
China				P	P	P			H	H						P	P	P			H	H		
India						P	P		H	H	H	H						P	P		H	H	H	H
Indonesia				P	P	P		H	H	H						P	P	P		H	H	H		
Iran				P	P	P		H	H							P	P	P		H	H			
Japan					P	P	P			H	H	H					P	P	P			H	H	H
Mexico	H	H			P	P	P	P	P	H	H	H	H	H			P	P	P	P	P	H	H	H
Myanmar		H	H	H						P	P	P		H	H	H						P	P	P
Pakistan				P	P	P	P	P	H	H	H					P	P	P	P	P	H	H	H	
Philippines			P	P			H	H							P	P			H	H				
South Africa			H	H	H	H				P	P	P			H	H	H	H				P	P	P
Thailand				P	P	P	P	H	H	H	H	H				P	P	P	P	H	H	H	H	H
Turkey				P	P	P			H	H	H					P	P	P			H	H	H	
U.S.					P	P			H	H	H						P	P			H	H	H	
Viet Nam	B	B	B	B	B	B	H	H	B	B	B	B	B	B	B	B	B	B	H	H	B	B	B	B
Bangladesh						P	P		H	H	H	H						P	P		H	H	H	H
Egypt				P	P					H	H					P	P					H	H	
Former USSR				P	P				H	H	H					P	P				H	H	H	
F Yugoslav				P	P	P		H	H	H						P	P	P		H	H	H		
France				P	P	P		H	H	H						P	P	P		H	H	H		
Germany				P	P	P		H	H	H						P	P	P		H	H	H		
Hungary				P	P	P		H	H	H						P	P	P		H	H	H		
Italy				P	P	P		H	H	H						P	P	P		H	H	H		
R. of North					P	P			H	H	H						P	P			H	H	H	
R. of South	H	H	H	H	H				P	P	P	P	H	H	H	H	H				P	P	P	P
Romania				P	P	P		H	H	H						P	P	P		H	H	H		
Spain				P	P	P		H	H	H						P	P	P		H	H	H		
UK				P	P	P		H	H	H						P	P	P		H	H	H		

P: Planting	H: Harvesting	B: Both Plant. And Harvest

Table A3. 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																								
Viet Nam																								

	Planting		Harvesting		Both Plant. And Harvest

Table A4. 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		
Viet Nam	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 B

Table B1. 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 Correc.	-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)
Constant	4.901**	0.988**	4.805**	0.954**
	(0.620)	(0.218)	(0.603)	(0.205)
*N (31*53)*	1643	1643	1643	1643
Test of parameter constancy (Swamy 1970) : chi-square				534.637
(p-value)				(0.000)

Note: 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 B2. 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 term	-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)
Constant	5.643**	5.979**	4.615**	4.933**
	(0.753)	(0.790)	(0.640)	(0.645)
*N (28*T)*	1423	1423	1423	1423

Note: 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 B3. 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 term	-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)
Constant	4.374**	5.148**	4.167**	4.400**	4.826**	5.292**	1.929**	3.431**
	(0.617)	(0.652)	(0.514)	(0.548)	(0.735)	(0.721)	(0.171)	(0.271)
N	1432	1432	1459	1458	1560	1560	1423	1423
Test of parameter constancy (Swamy 1970): Chi-square (p-value)	776.274 (0.000)		835.417 (0.000)		1533.622 (0.000)		3236.142 (0.000)	

Note: 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 B4. Estimates of Growing Area Response with Alternative Estimators

	Pooled OLS	Fixed Effect	GMM	Dynamic Fixed Effect	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 (12). 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 (2009). The lags used for instruments in (3) 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.