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# Three essays on agricultural supply analysis

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**Three essays on agricultural supply analysis**

by

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The student author and the program of study committee are solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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**DEDICATION**

I dedicate this dissertation to my parents, my siblings, and to my lovely wife Umma Farhana Khushi, without whose support I would not have been able to complete this work.

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## ABSTRACT

The three essays of this dissertation focus estimating agricultural supply response to price. Using country-specific data and estimating both static and dynamic supply models, this dissertation research provides new estimates and perspectives on global agricultural supply response. The first essay examines the endogeneity of futures prices in supply analysis of four main agricultural crops namely corn, rice, wheat, and soybeans, by revisiting the recent literature that finds substantial endogeneity bias when global crop supply is regressed on futures prices. Our results indicate that the endogeneity of futures price does not affect the estimates of global crop supply responses but affects the estimates of the US crop supply responses. The second essay investigates how the short- and long-run global growing area of corn, soybeans, wheat, and rice respond to international crop output futures prices, price volatilities, and production cost changes by adopting a dynamic heterogeneous panel model. The results indicate that the short- and long-run elasticity estimates of growing-area response with respect to price are considerably lower than the estimates obtained using traditional models. The third essay examines the extent to which crop output prices received by producers and other factors explain changes in intensive and extensive agricultural land use of all crops globally produced. We adopt both static and dynamic panel models to analyze land use response and estimate the respective model using a first-differenced (FD) estimator and a dynamic panel generalized instrumental variable or generalized method of moments (GMM) estimator. The results from FD and dynamic panel GMM estimators indicate that of the total land use response to prices, the response at the

intensive margin accounts for a 62-90% of the total response. These results imply that most of the growth in world harvested land 2004 to 2013 resulted from intensification rather than conversion of land that had not previously been cropped.

# CHAPTER 1. GENERAL INTRODUCTION

The three essays of this dissertation focus estimating agricultural supply response to price. Using country-specific data and estimating both static and dynamic supply models, this dissertation research provides new estimates and perspectives on global agricultural supply response.

The first essay in chapter 2 examines the endogeneity of futures prices in supply analysis of four main agricultural crops namely corn, rice, wheat, and soybeans, by revisiting the recent literature that finds substantial endogeneity bias when global crop supply is regressed on futures prices. We conduct our analysis using both global data and U.S. data for four crops over the period 1961 to 2014. Robustness of results is determined by using the full sample data and data from 1980 to 2014 that excludes the two large price spikes of 1974 and 1975. We estimate both aggregate and crop-specific supply models. Aggregate models are estimated using ordinary least squares (OLS) and two-stage least squares (2SLS) or instrumental variables (IV) estimators. Crop-specific models are estimated using OLS, 2SLS, and seemingly unrelated regressions (SUR) estimators.

In contrast to the literature's finding that current year's realized yield shock should be included as a control variable for the proxy of predictable yield shock, we find that it should not be. The evidence for predictability is not robust to sample period, outliers in the data, and the method by which futures prices are detrended. We then examine whether instrumenting futures prices is needed in supply equations. The 2SLS estimates of the global aggregate supply models indicate that futures price is not endogenous to global supply because the 2SLS estimates are either statistically insignificant or similar to the OLS estimates. The 2SLS results of the US aggregate supply response indicate that endogeneity bias substantially lowers the estimates of the US caloric and growing area supply elasticities that are obtained from the OLS regressions of supply on the futures price. We do not find endogeneity bias in the estimates of global crop-specific supply response whereas we find endogeneity bias for the US crop supply estimates.

The second essay in chapter 3 investigates how the short- and long-run global growing area of corn, soybeans, wheat, and rice respond to international crop output futures prices, price volatilities, and production cost changes. 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. In examining global growing-area response, the existing literature either assumes homogeneous response across countries, disregards time-series properties of the data, disregards aggregation bias by aggregating over countries in a dynamic supply framework, provides only a short-run response, or adopts a static model. In this study, we investigate the responses by developing a dynamic panel model which allow responses to vary across countries and provide both the short- and long-run estimates. We adopt econometric methods from the panel time-series literature to estimate the model. We utilize 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 price indices that are used as proxies for production costs. Our results indicate that the short- and long-run elasticity estimates of growing-area response with respect to price are considerably lower than the estimates obtained using traditional models. Previous findings appear biased due to the assumption of homogeneous response across countries. 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.

The third essay in chapter 4 examines the extent to which crop output prices received by producers and other factors explain changes in intensive and extensive agricultural land use of all crops globally produced. Ten years have passed since major agricultural crop prices started to increase in late 2005. This increase was the longest sustained increase since 1960 and thus provides a unique opportunity to estimate supply response to recent price changes. Supply response can occur in the form of land use or yield change or both. In this paper, we focus only on measuring changes in land use and not per-hectare yields. However, we differentiate between bringing new land into production (extensive response) and more intensive use of existing land. We decompose total harvested land use into extensive margin and intensive margin. We define extensive margin as the conversion of non-cropland into (from) cropland and intensive margin as the change in unharvested land, multiple cropping, temporary pasture, and fallow land.

We adopt both static and dynamic panel models to analyze land use response and estimate the respective model using a first-differenced (FD) estimator and a dynamic panel generalized instrumental variable or generalized method of moments (GMM) estimator. We utilize a unique dataset by compiling country-specific data on harvested, planted, and potentially arable cropland, crop prices of all crops received by the producer for a large panel of 79 countries covering the period 2004 to 2013. The results from FD and dynamic panel GMM estimators indicate that of the total land use response to prices, the response at the intensive margin accounts for a 62-90% of the total response. These results imply that most of the growth in world harvested land 2004 to 2013 resulted from intensification rather than conversion of land that had not previously been cropped. The main factors that explain intensification of agricultural land use are an increase of multiple cropping and reduction of unharvested land. We also find that one important factor that determines a country's response is the supply of potentially arable. Those countries that have more unused arable land expand more at the extensive margin than those countries that do not.

# CHAPTER 2. ARE FUTURES PRICES ENDOGENOUS IN SUPPLY ANALYSIS OF AGRICULTURAL CROPS? NEW EMPIRICAL EVIDENCE


## Abstract

In this chapter, we examine the advice given in the recent literature regarding the use of futures prices in supply analysis. The advice is to either control for the endogeneity of futures prices by including the current year's yield shock or to instrument futures prices using the previous year's yield shock or to do both. Our analysis is conducted using both global data and U.S. data for corn, rice, wheat, and soybeans over the period 1961 to 2014. Robustness of results is determined by using the full sample data and data from 1980 to 2014 that excludes the two large price spikes of 1974 and 1975.

The literature's conclusion that current year's yield shock should be included as a control variable only makes sense if yield shocks can be accurately forecasted when crops are planted. We find that the evidence for such predictability is not robust to sample period, outliers in the data, and the method by which futures prices are detrended. Therefore, there is no justification for including current year's yield shock in supply equations.

We then examine whether instrumenting futures prices is needed in supply equations. Aggregate models are estimated using ordinary least squares (OLS) and two-stage least squares (2SLS) or instrumental variables (IV) estimators. Crop-specific models are estimated using OLS, 2SLS, and seemingly unrelated regressions (SUR) estimators. The 2SLS estimates of the global aggregate supply models indicate that futures price is not endogenous to global supply because the 2SLS estimates are either statistically

insignificant or similar to the OLS estimates. The 2SLS results of the US aggregate supply response indicate that endogeneity bias substantially lowers the estimates of the US caloric and growing area supply elasticities that are obtained from the OLS regressions of supply on the futures price. We do not find endogeneity bias in the estimates of global crop-specific supply response whereas we find endogeneity bias for the US crop supply estimates.

## 2.1 Introduction

Recently, Roberts and Schlenker (2013) followed by Hendricks, Janzen, and Smith (2015) have revived the issue of endogeneity of futures prices when used in crop supply models. Both studies found substantial endogeneity bias in regressions of global supply on futures prices. The issue of endogeneity of futures prices is important for supply response models because if it exists and is not accounted for then estimates of supply elasticity are biased and inconsistent. Consistent and reliable estimates of supply response to prices are valuable inputs in measuring the magnitude of output and price changes caused by external forces such as the economic growth of emerging economies, the invention of new technologies, U.S. ethanol production, and population growth, among many other factors. The elasticity parameter for aggregate farm output measures the ability of the farming industry to adjust production to changing economic conditions continually confronting it in a dynamic economy (Tweeten and Quance, 1969).

The purpose of this paper is to revisit the endogeneity of futures prices in supply analysis of four main agricultural crops namely corn, rice, wheat, and soybeans, by examining the robustness of Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) results. The robustness analysis is conducted both with respect to model specification and to the time period covered.

Modeling supply response to prices has a long history in agricultural economics and has been modeled using different econometric and theoretical frameworks (Nerlove, 1958; Houck and Ryan, 1972; Gardner, 1976; Choi and Helmberger, 1993; Lee and Helmberger, 1985, Roberts and Schlenker, 2013; Hendricks, Janzen, and Smith, 2015; Haile, Kalkuhl, and von Braun , 2016; Miao, Khanna, and Huang, 2016). In developing supply models, the importance of appropriate modeling of price expectations is recognized because agricultural planting decisions, crop-management practices, and production depend largely on the farmers' expectation of output prices. The Nerlovian partial adjustment framework has been the most influential and extensively used supply response model. Under this framework, models use a lagged price and a lagged dependent variable as explanatory variables in supply model. The advantage of using lagged price is that it avoids the endogeneity problems created by the simultaneous determination of supply and demand (Gardner (1976). As an alternative to past prices, Gardner (1976) suggests using the planting time futures prices as a measure of expected price by treating futures prices as exogenous, justified by the hypothesis of rational expectations. Since then, many empirical studies have used planting-time (or pre-planting) futures prices of contracts for post-harvest delivery prices in econometric models of supply response (Orazem and Miranowski, 1994; Barr et al., 2011; Lin and Dismukes, 2007).

A central feature in the literature on rational expectations is that expected price and production are simultaneously determined (Sheffrin 1983). The theory of storage also implies that expected price is endogenous. Whether endogeneity of futures prices in supply analysis is empirically important was first addressed by Choi and Helmberger (1993) who estimated a structural model of the U.S soybean market that included demand for consumption, demand for storage, expected price, and supply of acreage. Expected price is measured by the futures price and is assumed endogenous. OLS and the three-stage least squares estimates of their acreage response function were essentially the same. In contrast, recent work by Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) find significant endogeneity bias in global caloric supply response to the futures price.

Endogeneity of futures prices may arise due to unobservable supply or demand shifters that become part of the supply equation's error term but are known to producers so they affect expected production levels and, in turn, pre-plant expected price. Any bias caused by endogeneity can be mitigated by either i) finding an appropriate instrumental variable for the endogenous variable or ii) finding suitable proxies for the omitted variables that cause the problem. Roberts and Schlenker (2013) use both approaches simultaneously. They estimate global supply response to futures price using the past year's yield shock as an instrument for the expected price on the basis that past yield shocks affect futures prices through storage. They also include current-year realized yield shock under the assumption that farmers can anticipate what their yield is going to be. In contrast, Hendricks, Janzen, and Smith (2015) suggest using current-year realized yield shock as an omitted variable without further instrumenting futures prices. Implicitly they assume that anticipated yield shocks are the primary source of endogenous futures prices. Both approaches provide almost identical results and both studies find substantial endogeneity bias in supply analysis caused from endogeneity of futures prices.[1]

Using their model and variables, we revisit their analysis and, in contrast, find that endogeneity of futures price has almost no impact on the estimates of global crop supply elasticities but, interestingly, endogeneity bias has some impact on the estimates of the US supply elasticities. Our global results indicate that including the current-year realized yield shock as a control variable does not reduce bias caused by endogenous futures prices but rather serves to reduce the variance of the dependent variable and by controlling for sampling error that causes futures prices to be correlated with current-year realized yield shock. Our results also indicate that using past-year yield shock as an instrument for futures prices results in a small bias reduction in both global production and growing area response models. For the US crop supply response model, we find endogeneity of futures price affects the estimates of aggregate caloric and growing area supply elasticities as well as crop-specific supply elasticities. Results from crop-specific model indicate the correlation between the futures price and current-year realized yield shock as we find in the aggregate model is the result of aggregation across crops level.

The remainder of the paper is organized as follows. Section 2.2 provides an econometric specification of supply response model. Section 2.3 describes the data and

[1] We reproduce their results in table A1 of appendix using the same model and the sample period.

variables. Section 2.4 discusses methodological issues relating to estimating supply models. Section 2.5 discusses the empirical results. Finally, section 2.6 concludes.

## 2.2 Econometric Model of Supply and Estimation Methods

We base our analysis on the model specification in Roberts and Schlenker (2009), Roberts and Schlenker (2013), and Hendricks, Janzen, and Smith (2015) who adopt a static supply model for investigating the global aggregate supply response of four crops (corn, soybeans, wheat, and rice) to expected output prices. Their model is a reduced form of the Nerlove (1958) model because it does not include lagged supply as an explanatory variable. We write the basic global aggregate supply model of four crops in aggregate as[2]

(1) $Q_t = \alpha + \beta P_t^e + \xi f(t) + u_t$

where $Q_t$ denotes the total global caloric production from corn, soybeans, wheat, and rice with subscript t for the time period, $P_t^{e\prime}$ denotes average expected crop output price, $u_t$ is random disturbances, and f (t) is a flexible time trend. In general, a time trend is used in supply models to identify monotonic time-related effects on overall production because of technological innovation in agriculture, development of infrastructure, and social advancement.[3]

[2] The importance of ignoring dynamics in supply models is examined in Chapter 3 of my dissertation. In this chapter we take the static model as given.
[3]Askari and Cummings (1977) note this point. They also mention that the decision to use a trend variable rather than a more direct measure of postulated influence on supply is generally based on difficulties in obtaining reliable time series data for the factors in question.

$Q_t$ can be decomposed into three components (Hendricks, Janzen, and Smith 2015), which is used to identify the source of bias caused by the endogeneity of futures prices. The components of $Q_t$ are i) total growing area ( $A_t$ ), (ii) average trend caloric production per unit of land (trend yield; $\hat{Y}_t$ ), and (iii) Yield shocks $(\Psi_t)$—which is the ratio of the average yield to trend. Yield shocks and trend yield are weighted averages of their country-crop counterparts. Thus, total global caloric production is

$$(2) \qquad Q_t = \sum_i \sum_c A_{cit} \kappa_c \hat{Y}_{cit} \Psi_{cit} = A_t \hat{Y}_t \Psi_t$$

where subscript i for the country, c for the crop, t for the time period, $\kappa_c$ is calories per unit of crop, $A_t = \sum_i \sum_c A_{cit}$ , $\hat{Y}_t = \dfrac{\sum_i \sum_c A_{cit} \kappa_c \hat{Y}_{cit}}{\sum_i \sum_c A_{cit}}$ , and $\Psi_t = \dfrac{\sum_i \sum_c A_{cit} \kappa_c \hat{Y}_{cit} \Psi_{cit}}{\sum_i \sum_c A_{cit} \kappa_c \hat{Y}_{cit}}$.

We now express world caloric production in natural logarithm using lower case letter as $q_t = a_t + \hat{y}_t + \psi_t$ , where $q_t \equiv \log(Q_t)$, $a_t = \log(A_t)$, $\hat{y}_t = \log(\hat{Y}_t)$ , $\psi_t = \log(\Psi_t)$. We also express other variables in log form so that the estimates from the model can be interpreted as supply elasticities. Thus, equation (1) takes the form

$$(3) \qquad q_t = \alpha + \beta p_t^e + \xi f(t) + u_t$$

In equation (3) if we were to use past lagged prices for the proxies of expected prices, we would be assuming that farmers have static expectations about expected prices (Nerlove 1958). When futures prices are used as proxies of expected prices, we assume farmers have rational expectations. As the objective of this paper is to revisit the endogeneity of futures prices, we assume farmers rely on rational expectations in formulating their price expectations.

In model (3), the futures price is suspected to be endogenous because of anticipated but unobservable supply or demand shocks which make the error term correlated with futures price, $\mathrm{E}(p_t^e, \mathrm{u}_t) \neq 0$ (Roberts and Schlenker 2009; Roberts and Schlenker 2013). Anticipated supply shocks can be categorized into two groups: they are a) predictable yield shocks caused by weather variation, where prediction is based on the available information at planting time t-1 and b) anticipated production shocks other than yield, say, pest attacks or changes in input costs. Thus, separating both production shocks from the error term we write the model (3) as

(4) $q_t = \alpha + \beta\ p_t^e + \delta\ E_{t-1}z_{1t} + \lambda\ E_{t-1}z_{2t} + \xi f\ (t) + \varepsilon_t$

Equation (4) is what we would like to estimate empirically. The main estimation challenge is to obtain available data on anticipated yield shocks and supply shocks other than yield. If all data are observable before or during the planting time, we can estimate equation (4) applying a simple OLS estimator. The resulting estimates of supply elasticity will be unbiased and consistent if $\mathrm{E}(u_t \mid p_t^e, z_{1t}, z_{2t}) = 0$. However, data on $z_{1t}$ and $z_{2t}$ are not observable before planting time. There are several strategies available to estimate equation (4) in this situation. First, we can ignore the unobservable variables and estimate the model as shown in equation (3) using OLS. However, these estimates will be biased and inconsistent because anticipated supply shocks are now part of the error term and may be correlated with futures price, i.e. $\mathrm{E}(p_t^e, \mathrm{v}_{1t}) \neq 0$, where $\mathrm{v}_{1t} = \delta E_{t-1}z_{1t} + \lambda E_{t-1}z_{2t} + \varepsilon_t$. Second, we can ignore the unobservable variables and estimate the model using a 2SLS estimator, where futures price can be instrumented using the previous year's yield shock.

Third, we can use proxies for both unobservable variables to avoid any bias caused from omitting variables and estimate the supply equation using OLS. Fourth, we can simultaneously use proxies for omitted predicted supply shocks and IV for the unobserved anticipated supply shocks and estimate the supply equation utilizing a 2SLS estimator. Thus, we have the following four possible empirical supply models:

(5) $q_t = \alpha_1 + \beta_1 p_t^e + \xi f\ (t) + v_{1t}$ , where $v_{1t} = \delta E_{t-1} z_{1t} + \lambda E_{t-1} z_{2t} + \varepsilon_t$

(6a) $q_t = \alpha_2 + \beta_2 p_t^e + \xi f\ (t) + v_{2t}$ , where $v_{2t} = \delta E_{t-1} z_{1t} + \lambda E_{t-1} z_{2t} + \varepsilon_t$

(6b) $p_t^e = \rho_0 + \rho_1 \psi_{t-1} + \xi f(t) + \eta_t$

(7) $q_t = \alpha_3 + \beta_3 p_t^e + \delta_3 \psi_t + \xi f\ (t) + v_{3t}$, where $E_{t-1} z_{1t} = \psi_t$ and $v_{3t} = \lambda E_{t-1} z_{2t} + \varepsilon_t$

(8a) $q_t = \alpha_4 + \beta_4 p_t^e + \delta_4 \psi_t + \xi f\ (t) + v_{4t}$, where $E_{t-1} z_{1t} = \psi_t$ and $v_{4t} = \lambda\ E_{t-1} z_{2t} + \varepsilon_t$

(8b) $p_t^e = \mu_0 + \mu_1 \psi_t + \mu_2 \psi_{t-1} + \xi f(t) + \vartheta_t$

Equation (5) is a model similar to the model (3) and does not use instrumented price. Equations (6a) and (6b) comprise a system of 2SLS regressions, where equation (6b) is the first stage that uses past year yield shock $\psi_{t-1}$ as an instrument for price and equation (6a) is the second stage regression. Equation (7) uses $\psi_t$ as a proxy for the expected yield shock as a control variable to account for the endogeneity of futures prices. Equation (8a) is the second stage of 2SLS regression, for which equation (8b) is the first stage—this system of equations simultaneously use a proxy for the expected yield shock as control and past-year yield shock as an instrumental variable for futures price. Roberts and Schlenker (2013) estimate the system (8a)-(8b) using a 2SLS regression. However, Hendricks, Janzen, and

Smith (2015) revisit this issue and show that the OLS regression (equation 7) of output on futures prices that only includes current-year realized yield shock as a control for the proxy of expected supply shock produces results similar to that of Roberts and Schlenker (2013). Hendricks, Janzen, and Smith (2015) conclude that IV is unnecessary in supply analysis. In their regressions, both Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) assume that yield shock is exogenous to price. Based on this assumption and our understanding of their empirical model, we discuss below if yield shock is truly exogenous to price. If it is not then, as we will show, the use of current-year yield shock as a proxy for anticipated yield shock does not address the endogeneity of futures price as claimed.

We focus first on the model (5) where it is suspected that futures price is endogenous because $\mathrm{E}(p_t^e, \mathrm{v}_{1t}) \neq 0$. We would like to account for the endogeneity of futures price while estimating the model. To do this, we need a proxy for the anticipated supply shock that is derived from outside the model and truly exogenous. Current-year realized yield shock $\psi_t$ is used as the proxy and is assumed exogenous by Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015).

One problem with using the current year's yield shock as an explanatory variable is that it is actually part of $q_t$. From the decomposition of $q_t$ we know $q_t = a_t + \hat{y}_t + \psi_t$. Yield shock $\psi_t$ is constructed from the current-year yield and by definition, is positively correlated with current-year production. Exogeneity of yield shock means both yield and trend yield is exogenous because $\psi_t = y_t / \hat{y}_t$. Thus, yield shock being exogenous and adding that as a control we only estimate growing area response, not the caloric supply. To see this suppose our true supply model is

(9) $q_t = \alpha + \beta\ p_t^e + \gamma\ E_{t-1} z_t + \xi f\ (t) + \varepsilon_t$

where $q_t = a_t + y_t$ is caloric supply[4], $p_t^e$ is expected crop output prices and $z_t$ is anticipated production shocks that are not observable before planting (t-1). All variables are in natural logarithmic form except time trend.

The difficulty in estimating the model (9) is that we do not observe $z_t$ because of data unavailability. Therefore, it is common to exclude the explanatory variable $z_t$ and estimate the following supply model

(10) $q_t = \alpha_1 + \beta_1 p_t^e + \xi f\ (t) + v_{1t}$, where $v_{1t} = \gamma E_{t-1} z_t + \varepsilon_t$

Differentiating model (10) with respect to $p_t^e$ gives supply elasticity with respect to price

(11) $$\frac{\partial q_t}{\partial p_t^e} = \frac{\partial (a_t + y_t)}{\partial p_t^e} = \frac{\partial a_t + \partial y_t}{\partial p_t^e} = \frac{\partial a_t}{\partial p_t^e} + \frac{\partial y_t}{\partial p_t^e} = \beta_1$$

From the model (10), we can also write separate regression equations for each component of $q_t$

(12.1) $a_t = \alpha^a + \beta_1^a p_t^e + \xi f^a(t) + v_{1t}^a$

(12.2) $y_t = \alpha_1^y + \beta_1^y p_t^e + \xi f^y(t) + v_{1t}^y$

---

[4] Instead of using yield shock $\psi_t$, we show the proof using realized yield $y_t$, where $y_t$ can be expressed as $y_t = \hat{y}_t + (y_t / \hat{y}_t) = \hat{y}_t + \psi_t$

Again, differentiating models (12.1) and (12.2) with respect to $p_t^e$, we have $\frac{\partial a_t}{\partial p_t^e} = \beta_1^a$ and $\frac{\partial y_t}{\partial p_t^e} = \beta_1^y$. Substituting these into (11), we obtain the identity

(12) $\beta_1^a + \beta_1^y = \beta_1$ .

We suspect that omitting anticipated production shock $z_t$ from the model (9) and then putting it in the error term $v_{1t}$ in model (10) causes the OLS estimate of $\beta_1$ to be biased if $p_t^e$ is correlated with $z_t$, i.e., $E(p_t^e, v_{1t}) = E(p_t^e, \gamma E_{t-1} z_t + \varepsilon_t) \neq 0$. This bias is called omitted variable bias and the correlation makes $p_t^e$ endogenous in supply analysis. We can eliminate (or at least mitigate) omitted variable bias by using a suitable proxy variable for the unobserved explanatory variable $z_t$. Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) add yield as a control. After adding control $y_t$ in model (10), we now write a new supply model as

(13) $q_t = \alpha_2 + \beta_2 p_t^e + \gamma_2 y_t + \xi f\ (t) + v_{2t}$

Differentiating $q_t$ with respect to $p_t^e$ in model (13), we get the supply elasticity with respect to price

(14) $\frac{\partial q_t}{\partial p_t^e} = \frac{\partial (a_t + y_t)}{\partial p_t^e} = \frac{\partial a_t + \partial y_t}{\partial p_t^e} = \frac{\partial a_t}{\partial p_t^e} + \frac{\partial y_t}{\partial p_t^e} = \beta_2$

In model (13), $y_t$ is controlled for the proxy of $z_t$. However, $y_t$ cannot be used as the proxy variable to account for the plausible endogeneity of futures price because $y_t$ is the part of the dependent variable $q_t = a_t + y_t$ in models (9), (10), and (13) and is itself endogenous because it correlated with the error $\varepsilon_t$ or $v_{2t}$ (Wooldridge 2009, p. 307, p. 517). Then what is the effect of including $y_t$ on the estimate of supply elasticity parameter $\beta$? To show this, from the model (13) we again write separate regression equations for each component of $q_t$

(14.1) $$a_t = \alpha_2^a + \beta_2^a p_t^e + \gamma_2^a y_t + \xi f^a(t) + v_{2t}^a$$

(14.2) $$y_t = \alpha_2^y + \beta_2^y p_t^e + \gamma_2^y y_t + \xi f^y(t) + v_{2t}^y$$

Again, differentiating models (14.1) and (14.2) with respect to $p_t^e$ gives $\frac{\partial a_t}{\partial p_t^e} = \beta_2^a$ and $\frac{\partial y_t}{\partial p_t^e} = \beta_2^y$. Substituting these in (14), we obtain the identity

(15) $$\beta_2^a + \beta_2^y = \beta_2^a + 0 = \beta_2 \quad \because R^2 = 1 \text{ and } \beta_2^y = 0 \text{ in model } (14.2).$$

This means when we are estimating model (13), we are estimating the supply elasticity of growing area model, not the caloric model. Therefore, models (10) and (13) are not comparable for the purpose of discerning whether there is omitted variable bias.

To explain the difference between the supply elasticity estimate in models (10) and (13), we write a regression of the omitted $y_t$ (in model 10) on the included variable $p_t^e$ as

(16) $$y_t = \pi_0 + \pi_1 p_t^e + \xi f \ (t) + k_t$$

Now, using the omitted variable bias formulas, we have the following algebraic relationship

$$
(17)\quad
\begin{aligned}
\beta_1 &= \beta_2 + \gamma_2 \pi_1 \\
&= \beta_2^a + \beta_2^y + \gamma_2^a \pi_1 + \gamma_2^y \pi_1 \\
&= \beta_2^a + \beta_2^y + \gamma_2^a \pi_1 + \pi_1 \quad \because \gamma_2^y = 1 \text{ from the model (14.2)} \\
&= \beta_2 + \gamma_2^a \pi_1 + \beta_1^y \quad \because \pi_1 = \beta_1^y \text{ from the models (12.2) and (16)}
\end{aligned}
$$

This implies the difference between $\beta_1$ and $\beta_2$ is

$$
(18)\quad \beta_1 - \beta_2 = \beta_1^y + \gamma_2^a \pi_1
$$

Equation (10) shows that the difference is due to correlation ( $\beta_1^y$ ) between $y_t$ and $p_t^e$ and not for excluding a variable that is a part of the error term in model (10) plus due to omitted variable bias

( $\gamma_2^a \pi_1$ ) that occurs in the model (12.1). Further manipulating the equation (18), we obtain

$$
(18)\quad
\begin{aligned}
&\beta_1^a + \beta_1^y - \beta_2^a - \beta_2^y = \beta_1^y + \gamma_2^a \pi_1 \\
&\Rightarrow \beta_1^a - \beta_2^a = \gamma_2^a \pi_1 \quad \because \beta_2^y = 0 \text{ from the model (14.2)}
\end{aligned}
$$

Equation (18) shows that when yield shock is included in a caloric supply equation as a proxy for anticipated yields, the resulting supply elasticity is an acreage supply elasticity, not a caloric supply elasticity, and any endogeneity of futures price in an acreage model is accounted for.

The next issue examined is whether including the current yield shock actually does what the literature claims it does. That is, is the current yield shock a good proxy for anticipated shock? Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) find a negative and statistically significant correlation between current-year yield shock and futures price. Hendricks, Janzen, and Smith (2015) are explicit in their interpretation of this negative correlation as evidence that yields are predictable. They note that an expected increase (decrease) in yield relative to trend yield decreases (increases) the futures price. Therefore, a negative correlation between yield shock and the futures price, which they find, is evidence that yield shocks are anticipated.

Current-year yield shock may be predictable if we can forecast accurately growing season weather. One way to make such a prediction is if growing season weather is serially correlated. The serial correlation would mean that good growing seasons tend to be followed by good growing seasons and bad tend to be followed by bad. The higher the correlation coefficient the more predictable are yields. A regression of current global yield shock and on lagged shock from 1961 to 2014 gives a coefficient of 0.14 with a p value of 0.3. Thus there is scant evidence of serial correlation.

Another way that yield shocks can be anticipated is if growing season weather can be accurately forecasted using information available to forecasters before planting. Given the dramatically increase in ability to solve detailed dynamic climate models over time, we should expect to see the increased accuracy of forecasts of growing season weather. Therefore, one piece of evidence that yield shocks are anticipated because of accurate growing season weather forecasts is an increasing degree of negative correlation between yield shocks and futures prices over time. There is a reason to doubt however that growing season weather can be forecasted accurately even today. For example, in 2012, U.S corn and soybean farmers faced a severe and extensive drought. Given the assumption that we can anticipate a negative yield shock, we would expect a significant pre-planting higher futures price relative to previous years. However, in reality, we saw a decrease in the futures price of major grains in 2012 relative to 2011. At the beginning of 2012 people were either expecting a positive yield shock or a large carryover of grains from the previous year caused the decline in futures price. USDA did not foresee the drought coming. Their 2012 corn yield was projected at a record 166.0 bushels per acre, 2.0 bushels above the 1990-2010 trend reflecting the rapid pace of planting and emergence (WASDE, May 2012).[5] 2012 had started out as a promising year for U.S. crop production, with favorable planting conditions supporting higher planted acreage and expectations of record or near-record production. In reality, 2012 brought some of the driest and most unfavorable growing conditions in decades.[6] Hence, we suspect that yield shock is not predictable.

We examine the degree and sign of the correlation between current-year yield shock and futures price in two ways. First, we run a simple OLS regression of yield shock on futures price for the entire sample, which is similar to that of Hendricks, Janzen, and Smith (2015) but we control for two potential outliers suspected to be present in the sample, which we discuss later in this paper. Second, we check the sensitivity of the correlation by limiting the sample size so that it begins in 1980. Our hypothesize is that the correlation should be more negative in the later sample because with the improvement of climate models it is likely that yield shocks should be more forecastable after 1980 than before. We now model the predictably of yield shock treating equation (12.1) regression with omitted variable relative to equation (14.1). Using omitted variable regression formulas, we regress the excluded variable on the included variable

(19) $\psi_t = \mu_0 + \mu_1 p_t^e + \xi f\ (t) + \tau_t$

[5] http://usda.mannlib.cornell.edu/usda/waob/wasde//2010s/2012/wasde-05-10-2012.pdf

[6] http://www.ers.usda.gov/topics/in-the-news/us-drought-2012-farm-and-food-impacts.aspx

Hendricks, Janzen, and Smith (2015) treat the parameter $\mu_1$ in model (19) as representing the predictability of yield shock. We expect that $\mu_1 < 0$ because any expected increase of yield relative to trend yield would lower the futures price and vice versa. We expected this would hold for any sample and model specification. We hypothesize if $\mu_1 < 0$ for t=1, 2,………, T, then it will hold for any subsample taken from full sample, i. e., $\mu_1 < 0$ for any t=d, d+1,……., T where d>1. We also expect $\mu_1$ will become more negative over time. Results of this analysis are reported later.

If our hypothesis holds, then we can include current-year realized yield shock $\psi_t$ as a control in the growing area response model to account for the endogeneity of futures price. If it does not hold, then a question arises about how to account for any endogeneity of futures price in the caloric supply or growing area response model. An option to address the endogeneity of futures price is to use a 2SLS (IV) regression which uses past-year yield shock as the instrument for futures price. The system of equations (6a)-(6b) show such model, where we assume yield is endogenous to price.

To summarize, we argue that when current-year realized yield shock is assumed to be exogenous and yield is forecastable, then when it is included in a calorie supply equation we account for the endogeneity of futures price in a growing area response model. If the assumption of predictability of yield shock does not hold, we cannot use as current yield shock as a control variable in the growing area model. Then the preferred method for estimating growing area response is to use simple OLS regression of growing area on futures price. We address the endogeneity of futures price in the caloric supply or growing area response model by using a 2SLS (IV) regression which uses past-year yield shock as the instrument for futures price and where we assume yield is endogenous to price.

*Crop-Specific Supply Response*

Aggregating across crops implicitly assumes that crops are perfectly substitutable in production and it assumes identical land and other input requirements for each crop (Haile, Kalkuhl, and von Braun 2016). This ignores the possibility that increasing the price of one commodity may increase the allocation of land to that crop and may decrease the production of other crops. As a result, the supply of substitutable crops falls and their price goes up. To account for these cross-price effects, we estimate supply elasticity of each crop simultaneously. A basic model for crop-specific supply response can be written as follows

(20) $q_{ct} = \alpha_c + p_c^{e'}\beta + \xi f\ (t) + u_{ct}$

where $q_{ct}$ denotes crop-specific caloric supply with subscript c for crop, $p_c^{e'}$ a vector of own and competing expected crop prices. We estimate a similar model as shown in equations (5)-(8b) while investigating the endogeneity of futures price for a particular crop.

### 2.3 Data and Variables

For the global supply response model, we use a comprehensive database covering all countries that produce at least one of the four key crops during the period 1961 to 2014. Data on production, growing area, and yield for each country are obtained from the FAOSTAT database of Food and Agricultural Organization (FAO). All crop futures prices are traded in Chicago Board of Trade (CBOT) and are obtained from the QUANDL database, The U.S. Consumer Price Index (CPI) used in this study is obtained from the U.S. Bureau of labor Statistics (BLS).

The variables we use are the same as used by Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015). Global caloric production in the aggregate model is the sum of the country-specific caloric production of corn, rice, soybeans, and wheat, which we calculate using the caloric conversion factors from Williamson and Williamson (1942). The global growing area is the amount of harvested land of four crops. The futures price in our aggregate econometric model is the calorie-weighted December (previous year) average of the harvest/delivery time price of corn, soybeans, and wheat, deflated by CPI. The delivery month for soybeans is November and for corn and wheat, the delivery month is December. Growing area used in the crop-specific model is the sum of country-level harvested area of respective crops. The futures price for each crop is the pre-planting harvest time futures price of the respective crop, weighted by crop-specific caloric share and deflated by CPI.

Yield shock is the log of the weighted average of the country and crop-specific yield shock, which is defined as the ratio of actual to trend yield. We model yield of each crop for each country using a flexible time trend to obtain trend yield and to construct yield shock. While constructing global yield shock, we construct a panel dataset of 31 countries. We construct a single country ((rest of the world (ROW)) by summing up the production of countries with a share of less than 0.5% of global caloric production. Flexible trends are approximated by restricted cubic splines, which places knots at equal or unequal intervals 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).

When we estimate supply response for the US, we use production, growing area, and yield data obtained from the USDA-NASS. Futures prices are the same as described above, except the weights are now US crop-specific caloric share in US total calories. Yield shock is the log of the weighted average of the US states and crop-specific yield shocks. We model yield of each crop for each state on flexible time trend to obtain trend yield and to construct yield shock (Figures A1-A4 of appendix). The flexible time trend is approximated using both cubic splines in time with equidistant and un-equidistant knots.

We estimate the response of global and US aggregate caloric production and growing area to futures prices and yield shock using OLS and IV or 2SLS regressions. OLS provides a mean response of unknown population parameter using sample data and assuming all control variables used in the regression as exogenous. The 2SLS regression addresses endogeneity problems associated with control variables by regressing the specific endogenous variable on the appropriate instrumental variable(s). Crop-specific supply responses are estimated using OLS, 2SLS, and Seemingly Unrelated Regression (SUR) estimators.

### 2.4 Methodological Issues Estimating Equations

Estimating the relationship between supply and futures prices using time-series data needs to be examined carefully because without addressing the time-series properties of the data properly, we may end up with results based on the spurious correlation. Another issue is how we address technological change and/or structural break if we deal with longer time-series data and want to produce results that are based on recent data most relevant to policy makers. Thus we discuss below two most important methodological issues related to estimating our equations.

### 2.4.1 Time Series Properties of the Data

Our key variables are production, futures prices, and yield shocks. Production is trend stationary (a unit root can be rejected: see figure A5 of appendix) and yield shock is stationary (see figure A6 of appendix). The time series properties of agricultural crop prices are the subject of much debate in the literature. The theory of financial market efficiency considers price as nonstationary (has a unit root). On the other hand, competitive storage theory suggests that price is stationary with high autocorrelation (Williams and Wright 1991) but stationarity of prices is not directly predicted by the theory. Though both theories are based on rational expectations, one predicts stationarity and the other predicts non-stationarity. A series of path-breaking papers by Deaton and Laroque (1992, 1995, and 1996) investigate the empirical relevance of the storage model by assuming price as stationary. These authors argue that price fluctuations seem to be temporary for the commodities where weather plays a major role in the changes in crop price, but a random walk requires all fluctuations in price to be permanent (Deaton and Laroque 1992). But, these authors themselves challenged the storage model because their model could not replicate actual historical price patterns. Recently, Cafiero, Bonenrieth, and Bonenrieth (2011) argue that the presence of a trend in agricultural commodity price poses challenges to the storage model that assumes the series is originally stationary. They show that the detrended price series is stationary and the storage model is able to fit the de-trended price with high autocorrelation. This implies that if a price series is de-trended and the model is based on storage theory (production and price are linked between periods through storage), then we will have a stationary time series model. This works for IV regression as the IV model is motivated from the storage theory. However, our simple OLS regression is not motivated from the storage theory. In that case, the stationarity of the overall model primarily depends on how we de-trend the data. We use flexible time trend approximated by a cubic spline with a different order of knots to detrend the data. For regression spline, a trivial choice is to use equidistant knots or knots at equally spaced sample quantiles of x (Kagerer, 2013). But knots can be chosen at unequal intervals as long as the support of each spline basis function contains, at least, one design point, the residual sum-of-squares surface is continuous, and the corresponding spline is well defined (Lindstrom 1999). We use both equidistant and un-equidistant knots to remove trend from the price series to avoid spurious correlation in the regression.

Figure 1 plots actual futures price and the trend line using cubic spline in time with six knots (equidistant). Knots are at 1962, 1972, 1982, 1992, 2002, and 2012 and they are chosen on an ad-hoc basis. The objective of using cubic spline is to remove a flexible deterministic trend from the data that reduce the risk of spurious correlation among variables in the model. The chance of getting spurious correlation is low in a regression if predicted values are well approximated by cubic spline regression. A simple visual inspection of figure 1 reveals that the use of equidistant knots does not seem to approximate the data well. In particular, the price spikes in 1974 and 1975 do not seem to be well approximated. As a result, it is likely that we may get spurious correlation if we estimate the correlation between price and the variables of our interest if we use these data points. To compare with the knots that work best for the data in the sample, we use the free-knot least-square method suggested by Spiriti et al. (2013). This method does not fit the knot beforehand rather it uses a stochastic search algorithm to select a number of knots and allows knots to be chosen freely depending on the characteristics of the data. Figure 2 shows the predicted line for futures price fitted by a free-knot least-squares spline. The plot reveals that the free-knot method improves the fit. In figure 3, we reproduce this plot using cubic spline function with an unequal interval of knots for our regression purpose. The knots are at 1962, 1972, 1976, 1982, 1992, 2002, and 2012.

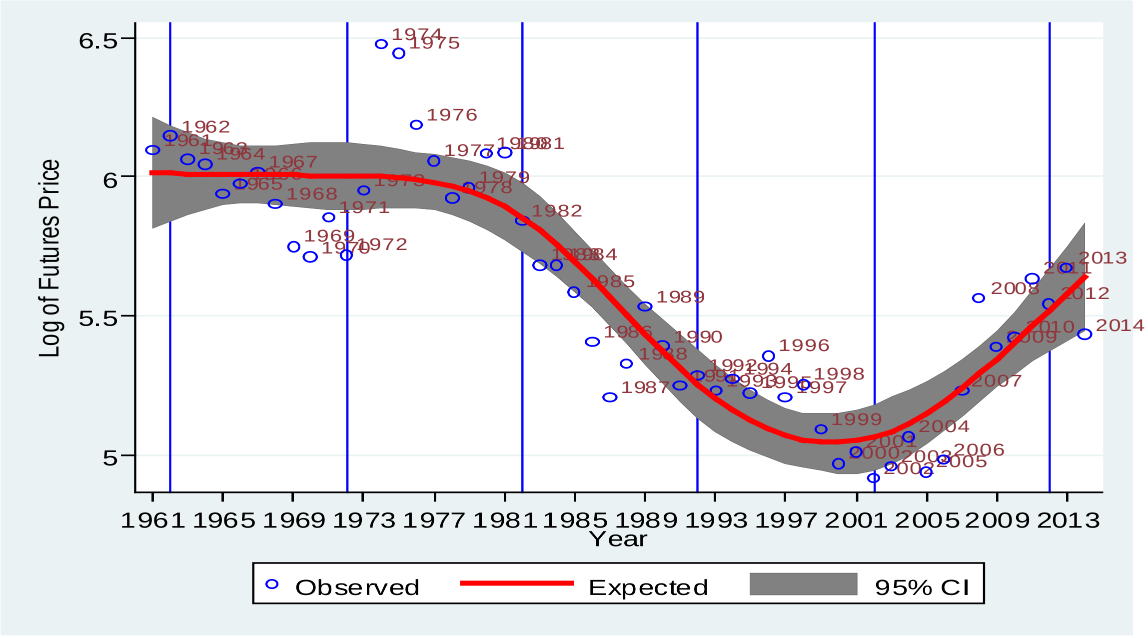


Figure 1. Average futures price approximated by flexible time trend with equidistant knots

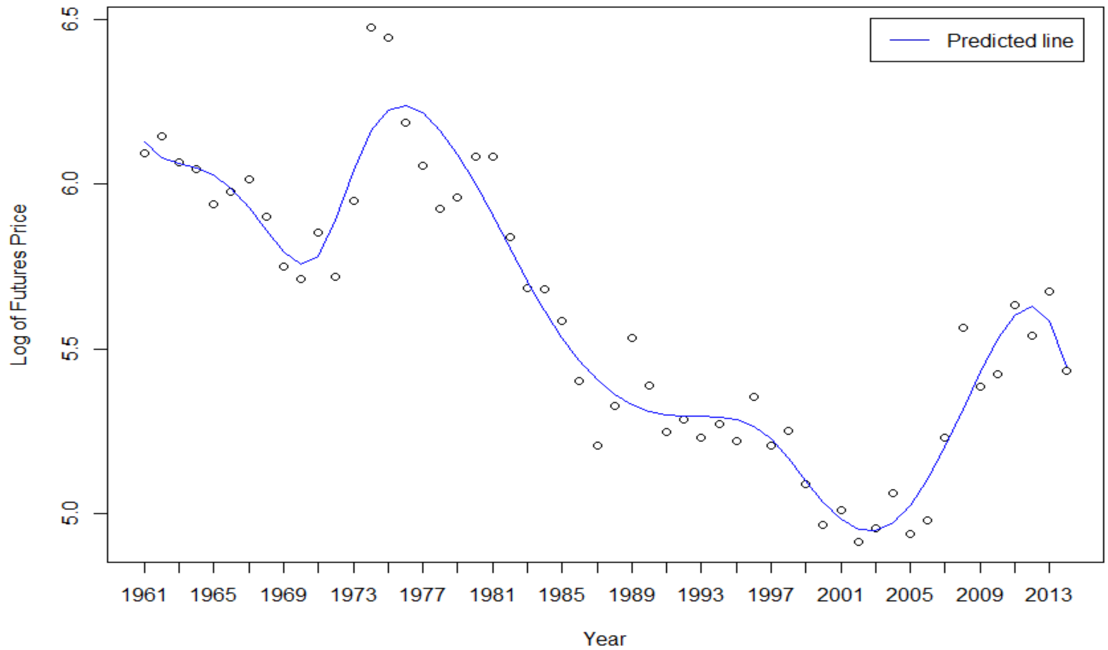


Figure 2. Average futures price approximated by free-knots spline

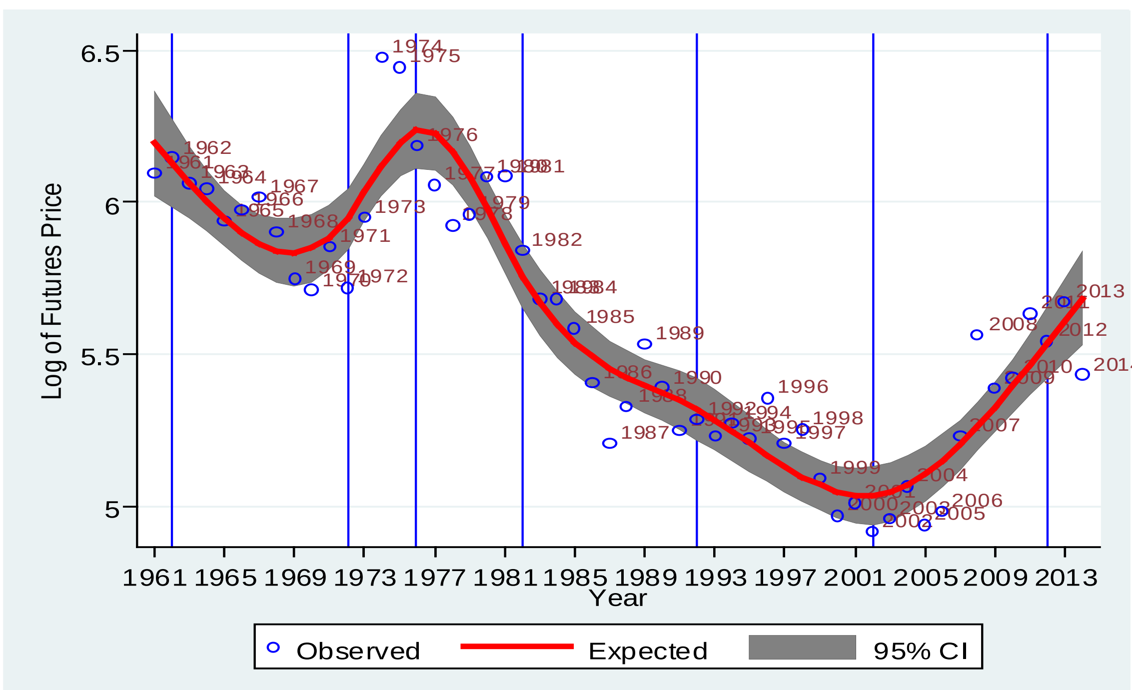


Figure 3. Average futures price approximated by unequal interval of knots

### 2.4.2 Stability of the Parameters

A stable supply elasticity estimate is very important to policymakers to undertake agricultural policy relevant to supply analysis. Hendricks, Janzen, and Smith (2015) note that endogeneity bias and regression estimates of supply elasticities are specific to the time period covered, among many other factors. Thus, to check the stability or to check the sensitivity of the estimated parameters with respect to the time period covered, we use two main methods. First, we limit the sample so that it begins in 1980. Second, we apply a rolling regression method to investigate supply response. These approaches also check whether endogeneity of futures price depends on the sample size.

## 2.5 Results and Discussion

### 2.5.1 Correlation between Yield Shock and Futures Price

Tables 1 and 2 present results on the correlation between current-year yield shock and futures price. Table 1 uses the same sample data as used by Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) whereas table 2 includes data to 2014. Columns (1)-(4) in panel A of table 1 report OLS estimates of the correlation using full sample data whereas columns (5)-(8) provide estimates using data from 1980. Columns (1)–(4) in panel B use full sample data but remove two outliers (years 1974 and 1975). The number of knots used in the cubic spline trend varies by column. Columns (1)-(3) in table 1 use the same knot specification as those used by Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015). Column (4) uses knots that are more flexible for a better approximation. Because the sample size is different in table 2, the knot specifications also differ.

In panel B of each table we remove two data points because we suspect that they are potential outliers. From the plot of futures price (figure 1), we see that the futures price was very high in 1974 and 1975 relative to other observations in the sample and the increase in 1973 was significantly higher than the previous year. We also see a large negative yield shock in both years (figure A6 in appendix). A very strong macroeconomic performance during 1972 and 1973, two consecutive years of widespread crop failures, low inventories both for food and agricultural raw materials, and the very sharp price increases instituted by the oil cartel late in 1973 were the contributing factors for higher commodity prices in 1974 (Radetzki 1974; Radetzki 2006). Moreover, the speculative demand for commodity inventories as a ‘‘safe’’ store of value was a further contributory factor to the commodity boom (Cooper and Lawrence 1975). Thus, it is not the expected negative yield shock that causes the futures price to rise dramatically in 1973 and 1974. In fact, farmers around the world were expecting good yields in 1974 (FAO, 1974, 1975). For example, in 1974 the projected corn yield of the U.S was around 97.0 bushels per acre, which was significantly higher than 1973. The projected soybean yield in 1974 was also higher than the previous year (WASDE, April 1974).[7] The higher futures price in 1975 was due to large past yield shocks not due to farmers expecting another yield shock. After 1975, futures prices fall significantly even though the yield shock was negative until 1977. Thus, we consider years 1974 and 1975 as two potential outliers in the sample.

[7] http://usda.mannlib.cornell.edu/usda/waob/wasde//1970s/1974/wasde-04-25-1974.pdf

The OLS estimates in columns (1)-(3) of panel A show that the correlation between current-year realized yield shock and futures price is negative and statistically significant (table 1). Given the assumption that yield shock is exogenous, this result implies yield shock is predictable and a predictable increase in yield caused futures price to decrease. Hendricks, Janzen, and Smith (2015) to justify inclusion of current yield shock in their supply equation using these results. However, the estimates in panel B (columns 1-3) are less negative and statistically insignificant after we control for the two potential outliers. Moreover, when we use the sample that begins in 1980 (columns 5-7), we find a positive correlation between current-year yield shock and futures price. If yield shocks were predictable one would expect that they would be more predictable on average from 1980 to 2007 than from 1961 to 2007. Higher predictability would result in a more negative correlation, not a positive and insignificant correlation. These results indicate that the yield shock is not predictable, the correlation is due to sampling noise, and the inclusion of the current yield shock in a supply equation is unwarranted.

These conclusions are confirmed using the longer sample period. Adding years lowers the level of negative correlation and its significance, as reported in columns 1-3 in table 2. Discarding the outlier years makes the correlation practically zero. And the coefficient using the sample from 1980 to 2014 is positive and insignificant. We also plot the estimates of the correlation in figure 4 using rolling regression method. The plot supports our finding that the yield shock is not predictable because we find a positive correlation as our models use more recent data.

**Table 1. Correlation between Global Yield Shock and Futures Price**

| | Full Sample: 1961-2007 | | | | Subsample:1980-2007 | | |
|---|---|---|---|---|---|---|---|
| | Shock | Shock | Shock | Shock | Shock | Shock | Shock |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Panel A. | | | | | | | |
| Futures Price | -0.047$^{**}$ | -0.052$^{**}$ | -0.051$^{**}$ | -0.028 | 0.032 | 0.030 | 0.052 |
| | (0.015) | (0.018) | (0.018) | (0.023) | (0.031) | (0.032) | (0.043) |
| N | 46 | 46 | 46 | 46 | 27 | 27 | 27 |
| F-Stat | 3.315 | 2.525 | 2.025 | 2.139 | 0.899 | 0.684 | 0.644 |
| R square | 0.191 | 0.198 | 0.202 | 0.248 | 0.105 | 0.111 | 0.133 |
| Adj-R square | 0.134 | 0.119 | 0.102 | 0.132 | -0.012 | -0.051 | -0.074 |
| Knot | 3 | 4 | 5 | 6 | 3 | 4 | 5 |
| Panel B. | Controlling for 1974 and 1975 | | | | | | |
| Futures Price | -0.028 | -0.032 | -0.026 | 0.025 | | | |
| | (0.018) | (0.021) | (0.022) | (0.028) | | | |
| N | 44 | 44 | 44 | 44 | | | |
| F-Stat | 1.105 | 0.878 | 0.959 | 2.099 | | | |
| R square | 0.077 | 0.083 | 0.112 | 0.254 | | | |
| Adj-R square | 0.007 | -0.011 | -0.005 | 0.133 | | | |
| Knot | 3 | 4 | 5 | 6 | | | |

*Notes:* Standard errors in parentheses: $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table 2. Correlation between Global Yield Shock and Futures Price**

| | Full sample: 1961-2014 | | | | Subsample: 1980-2014 | | | |
|---|---|---|---|---|---|---|---|---|
| | Shock | Shock | Shock | Shock | Shock | Shock | Shock | Shock |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A. | | | | | | | | |
| Futures Price | -0.036$^{*}$ | -0.039$^{*}$ | -0.040$^{*}$ | -0.009 | 0.024 | 0.026 | 0.030 | 0.046 |
| | (0.017) | (0.017) | (0.017) | (0.021) | (0.021) | (0.025) | (0.026) | (0.036) |
| N | 53 | 53 | 53 | 53 | 34 | 34 | 34 | 34 |
| F-Stat | 1.143 | 1.418 | 1.225 | 1.982 | 0.935 | 0.693 | 0.580 | 0.551 |
| R square | 0.087 | 0.131 | 0.138 | 0.236 | 0.086 | 0.087 | 0.094 | 0.109 |
| Adj-R square | 0.011 | 0.039 | 0.025 | 0.117 | -0.006 | -0.039 | -0.068 | -0.089 |
| Knot | 4 | 5 | 6 | 7 | 3 | 4 | 5 | 6 |
| Panel B. | Controlling for 1974 and 1975 | | | | | | | |
| | -0.011 | -0.016 | -0.012 | 0.027 | | | | |
| | (0.019) | (0.019) | (0.020) | (0.023) | | | | |
| N | 51 | 51 | 51 | 51 | | | | |
| F-Stat | 0.362 | 0.412 | 0.561 | 1.795 | | | | |
| R square | 0.031 | 0.044 | 0.071 | 0.226 | | | | |
| Adj-R square | -0.054 | -0.062 | -0.056 | 0.100 | | | | |
| Knot | 4 | 5 | 6 | 7 | | | | |

*Notes*: Standard errors in parentheses: $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

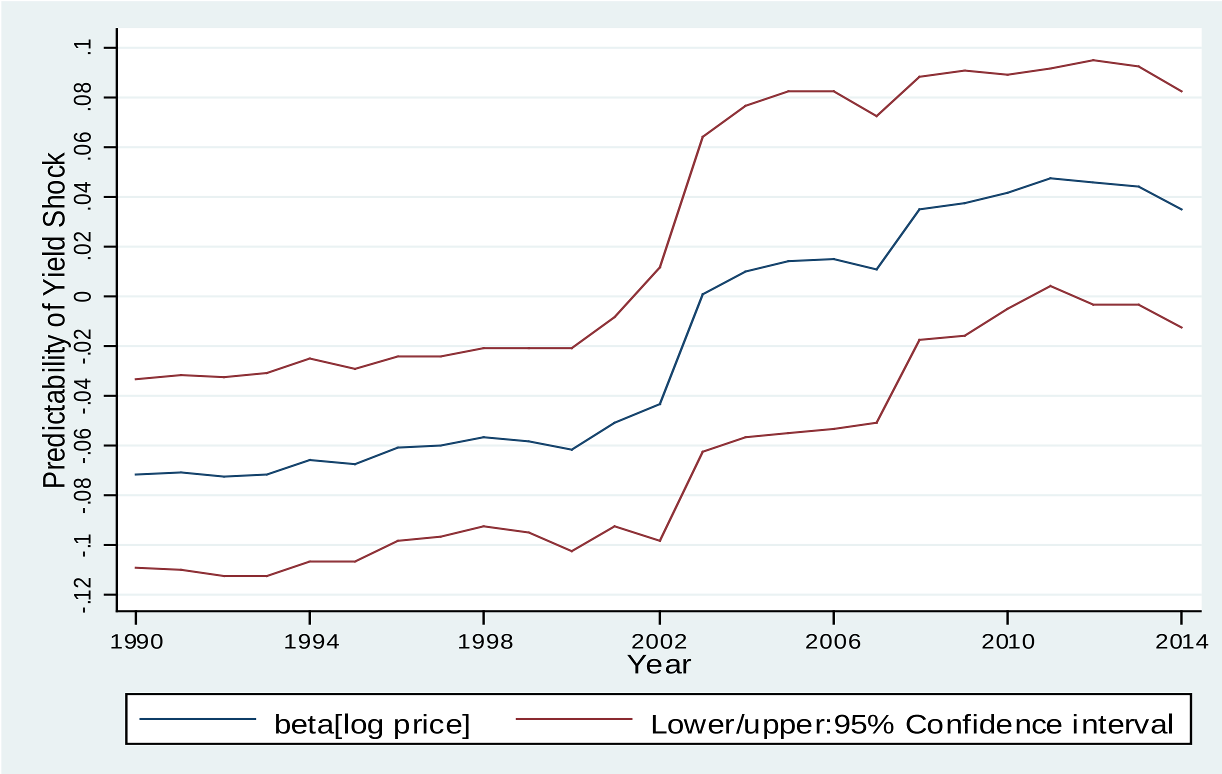


**Figure 4. Time-varying estimates of the predictability of global yield shock estimated applying rolling estimation method in the OLS regression of current-year realized yield shock the futures price**

### 2.5.2 Global Aggregate Crop Supply Response

The results in tables 1 and 2 indicate that the current year yield shock should not be used as a control in supply equations because yield shocks are not predictable. However, we go ahead and include the yield shock in some of the regressions to allow for a comparison of results with previous studies.

Table 3 shows the main results obtained from estimating equations (5)-(8b). Estimation results are based on OLS and 2SLS estimators. All models vary with multiple specifications of the time trend. Results of columns (a)-(b) are based on equidistant spline knots whereas column (c) results are based on the unequal interval of spline knots. Panel A reports OLS estimates of supply elasticity without controlling for current-year yield shock and panel C reports OLS estimates with the yield shock as a control. The elasticity estimates in Panel B are from IV regression that omits current yield shock as a control but uses past yield shock as an instrument for futures price. Panel D is 2SLS estimates with the current-year yield shock as control and past year yield shock as an instrument. Panel A, C, and D use the same model as estimated by Roberts and Schlenker (2013), and Hendricks, Janzen, and Smith (2015). The only difference is that we include updated data and use the alternate specification of time trend.

*Yield is Exogenous*

We start our discussion by explaining results when we assume yield shock (yield) is exogenous. First, we compare the results between panel A and C of table 3. The OLS estimates of the caloric supply elasticity in columns (1a)-(1c) of panel C are substantially higher than the corresponding estimates of panel A for all the specifications of cubic spline time trend. It seems that these noticeable differences in estimates are due to omitting anticipated supply shocks. However, that is not necessarily the reason here. Our formal proof in section 2 shows these differences are due to a correlation between current-year yield shock and the futures price. Based on the formulas as shown in equation (18) of section 2, we can measure the magnitude of these differences. The formula for the differences in estimates between panel A and C is $\beta_1^{a_t} + \beta_1^{\hat{y}_t} + \beta_1^{\psi_t} - \beta_2^{a_t} - \beta_2^{\hat{y}_t} = \beta_1^{\psi_t} + (1+\gamma_2)\pi_1$. Using the estimates in panel A of column (3a) and in panel C of column (1a) from table 3, we find $\hat{\beta}_1^{\psi_t} + (1+\hat{\gamma}_2)\hat{\mu}_1$ = -0.036+1.239*(-

0.036) = -0.045, which is equivalent to difference (0.032-0.077= -0.045) in the OLS estimates between panels A and C of column (1a). Our formal proof in section 2 also shows when yield shock (yield) is assumed exogenous, we essentially estimate the growing area response model and account for the endogeneity of futures price in growing area response model by including yield shock as a control variable in the supply model, assuming that it is predictable. Thus, we now compare the OLS estimates in panels A and C of columns (2a)-(2c). We see that the elasticity estimates of growing area response in panel A are close to the estimates in panel C, which confirms that current yield shock should not be included in the regression equation. We conduct a test of omitted variable bias between the models in panels A and C. The p-values (reported at the bottom of table 3) for all the specifications of time trend show that we fail to reject the null hypothesis of no omitted variables bias.

Next, we compare between OLS estimates in panel C and the 2SLS estimates in panel D for the growing area response models (columns 2a-2c of table 3) to see whether other possible sources of omitted variable bias are important. Roberts and Schlenker (2013) advocate using the model that generates Panel D results. Hendricks, Janzen, and Smith (2015) advocate using the model in Panel C. We find that the IV estimates of growing area supply elasticity in panel D are slightly larger than the OLS estimates in panel C. This difference provides some indication that omitted supply shocks other than current yield may be correlated with futures prices, leading to biased estimates. We test this assumption using the Durbin-Wu-Hausman (DWH) test to examine whether 2SLS is necessary. The p-values for all the specifications of time trend suggest that we fail to reject the null hypothesis of no omitted variable bias. These results also imply that a higher F-value (>10:

sign for the strong instrument) does not necessarily indicate that significant omitted variable bias is present. The F-values from the first stage regressions are reported in the bottom panel of table 3.

Results of table 3 also reveal that the OLS estimates of caloric supply elasticity in panel A are lower than OLS estimates in panel C because yield shock (or yield) is negatively correlated with futures price (columns 4a-4c in panel A). The results indicate that about 78% of the difference between the elasticity estimates in panel A and panel C is because of the sampling noise created by the negative correlation between the futures price and yield shock.[8]

With regard to the flexible time trend, we see that the use of cubic spline in time with seven knots produces a result that show the correlation between yield shock and futures price is almost zero and statistically insignificant (column 4c in panel A of table 3). As we showed earlier, this knot specification (unequal) approximates the data better than the other order of knots and is likely to account for the plausible spurious correlation better than other knots specification.

*Yield is Endogenous*

We now turn our discussion to the issue of endogeneity of futures price in caloric as well growing area response models when yield is possibly endogenous to the futures price. A difference between the OLS estimates in panel A and the 2SLS estimates in panel B of

[8] We report regression results in table A2 of appendix, using actual weather data for the proxy of expected yield shock downloaded from Roberts and Schlenker (2013). In general, the OLS estimates with weather as controls are found to be very low and statistically insignificant. The p values for the test of omitted variable bias are greater than 0.10 in all models, indicating no omitted variable bias. These results also confirm that the use of current-year realized yield shock as the proxy of expected production shock is not valid.

columns (1a)-(1c) is an indication that instrumenting futures price is appropriate. From the columns (1a)-(1c) of table 3, we find that except for the cubic spline in time with seven knots (column 1c), the OLS (panel A) and 2SLS (panel B) estimates of caloric supply elasticities are similar in value and insignificant. When the seven-knot spline is used then the elasticities differ substantially with the elasticity being barely significant at the 10% level. Overall these results do not seem to support the hypothesis that IV estimation is needed to estimate the impact of changes of futures price on global caloric supply. The p-values for all the specifications of time trend suggest that we fail to accept alternative hypothesis that the effects of endogeneity of the futures price on the estimates are meaningful and thereby IV techniques are required. These results also imply that a higher F-value (>10: sign for the strong instrument) does not necessarily indicate that the futures price is endogenous.

For growing area response model, the elasticities are positive and significant and the 2SLS elasticity estimates are somewhat higher than the OLS estimates. However, the p-values for the test of omitted variables bias are greater than 0.3, suggesting that there is limited support for the hypothesis that IV estimation is needed when estimating acreage response. With regards to yield response, trend yield specifications reported in columns 3a and 3b show a positive and significant elasticity with respect to the futures price. The IV estimates are close to the OLS estimates and the p-values of the test of omitted variables bias are small. Thus there seems to be no evidence of the need to instrument futures price to model global trend yield. When the seven knot spline is used to estimate trends in expected price then there is no evidence that trend yield is endogenous.

## Table 3. Global Supply Estimates and Sources of Endogeneity Bias

| | Caloric Supply | | | Growing Area | | | Trend Yield | | | Yield Shock | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) | (4a) | (4b) | (4c) |
| Panel A. OLS: Does not control current yield shock (equation 5): | | | | | | | | | | | | |
| Futures Price | 0.032 | 0.025 | 0.047 | 0.049$^{**}$ | 0.045$^{**}$ | 0.046$^{**}$ | 0.018$^{**}$ | 0.019$^{**}$ | 0.008 | -0.036$^{*}$ | -0.040$^{*}$ | -0.009 |
| | (0.024) | (0.024) | (0.030) | (0.009) | (0.009) | (0.011) | (0.006) | (0.006) | (0.007) | (0.017) | (0.017) | (0.021) |
| Panel B. IV Regression: does not control current yield shock (equations 6a-6b) | | | | | | | | | | | | |
| | 0.047 | 0.054 | 0.140$^{+}$ | 0.064$^{**}$ | 0.062$^{**}$ | 0.087$^{*}$ | 0.021$^{+}$ | 0.022$^{+}$ | -0.000 | -0.037 | -0.037 | -0.037 |
| | (0.046) | (0.039) | (0.085) | (0.019) | (0.018) | (0.043) | (0.012) | (0.012) | (0.025) | (0.035) | (0.035) | (0.035) |
| Panel C. OLS: control current yield shock (equation 7) | | | | | | | | | | | | |
| Futures Price | 0.077$^{**}$ | 0.075$^{**}$ | 0.058$^{**}$ | 0.056$^{**}$ | 0.052$^{**}$ | 0.047$^{**}$ | 0.018$^{**}$ | 0.020$^{**}$ | 0.009 | 0 | 0 | 0 |
| | (0.011) | (0.011) | (0.013) | (0.009) | (0.009) | (0.011) | (0.006) | (0.006) | (0.007) | | | |
| Shock | 1.239$^{**}$ | 1.230$^{**}$ | 1.299$^{**}$ | 0.187$^{*}$ | 0.166$^{*}$ | 0.186$^{*}$ | 0.017 | 0.026 | 0.073 | 1 | 1 | 1 |
| | (0.088) | (0.091) | (0.092) | (0.074) | (0.072) | (0.077) | (0.050) | (0.052) | (0.051) | | | |
| Panel D. IV Regression: control current yield shock (equations 8a-8b) | | | | | | | | | | | | |
| Futures Price | 0.094$^{**}$ | 0.091$^{**}$ | 0.065$^{*}$ | 0.072$^{**}$ | 0.068$^{**}$ | 0.076$^{*}$ | 0.022$^{+}$ | 0.023$^{+}$ | -0.004 | 0 | 0 | 0 |
| | (0.021) | (0.020) | (0.033) | (0.020) | (0.018) | (0.037) | (0.013) | (0.012) | (0.024) | | | |
| Shock | 1.278$^{**}$ | 1.271$^{**}$ | 1.303$^{**}$ | 0.224$^{**}$ | 0.207$^{**}$ | 0.198$^{**}$ | 0.025 | 0.033 | 0.067 | 1 | 1 | 1 |
| | (0.103) | (0.095) | (0.082) | (0.082) | (0.079) | (0.076) | (0.054) | (0.055) | (0.049) | | | |
| **Panel A vs B** | | | | | | | | | | | | |
| F-first stage | 13.241 | 14.305 | 3.775 | 13.24 | 14.30 | 3.775 | 13.24 | 14.30 | 3.775 | 13.24 | 14.30 | 3.775 |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.764 | 0.481 | 0.276 | 0.420 | 0.315 | 0.300 | 0.785 | 0.806 | 0.743 | 0.980 | 0.728 | 0.323 |
| **Panel A vs C** | | | | | | | | | | | | |
| p-value for test of omitted variable bias | 0.0561 | 0.0286 | 0.723 | 0.182 | 0.112 | 0.737 | 0.699 | 0.601 | 0.718 | N/A | N/A | N/A |
| **Panel C vs D** | | | | | | | | | | | | |
| F-first stage | 11.833 | 13.379 | 3.999 | 11.83 | 13.38 | 3.999 | 11.83 | 13.38 | 3.999 | N/A | N/A | N/A |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.409 | 0.423 | 0.810 | 0.389 | 0.352 | 0.461 | 0.786 | 0.827 | 0.584 | N/A | N/A | N/A |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| Spline Knot | 4 | 6 | 7 | 4 | 6 | 7 | 4 | 6 | 7 | 4 | 6 | 7 |

***Notes:*** Table shows regression results for the global supply of calories $(q_t)$ and its components ($a_t$, $\hat{y}_t$, and $\psi_t$). The first three columns (1a-1c) present results for caloric supply. Columns 2a-2c show results for growing area and columns 3a-3c show results for trend yield. The last three columns 4a-4c present results for yield shock. Columns a-c differ by the knots (4, 6, and 7) used in cubic spline time trend. 4 knots are at year 1963, 1980, 1997, and 2010; 6 knots are at year 1962, 1974, 1986, 2000, and 2012; 7 knots are at year 1962, 1972, 1976, 1982, 1992, 2002, and 2012. Panels A and C use simple OLS while panels B and D use IVs or 2SLS methods. Coefficients of time trend are nor reported here. Global caloric supply is the sum of calories of four crops namely corn, soybeans, wheat, and rice. Futures Price is the weighted average of corn, soybeans, and wheat futures price traded in CBOT, weighted by caloric share. Shock is current-year realized yield shock constructed by taking the ratio of actual to trend yield. Standard errors in parentheses; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

Overall, our findings in table 3 indicate little support for the contention that futures prices must be instrumented in analyzing the response of global calorie supply or global acreage supply to expected price. Furthermore, we find no support for the contention that current year yield shock should be added to the supply equation to control for predictable yield shocks. We show that yield shocks are not predictable on a global level and that including yield as an explanatory variable when estimating the response of total supply is inappropriate because the resulting supply elasticity becomes an acreage elasticity rather than a total supply elasticity. These findings suggest that the preferred method for estimating a static supply elasticity is to regress aggregate growing area on the futures price.

*Stability*

We limit the sample size so that it begins in 1980, to see what happens to the estimates of supply elasticity and the sources of endogeneity if we start our analysis after the two large price spikes in 1974 and 1975 (see figure 1 for the price spikes). Table 4 presents results for this subsample. The OLS estimates in panel A are larger than the estimates in all panels. For the global caloric response, the 2SLS estimates in panel B are statistically insignificant and smaller than the estimates in panel A, indicating anticipated supply shocks do not make futures price endogenous to caloric supply. The OLS estimates in panel C are statistically significant and smaller than the estimates in panel A. From the decomposition of $q_t$ , we find that this is because of the noise created by the positive correlation between price and yield shock. The 2SLS estimates in panel D are similar to the OLS estimates in panel C, indicating supply shocks other than yield do not cause any bias for the supply estimates.

The supply elasticity estimates for each component of $q_t$ are almost similar across all estimation methods. The specification tests as shown in the bottom panel do not support the evidence that the futures price is endogenous to supply analysis because the p-values from DWH test of endogeneity are greater than 0.10 in all cases.

Comparing the supply estimates of table 4 with the estimates of table 3, we find that the estimates in panels C and D are similar to the corresponding estimates of table 3 but somewhat more inelastic in panel D, which uses IVs. The estimates in panel B of table 4 are larger than the estimates in panel B of table 3 but are statistically insignificant. Surprisingly, the correlation between the futures price and yield shock turns out to positive as opposed to negative correlation as shown in table 3. This implies that the correlation between price and current year yield shock is just a statistical relation and depends on the model specification.

Figures A7-A14 of appendix plot time-varying supply elasticities for global caloric supply and growing area by applying rolling regression method. Rolling regression method uses a series of windows of observations at each time and performs both OLS and IV regression analysis. We have data from 1961 to 2014. We use a window size of 30 periods. The first regression uses the data from 1961 to 1990, the second regression uses the data from 1962 to 1991, and so on, with the last one uses from 1985 to 2014.

**Table 4. Global Supply Estimates and Sources of Endogeneity Bias: 1980-2014**

| | Caloric Supply | | | Growing Area | | | Trend Yield | | | Yield Shock | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) | (4a) | (4b) | (4c) |
| Panel A. OLS Omitting Yield Shock | | | | | | | | | | | | |
| | 0.111$^{**}$ | 0.094$^{*}$ | 0.136$^{*}$ | 0.068$^{**}$ | 0.057$^{**}$ | 0.069$^{**}$ | 0.019* | 0.007 | 0.021 | 0.020 | 0.022 | 0.048 |
| | (0.032) | (0.039) | (0.053) | (0.011) | (0.012) | (0.017) | (0.008) | (0.009) | (0.013) | (0.023) | (0.028) | (0.038) |
| Panel B. IV Regression Omitting Yield Shock | | | | | | | | | | | | |
| | 0.082 | 0.089 | 0.087 | 0.049$^{+}$ | 0.056$^{*}$ | 0.053$^{*}$ | 0.014 | 0.013 | 0.011 | 0.018 | 0.018 | 0.018 |
| | (0.071) | (0.063) | (0.055) | (0.029) | (0.025) | (0.022) | (0.021) | (0.019) | (0.017) | (0.053) | (0.053) | (0.053) |
| Panel C. OLS Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.079$^{**}$ | 0.054$^{**}$ | 0.075$^{**}$ | 0.064$^{**}$ | 0.053$^{**}$ | 0.059$^{**}$ | 0.017$^{*}$ | 0.005 | 0.018 | 0 | 0 | 0 |
| | (0.015) | (0.017) | (0.023) | (0.010) | (0.011) | (0.016) | (0.008) | (0.009) | (0.013) | | | |
| Shock | 1.328$^{**}$ | 1.353$^{**}$ | 1.330$^{**}$ | 0.217$^{**}$ | 0.208$^{**}$ | 0.205$^{*}$ | 0.080 | 0.091 | 0.074 | 1 | 1 | 1 |
| | (0.129) | (0.118) | (0.118) | (0.076) | (0.075) | (0.077) | (0.064) | (0.061) | (0.063) | | | |
| Panel D. IV Regression Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.057 | 0.062$^{*}$ | 0.057$^{+}$ | 0.044$^{+}$ | 0.051$^{*}$ | 0.049$^{*}$ | 0.012 | 0.011 | 0.009 | 0 | 0 | 0 |
| | (0.037) | (0.031) | (0.029) | (0.026) | (0.022) | (0.019) | (0.021) | (0.018) | (0.016) | | | |
| Shock | 1.366$^{**}$ | 1.341$^{**}$ | 1.352$^{**}$ | 0.274$^{**}$ | 0.250$^{**}$ | 0.256$^{**}$ | 0.092 | 0.091 | 0.095 | 1 | 1 | 1 |
| | (0.146) | (0.105) | (0.099) | (0.092) | (0.077) | (0.073) | (0.074) | (0.065) | (0.062) | | | |
| Panel A vs B | | | | | | | | | | | | |
| F-first stage | 4.795 | 7.775 | 26.536 | 4.795 | 7.775 | 26.54 | 4.795 | 7.775 | 26.54 | 4.795 | 7.775 | 26.54 |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.683 | 0.931 | 0.263 | 0.494 | 0.964 | 0.394 | 0.822 | 0.765 | 0.455 | 0.921 | 0.852 | 0.517 |
| Panel A vs C | | | | | | | | | | | | |
| p-value for test of omitted variable bias | 0.150 | 0.174 | 0.0526 | 0.262 | 0.308 | 0.0614 | 0.357 | 0.360 | 0.201 | N/A | N/A | N/A |
| Panel C vs D | | | | | | | | | | | | |
| F-first stage | 4.536 | 7.386 | 26.078 | 4.536 | 7.386 | 26.08 | 4.536 | 7.386 | 26.08 | N/A | N/A | N/A |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.531 | 0.767 | 0.310 | 0.478 | 0.953 | 0.552 | 0.838 | 0.720 | 0.548 | N/A | N/A | N/A |
| Observations | 34 | 34 | 34 | 35 | 35 | 35 | 35 | 35 | 35 | 35 | 35 | 35 |
| Spline Knot | 3 | 5 | 6 | 3 | 5 | 6 | 3 | 5 | 6 | 3 | 5 | 6 |

*Notes:* Table replicates results in table 1 expect that we use data from 1980 to 2014. 3 knots are at year 1982, 1994, and 2006; 5 knots are at year 1984, 1991, 1998, 2005, and 2012; 6 knots are at year 1982, 1989, 1996, 2003, 2010, and 2013. Standard errors in parentheses; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

From the figures A7-A10, we see that caloric supply elasticity changes over time across all models. The estimates that are obtained from the OLS regression of production on the futures price and the 2SLS regression (price is instrumented on past shock only) go up as new data is included whereas the estimates that are obtained from the OLS and 2SLS regressions (include current year yield shock as control) go down over time. Results from the plot also indicate that about 50% of the total supply response in the recent period comes more the intensive margin (comparing figure A8 and A12 as well A9 and A12). The plots also reveal that endogeneity of futures price does not seem to an issue of concern in the growing area response model because we only find negligible differences in estimates across the models (figures A11-A14). Overall the lack of stability of estimated elasticities indicates that it is difficult, if not impossible to accurately estimate aggregate calorie or acreage supply with respect to expected price using a static model. We next turn to whether estimation of US aggregate supply using the same approach provides more consistent results.

**2.5.3 US Aggregate Crop Supply Response**

Futures prices used in this paper are traded in Chicago on the CBOT. Therefore, if futures prices need to be instrumented to estimate supply response, then it should show up in the analysis of US crop supply estimates. Furthermore, if yield shocks are predictable, they should be predictable in the U.S. given the concentration of production in the U.S. Midwest. Thus, we replicate the global analysis for the United States.

Table 5 shows results for US aggregate crop supply response. Estimated results are again based on OLS and 2SLS estimators. All models vary with multiple specifications of the time trend. The 2SLS estimates of caloric supply elasticity in panel B (columns 1a-1c) are much higher than the OLS estimates in panel A. This large difference seems to indicate the need to instrument futures price. Interestingly, the difference in elasticity of calorie supply is due to differences in yield response, not acreage response. The acreage response estimates are quite close. And most of the difference in yield response is due to differences in the response of the yield shock to expected price. OLS estimates of the response of yield shock are negative (and significant in columns 4a and 4b), whereas the 2SLS estimates are positive and insignificant. The magnitude of the difference in the OLS estimates of yield response to expected price and the 2SLS estimates are what drive the OLS vs. 2SLS differences in the caloric supply response.

The question then becomes what is driving this result. The lack of significance of yield response to expected price suggests that it is mainly the large and negative OLS estimate of yield response to the expected price which is driving the difference. This conjecture is verified by repeating the global analysis that was presented in Tables 1 and 2. The significantly negative OLS coefficient between yield shock and futures price for the full sample changes to practically zero and insignificant for the 1980 to 2014 sample. The coefficient becomes much less negative and insignificant when 1974 and 1975 are dropped from the sample. This suggests that yield shocks are not predictable, which implies that current yield should not be included as a control variable. This result also suggests that the large difference between OLS and 2SLS calorie supply response is caused by the sampling error, rather than by an omitted variable.

*Stability*

Table 6 presents results covering the time period from 1980 to 2014. Three changes are noteworthy compared to the estimates of table 5, which are based on the full sample data. First, as discussed above, the correlation between current year yield shock and futures price becomes quite small and is statistically insignificant (columns 4a-4c in panel B). Second, the 2SLS estimates of acreage response (columns 2a-2c) in panel B of table 6 are quite a bit more elastic than the corresponding OLS estimates. These results indicate that it may be appropriate to instrument expected futures price in an aggregate acreage supply model. Two of the three corresponding p values of the test of mitted variable bias confirm this indication.

Figures A15-A22 of appendix plot time-varying supply elasticities for the US caloric and growing area supply, obtained applying rolling regression method. Similar to global analysis, we use a window size of 30 periods. Our results indicate that both caloric (figures A15-A18) and growing area supply responses (figures A19-A22) are more inelastic in the recent period.

To summarize, we find some evidence that IV estimation is appropriate to model aggregate US acreage response to expected price. Omitted variable bias lowers the acreage response by between 40% and 47% (comparing OLS vs 2SLS estimates in columns 2a – 2c in panels A and B of table 6). The correlation between futures price and yield is found to be insignificant and close to zero when we change the sample period and time trend specification. The next issue to be addressed is whether the global and US results are robust to crop-specific response. If not, then these results could be caused by aggregation bias.

**Table 5. US Supply Estimates and Sources of Endogeneity Bias**

| | Caloric Supply | | | Growing Area | | | Trend Yield | | | Yield Shock | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) | (4a) | (4b) | (4c) |
| Panel A. OLS Omitting Yield Shock | | | | | | | | | | | | |
| | 0.099 | 0.119 | 0.105 | 0.233$^{**}$ | 0.247$^{**}$ | 0.244$^{**}$ | -0.015 | -0.015 | -0.036$^{+}$ | -0.119$^{+}$ | -0.113$^{+}$ | -0.104 |
| | (0.096) | (0.095) | (0.123) | (0.042) | (0.037) | (0.048) | (0.015) | (0.015) | (0.019) | (0.065) | (0.067) | (0.087) |
| Panel B. IV Regression Omitting Yield Shock | | | | | | | | | | | | |
| | 0.405$^{+}$ | 0.523$^{*}$ | 0.693$^{*}$ | 0.231$^{**}$ | 0.296$^{**}$ | 0.316$^{**}$ | 0.028 | 0.028 | 0.033 | 0.146 | 0.146 | 0.146 |
| | (0.216) | (0.255) | (0.298) | (0.087) | (0.079) | (0.103) | (0.036) | (0.036) | (0.052) | (0.169) | (0.169) | (0.169) |
| Panel C. OLS Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.260$^{**}$ | 0.269$^{**}$ | 0.242$^{**}$ | 0.271$^{**}$ | 0.280$^{**}$ | 0.274$^{**}$ | -0.011 | -0.011 | -0.032$^{+}$ | 0 | 0 | 0 |
| | (0.038) | (0.035) | (0.044) | (0.038) | (0.033) | (0.042) | (0.015) | (0.015) | (0.019) | | | |
| Shock | 1.355$^{**}$ | 1.326$^{**}$ | 1.328$^{**}$ | 0.316$^{**}$ | 0.285$^{**}$ | 0.286$^{**}$ | 0.039 | 0.041 | 0.043 | 1 | 1 | 1 |
| | (0.082) | (0.075) | (0.075) | (0.082) | (0.070) | (0.071) | (0.032) | (0.032) | (0.032) | | | |
| Panel D. IV Regression Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.211$^{**}$ | 0.261$^{**}$ | 0.237$^{**}$ | 0.191$^{*}$ | 0.244$^{**}$ | 0.223$^{**}$ | 0.020 | 0.017 | 0.014 | 0 | 0 | 0 |
| | (0.078) | (0.065) | (0.088) | (0.077) | (0.057) | (0.078) | (0.031) | (0.030) | (0.042) | | | |
| Shock | 1.328$^{**}$ | 1.322$^{**}$ | 1.326$^{**}$ | 0.272$^{**}$ | 0.266$^{**}$ | 0.270$^{**}$ | 0.056 | 0.055 | 0.056$^{+}$ | 1 | 1 | 1 |
| | (0.107) | (0.104) | (0.103) | (0.089) | (0.081) | (0.080) | (0.035) | (0.034) | (0.033) | | | |
| Panel A vs B | | | | | | | | | | | | |
| F-first stage | 10.669 | 9.469 | 7.312 | 10.67 | 9.469 | 7.312 | 10.67 | 9.469 | 7.312 | 10.67 | 9.469 | 7.312 |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.119 | 0.049 | 0.051 | 0.981 | 0.390 | 0.389 | 0.169 | 0.184 | 0.133 | 0.0540 | 0.0332 | 0.0358 |
| Panel A vs C | | | | | | | | | | | | |
| p-value for test of omitted variable bias | 0.0511 | 0.0921 | 0.185 | 0.0443 | 0.0873 | 0.195 | 0.382 | 0.352 | 0.389 | N/A | N/A | N/A |
| Panel C vs D | | | | | | | | | | | | |
| F-first stage | 14.110 | 13.242 | 9.919 | 14.11 | 13.24 | 9.919 | 14.11 | 13.24 | 9.919 | N/A | N/A | N/A |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.533 | 0.885 | 0.947 | 0.334 | 0.514 | 0.525 | 0.278 | 0.322 | 0.250 | N/A | N/A | N/A |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 35 | 35 | 35 |
| Spline Knot | 4 | 6 | 7 | 4 | 6 | 7 | 4 | 6 | 7 | 3 | 5 | 6 |

***Notes:*** Table shows regression results for the US supply of calories $(q_t)$ and its components ($a_t$, $\hat{y}_t$, and $\psi_t$). The first three columns (1a-1c) present results for caloric supply. Columns 2a-2c show results for growing area and columns 3a-3c show results for trend yield. The last three columns 4a-4c present results for yield shock. Columns a-c differ by the knots (4, 6, and 7) use in cubic spline time trend. 4 knots are at year 1963, 1980, 1997, and 2010; 6 knots are at year 1962, 1974, 1986, 2000, and 2012; 7 knots are at year 1962, 1972, 1976, 1982, 1992, 2002, and 2012. Panels A and C use simple OLS while panels B and D use IVs or 2SLS methods. Coefficients of time trend are nor reported here. Global caloric supply is the sum of calories of four crops namely corn, soybeans, wheat, and rice. Futures Price is the weighted average of corn, soybeans, and wheat futures price traded in CBOT. Shock is current-year realized yield shock constructed by taking the ratio of actual yield to trend yield. Standard errors in parentheses; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

**Table 6. US Supply Estimates and Sources of Endogeneity Bias: 1980-2014**

| | **Caloric Supply** | | | **Growing Area** | | | **Trend Yield** | | | **Yield Shock** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) | (4a) | (4b) | (4c) |
| Panel A. OLS Omitting Yield Shock | | | | | | | | | | | | |
| | 0.103 | 0.211 | 0.190 | 0.144$^{*}$ | 0.199$^{**}$ | 0.185$^{*}$ | 0.007 | 0.005 | 0.020 | -0.047 | 0.004 | -0.015 |
| | (0.137) | (0.172) | (0.238) | (0.056) | (0.060) | (0.081) | (0.019) | (0.024) | (0.033) | (0.090) | (0.118) | (0.164) |
| Panel B. IV Regression Omitting Yield Shock | | | | | | | | | | | | |
| | 0.535$^{+}$ | 0.846$^{+}$ | 0.728$^{+}$ | 0.248$^{*}$ | 0.376$^{**}$ | 0.332$^{**}$ | 0.055 | 0.071 | 0.062 | 0.212 | 0.212 | 0.212 |
| | (0.324) | (0.466) | (0.375) | (0.118) | (0.138) | (0.111) | (0.044) | (0.063) | (0.047) | (0.213) | (0.213) | (0.213) |
| Panel C. OLS Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.170$^{**}$ | 0.206$^{**}$ | 0.211$^{*}$ | 0.162$^{**}$ | 0.197$^{**}$ | 0.190$^{**}$ | 0.009 | 0.005 | 0.020 | 0 | 0 | 0 |
| | (0.049) | (0.057) | (0.078) | (0.046) | (0.046) | (0.062) | (0.019) | (0.024) | (0.032) | | | |
| Shock | 1.423$^{**}$ | 1.380$^{**}$ | 1.377$^{**}$ | 0.382$^{**}$ | 0.326$^{**}$ | 0.320$^{**}$ | 0.041 | 0.055 | 0.057 | 1 | 1 | 1 |
| | (0.100) | (0.092) | (0.092) | (0.092) | (0.075) | (0.073) | (0.039) | (0.038) | (0.038) | | | |
| Panel D. IV Regression Including Yield Shock | | | | | | | | | | | | |
| Futures Price | 0.218$^{*}$ | 0.299$^{**}$ | 0.274$^{**}$ | 0.167$^{+}$ | 0.245$^{**}$ | 0.226$^{**}$ | 0.044 | 0.049 | 0.043 | 0 | 0 | 0 |
| | (0.094) | (0.101) | (0.076) | (0.090) | (0.088) | (0.064) | (0.040) | (0.055) | (0.042) | | | |
| Shock | 1.432$^{**}$ | 1.380$^{**}$ | 1.379$^{**}$ | 0.383$^{**}$ | 0.325$^{**}$ | 0.321$^{**}$ | 0.048 | 0.054 | 0.058$^{+}$ | 1 | 1 | 1 |
| | (0.122) | (0.127) | (0.131) | (0.096) | (0.094) | (0.097) | (0.039) | (0.036) | (0.033) | | | |
| Panel A vs B | | | | | | | | | | | | |
| F-first stage | 7.469 | 5.179 | 19.246 | 7.584 | 5.073 | 19.26 | 7.584 | 5.073 | 19.26 | 7.584 | 5.073 | 19.26 |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.113 | 0.106 | 0.093 | 0.241 | 0.0990 | 0.0584 | 0.226 | 0.250 | 0.283 | 0.153 | 0.156 | 0.0751 |
| Panel A vs C | | | | | | | | | | | | |
| p-value for test of omitted variable bias | 0.440 | 0.967 | 0.878 | 0.417 | 0.939 | 0.887 | 0.545 | 0.939 | 0.885 | N/A | N/A | N/A |
| Panel C vs D | | | | | | | | | | | | |
| F-first stage | 8.544 | 5.354 | 21.276 | 8.601 | 5.206 | 21.28 | 8.601 | 5.206 | 21.28 | N/A | N/A | N/A |
| p-value for Hausman test ($H_0$=Exogeneity) | 0.515 | 0.267 | 0.246 | 0.947 | 0.506 | 0.436 | 0.334 | 0.419 | 0.536 | N/A | N/A | N/A |
| Observations | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 |
| Spline Knot | 3 | 5 | 6 | 3 | 5 | 6 | 3 | 5 | 6 | 3 | 5 | 6 |

*Notes*: 3 knots are at year 1982, 1994, and 2006; 5 knots are at year 1984, 1991, 1998, 2005, and 2012; 6 knots are at year 1982, 1989, 1996, 2003, 2010, and 2013. Table replicates results in table 4 expect that we use data from 1980 to 2014. Standard errors in parentheses; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

### 2.5.4 Estimates of Crop-Specific Supply Responses

*Global Crop-Specific Supply*

Tables 7 and 8 report results for the global crop-specific caloric and growing area supply elasticities, respectively.[9] Panel A does not include yield shocks as controls whereas panel B does. In general, own-price caloric supply elasticities are positive and statistically significant, especially in the restricted (symmetry of cross-price imposed) model, which are consistent with economic theory. These are evident in both panels A and B of table 7. In panel A with symmetric restriction, the own-price caloric supply elasticities range from 0.032 (rice) to 0.254 (maize) whereas, in panel B these range from 0.022 (rice) to 0.246 (soybeans). In general, the own-price supply estimates in panel B are smaller than the estimates in panel A (columns 2a-2d of table 7), indicate that the correlation between yield shock and futures price is zero or positive and the significant correlation as we have found in the aggregate model is the result of aggregation bias. This is confirmed by the correlations of global crop-specific yield shock and price reported in table A3 of appendix.

The crop-specific growing response to own-price is positive and statistically significant for all crops (columns 2a-2d of table 8). In general, the own-price estimates in panel B is smaller than the estimates in panel A (columns 2a-2d of table 7), indicate that including yield shock as a control does not impact the estimate of growing area response to price. Comparing results of table 8 with the results of table 7, we also find that new supply comes from both at the extensive margin (growing area response) and intensive

[9] We consider all crops simultaneously to estimate the crop-specific response, which is similar to the approach as shown in Roberts and Schlenker (2013).

margin (yield response). For maize, the intensive margin accounts for almost 50% of the total supply response. For wheat, it is more than 50%. For soybeans and rice, the responses occur mostly at the extensive margin.

**Table 7. Global Crop Specific Caloric Supply Responses to Futures Prices**

| | Unrestricted | | | | Symmetry | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| *Panel A. Model omits Yield Shock* | | | | | | | | |
| Maize price | 0.242** | -0.015 | -0.053 | 0.009 | 0.254** | -0.009 | -0.090** | -0.023 |
| | (0.078) | (0.074) | (0.064) | (0.038) | (0.046) | (0.037) | (0.034) | (0.020) |
| Soybeans price | 0.107 | 0.335** | -0.063 | -0.000 | -0.009 | 0.253** | -0.130** | -0.007 |
| | (0.075) | (0.071) | (0.062) | (0.037) | (0.037) | (0.054) | (0.038) | (0.022) |
| Wheat price | -0.180** | -0.192** | 0.084 | -0.023 | -0.090** | -0.130** | 0.152** | 0.003 |
| | (0.067) | (0.064) | (0.055) | (0.033) | (0.034) | (0.038) | (0.041) | (0.018) |
| Rice price | -0.034 | -0.008 | 0.002 | 0.031+ | -0.023 | -0.007 | 0.003 | 0.032+ |
| | (0.036) | (0.034) | (0.029) | (0.017) | (0.020) | (0.022) | (0.018) | (0.016) |
| *Panel B. Model includes Yield Shock* | | | | | | | | |
| Maize price | 0.213** | -0.165** | 0.031 | 0.031+ | 0.205** | -0.096** | 0.004 | -0.006 |
| | (0.033) | (0.037) | (0.035) | (0.017) | (0.029) | (0.021) | (0.022) | (0.010) |
| Soybeans price | -0.003 | 0.281** | -0.034 | 0.043** | -0.096** | 0.246** | -0.067** | 0.006 |
| | (0.031) | (0.035) | (0.033) | (0.016) | (0.021) | (0.032) | (0.021) | (0.011) |
| Wheat price | -0.051+ | -0.040 | 0.026 | -0.027+ | 0.004 | -0.067** | 0.073** | 0.023* |
| | (0.029) | (0.033) | (0.031) | (0.015) | (0.022) | (0.021) | (0.024) | (0.009) |
| Rice price | -0.022 | -0.003 | 0.034* | 0.022** | -0.006 | 0.006 | 0.023* | 0.022** |
| | (0.015) | (0.016) | (0.015) | (0.008) | (0.010) | (0.011) | (0.009) | (0.007) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 |

*Notes:* Estimates of Crop-specific elasticity are from Seemingly Unrelated Regressions (SUR). Columns (1a)-(1d) do not impose symmetry while columns (2a)-(2d) impose symmetry. A cubic spline in time trend with 6 knots has been included in all models to remove trend from the futures price data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

Tables A4-A5 and A6-A7 of appendix report results for crop-specific caloric and growing area supply response, respectively, obtained using 2SLS estimator. The results indicate neither caloric nor growing area supply response to futures prices is statistically significant. Some own-price elasticity estimates are even negative. These estimates seem to indicate a misspecified model, an issue that is addressed in later chapters.

To sum up, we find that crop-specific supply response to its own- and competing-crop futures price can be reasonably estimated using a SUR estimator, which estimates crop supply response simultaneously. The correlation between yield shock and future price found in the aggregate model does not hold for the crop-specific supply analysis. The application of IV regression does not seem to a useful tool to investigate global crop supply response.

**Table 8. Global Crop Specific Growing Area Responses to Futures Prices**

| | Unrestricted | | | | Symmetry | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| *Panel A. OLS Omitting Yield Shock* | | | | | | | | |
| Maize price | 0.127$^{**}$ | -0.166$^{**}$ | 0.011 | 0.017 | 0.135$^{**}$ | -0.066$^{**}$ | 0.009 | -0.017$^{+}$ |
| | (0.022) | (0.034) | (0.029) | (0.018) | (0.022) | (0.018) | (0.016) | (0.009) |
| Soybeans price | 0.013 | 0.279$^{**}$ | -0.007 | 0.030$^{+}$ | -0.066$^{**}$ | 0.216$^{**}$ | -0.050$^{**}$ | 0.000 |
| | (0.021) | (0.033) | (0.028) | (0.017) | (0.018) | (0.029) | (0.019) | (0.011) |
| Wheat price | -0.026 | -0.029 | 0.018 | -0.018 | 0.009 | -0.050$^{**}$ | 0.048$^{*}$ | 0.021$^{*}$ |
| | (0.019) | (0.030) | (0.025) | (0.015) | (0.016) | (0.019) | (0.020) | (0.009) |
| Rice price | -0.030$^{**}$ | -0.003 | 0.023$^{+}$ | 0.020$^{*}$ | -0.017$^{+}$ | 0.000 | 0.021$^{*}$ | 0.024$^{**}$ |
| | (0.010) | (0.016) | (0.013) | (0.008) | (0.009) | (0.011) | (0.009) | (0.008) |
| *Panel B. OLS including Yield Shock* | | | | | | | | |
| Maize price | 0.123$^{**}$ | -0.168$^{**}$ | 0.031 | 0.024 | 0.118$^{**}$ | -0.072$^{**}$ | 0.021 | -0.016$^{+}$ |
| | (0.023) | (0.035) | (0.028) | (0.018) | (0.022) | (0.018) | (0.017) | (0.009) |
| Soybeans price | 0.004 | 0.261$^{**}$ | -0.013 | 0.043$^{**}$ | -0.072$^{**}$ | 0.215$^{**}$ | -0.047$^{*}$ | 0.005 |
| | (0.021) | (0.034) | (0.027) | (0.017) | (0.018) | (0.031) | (0.019) | (0.011) |
| Wheat price | -0.020 | -0.016 | 0.013 | -0.026$^{+}$ | 0.021 | -0.047$^{*}$ | 0.044$^{*}$ | 0.022$^{*}$ |
| | (0.020) | (0.031) | (0.025) | (0.016) | (0.017) | (0.019) | (0.021) | (0.009) |
| Rice price | -0.028$^{**}$ | -0.002 | 0.026$^{*}$ | 0.021$^{**}$ | -0.016$^{+}$ | 0.005 | 0.022$^{*}$ | 0.024$^{**}$ |
| | (0.010) | (0.015) | (0.012) | (0.008) | (0.009) | (0.011) | (0.009) | (0.008) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 |

*Notes:* Estimates of Crop-specific elasticity are from Seemingly Unrelated Regressions (SUR). Columns (1a)-(1d) do not impose symmetry while columns (2a)-(2d) impose symmetry. Results of the effects of yield shocks are not reported here in panel B. A cubic spline in time trend with 6 knots has been included in all models to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

*US Crop-specific Supply*

In estimating US crop-specific supply response, we make two assumptions based on the planting time of each crop and the states that produce a crop most. First, we assume that maize and soybeans compete for the same land so we estimate both crops simultaneously. Second, we assume wheat and rice do not compete with maize and soybeans for the same land as much as soybeans and maize do for each other. The planting time of wheat is not the same as that of maize and soybeans and rice is mainly grown in the states where corn, soybeans, and wheat are not the main crops.[10] Therefore, we estimate wheat and rice supply response separately.

Tables 9 and 10 report results for the US crop-specific caloric and growing area supply elasticities, respectively. Results of columns (1a)-(1d) are estimated using SUR models whereas columns (2a)-(2d) are from 2SLS regressions. Columns (a-b) are based on unrestricted models while columns (c-d) impose cross-price symmetry. Panel A does not include yield shocks as controls whereas panel B does. We focus our discussion on the results obtained from imposing symmetry. Our main findings from the crop-specific caloric supply response are as follows (table 9). First, the 2SLS estimate (column 2c in panel A) of maize caloric supply elasticity is much larger than the OLS estimate (column 1c in panel A), indicating a correlation between futures prices and the error term.  endogeneity of maize futures price biases maize supply elasticity downward by about 48%. Supply shocks other than yield has a negligible impact on the maize caloric supply elasticity (comparing

[10] We mainly refer to winter wheat. Winter wheat accounts for about 75% (average of 1961-2014) of the US total wheat production—calculated based on the data downloaded from USDA-NASS Quick Stats: accessed on February 4, 2017. Winter wheat is planted in the fall whereas maize and soybeans are planted in the spring.

between column 1c and 2c in panel B). From column 1c in panels A and B, we see that the estimated maize supply elasticity in panel A is about 20% lower than in panel B due to a negative correlation between maize yield shock and futures price but this correlation is statistically insignificant (see table A7 of appendix). Second, though the 2SLS estimate (column 2d in panel A) of soybeans caloric supply elasticity is larger than the OLS estimate (column 1d in panel A), it is statistically insignificant. The correlation between soybeans yield shock and futures price is close to zero as indicated by the similar estimates of supply response (column 1d in panels A and B). Third, the estimate of wheat supply response shows some degree of omitted variable bias (there is a 22% difference between the 2SLS and the OLS estimates in columns (3) and (5)). The negative correlation between wheat yield shock and futures price decreases the estimate of wheat supply response in column (3) of panel A compared to the estimate of the same column in panel B. Column (5) in table A8 of appendix supports this evidence. Fourth, the 2SLS estimate of rice supply response is found to be statistically insignificant, indicate the absence of endogeneity in futures price. The negative correlation between rice yield shock and futures price lowers estimate of wheat supply response in column (3) of panel A compared to the estimates of the same column in panel B. Column (6) in table A8 of appendix also supports this evidence.

**Table 9. US Crop-specific Caloric Supply Responses to Futures Prices**

| | SUR | | | | 2SLS | | | | OLS | OLS | 2SLS | 2SLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unrestricted | | Symmetry | | Unrestricted | | Symmetry | | | | | |
| | Maize | Soy | Maize | Soy | Maize | Soy | Maize | Soy | Wheat | Rice | Wheat | Rice |
| Price | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) | (3) | (4) | (5) | (6) |
| Panel A. does not control current-year shock | | | | | | | | | | | | |
| Maize | 0.392$^{**}$ | -0.133 | 0.321$^{**}$ | -0.19$^{**}$ | 0.001 | -0.420 | 0.620$^{*}$ | -0.253 | | | | |
| | (0.136) | (0.099) | (0.085) | (0.061) | (0.970) | (0.559) | (0.269) | (0.358) | | | | |
| Soybeans | -0.278$^{+}$ | 0.228$^{*}$ | -0.19$^{**}$ | 0.289$^{**}$ | 1.328 | 1.086 | -0.253 | 0.746 | | | | |
| | (0.151) | (0.110) | (0.061) | (0.062) | (2.207) | (1.272) | (0.358) | (0.823) | | | | |
| Wheat | | | | | | | | | 0.228$^{**}$ | | 0.293$^{*}$ | |
| | | | | | | | | | (0.050) | | (0.120) | |
| Rice | | | | | | | | | | 0.231$^{**}$ | | 0.087 |
| | | | | | | | | | | (0.044) | | (0.08) |
| Panel B. control current-year shock | | | | | | | | | | | | |
| Maize | 0.392$^{**}$ | -0.16$^{**}$ | 0.400$^{**}$ | -0.15$^{**}$ | 0.410$^{*}$ | -0.112 | 0.351$^{**}$ | -0.146 | | | | |
| | (0.042) | (0.042) | (0.032) | (0.027) | (0.165) | (0.163) | (0.084) | (0.125) | | | | |
| Soybeans | -0.14$^{**}$ | 0.304$^{**}$ | -0.15$^{**}$ | 0.295$^{**}$ | -0.276 | 0.170 | -0.146 | 0.231 | | | | |
| | (0.047) | (0.047) | (0.027) | (0.037) | (0.327) | (0.322) | (0.125) | (0.253) | | | | |
| Wheat | | | | | | | | | 0.313$^{**}$ | | 0.454$^{**}$ | |
| | | | | | | | | | (0.033) | | (0.100) | |
| Rice | | | | | | | | | | 0.305$^{**}$ | | 0.156 |
| | | | | | | | | | | (0.043) | | (0.12) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 |
| R-squared | 0.898 | 0.961 | 0.897 | 0.961 | 0.621 | 0.907 | 0.881 | 0.938 | 0.864 | 0.951 | 0.848 | 0.936 |

*Notes:* A flexible time trend in cubic spline with 6 knots has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table 10. US Crop-specific Growing Area Responses to Futures Prices**

| | SUR | | | | 2SLS | | | | OLS | OLS | IV | IV |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unrestricted | | Symmetry | | Unrestricted | | Symmetry | | | | | |
| | Maize | Soy | Maize | Soy | Maize | Soy | Maize | Soy | Wheat | Rice | Wheat | Rice |
| Price | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) | (3) | (4) | (5) | (6) |
| Panel A. does not control current-year shock | | | | | | | | | | | | |
| Maize | 0.377$^{**}$ | -0.16$^{**}$ | 0.383$^{**}$ | -0.15$^{**}$ | 0.334$^{+}$ | -0.165 | 0.371$^{**}$ | -0.145 | | | | |
| | (0.043) | (0.047) | (0.033) | (0.029) | (0.172) | (0.178) | (0.090) | (0.148) | | | | |
| Soybeans | -0.15$^{**}$ | 0.30$^{**}$ | -0.15$^{**}$ | 0.290$^{**}$ | -0.052 | 0.341 | -0.145 | 0.299 | | | | |
| | (0.048) | (0.052) | (0.029) | (0.039) | (0.391) | (0.406) | (0.148) | (0.344) | | | | |
| Wheat | | | | | | | | | 0.228$^{**}$ | | 0.360$^{**}$ | |
| | | | | | | | | | (0.030) | | (0.083) | |
| Rice | | | | | | | | | | 0.301$^{**}$ | | 0.218$^{**}$ |
| | | | | | | | | | | (0.039) | | (0.072) |
| Panel B. control current-year shock | | | | | | | | | | | | |
| Maize | 0.374$^{**}$ | -0.16$^{**}$ | 0.387$^{**}$ | -0.15$^{**}$ | 0.392$^{*}$ | -0.119 | 0.350$^{**}$ | -0.150 | | | | |
| | (0.04) | (0.044) | (0.031) | (0.028) | (0.153) | (0.169) | (0.082) | (0.127) | | | | |
| Soybeans | -0.13$^{**}$ | 0.31$^{**}$ | -0.15$^{**}$ | 0.298$^{**}$ | -0.245 | 0.176 | -0.150 | 0.231 | | | | |
| | (0.044) | (0.049) | (0.028) | (0.039) | (0.302) | (0.333) | (0.127) | (0.259) | | | | |
| Wheat | | | | | | | | | 0.219$^{**}$ | | 0.367$^{**}$ | |
| | | | | | | | | | (0.031) | | (0.097) | |
| Rice | | | | | | | | | | 0.305$^{**}$ | | 0.145 |
| | | | | | | | | | | (0.044) | | (0.123) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 |
| R-squared | 0.898 | 0.961 | 0.897 | 0.961 | 0.621 | 0.907 | 0.881 | 0.938 | 0.864 | 0.951 | 0.848 | 0.936 |

*Notes:* A flexible time trend in cubic spline with 6 knots has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

## 2.6 Conclusions

In this chapter, we examine the advice given in the recent literature regarding the use of futures prices in supply analysis. The advice is to either control for the endogeneity of futures prices by including the current year's yield shock or to instrument futures prices using the previous year's yield shock or to do both (Roberts and Schlenker (2013), Hendricks, Janzen, and Smith (2015)). Our analysis is conducted using both global data and U.S. data for corn, rice, wheat, and soybeans over the period 1961 to 2014. Robustness of results is determined by using the full sample data and data from 1980 to 2014 that excludes the two large price spikes of 1974 and 1975.

The previous conclusion of Hendricks, Janzen, and Smith (2015) that current year's yield shock should be included as a control variable only makes sense if yield shocks can be accurately forecasted when crops are planted. Their finding of a significant negative correlation between yield shock and futures price using data from 1961 to 2007 seems to suggest that this is indeed the case. This result is surprising because crop yields are not strongly serially correlated and the ability to forecast growing season weather before planting is quite poor. The first result of this study was to demonstrate that the Hendricks, Janzen, and Smith (2015) finding of a negative correlation is not robust to sample period, outliers in the data, and the method by which futures prices are detrended. When 1974 and 1975 are dropped from the sample, the significance of the negative correlation disappears. When a more flexible de-trending method is used, the correlation becomes close to zero and insignificant. If yield shocks are predictable then the correlation should become larger and more negative over time because of improvements in modeling climate. However, when the sample only includes data from 1980 the correlation becomes small and positive. We find no evidence that the conclusion of Hendricks, Janzen, and Smith (2015) to control for the endogeneity of futures prices by including current year yield shocks as control variables as no basis.

The above conclusion does not mean, however, that there is no need to instrument futures prices in supply analysis. OLS estimates and IV estimates of supply response are then conducted. For the global aggregate supply response, we find little empirical evidence for the view that endogeneity of futures price in the supply analysis poses a risk of producing downward-biased estimates of supply elasticities as indicated by statistically insignificant 2SLS estimates. The OLS estimates of the regression of total production on the futures price are lower or higher than the estimates obtained from other OLS regressions that control current-year yield shock, are due to the existence of a correlation between the futures price and current-year realized yield shock not the endogeneity of future prices. These results are in contrast to the results of Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015). The use of 2SLS to account for the source of endogeneity bias arise from omitting supply shocks other than to yield is also unnecessary because the little empirical evidence is found for the view that the futures price is endogenous and IVs also make supply estimates less efficient.

For the US aggregate supply response, we find that futures price is endogenous to both US aggregate caloric and growing area response models. Endogeneity bias lowers the caloric supply response by about 30% to 80% and growing area response by about 17% to

47%. The correlation between futures price and yield is found to be insignificant and close to zero when we change the sample period and the time trend specification.

The estimates of global crop-specific supply response do not indicate any sort of endogeneity bias. The estimates also indicate that the correlation between the futures price and yield shock is the result of the aggregation of four crops. Crop-specific supply response to its own- and competing-crop futures price can be estimated consistently using SUR estimator, which estimates crop supply response simultaneously.

For the US crop-specific supply response, we find that endogeneity of futures prices lower the estimates of maize and wheat caloric supply elasticities by about 48% and 22%, respectively. A SUR regression estimate of soybeans supply on its own- and competing-crop prices produce results that are empirically relevant. The correlation between yield shock and future price affect wheat and rice caloric supply response. The estimates of crop-specific growing area supply response to futures price do not seem to indicate any endogeneity bias.

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## Appendix. Tables and Figures

**Table A1. Estimates of Word Caloric and Growing Area Supply Response to Futures Price: A Comparison**

| | | **Caloric Supply** | | | **Growing Area** | | |
|---|---|---|---|---|---|---|---|
| Cubic spline in time | | Roberts and Schlenker 2013 | Hendrick et al. 2014 | This paper | Roberts and Schlenker 2013 | Hendrick et al. 2014 | This paper |
| Knot 3 | Supply Elasticity: OLS omitting Shock | 0.051* | 0.049** | 0.051** | | 0.070*** | 0.071*** |
| | Supply Elasticity: OLS with shock | | 0.112*** | 0.114*** | | 0.081*** | 0.083*** |
| | Supply Elasticity: IV | 0.102*** | 0.108*** | 0.108*** | 0.082*** | 0.086*** | 0.086*** |
| Knot 4 | Supply Elasticity: OLS omitting Shock | 0.02 | 0.023 | 0.025 | | 0.053*** | 0.054*** |
| | Supply Elasticity: OLS with shock | | 0.09*** | 0.093*** | | 0.064*** | 0.066*** |
| | Supply Elasticity: IV | 0.096*** | 0.103*** | 0.104*** | 0.078*** | 0.082*** | 0.083*** |
| Knot 5 | Supply Elasticity: OLS omitting Shock | 0.023 | 0.022 | 0.023 | | 0.051*** | 0.053*** |
| | Supply Elasticity: OLS with shocks | | 0.089*** | 0.092*** | | 0.064*** | 0.065*** |
| | Supply Elasticity: IV | 0.087*** | 0.088*** | 0.089*** | 0.071*** | 0.072*** | 0.072*** |

*Notes:* *** p<0.01, ** p<0.05, * p<0.10

**Table A2. Estimates of Global Caloric Supply Response: Current-year Weather as Proxies of Yield Shock**

| | ln(prod) | ln(prod) | ln(prod) | ln(prod) | ln(prod) | ln(prod) | ln(prod) | ln(prod) |
|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Futures Price | 0.074$^{**}$ | 0.032 | 0.029 | 0.057$^{+}$ | 0.060$^{*}$ | -0.001 | -0.003 | 0.047 |
| | (0.021) | (0.025) | (0.025) | (0.033) | (0.024) | (0.026) | (0.027) | (0.034) |
| Temperature | | | | | 0.151 | 0.232 | 0.212 | 0.150 |
| | | | | | (0.177) | (0.153) | (0.159) | (0.154) |
| Temperature^2 | | | | | -0.005 | -0.007$^{+}$ | -0.006 | -0.005 |
| | | | | | (0.004) | (0.004) | (0.004) | (0.004) |
| Precipitation | | | | | 0.643 | 0.841$^{*}$ | 0.887$^{*}$ | 1.070$^{**}$ |
| | | | | | (0.436) | (0.375) | (0.385) | (0.375) |
| Precipitation^2 | | | | | -0.412$^{*}$ | -0.519$^{**}$ | -0.528$^{**}$ | -0.650$^{**}$ |
| | | | | | (0.195) | (0.169) | (0.171) | (0.171) |
| *N* | 47 | 47 | 47 | 47 | 47 | 47 | 47 | 47 |
| p-value for test of omitted variable bias | | | | | 0.191 | 0.250 | 0.767 | 0.767 |
| Time trend/ Spline knot | quadratic | Knot 4 | Knot 6 | Knot 7 | quadratic | Knot 4 | Knot 6 | Knot 7 |

*Notes:* Weather data are downloaded from Roberts and Schlenker (2013). Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

**Table A3. Correlation between Crop-Specific Yield Shocks and Futures Prices**

| | Unrestricted | | | | Symmetry | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Maize price | 0.010 | 0.142$^{*}$ | -0.102$^{+}$ | -0.016 | 0.010 | 0.121$^{**}$ | -0.084$^{**}$ | -0.036$^{*}$ |
| | (0.065) | (0.066) | (0.061) | (0.037) | (0.038) | (0.033) | (0.030) | (0.016) |
| Soybeans price | 0.159$^{*}$ | 0.061 | -0.050 | -0.023 | 0.121$^{**}$ | 0.036 | -0.107$^{**}$ | -0.015 |
| | (0.070) | (0.072) | (0.066) | (0.040) | (0.033) | (0.052) | (0.036) | (0.020) |
| Wheat price | -0.097$^{+}$ | -0.138$^{*}$ | 0.065 | -0.000 | -0.084$^{**}$ | -0.107$^{**}$ | 0.074$^{+}$ | 0.006 |
| | (0.055) | (0.056) | (0.052) | (0.031) | (0.030) | (0.036) | (0.039) | (0.016) |
| Rice price | -0.056$^{+}$ | -0.022 | -0.014 | -0.008 | -0.036$^{*}$ | -0.015 | 0.006 | -0.009 |
| | (0.030) | (0.030) | (0.028) | (0.017) | (0.016) | (0.020) | (0.016) | (0.015) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 54 |

*Notes:* Estimates are from Seemingly Unrelated (SUR) regressions. Columns (1a) -(1d) do not impose symmetry while columns (2a) -(2d) impose symmetry. A cubic spline in time trend with 6 knots has been included in all models to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$.

**Table A4. Global Crop Specific Caloric Responses to Futures Prices: Estimated Using Two-stage Least Squares**

| | | Unrestricted | | | | Symmetry | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Maize price | 0.312 | 0.005 | 0.188 | 0.245 | 0.269 | 0.016 | -0.152 | 0.033 |
| | (0.358) | (0.624) | (0.417) | (0.255) | (0.185) | (0.130) | (0.175) | (0.129) |
| Soybeans price | 0.163 | 0.434 | -0.500$^{+}$ | -0.141 | 0.016 | 0.492$^{**}$ | -0.320$^{*}$ | 0.053 |
| | (0.234) | (0.407) | (0.272) | (0.166) | (0.130) | (0.175) | (0.129) | (0.098) |
| Wheat price | -0.365 | -0.553 | 0.040 | -0.220 | -0.152 | -0.320$^{*}$ | 0.380$^{+}$ | -0.074 |
| | (0.433) | (0.755) | (0.504) | (0.308) | (0.175) | (0.129) | (0.228) | (0.157) |
| Rice price | 0.121 | 0.449 | 0.212 | 0.156 | 0.033 | 0.053 | -0.074 | -0.007 |
| | (0.328) | (0.572) | (0.382) | (0.233) | (0.129) | (0.098) | (0.157) | (0.133) |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| R-squared | 0.981 | 0.976 | 0.948 | 0.984 | 0.985 | 0.994 | 0.970 | 0.994 |
| Chi-square-p value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* Columns (1a) -(1d) do not impose symmetry while columns (2a) -(2d) impose symmetry. A flexible time trend has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table A5. Global Crop Specific Caloric Responses to Futures Prices: Estimated Using Two-stage Least Squares**

| | | Unrestricted | | | | Symmetry | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Maize price | -0.179 | -0.142 | 0.227 | 0.059 | 0.101 | -0.191 | 0.260 | -0.173 |
| | (1.389) | (0.472) | (1.155) | (0.141) | (0.179) | (0.196) | (0.390) | (0.223) |
| Soybeans price | -0.405 | 0.465 | 0.274 | 0.062 | -0.191 | 0.307 | -0.002 | -0.009 |
| | (1.841) | (0.626) | (1.531) | (0.187) | (0.196) | (0.269) | (0.505) | (0.282) |
| Wheat price | 0.890 | -0.268 | -0.653 | -0.072 | 0.260 | -0.002 | -0.343 | 0.306 |
| | (3.611) | (1.227) | (3.003) | (0.367) | (0.390) | (0.505) | (1.005) | (0.560) |
| Rice price | -0.553 | 0.157 | 0.503 | 0.053 | -0.173 | -0.009 | 0.306 | -0.168 |
| | (2.004) | (0.681) | (1.666) | (0.203) | (0.223) | (0.282) | (0.560) | (0.329) |
| Shock Maize | 1.502 | 0.082 | -0.019 | -0.069 | 1.279$^{**}$ | 0.221 | 0.205 | 0.026 |
| | (1.739) | (0.591) | (1.446) | (0.177) | (0.237) | (0.268) | (0.554) | (0.336) |
| Shock Soybeans | 0.361 | 0.811 | -0.433 | -0.001 | 0.080 | 0.879$^{**}$ | -0.421 | 0.214 |
| | (1.469) | (0.499) | (1.222) | (0.149) | (0.226) | (0.227) | (0.489) | (0.304) |
| Shock Wheat | -1.163 | 0.347 | 1.753 | 0.177 | -0.394 | 0.011 | 1.347 | -0.273 |
| | (4.424) | (1.504) | (3.679) | (0.449) | (0.498) | (0.627) | (1.253) | (0.721) |
| Shock Rice | 0.355 | -0.054 | -0.349 | 0.907$^{**}$ | 0.012 | 0.064 | -0.252 | 1.132$^{**}$ |
| | (1.786) | (0.607) | (1.485) | (0.181) | (0.313) | (0.298) | (0.670) | (0.434) |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| R-squared | 0.916 | 0.996 | 0.885 | 0.999 | 0.990 | 0.999 | 0.958 | 0.982 |
| Chi-square-p value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* Columns (1a) -(1d) do not impose symmetry while columns (2a) -(2d) impose symmetry. A flexible time trend (cubic spline with 6 knots) has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table A6. Global Crop Specific Growing Area Responses to Future Price: Estimated Using Two-stage Least Squares**

| | Unrestricted | | | | Symmetry | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Maize price | 0.033 | -0.124 | 0.078 | 0.047 | 0.095 | -0.026 | 0.082 | -0.067 |
| | (0.149) | (0.169) | (0.192) | (0.077) | (0.077) | (0.052) | (0.083) | (0.063) |
| Soybeans price | 0.038 | $0.285^{*}$ | -0.104 | -0.030 | -0.026 | $0.235^{**}$ | $-0.129^{*}$ | 0.051 |
| | (0.097) | (0.110) | (0.125) | (0.050) | (0.052) | (0.075) | (0.064) | (0.054) |
| Wheat price | 0.116 | -0.120 | -0.069 | 0.017 | 0.082 | $-0.129^{*}$ | -0.034 | 0.120 |
| | (0.180) | (0.205) | (0.232) | (0.093) | (0.083) | (0.064) | (0.116) | (0.084) |
| Rice price | -0.111 | 0.083 | 0.148 | 0.017 | -0.067 | 0.051 | 0.120 | -0.078 |
| | (0.136) | (0.155) | (0.176) | (0.070) | (0.063) | (0.054) | (0.084) | (0.078) |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| R-squared | 0.967 | 0.996 | 0.195 | 0.974 | 0.981 | 0.996 | 0.361 | 0.900 |
| Chi-square-p value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* Columns (1a) -(1d) do not impose symmetry while columns (2a) -(2d) impose symmetry. A flexible time trend (cubic spline with 6 knots) has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table A7. Global Crop Specific Growing Area Responses to Future Price: Estimated Using Two-stage Least Squares**

| | Unrestricted | | | | Symmetry | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Maize | Soybean | Wheat | Rice | Maize | Soybean | Wheat | Rice |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (2c) | (2d) |
| Maize price | -0.102 | -0.151 | 0.108 | 0.015 | 0.070 | -0.165 | 0.221 | -0.124 |
| | (0.868) | (0.360) | (0.612) | (0.163) | (0.115) | (0.133) | (0.259) | (0.147) |
| Soybeans price | -0.279 | 0.400 | 0.134 | -0.014 | -0.165 | 0.268 | 0.027 | -0.028 |
| | (1.151) | (0.478) | (0.811) | (0.216) | (0.133) | (0.186) | (0.342) | (0.191) |
| Wheat price | 0.594 | -0.174 | -0.321 | 0.062 | 0.221 | 0.027 | -0.314 | 0.256 |
| | (2.257) | (0.937) | (1.591) | (0.424) | (0.259) | (0.342) | (0.674) | (0.375) |
| Rice price | -0.353 | 0.104 | 0.273 | -0.016 | -0.124 | -0.028 | 0.256 | -0.130 |
| | (1.253) | (0.520) | (0.883) | (0.235) | (0.147) | (0.191) | (0.375) | (0.219) |
| Shock Maize | 0.331 | 0.093 | 0.032 | -0.014 | 0.206 | 0.209 | 0.106 | 0.020 |
| | (1.087) | (0.451) | (0.767) | (0.204) | (0.152) | (0.190) | (0.363) | (0.222) |
| Shock Soybeans | 0.224 | -0.108 | -0.239 | 0.051 | 0.051 | -0.070 | -0.319 | 0.176 |
| | (0.918) | (0.381) | (0.647) | (0.172) | (0.141) | (0.161) | (0.317) | (0.198) |
| Shock Wheat | -0.698 | 0.239 | 0.530 | 0.009 | -0.243 | -0.018 | 0.504 | -0.221 |
| | (2.766) | (1.148) | (1.950) | (0.519) | (0.328) | (0.426) | (0.837) | (0.481) |
| Shock Rice | 0.225 | 0.007 | -0.168 | 0.134 | 0.011 | 0.099 | -0.197 | 0.261 |
| | (1.116) | (0.463) | (0.787) | (0.209) | (0.193) | (0.218) | (0.428) | (0.281) |
| Observations | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| R-squared | 0.675 | 0.995 | -1.331 | 0.966 | 0.950 | 0.998 | -1.143 | 0.786 |
| Chi-square-p value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* Columns (1a) -(1d) do not impose symmetry while columns (2a) -(2d) impose symmetry. A flexible time trend (cubic spline with 6 knots) has been included in the model to remove trend from the data. Standard errors are in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

**Table A8. Correlation between Crop-Specific Yield Shock and Prices for the US crops**

| | SUR | | | | OLS | | | |
|---|---|---|---|---|---|---|---|---|
| | Unrestricted | | Symmetry | | | | | |
| | Maize | Soybeans | Maize | Soybeans | Maize | Soybeans | Wheat | Rice |
| | (1a) | (1b) | (2a) | (2b) | (3) | (4) | (5) | (6) |
| Maize price | -0.004 | 0.027 | -0.077 | -0.027 | -0.071 | | | |
| | (0.111) | (0.081) | (0.070) | (0.050) | (0.059) | | | |
| Soybeans price | -0.122 | -0.065 | -0.027 | -0.003 | | -0.027 | | |
| | (0.124) | (0.090) | (0.050) | (0.052) | | (0.050) | | |
| Wheat price | | | | | | | -0.09** | |
| | | | | | | | (0.035) | |
| Rice price | | | | | | | | -0.069** |
| | | | | | | | | (0.020) |
| Observations | 54 | | 54 | | 54 | 54 | 54 | 54 |
| R-square | 0.070 | 0.018 | 0.059 | 0.008 | 0.053 | 0.014 | 0.108 | 0.361 |
| F/chi2 | 4.043 | 0.982 | 3.624 | 0.725 | 3.840 | 0.732 | 8.253 | 29.987 |

Notes: Columns (1a) -(2b) are estimated using SUR estimators whereas columns (3) -(6) are using OLS estimators. Columns (1a) -(1b) do not impose symmetry while columns (2a) -(2b) impose symmetry. Standard errors in parentheses.
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

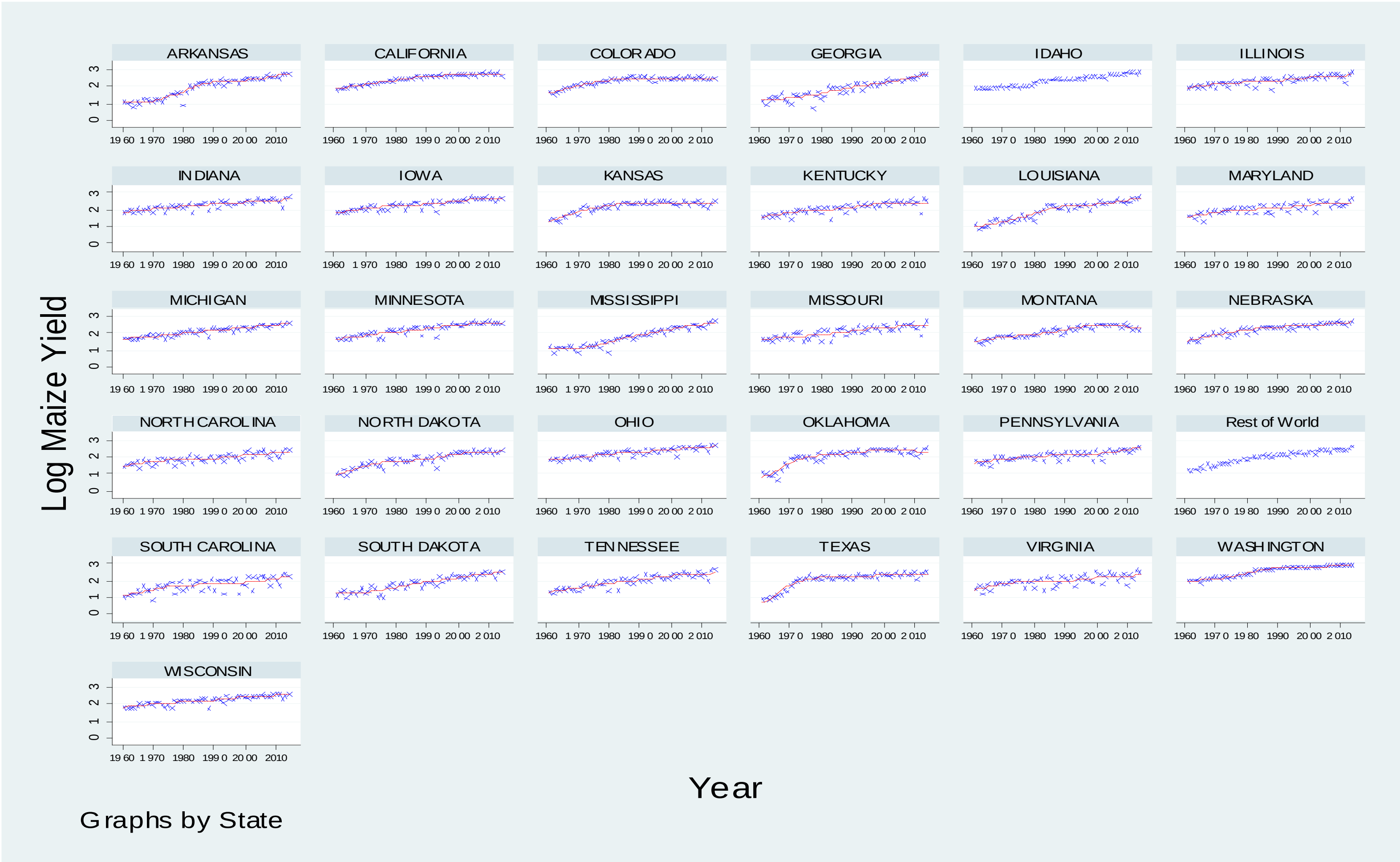


**Figure A1. Maize yields and trend (restricted cubic spline with 6 knots)**

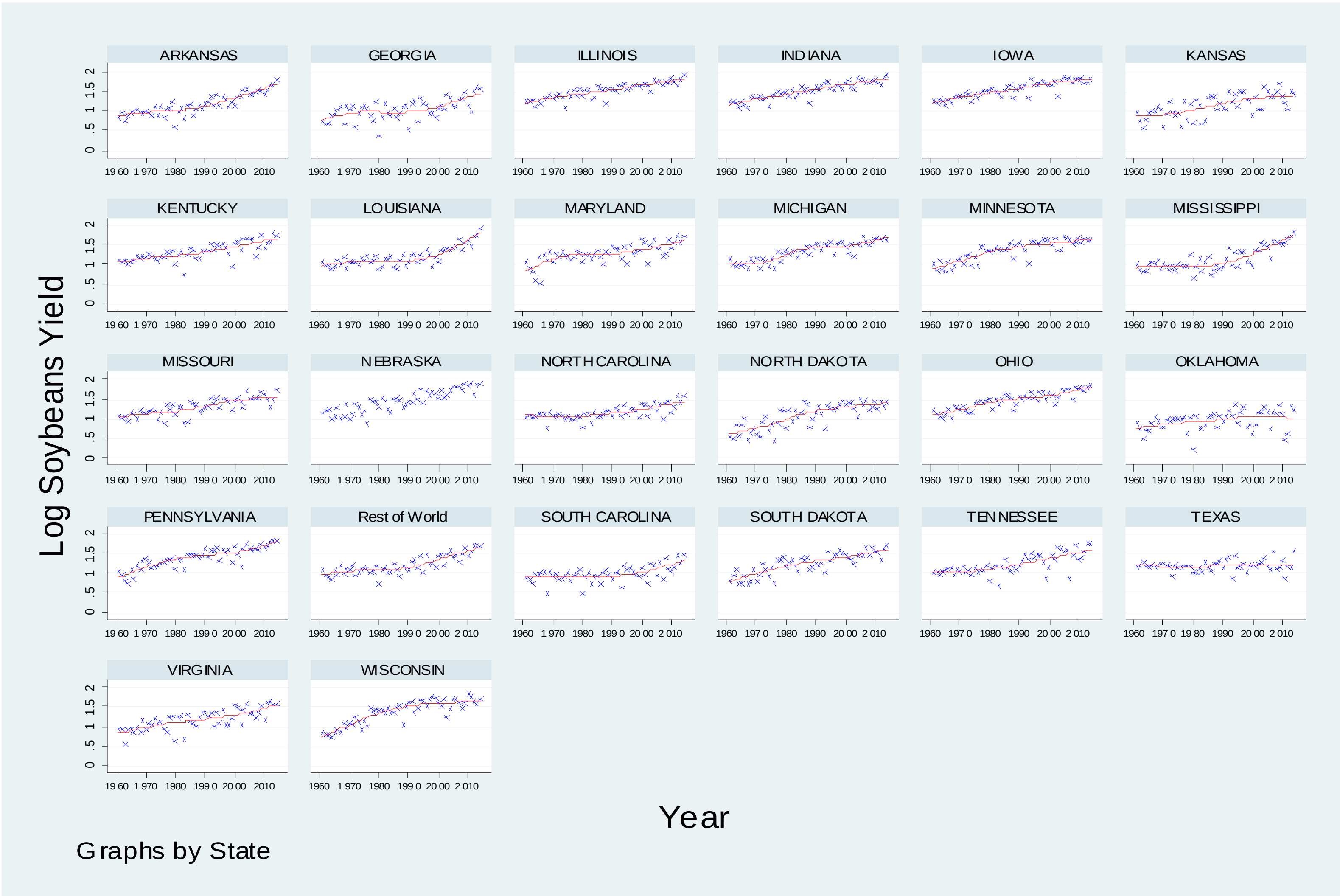


**Figure A2. Soybeans yields and trend (restricted cubic spline with 6 knots)**

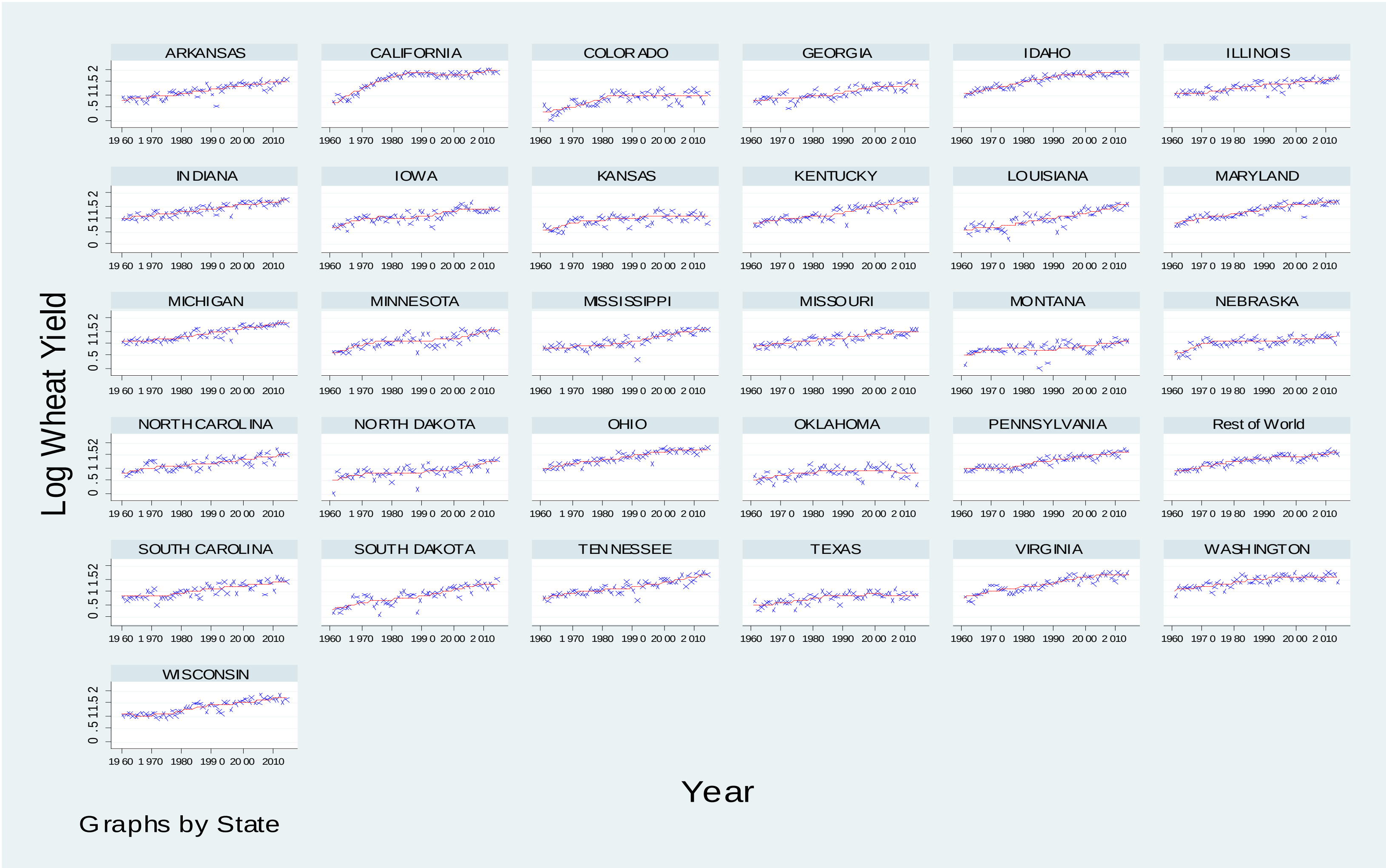


**Figure A3. Wheat yields and trend (restricted cubic spline with 6 knots)**

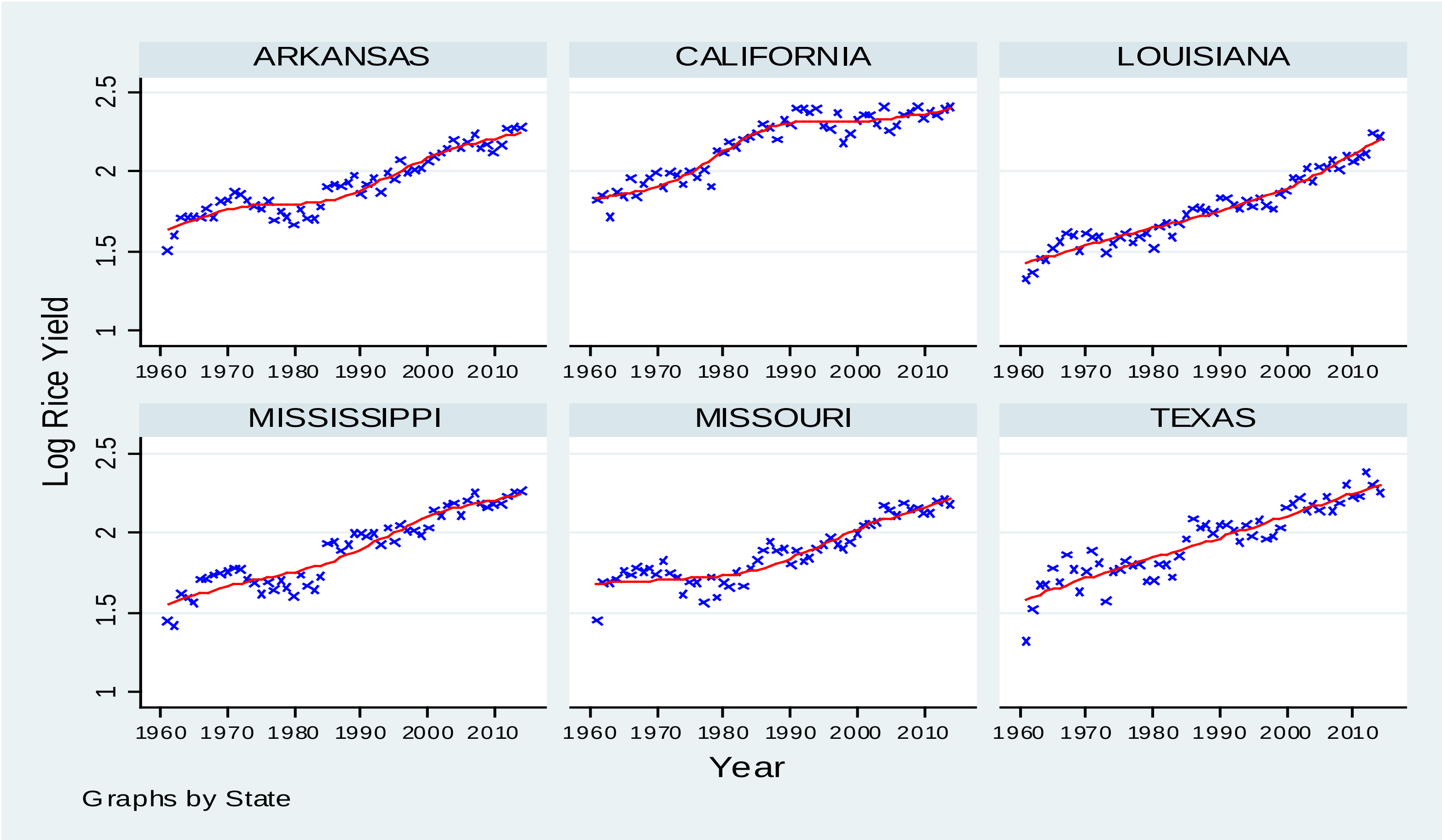


**Figure A4. Rice yield and trend (restricted cubic spline with 6 knots)**

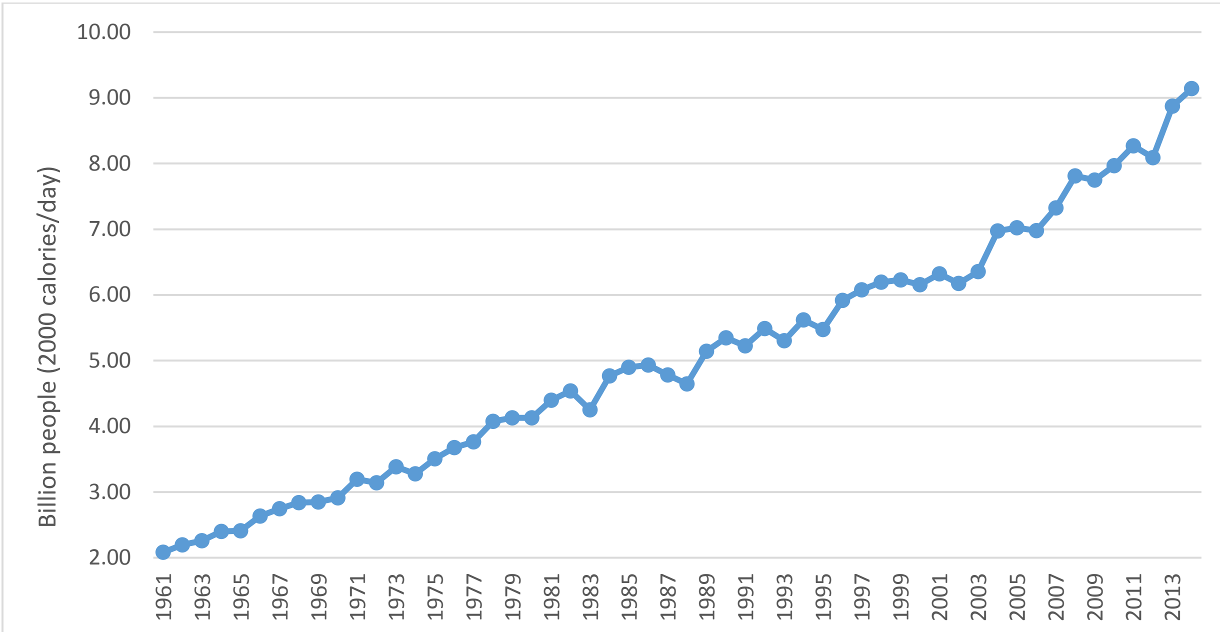


**Figure A5. World caloric production of four crops**

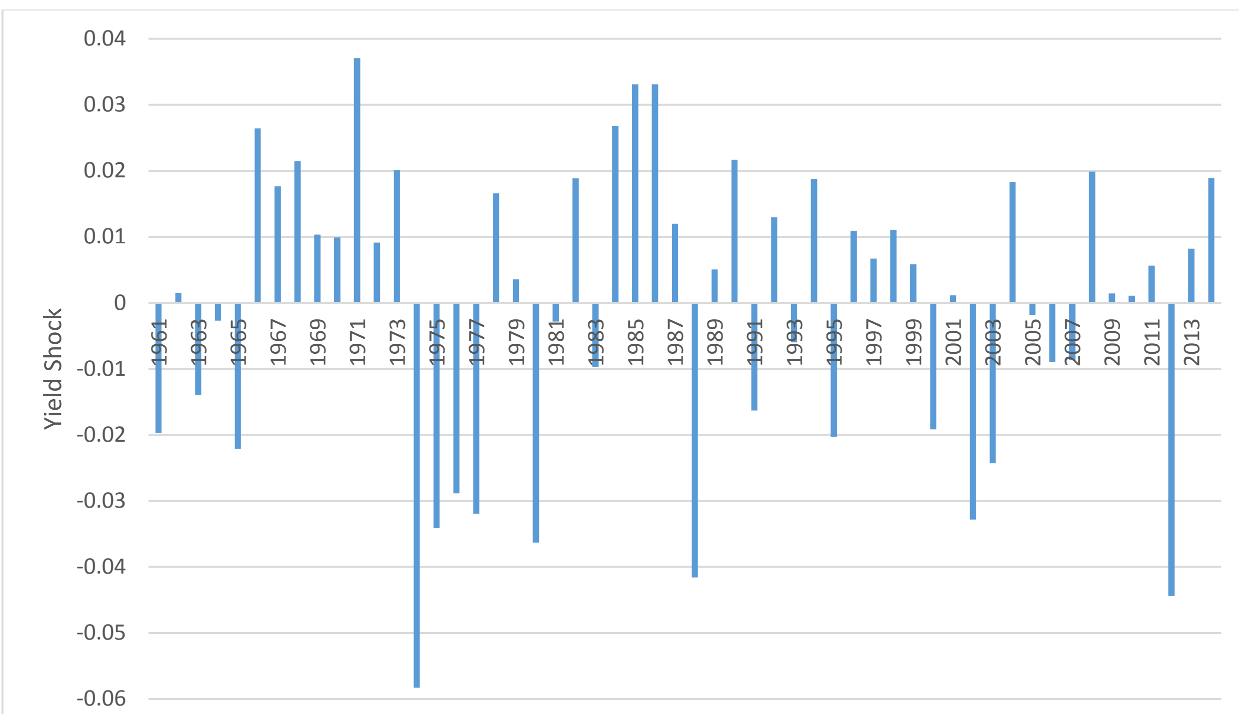


**Figure A6. World yield shock of four crops**

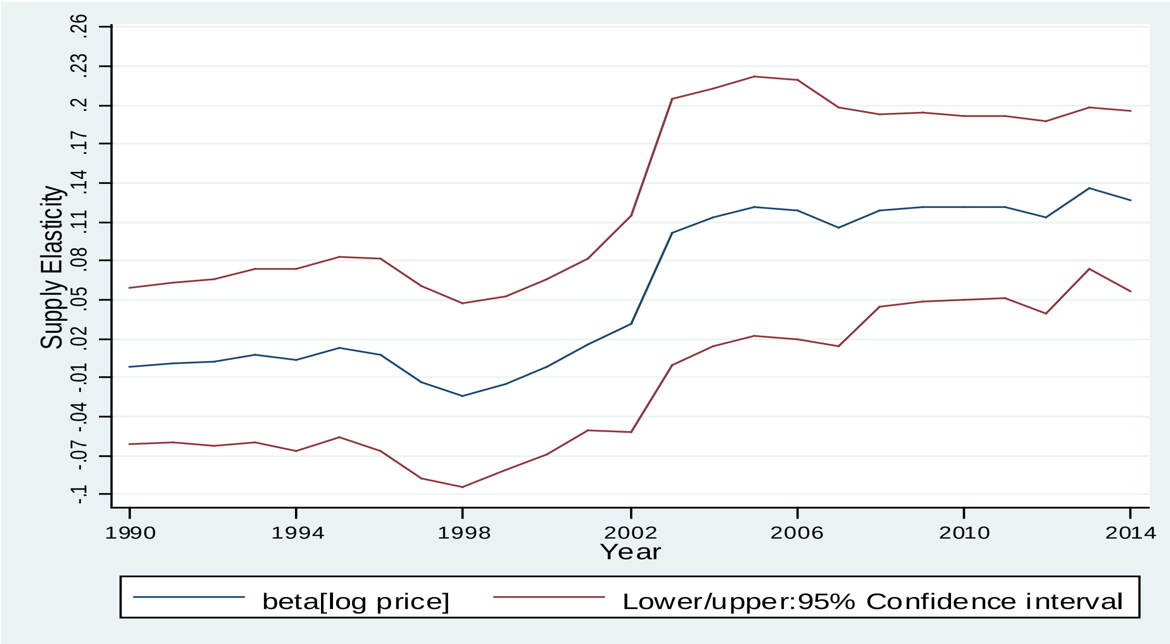


Figure A7. Time-varying caloric supply response estimated applying rolling estimation method in the OLS regression of production on the futures price

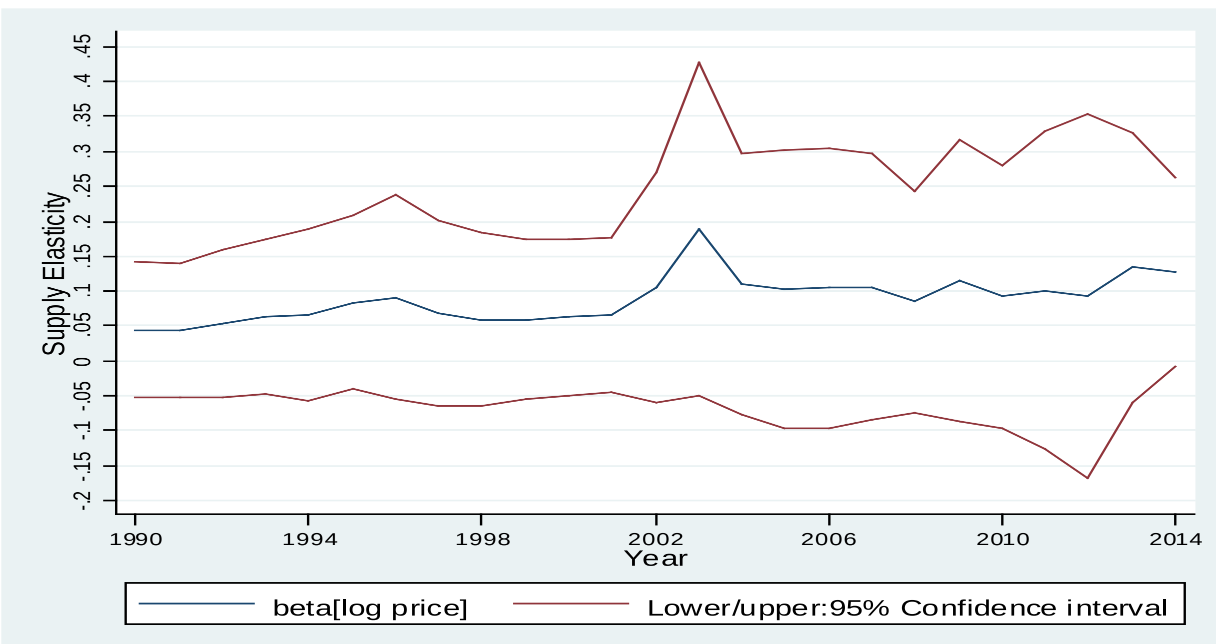


Figure A8. Time-varying caloric supply response estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on past-year yield shock

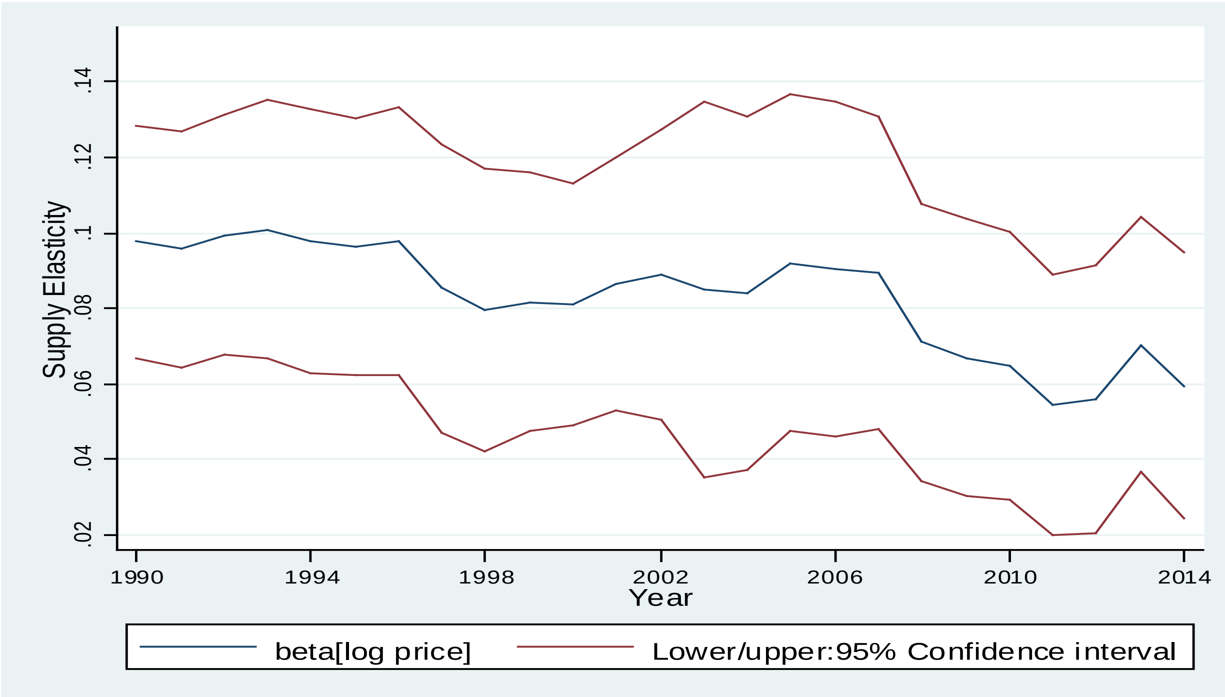


Figure A9. Time-varying caloric supply response estimated applying rolling estimation method in the OLS regression of production on the futures price and current-year yield shock

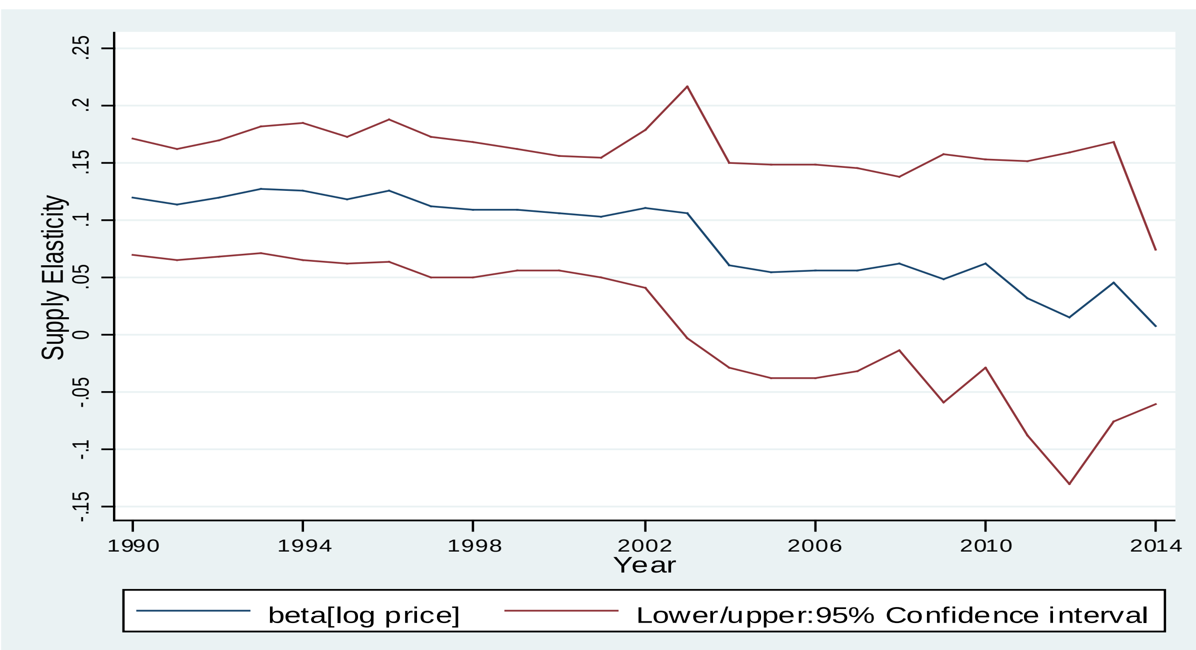


Figure A10. Time-varying caloric supply response estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on current- and past-year yield shock


Figure A11. Time-varying growing area response estimated applying rolling estimation method in the OLS regression of production on the futures price

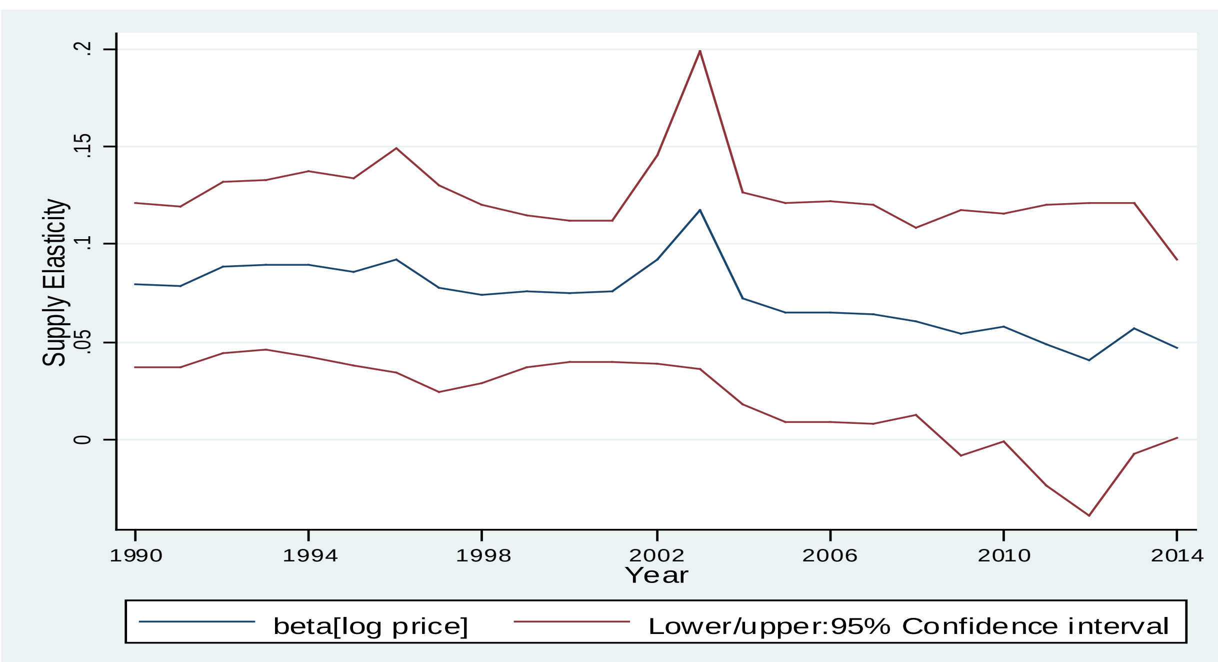


Figure A12. Time-varying growing area response estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on past-year yield shock

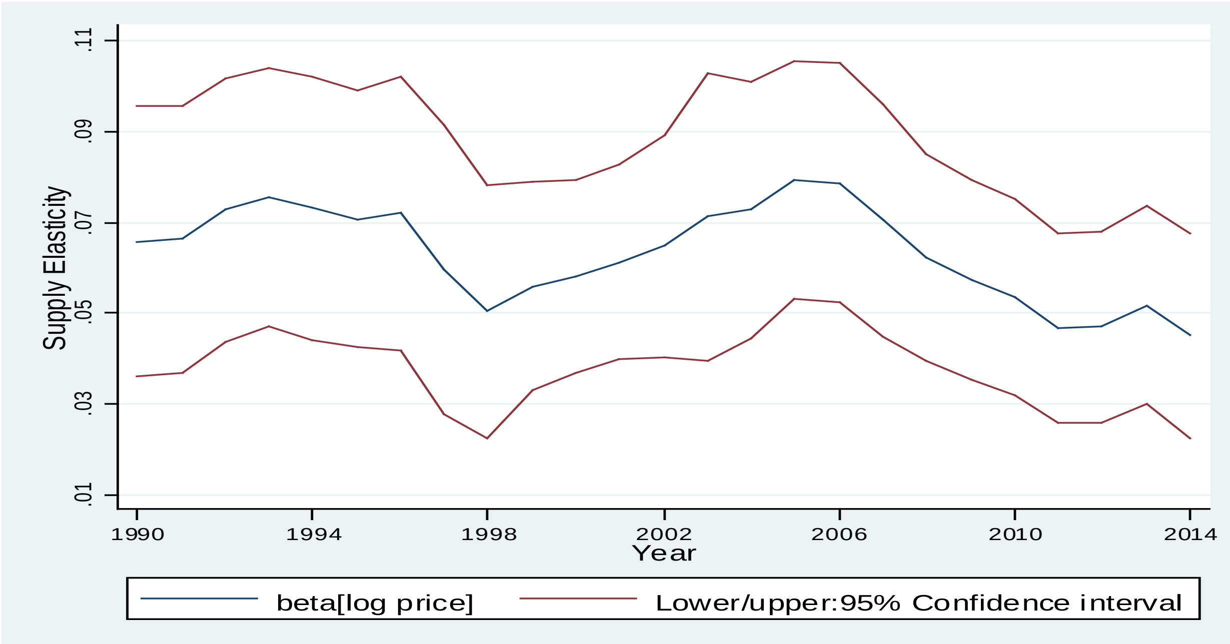


Figure A13. Time-varying growing area response estimated applying rolling estimation method in the OLS regression of production on the futures price and current-year yield shock

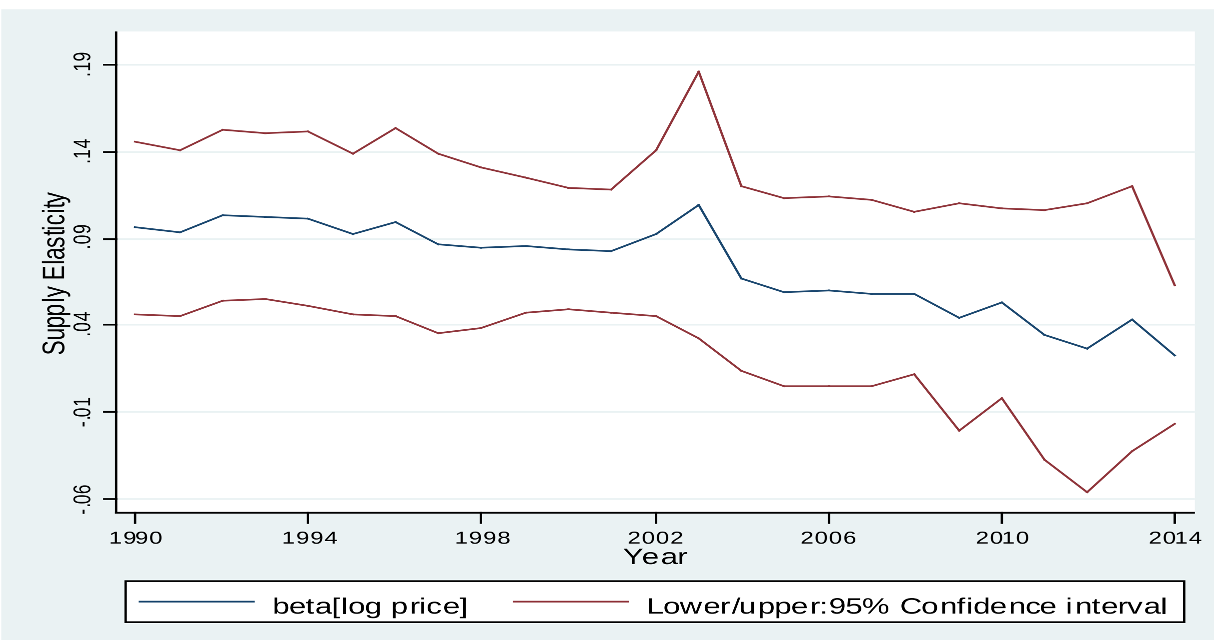


Figure A14. Time-varying growing area response estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on current- and past-year yield shock

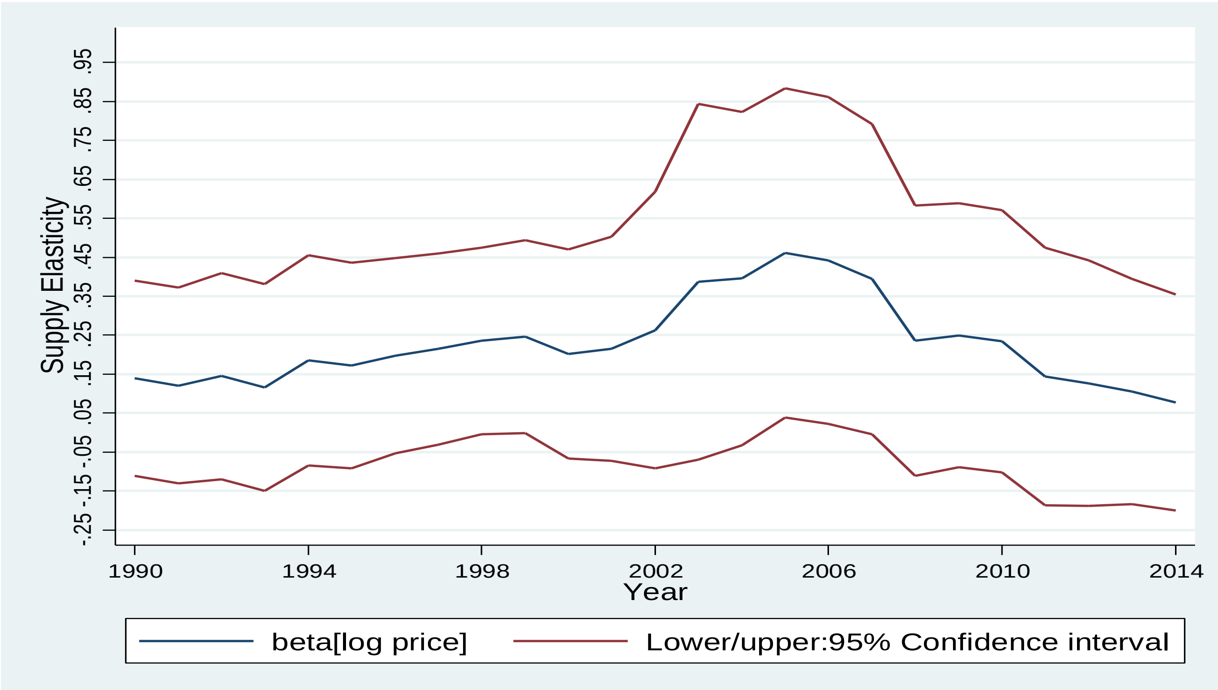


Figure A15. Time-varying caloric supply response of US aggregate crop estimated applying rolling estimation method in the OLS regression of production on the futures price

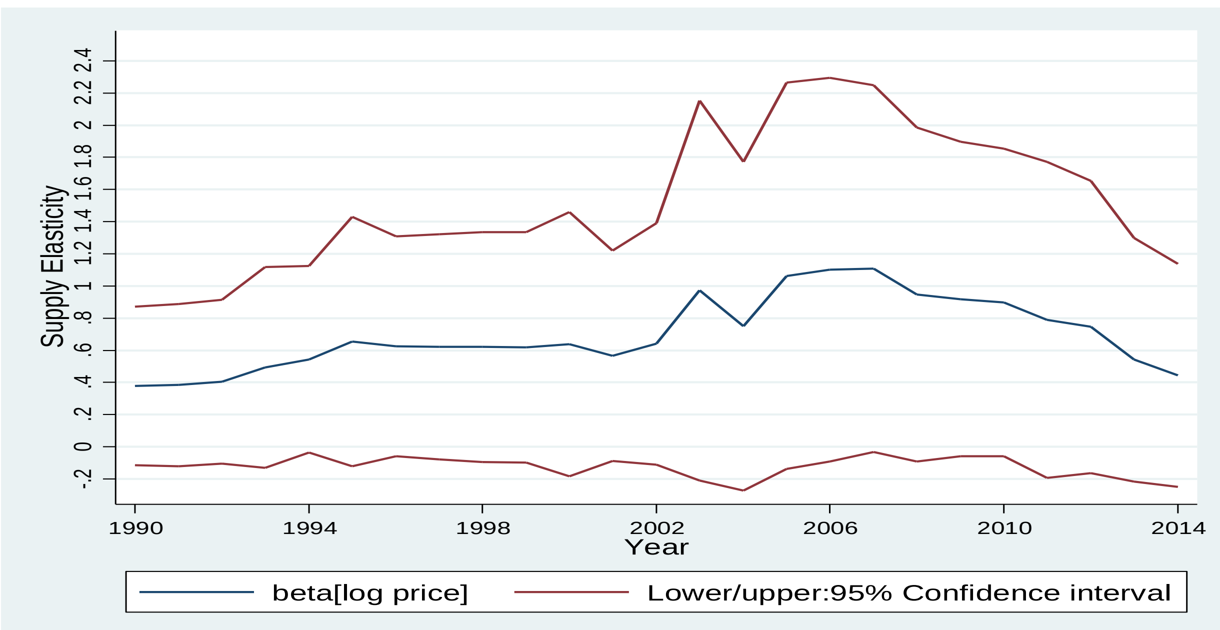


Figure A16. Time-varying caloric supply response of US aggregate crop estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on past-year yield shock

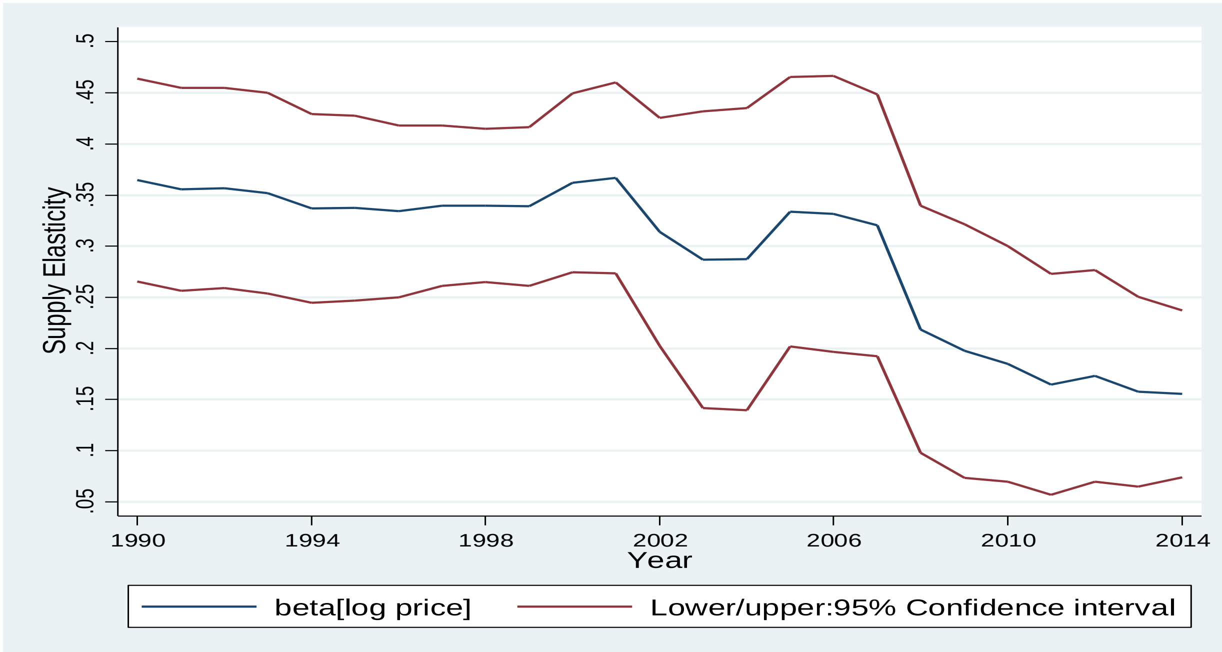


Figure A17. Time-varying caloric supply response of US aggregate crop estimated applying rolling estimation method in the OLS regression of production on the futures price and current-year yield shock

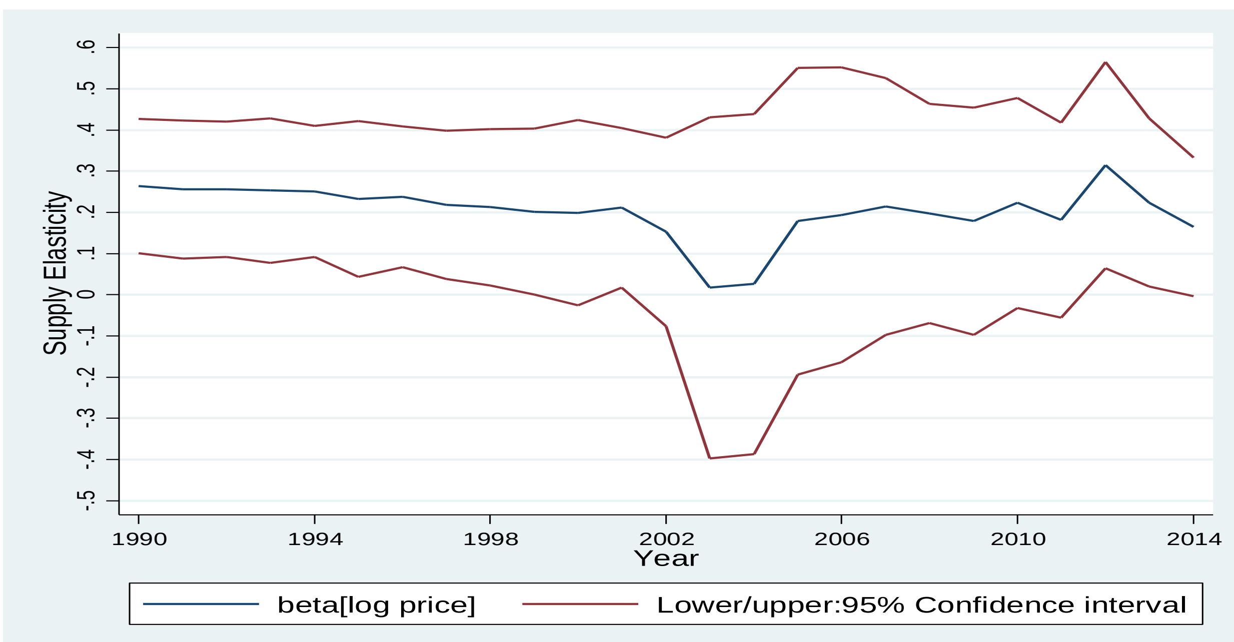


Figure A18. Time-varying caloric supply response of US aggregate crop estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on current- and past-year yield shock

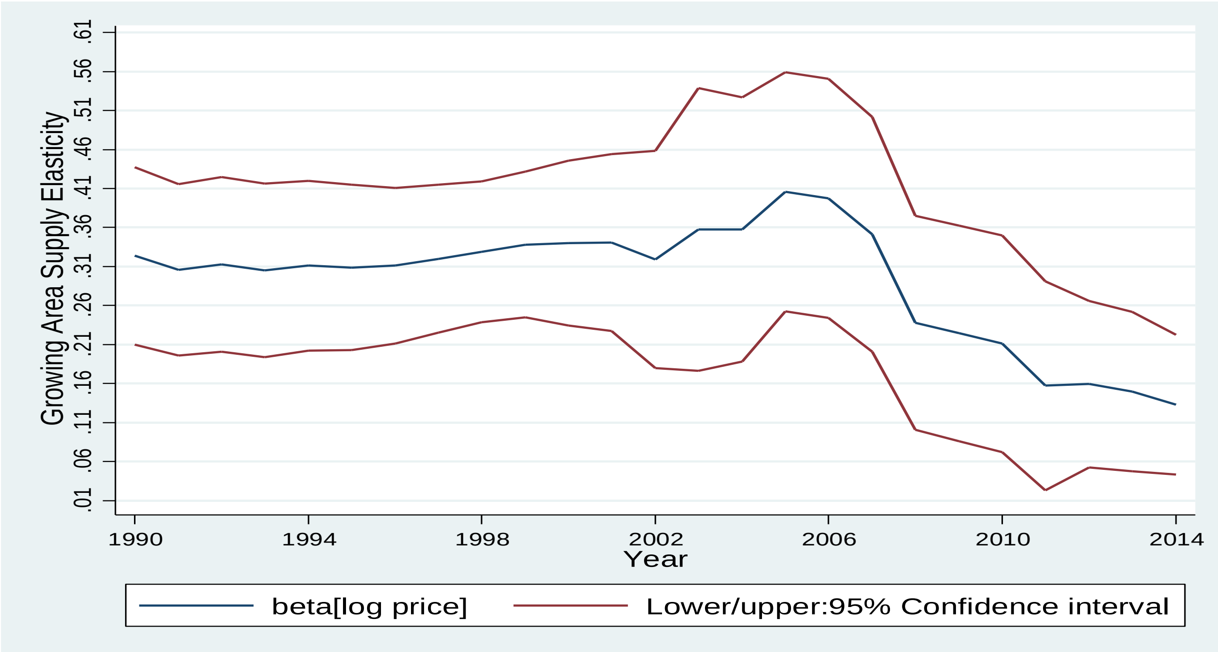


Figure A19. Time-varying growing are supply response of US aggregate crop estimated applying rolling estimation method in the OLS regression of production on the futures price

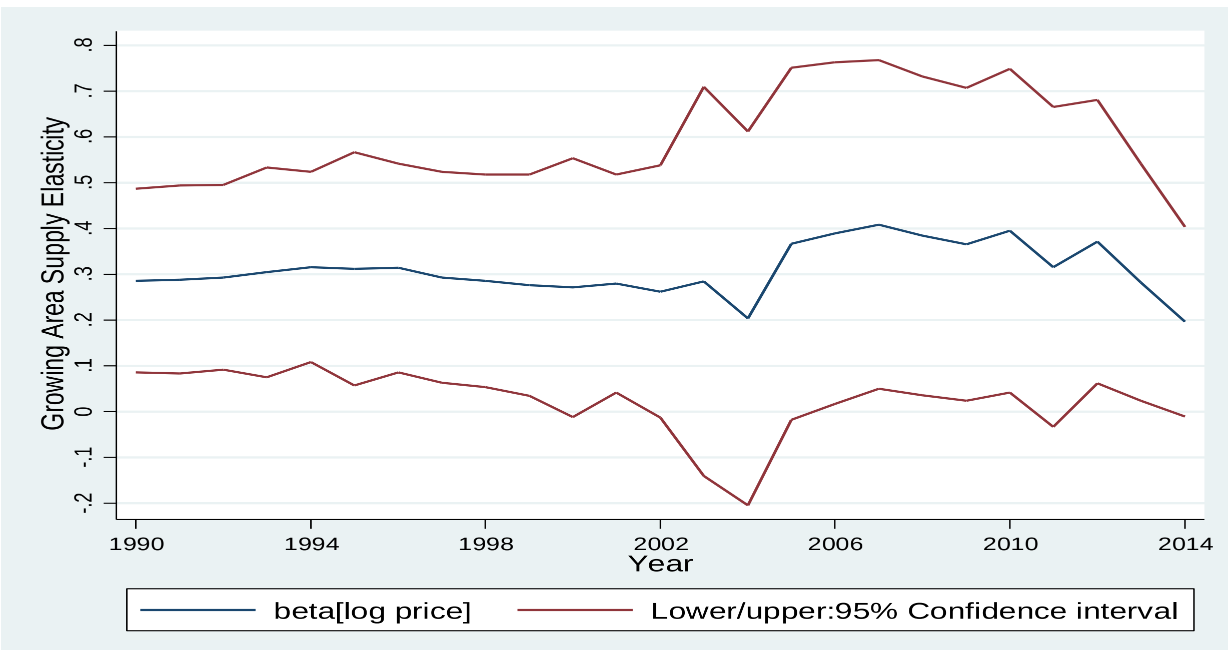


Figure A20. Time-varying growing-area supply response of US aggregate crop estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on past-year yield shock

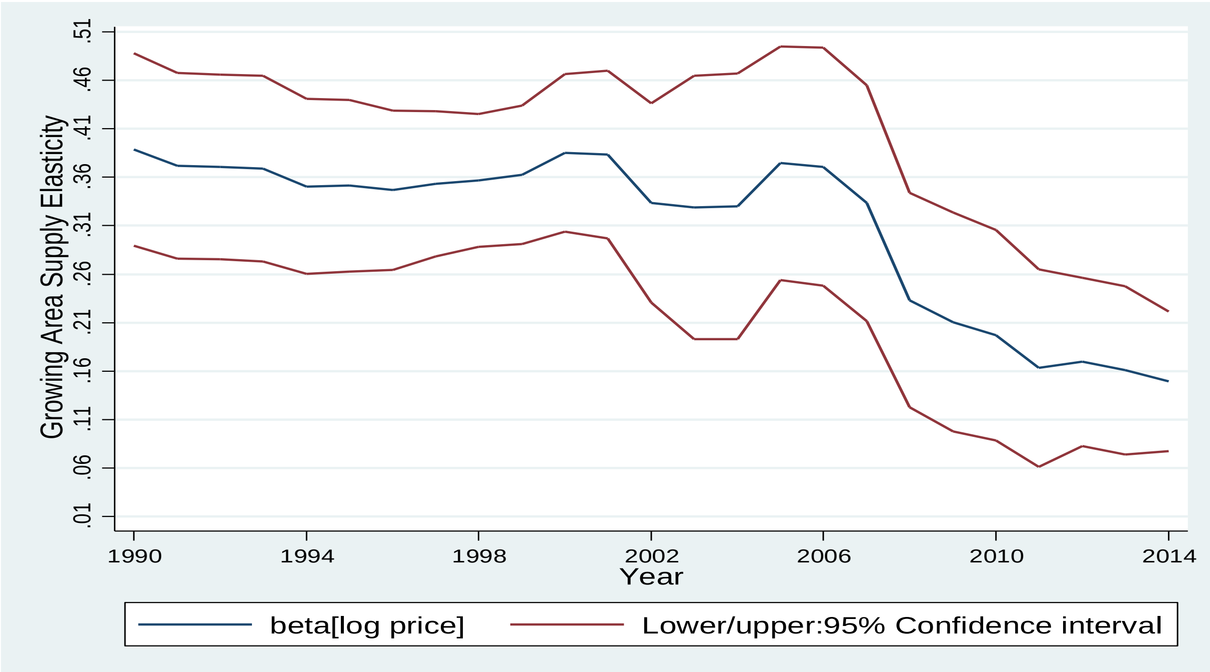


Figure A21. Time-varying growing-area supply response of US aggregate crop estimated applying rolling estimation method in the OLS regression of production on the futures price and current-year yield shock

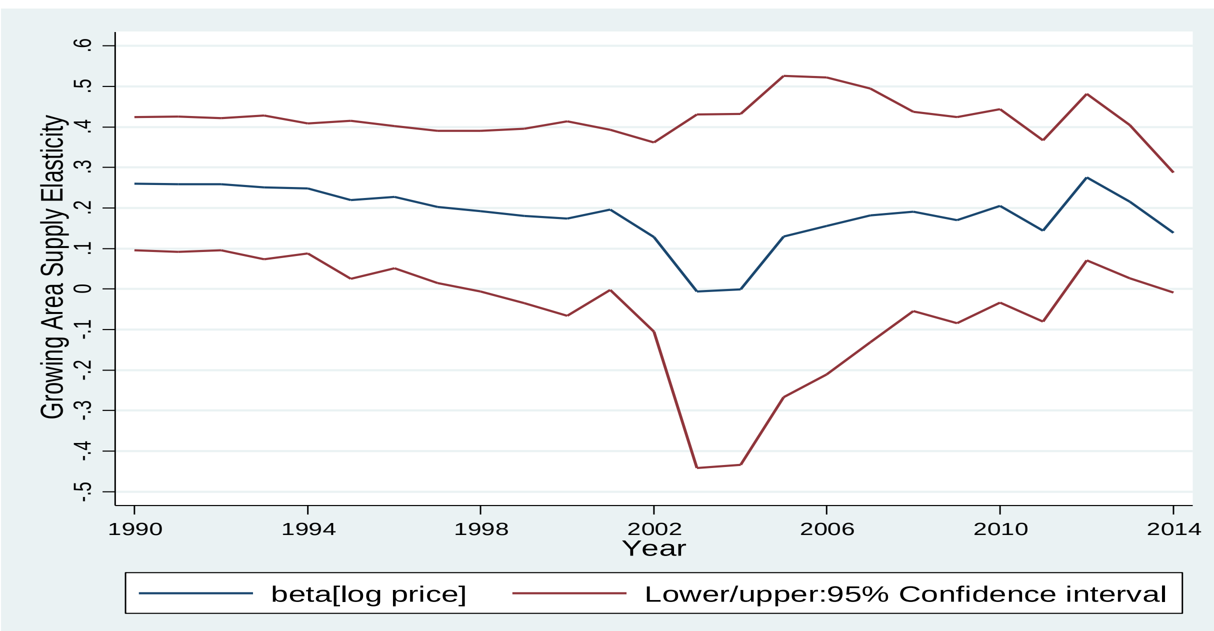


Figure A22. Time-varying growing-area supply response of US aggregate crop estimated applying rolling estimation method in the IV regression of production on the futures price, where futures price is instrumented on current- and past-year yield shock

# CHAPTER 3. GLOBAL GROWING AREA ELASTICITIES OF KEY AGRICULTURAL COMMODITIES ESTIMATED USING DYNAMIC HETEROGENEOUS PANEL METHODS


## 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.


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

## 3.1 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., 2016b). 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.[11]

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., 2016; Haile et al., 2016a). Recently, Roberts and Schlenker (2013), Haile et al. (2014), Hendricks et al. (2015), and Haile et al. (2016b) 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,

[11]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.

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. (2016b) 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. 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 3.2 provides an overview of the existing supply response model and discusses the proposed empirical model. Section 3.3 describes data. Section 3.4 presents the empirical findings and an interpretation of the findings. Section 3.5 concludes.

## 3.2 The Economic Model and Empirical Strategy

### 3.2.1 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)

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

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, $\pi$ and $\gamma$ 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 $\mathrm{A}_t^* = A_t$, then the reduced form of the above structural model can be expressed as[12]

(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

[12] 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.

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 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

(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 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 $\pi$ and $\gamma$ 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.

### 3.2.2 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

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

where $A_{ict}$ denotes actual planted area of crop c (corn, soybeans, wheat, and rice) at time t, $P^{e}_{ikt}$ 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 $\delta_{10ick}$ 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

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

with the short-run parameters $\delta_{10i}$ and $\lambda_i$ 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:[13]

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

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

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 $N \rightarrow \infty$ *and* $T \rightarrow \infty$ (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 $\delta_{10}$ and $\lambda$. However, under two special cases, the OLS estimator will be consistent. Lewbel (1994) shows that if $\lambda_i$ and $\delta_{10i}$ 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 $\bar{A}_t$ and $\bar{P}_t^e$ (Pesaran and Smith, 1995).

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

(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 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, $\alpha_i$ 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 $\alpha_i$ 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 $\upsilon_{it}$ (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 $N \rightarrow \infty$ (e.g., Nickell, 1981). When we use the FE estimator to estimate equation (8), the estimates of the long-run effect, $\theta$, 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 $\upsilon_{it}$ in equation (13) contains a lagged dependent variable. This means $\upsilon_{it}$ 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 $\varepsilon_{it}$ and $P_{it}^{e}$, have a zero correlation with $\upsilon_{it}$, 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)[14]. 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.

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[15]

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

This ARDL specification improves on the usual autoregressive lag (ADL) model equation (7) in several ways. First, the assumption that the disturbances $\varepsilon_{ict}$ are distributed

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[14] Section A1 in appendix shows mathematical details of the consistency of MG estimator.
[15] Griliches (1967) discusses adding lags of explanatory variables as additional controls in the Nerlove's partial adjustment model.

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

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

where $\Delta$ 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, $\delta_{11ic}$, and its mean; the long-run own-price growing-area elasticity, $\theta_{1ic}$, and its mean; and the error correction speed of adjustment parameter, $\phi_{ic}$, and its mean. As long as the adjustment parameter, $\lambda_{ic}$ 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

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

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

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

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 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 MG 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) who use current-year yield shock as a control variable in their supply model to account for the endogeneity of futures prices that may arise from the anticipation of production shocks.

## 3.3 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 A1, A2, A3, and A4 in section A2 of appendix.[16] 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. (2016b) and Miao et al. (2016) model the farmers' price expectation in a similar fashion. Haile et al. (2016b) model for countries around the world and Miao et al. (2016) 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 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.

[16] Crop calendar for each crop is from http://www.amis-outlook.org/amis-about/calendars/en/ and Haile et al. (2016).

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.

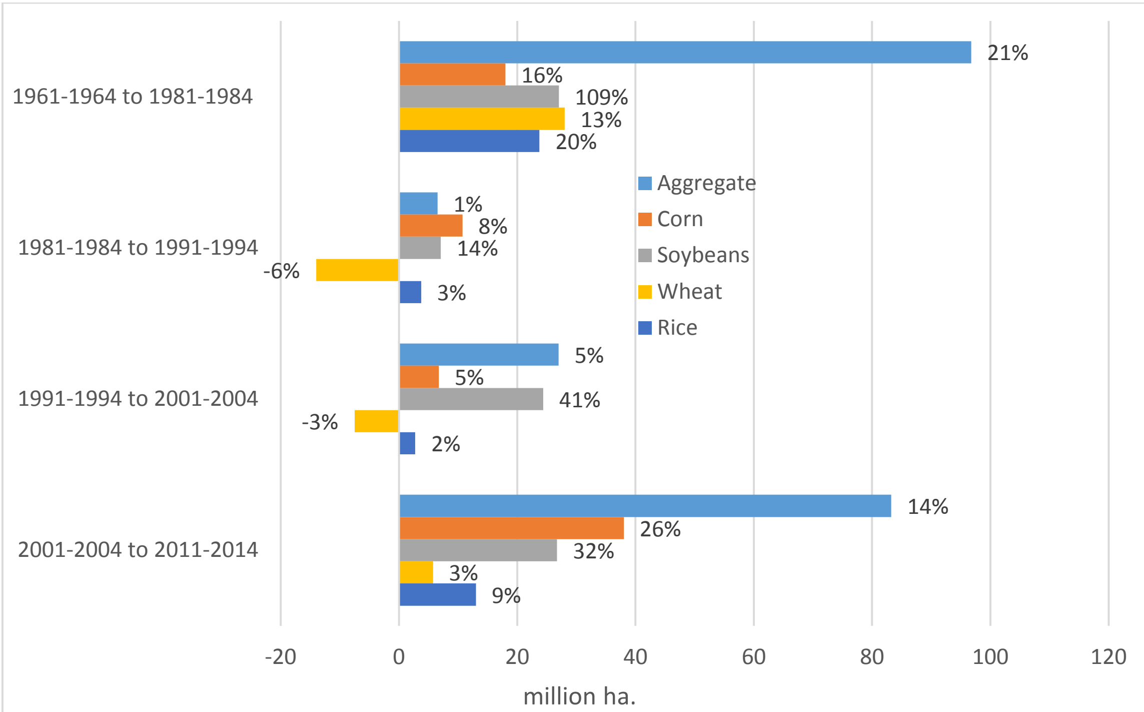


**Figure 1. Changes in global growing area from 1961 to 2014.**

### 3.4 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 $\phi_i$ .

**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.[17] 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

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

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.

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 tables A1 and A2 in section A2 of 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, 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 tables A3 and A4 in section A2 of appendix.

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. (2016a) find a negative cross-price elasticity between soybeans and wheat.[18]

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.

[18] 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.

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 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., 2016a; 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 $\phi_i$ 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 tables A5, A6, A7, and A8 in section A3 of appendix, 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.

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 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.

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.

### 3.5 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., 2016b). 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.

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## Appendix. Additional Materials

### A1. 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

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

where $x_{it} = (P_{it}'^{e}, A_{i,t-1})'$ and $\gamma_i = (\delta_{10i}, \lambda_i)$. The disturbance $\varepsilon_{it}$ 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 $\gamma_i$ for each group i given by

$$\hat{\gamma}_i = (X_i' H_T X_i)^{-1} X_i' H_T A_i, \quad i = 1, 2, ....., N \tag{A1.2}$$

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 $i$th 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 $\gamma_i$ as

$$\hat{\gamma}_{MG} = \sum_{i=1}^{N} \hat{\gamma}_i \, / \, N \tag{A1.3}$$

which can be expressed as

$$\hat{\gamma}_{MG} = \overline{\gamma} + \frac{1}{N}\sum_{i=1}^{N}(X_i' H_T X_i)^{-1} X_i' H_T \varepsilon_i \quad \text{(A1.4)}$$

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

$$\text{plim}_{T\to\infty}(\hat{\gamma}_{MG}) = \overline{\gamma} + \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i' H_T X_i}{T}\right)^{-1} + \text{plim}_{T\to\infty}\left(\frac{X_i' H_T \varepsilon_i}{T}\right) = \overline{\gamma} \quad \text{(A1.5)}$$

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 $\overline{\gamma} \xrightarrow{p} \gamma$ . This confirms the consistency of the MG estimator $\hat{\gamma}_{MG}$ .

## A2. Planting and Harvesting Calendar

**Table A1. 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 | | | H | H | H | | | | P | P | P | P | | | H | H | H | | | | P | P | P | P |
| Australia | | | H | H | H | | | | | P | P | P | | | H | H | H | | | | | P | P | P |
| Bangladesh | P | P | | H | H | H | | | | P | P | P | P | P | | H | H | H | | | | P | P | P |
| Brazil | P | B | H | H | H | H | H | | P | P | P | P | P | B | H | H | H | H | H | | P | P | P | P |
| Canada | | | | | P | P | P | | | H | H | | | | | | P | P | P | | | H | H | |
| China | | P | P | P | P | P | H | H | H | H | | | | P | P | P | P | P | H | H | H | H | | |
| Egypt | | | | P | P | | | | | H | H | | | | | P | P | | | | | H | H | |
| India | | H | H | | | P | P | | H | H | P | P | | H | H | | | P | P | | H | H | P | P |
| Indonesia | | | | | | P | P | P | | H | H | H | | | | | | P | P | P | | H | H | H |
| Iran | | | | P | P | | | H | H | | | | | | | P | P | | | H | H | | | |
| Japan | | | P | P | P | | | H | H | H | | | | | P | P | P | | | H | H | H | | |
| Mexico | B | B | P | B | B | B | B | P | P | B | B | B | B | B | P | B | B | B | B | P | P | B | B | B |
| Myanmar | H | H | H | H | | | | | P | P | P | P | H | H | H | H | | | | | P | P | P | P |
| Pakistan | | | | P | P | P | P | P | H | H | H | | | | | P | P | P | P | P | H | H | H | |
| Philippines | | | | P | P | P | H | H | H | | | | | | | P | P | P | H | H | H | | | |
| South Africa | P | | | H | H | H | H | | | P | P | P | P | | | H | H | H | H | | | P | P | P |
| Thailand | H | | P | P | P | P | P | H | H | H | H | | H | | P | P | P | P | P | H | H | H | H | |
| Turkey | | | | P | P | P | | | H | H | | | | | | P | P | P | | | H | H | | |
| U.S. | | | | P | P | | | | H | H | H | | | | | P | P | | | | H | H | H | |
| Vietnam | H | H | H | B | B | B | H | H | B | B | B | B | H | H | H | B | B | B | H | H | B | B | B | B |
| F. USSR | | | | P | P | P | | H | H | H | H | | | | | P | P | P | | H | H | H | H | |
| F. Yugoslav | | | 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 | | | | H | H | H | | | | | P | P | | | | H | H | H | |
| Rest of South | | | H | H | H | | | | P | P | P | P | | | H | H | H | | | | P | 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. |

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

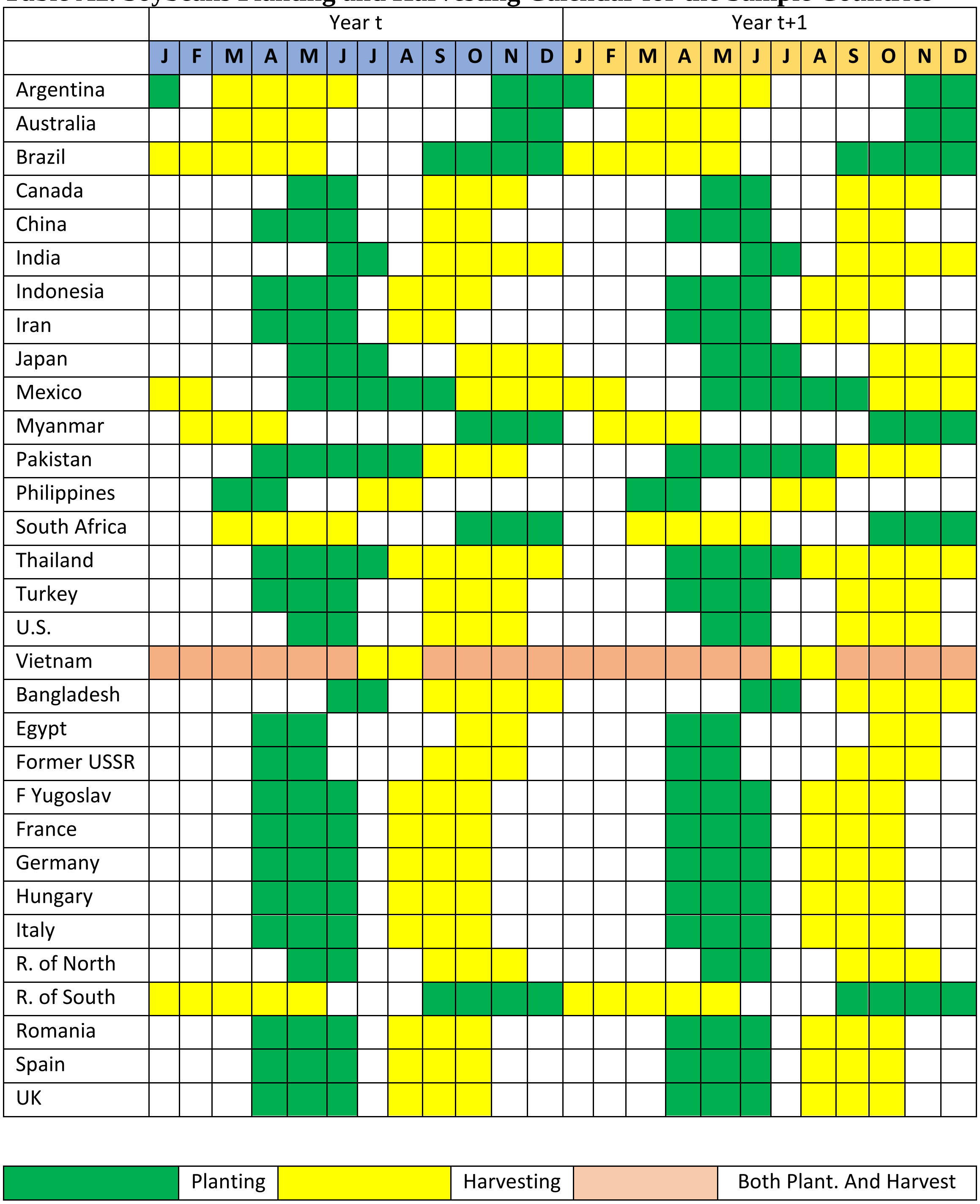
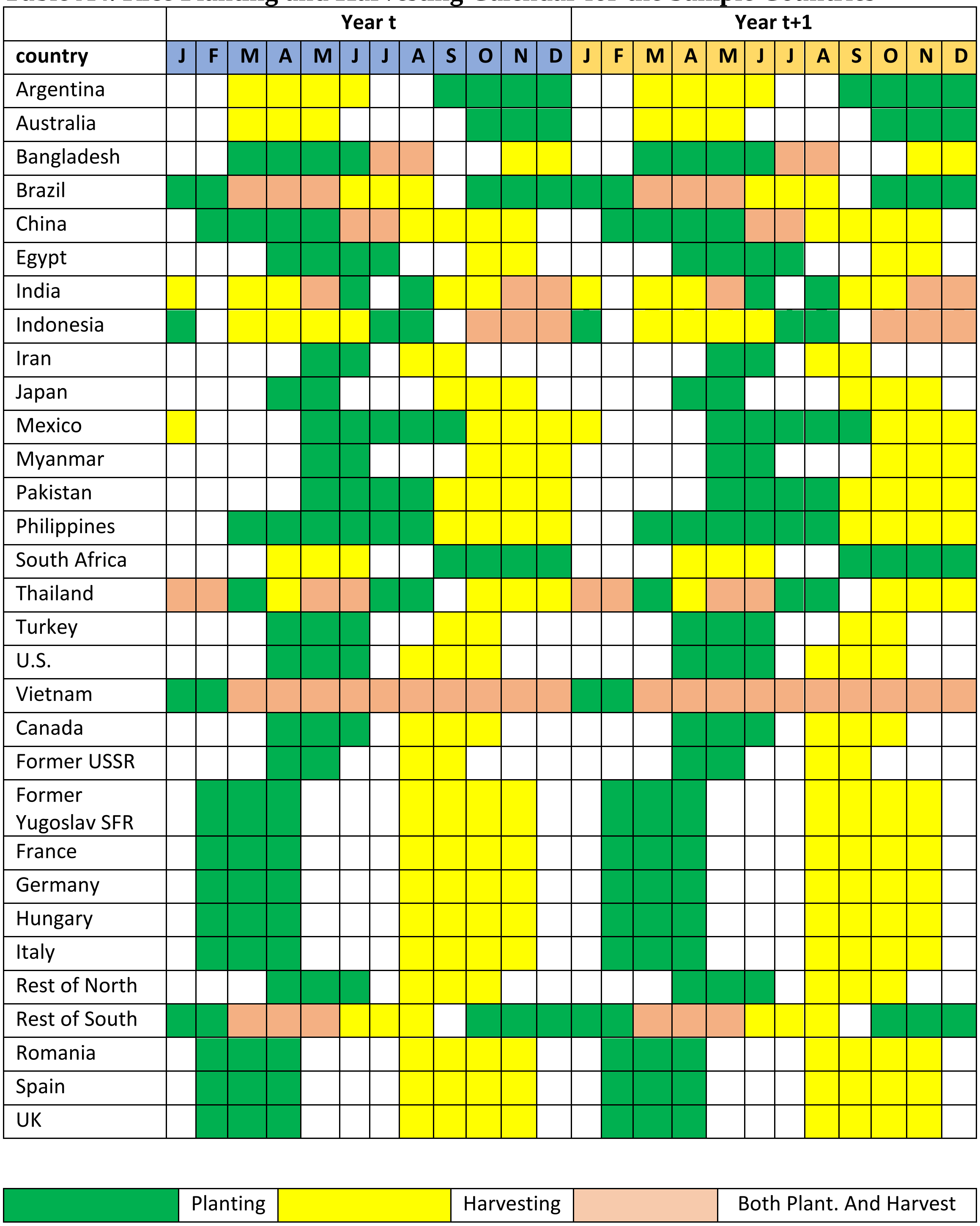


**Table A3. Wheat Planting and Harvesting Calendar for the Sample Countries**

| | 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 | H | | | | P | P | P | P | | | H | H | H | | | | P | P | P | P | | | H | H |
| Australia | H | | | P | P | P | | | | H | H | H | H | | | P | P | P | | | | H | H | H |
| Bangladesh | P | | H | H | | | | | | | P | P | P | | H | H | | | | | | | P | P |
| Brazil | | | | P | P | P | | | H | H | H | H | | | | P | P | P | | | H | H | H | H |
| Canada | | | | P | P | P | | H | H | H | | | | | | P | P | P | | H | H | H | | |
| China | | | | | H | H | | | P | P | P | | | | | | H | H | | | P | P | P | |
| Egypt | | | | H | H | H | | | P | P | P | | | | | H | H | H | | | P | P | P | |
| India | P | | H | H | H | | | | | P | P | P | P | | H | H | H | | | | | P | P | P |
| Iran | | | | | | H | H | | P | P | P | | | | | | | H | H | | P | P | P | |
| Japan | | | | | H | H | H | | P | P | P | | | | | | H | H | H | | P | P | P | |
| Mexico | P | P | P | H | H | H | H | | | P | P | P | P | P | P | H | H | H | H | | | P | P | P |
| Myanmar | | H | H | H | H | | | | P | P | P | | | H | H | H | H | | | | P | P | P | |
| Pakistan | | | H | H | H | H | | | P | P | P | P | | | H | H | H | H | | | P | P | P | P |
| South Africa | | | | P | P | P | | | | H | H | | | | | P | P | P | | | | H | H | |
| Turkey | | | | | | H | H | H | P | P | P | | | | | | | H | H | H | P | P | P | |
| U.S. | | | | P | P | H | H | H | B | P | P | | | | | P | P | H | H | H | B | P | P | |
| FUSSR | | | | | P | P | | H | H | | | | | | | | P | P | | H | H | | | |
| F Yugoslav | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| France | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Germany | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Hungary | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Indonesia | | | | | | P | P | P | | H | H | H | | | | | | P | P | P | | H | H | H |
| Italy | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Philippines | | | P | P | P | P | P | P | H | H | H | H | | | P | P | P | P | P | P | H | H | H | H |
| Rest of North | | | | P | P | H | H | H | B | P | P | | | | | P | P | H | H | H | B | P | P | |
| Rest of South | | | | P | P | P | | | H | H | H | H | | | | P | P | P | | | H | H | H | H |
| Romania | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Spain | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Thailand | H | | P | P | P | P | P | H | H | H | H | | H | | P | P | P | P | P | H | H | H | H | |
| UK | | | | | | H | H | H | P | P | P | P | | | | | | H | H | H | P | P | P | P |
| Vietnam | H | H | H | B | B | B | H | H | B | B | B | B | H | H | H | B | B | B | H | H | B | B | B | B |

| | | | | | |
|---|---|---|---|---|---|
| P | Planting | H | Harvesting | B | Both Plant. And Harvest |

**Table A4. Rice Planting and Harvesting Calendar for the Sample Countries**



## A3. Further Empirical Results

**Table A5. 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 A6. 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 A7. 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 A8. 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.

# CHAPTER 4. AGGREGATE AGRICULTURAL INTENSIVE AND EXTENSIVE LAND SUPPLY RESPONSE TO PRICE AND NON-PRICE FACTORS

## Abstract

Do crop output prices and non-price factors explain changes in intensive and extensive agricultural land use? We study this question in a large panel of 79 countries covering the period 2004 to 2013. The dataset includes country-specific data on harvested, planted, and potentially arable cropland, producer prices, per capita real income, and population density. We define intensive margin as the change in unharvested land, multiple cropping, temporary pasture, and fallow land. The extensive margin is defined as the conversion of non-cropland into (from) cropland. We adopt both static and dynamic panel models to analyze land use response and estimate the respective model using a first-differenced (FD) estimator and a dynamic panel generalized instrumental variable or generalized method of moments (GMM) estimator. The FD estimator produces a global (harvested) land use elasticity with respect to output price equal to 0.134—of this, intensive and extensive margin elasticities equal 0.093 and 0.042, respectively. The elasticity estimates from the dynamic GMM estimator at the total, intensive margin, and extensive margin equal 0.091, 0.067, and 0.017, respectively. These results imply that global land use has responded more at the intensive margin than at the extensive margin during the recent era of high crop prices. We also find that over the last decade countries with more potentially arable cropland have expanded more at the extensive margin. Last, we show that controlling for the effect of potentially arable cropland lowers the extensive margin elasticity and increases the intensive margin elasticity.

## 4.1 Introduction

Ten years have passed since major agricultural crop prices started to increase in late 2005. This increase was the longest sustained increase since 1960 (figure A1 in section A1 of appendix). Since then, a number of empirical studies have investigated the response of agricultural crop output or land use to output price at both the national and global level. Examples of such works are Roberts and Schlenker (2013), Haile, Kalkuhl, and von Braun (2014), Hendricks, Janzen, and Smith (2015), Haile, Kalkuhl, and von Braun (2016), and Miao, Khanna, and Huang (2016). Except for Miao, Khanna, and Huang (2016) which estimates the U.S. supply response of corn and soybeans, the studies estimate global supply response for four key crops—corn, soybeans, wheat, and rice—to price changes while controlling for the effects of non-price factors using historical time series data. The time period covered in these studies is primarily before the most recent commodity price boom. In this paper, we focus on global aggregate agricultural supply response using recent data.

The above-cited literature provides two opposing results on the magnitude and source of agricultural supply response to price changes. The first group provides empirical evidence that shows agricultural supply response to prices as coming more from land use change at the extensive margin (change in land cover) than at intensive margin (higher yield)[19]. The second group provides empirical evidence that shows supply response to prices is the result of response both at the extensive and intensive margin.[20] In this paper,

[19] Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) are in this group.
[20] Miao, Khanna, and Huang (2016) and Haile, Kalkuhl, and von Braun (2016) are in this group.

we focus only on measuring changes in land use and not per-hectare yields. However, we differentiate between bringing new land into production and more intensive use of existing land.

Higher agricultural supply response means higher food production which plays a major role in global food security (Parry et al 2009). But, there can be a trade-off between food production and environmental quality if supply response occurs at the extensive margin. Higher extensive supply response has negative effects on the environment in terms of ecological destruction and greenhouse gas (GHG) emissions. In contrast, when supply response occurs at the intensive margin (yield gains), higher food production is associated with smaller environmental costs because negative externalities associated with agricultural intensification is much smaller than with extensification (Burney, Davis, and Lobell 2010). This paper investigates the supply response in the form of land use rather than in the form of both land use and yield response.[21] Estimates of supply response in the form of land expansion are important to environmentalists and policymakers because it affects the environment by generating greenhouse gas (GHG) caused by land conversion from forest or pasture land.

In examining global aggregate land use response of all crops, we use three measures of land use. We know total agricultural crop production is the product of land harvested and yield. Following Babcock (2015), we modify this definition by decomposing changes of harvested land into two measures: responses at the extensive margin and intensive margin. We define land use response at the extensive margin as the conversion of non-

[21] The remainder of this paper, we will use supply response and land use response interchangeably.

cropland into (from) cropland. The changes at the intensive margin are defined as the change in unharvested but planted land, multiple cropping, temporary pasture, and fallow land. Thus, we have three measures of land use namely total (harvested), extensive, and intensive margin to investigate land use response.

We estimate global aggregate land use response of all crops to output prices while controlling for the effects of demand shifters such as income and population density as well as available land resources such as potentially arable cropland. We use both a two-period static panel supply model and a dynamic panel supply model to investigate supply response. Estimating land use response to prices and non-price factors face several methodological challenges and problems. First, the incorrect treatment of country-specific fixed effects representing differences in infrastructure, or technologies, or production cultures leads to omitted variable bias because in general such effects are typically correlated with the explanatory variables. As a result, cross-country regressions such as those in Peterson (1979) are subject to this bias and provide inconsistent estimates of the impact of prices on aggregate agricultural supply.

Second, incorrect specification of supply response models, such as failure to properly model land use dynamics, may lead to biased estimates of price impact on supply. As a result, time series regressions such as those in Roberts and Schlenker (2013) and Hendricks, Janzen, and Smith (2015) may overestimate or underestimate the true supply response to prices.

Third, aggregating over cross-sectional units in a dynamic model that includes a lagged dependent variable as an explanatory variable and estimating the model using a simple ordinary least square (OLS) may provide biased estimates of the coefficients on the lagged dependent variable as well as on the other explanatory variables. Time-series regressions such as that in Haile, Kalkuhl, and von Braun (2014), are potentially subject to this problem.

Fourth, we use crop output prices received by producers as a proxy of expected prices in our supply model. These prices may suffer in expectation error or may be endogenous to supply analysis. To the best of our knowledge, the endogeneity problem has been addressed in a few recent studies whereas no attempts to address expectation error have been made.

Last, a dynamic panel model that includes a lagged dependent variable as the explanatory variable may suffer from dynamic panel bias or Nickell bias if the model is estimated using traditional fixed effects (FE) estimator[22]. This bias arises because the lagged dependent variable is correlated with the error term. Because of the presence of this bias, the estimates from FE estimator is biased and inconsistent.

In this paper, we propose to address these methodological challenges mainly using two econometric methods: (1) first-differenced (FD) estimator and (2) dynamic panel generalized method of moments (GMM) estimator. The FD estimator addresses country-specific omitted fixed effects bias. The dynamic panel GMM estimator exploits the time-series variation in dependent and explanatory variables within each observation, controls for unobserved country-specific fixed effects, accounts explicitly for the bias induced by the inclusion of lagged dependent variable as explanatory variable, and controls for the

[22] Econometric literature also calls this estimator as within-group (WG) estimator.

expectation error or endogeneity of explanatory variable that we anticipate to be relevant with respect to expected prices.

Our first econometric method is the traditional FE estimator, which investigates the effects of price and non-price factors on land use in a two-period static panel model. We collect and construct a new panel dataset of 79 countries world for the period 2004 to 2013. We then average data for 79 countries over the two periods 2004-2006 and 2011-2013 and write a static supply model for each period. Finally, we take the first difference of the equations to eliminate the country-specific fixed effects and estimate the FD model using a pooled OLS estimator. The resulting estimator from this procedure is called the FD estimator and is equivalent to a two-period FE panel estimator. Unlike the dynamic panel estimator, the FD estimator does not address potential problems induced by endogeneity, expectation error, and measurement error, but it controls for country-specific omitted fixed effects bias and its estimates serve as the consistency check on the dynamic panel findings.

Our second method is a generalized instrumental variables (IV) regression, which uses internal instruments from the system to address potential endogeneity problems and methodological challenges associated with estimating our dynamic panel supply model. The estimator that we use in our dynamic panel framework is called the dynamic panel GMM estimator. The dynamic GMM estimator is mainly designed for estimating linear dynamic panel models where time period T is fixed (small T) and panel unit (N) is large. Our dataset has small T and large N. We use annual data that ranges from 2004 to 2013 for 79 countries around the world. The dependent variable is one of three measures of land use. The explanatory variables include lagged dependent variable, crop output price, per capita income, and population density. We employ two distinct dynamic GMM estimators: (1) difference GMM (DIF-GMM) and (2) system GMM (SYS-GMM). We prefer the second estimator over the first because it performs better when the times-series data are persistent.

By applying the proposed econometric methods to the static and dynamic panel supply models, we obtain several important findings. First, the effects of prices on land use are positive across all three land use categories. Second, of the total supply response to prices, the response at the intensive margin accounts for a 62-90% of the total response. This result implies that since 2004 the world's land supply response to price changes was mainly to use existing cropland more efficiently through an increase of multiple-cropped land and reduction of unharvested land. Third, the impact of the supply of potentially arable cropland in a country on extensive land use is positive whereas it is negative on intensive land use. This implies that over the last decade countries with higher potentially arable cropland have expanded at the extensive margin. Fourth, the impact of population density is found to be positive across all three land use categories. This result suggests that higher population growth increases the demand for food and therefore domestic producers respond by producing more through increasing land use. Fifth, expectation error or endogeneity in crop output prices leads to a downward-biased estimation of price elasticities when we use traditional FE estimator to estimate dynamic supply model. Sixth, the incorrect specification of land use models such as ignoring dynamics of land use, overestimates supply response to prices. Finally, omitted variable bias caused by omitting potentially arable cropland produces downward-biased estimates of price elasticity for land use response at the intensive margin and upward-biased estimates at the extensive margin.

The remainder of the paper is organized as follows. Section 4.2 provides a conceptual framework on how we decompose total supply (harvested) response into the extensive and intensive margin. Section 4.3 describes the data and presents descriptive analysis. Section 4.4 lays out details of the proposed empirical models and econometric methods. This section also discusses the sources of bias and inconsistency associated with traditional econometric methods. Section 4.5 presents the empirical results. Finally, section 4.6 concludes.

## 4.2 Measures of Land Use Response

Total agricultural crop production $Q$ is usually defined as the product of cropland harvested $H$ and yield per hectare $Y$. Its change is given by $dQ = YdH + HdY$. Based on this definition, it makes sense for studies (e. g. Taheripour and Tyner 2013 and Roberts and Schlenker 2013) to consider the change in harvested land as the extensive margin and the change in yield as the intensive margin. In this paper, we modify the common sources of production response following Babcock and Iqbal (2014) and Babcock (2015) who redefine total production response by decomposing the total harvested land use change into extensive margin and intensive margin. Instead of using changes in area harvested as a measure of extensive margin, they use a change of total land under cultivation (planted) as the response at the extensive margin. Along with the usual definition of intensive margin as a change in yield, these authors propose another measure of intensive margin, which they define as the sum of the change in cropping intensity resulted from a change in land that grows more than one crop per year, and a change in planted but not harvested land. This definition of intensive margin implies that with no change in either yield or planted land, it is possible to increase crop production by reducing unharvested land and planting a crop on the same land twice or multiple times. Accounting for this land intensification implies that harvested land is an imperfect measure of response at the extensive margin.

Harvested and planted cropland are not the same—harvested cropland differs from planted cropland by the amount of unharvested cropland and by the amount of cropland that is double or triple cropped. In a given year, a portion of planted land may remain unharvested due to crop failure caused by bad weather or lack of irrigation. Good weather and/or an increase of irrigation may allow harvesting a greater portion of the land that is planted, implying that harvested cropland can increase even without any increase in total planted land. If a country adopts shorter-season varieties and plants it on the same land more than once in a given year, then harvested cropland will increase with no change in non-cropland. Thus, use of the change in harvested land as a measure of the extensive margin may overestimate or underestimate the amount of land that is converted from non-cropland to (from) planted cropland. Putting these ideas together, for any period t we have the following decomposition of total planted cropland

(1) $$A_t = A_{1,t} + A_{2,t} = H_{1,t} + UH_{1,t} + H_{2,t} + UH_{2,t}$$

where A and H denote planted and harvested cropland, respectively; UH is unharvested land, which was sown or planted but there was no harvest due to damage or crop failure;

subscript 1 and 2 are for the first crop and second crop respectively[23]; t is the time period. The key term in equation (1) is the area planted to the first crop, $A_1$ , because this is the amount of land that is used for aggregate agricultural production and its change over time is the most relevant to environmental regulators around the world. Thus, for any two periods t=T and t=0, we have

$$A_{1,T} - A_{1,0} = (H_T - H_0) - (A_{2,T} - A_{2,0}) + (UH_T - UH_0) \text{ or,}$$

(2) $$H_T - H_0 = \underbrace{(A_{1,T} - A_{1,0})}_{\theta_1 = \Delta_t A_1} + \underbrace{(A_{2,T} - A_{2,0})}_{\theta_2 = \Delta_t A_2} - \underbrace{(UH_T - UH_0)}_{-\lambda = \Delta_t UH}$$

where $H = H_1 + H_2$ is total harvested land and $UH = UH_1 + UH_2$ is total unharvested land. Of the three terms as shown in expression (2), only the first one, the change in land used for first crop planting, $\theta_1$ measures land use change at the extensive margin whereas the other two, change in cropland used for second crop planting, $\theta_2$ and the change in unharvested land, $\lambda$ measures land use change at the intensive margin. From this expression, we can make the following two statements

**Statement 1:** Given $\theta_1$ is unchanged between two time periods, an increase of land used for the second crop in period T over period 0 will overstate the land use change at the extensive margin if we use harvested land to measure changes in land cover.

**Statement 2:** When $\lambda>0$ ($\lambda <0$) and if we use harvested land to measure changes in land cover, then the land use change at the extensive margin will be upward (downward) biased.

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[23] In this paper first crop means total land that are used for planting all crops and second crops means the portion of the land that is double or triple cropped.

The main challenge in identifying extensive and intensive land use change is to obtain worldwide country-specific data on land used for planting the first crop. To our knowledge, this data is not widely available. However, a measure to this is available in the Food and Agricultural Organization database (FAOSTAT). Arable land in the database is defined as the land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). Abandoned land resulting from shifting cultivation is not included in this category (FAO). Adding FAO's measure of arable land to land that is in permanent crop seems to provide a measure of land use change that would be appropriate to use in determining the amount of new land that has been brought into production (Babcock and Iqbal 2014). According to this definition, we rearrange the expression (2) as follows

(3) $$\underbrace{\Delta_t A_2 - \Delta_t UH}_{\text{Intensive Margin}} = \Delta_t H \;-\underbrace{(\Delta_t A_1 + \Delta_t \,\mathrm{TP})}_{\text{Extensive Margin}}$$

where TP is temporary pasture/fallow land. The left-hand side provides land use change at the intensive margin and the term I parentheses on the right-hand side measures changes at the extensive margin. It is worth mentioning that for a zero value of $\Delta_t A_1$, a change in TP will either overestimate or underestimate actual land use change at the intensive margin. For example, if TP increases due to the conversion of forest land and $A_1$ remains unchanged between two periods, then the above expression will provide us an underestimation of land use change at the intensive margin holding everything else constant. Similarly, if $\Delta_t UH < 0$, land use change at the intensive margin will increase even without converting forest and/or permanent pasture land into cropland. However, as we mentioned earlier, separate data on land used for planting the first crop and temporary pasture is not available, so in this paper, we define changes at the extensive margin as the sum of changes in planted land for the first crop and temporary pasture or fallow land. Changes at the intensive margin equal the sum of changes in planted land for the second crop and changes in unharvested land.

Now, using the above definition of extensive and intensive margin, we decompose total production as the identity $Q = YH = Y_1 H_1 + Y_2 H_2$, where $Y_1$ and $Y_2$ are yield per hectare from the first crop and second crop, respectively and all other terms are defined before. With total differentiation, this identity can be expressed as

(4) $$dQ = YdH + HdY = Y_1\, dH_1 + H_1\, dY_1 + Y_2\, dH_2 + H_2 dY_2$$

Since our main goal is to estimate supply response to prices, differentiating equation (4) with respect to price we have

(5) $$\frac{dQ}{dP} = Y\frac{dH}{dP} + H\frac{dY}{dP} = Y_1\frac{dH_1}{dP} + H_1\frac{dY_1}{dP} + Y_2\frac{dH_2}{dP} + H_2\frac{dY_2}{dP}$$

Manipulating equation (5), we can express change in output into elasticity terms as follows

(6) $$\begin{aligned} \varepsilon_Q &= \varepsilon_H + \varepsilon_Y &&= \alpha_1 \varepsilon_{H_1} + \alpha_1 \varepsilon_{Y_1} + \alpha_2 \varepsilon_{H_2} + \alpha_2 \varepsilon_{Y_2} \\ \varepsilon_Q &= \varepsilon_A + \varepsilon_w + \varepsilon_Y &&= \alpha_1 (\varepsilon_{A_1} + \varepsilon_{w_1} + \varepsilon_{Y_1}) + \alpha_2 (\varepsilon_{A_2} + \varepsilon_{w_2} + \varepsilon_{Y_2}) \\ & &&= \underbrace{\alpha_1 \varepsilon_{A_1}}_{\text{extensive margin}} + \underbrace{(\alpha_1 \varepsilon_{w_1} + \alpha_2 \varepsilon_{w_2} + \alpha_2 \varepsilon_{A_2})}_{\text{intensive margin from land intensification}} + \underbrace{(\alpha_1 \varepsilon_{Y_1} + \alpha_2 \varepsilon_{Y_2})}_{\text{intensive margin from yield}} \end{aligned}$$

where, $\alpha_1 (= H_1 Y_1 / HY)$ and $\alpha_2 (= H_2 Y_2 / HY)$ are the share of output that comes from the first and second crops, respectively, $w_1 (= H_1 / A_1)$ and $w_2 (= H_2 / A_2)$ are the proportion of planted first and second crops that are harvested, $\varepsilon_{H_1} = \varepsilon_{A_1} + \varepsilon_{w_1}$, $\varepsilon_{H_2} = \varepsilon_{A_2} + \varepsilon_{w_2}$, and $\varepsilon_H = \varepsilon_w + \varepsilon_A$.

In this paper, we focus on output response at the extensive margin and intensive margin that comes from land intensification. Of these two, the estimates of land use response at the extensive margin are important to the U.S. and world environmental regulators, who are concerned about the impact of the conversion of non-cropland on greenhouse gas (GHG) emissions caused by higher crop prices. Figure 1 shows how an economy responds to higher crop prices by producing more even without any increase in extensive land use and yield rate. Panel a shows the tradeoff between cropland and other land (forest and permanent pasture) using a production possibility frontier (PPF) curve. Panel b presents the impact of higher prices on production using a simple output demand and supply curve.

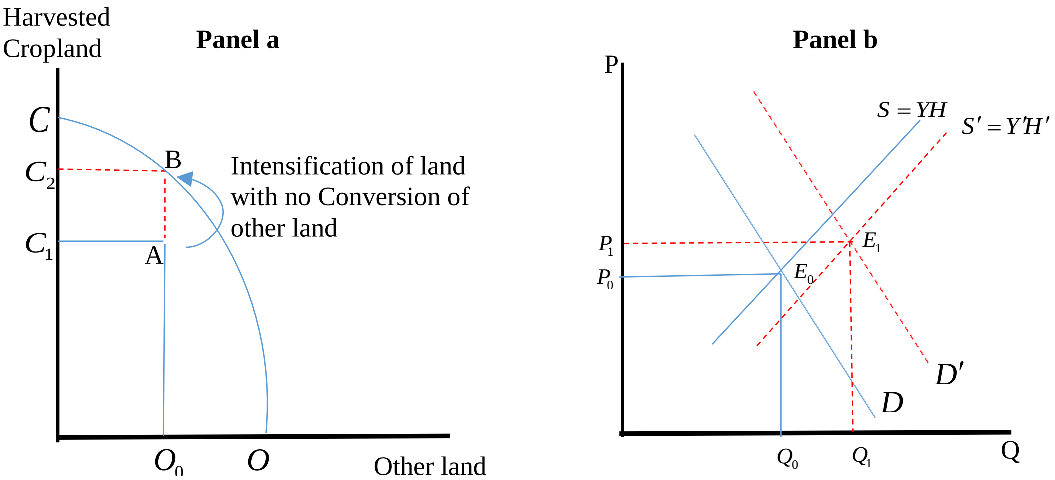


**Figure 1. The response of output to higher crop prices without any change in extensive margin and yield rate.**

The PPF (CO) is assumed to be concave. The crop demand and supply curve are assumed to be negatively and positively sloped, respectively. Assume initially that the economy is at point A (below efficient level) in panel a— indicating that the economy has the opportunity to produce more by reducing unharvested land through increased irrigation or by using the same land for the second or third crop. The corresponding point in panel b is $E_0$ , where the supply of crops intersect with its demand curve. At $E_0$ , the output supply is $Q_0$ and the price is $P_0$ . Suppose, crop demand rises because of t higher economic growth and/or increased population. As a result, the demand curve shifts from $D$ to $D'$ and price rises. In response to higher prices, farmers can produce more through either of the following ways: i) conversion of forest/permanent pasture to cropland, ii) increase of multiple cropping, iii) reduction of unharvested land through irrigation or technological innovation, and iv) increase of yield through use of improved seed or use of more fertilizer. Even if we assume yield response to price is zero and conversion of noncropland to cropland is very minimal or none, the supply of crop output shifts from $S$ to $S'$ because of the reduction of unharvested land and increase of multiple cropping. As a result, the equilibrium moves from $E_0$ to $E_1$ , where production is higher than before. This higher production is brought about by the intensive use of existing land. In this analytical example, supply response to prices at the intensive margin is positive and equal to the response of total (harvested) land use. The response at the extensive margin is zero.

### 4.3 The Data and Descriptive Statistics

We construct a comprehensive database covering 79 countries around the world for the period 2004 to 2013. Our sample countries include both leading and small agricultural crop-producing countries. For each country, $i = 1, 2, ......., 79$, we gather yearly data on total arable and harvested cropland, crop output prices received by producers, per capita real income, and population density. The data also include potentially arable cropland available for future agricultural crop production. Our measure of potentially arable cropland does not vary over time even if land is converted to agriculture. Land is measured in hectares and prices are measured in US dollar per metric ton. Per capita real income is in US dollars. The sample countries account for about 88 percent of total global agricultural arable and harvested cropland.

We obtain country-level data on arable, potentially arable, and harvested cropland from the FAOSTAT database published by the Food and Agricultural Organization (FAO), United Nations. We gather data on per capita real income and population density from the World Development Indicators (WDI) database of The World Bank.

In analyzing supply response to price, we use three categories of land use as we defined previously. They are (1) total harvested land, (2) planted land (extensive margin), and (3) intensive land. We construct an aggregate average price index for each country to represent the aggregate crop price received by producers. Total harvested land for each country for any period t is the sum of all individual crop hectares harvested in a country. Planted land use for each country is the sum of arable and permanent crops that also includes temporary pasture or fallow land. Intensive land use for any period t is the difference between harvested and planted land use. Change in harvested land is defined as the change in total land use. Change in planted land is defined as land use change at the extensive margin. The difference between the change in total and extensive margins is the response at intensive margin. The aggregate price index $P_{it}$ is the geometric mean of major crop prices where individual crop price is weighed by each crop's revenue share in total revenue earned by producers. This is computed as $P_{it} = \prod_{c=1}^{n_i} p_{ct}^{\theta_{ct}}$ , where $p_{ct}$ is the individual crop price at time t, $\theta_{ct}$ is the share of revenue by crop c in total revenue at time t and $n_i$ is the country-specific total number of crops. The major crops that we include to calculate the price index cover at least 80 percent of total cropland harvested for each country and 78 percent of cropland harvested globally during the period 2004-2013. The major crops are ranked in each country according to total cropland harvested. Producers around the world are assumed to make their planting decision based on the prices that they expect at harvest time. In modeling their expectation, we use one year lagged price as the proxy of expected price.[24]

We include population density, per capita real income, and potentially arable land as control variables in the supply equation. The first two variables work as expected demand shifters and the last variable works as a proxy of natural endowment or future production capacity. Hazell and Wood (2008) note that expected increases in agricultural demand associated with population growth, urbanization and rising per capita incomes will require

[24] Futures prices are not available for all countries around the world. Moreover, existing literature suggests that futures prices and lagged prices received by producers can be used interchangeably and both prices provide similar supply elasticity estimates (see Chavas, Pope, and Kao 1983 and Shideed and White 1989).

continuing increases in agricultural production in many countries around the globe. Deininger and Byerlee (2011) note that three key factors explain the area expansion over the period 1990-2007, which are (1) increase of demand for food driven by population and income (2) increase of demand for biofuel feedstocks, and (3) shifts of production of bulk commodities to potentially arable land-abundant regions such as in Africa and South America. Thus, we use the above three variables as controls to explain land use response. We use past-year population density and per capita income for the proxies of demand shifters so that we can avoid simultaneous bias problem—current-year expected price may be correlated with current-year income. We use potentially arable land that was available in the late 1990s. This data is available only for one year. The Global Agro- ecological Zones (GAEZ) study published in 2002 (Fischer et al 2002) estimates this land in terms of land extents and attainable yield levels.

Table 1 presents summary statistics of the variables. As expected, we observe considerable heterogeneity in the values of all variables. For example, cropland harvested ranges from 53.03 thousand hectares to 199,000 thousand hectares with a mean value of 13,000 thousand hectares, indicating the inclusion of both large and smaller countries in the sample. Similarly, the price index ranges from 68.01 to 2445.26 with a mean value of 320.76, indicating the inclusion of developed, developing, and less developing countries in the sample with the hypothesis that farmers in developed countries receive higher prices than other countries. The significant heterogeneity in crop prices is also due to the different crops produced in each country.

**Table 1. Summary Statistics**

| Variable | Period | Observation N (79)*T(10) | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Area harvested (1000 ha.) | 2004-2013 | 790 | 13000 | 31100 | 53.06 | 199000 |
| Area Planted (1000 ha.) | 2004-2013 | 790 | 15544.90 | 33060.91 | 52.00 | 170000 |
| Price Index | 2004-2013 | 790 | 388.26 | 320.26 | 68.01 | 2445.26 |
| Population Density (per sq. km of land area) | 2004-2013 | 790 | 118.61 | 157.26 | 2.43 | 1207.32 |
| Per Capita Real GDP | 2004-2013 | 790 | 12234.21 | 15413.11 | 268.91 | 59082.3 |

We analyze our data and supply response using both a two-period static panel data model as well as a dynamic panel data model. When we use a two-period panel model (details in the next section) in explaining supply response, we construct two three-year periods from the data in table 1: 2004-2006 and 2011-2013[25]. The 2004-2006 is the pre-boom commodity price period and 2011-2013 is the boom or post-boom commodity price period. This approach mitigates year-to-year price fluctuations and smooths out the variability of seasonality in the single year's land use change and allows for a minimum two years to pass for price effects to provide a short/medium term response measure (Peterson 1979 and Barr et al 2011). When we adopt a dynamic supply model (details in the next section), we use the annual data as shown in table 1.

Figure 2 shows land use changes that have occurred at the extensive and intensive margin. This measure is the absolute change in land use as measured by the average of 2011-2013 minus the average of 2004-2006. Extensive land use change is the change in planted land between the two time periods. Intensive land use changes equal total (harvested)

[25] Table A1 in section A1 of appendix presents summary statistic of these two-period data.

changes minus extensive margin changes. Countries that have harvested less than 0.3 percent of the total global cropland in both periods are included in the Rest of the World (ROW).

Based on the land use patterns, we divide countries in figure 2 into several groups. The first group includes countries where land use has increased significantly at the intensive margin but have decreased at the extensive margin. Countries in this group include China, India, Ukraine, Australia, Canada, Nigeria, Russia, Poland, Turkey, and Bangladesh. For example, the land use change at the extensive margin between 2004-2006 and 2011-2013 was negative both in China and India but they together have contributed 42% of the world's total land use increase, which indicates more intensive use of existing land.

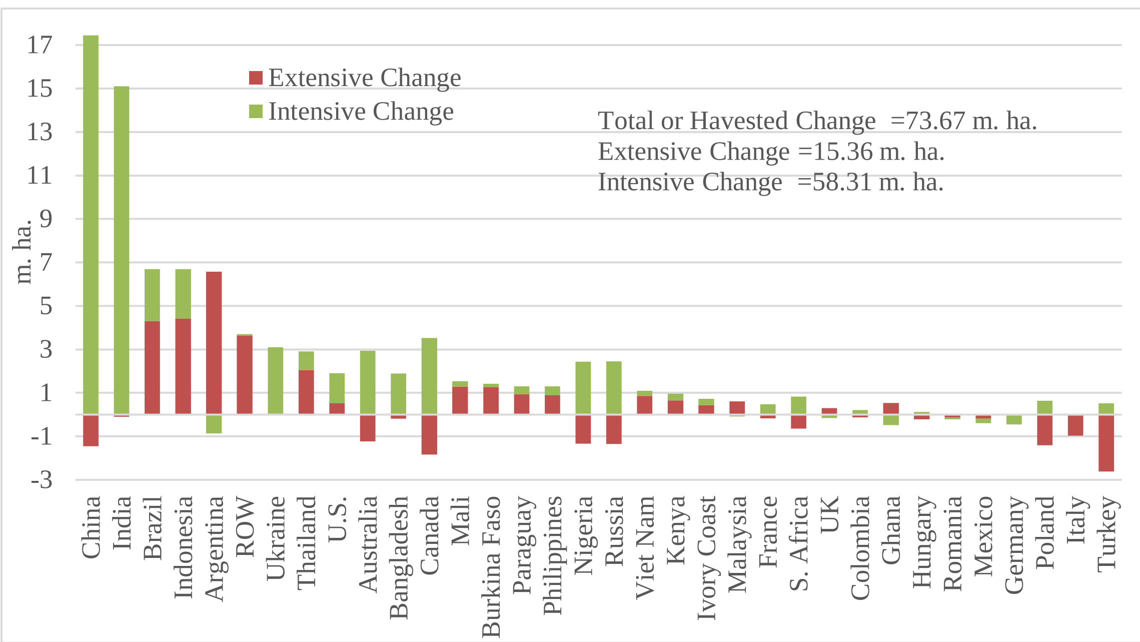


**Figure 2. Decomposition of total land (harvested) use changes in extensive and intensive margin: an average of 2011-2013 relative to the average of 2004-2006.**

The second group constitutes countries which went through mixed changes. Brazil, Indonesia, Thailand and the United States are in this group. In these countries, an increase of harvested land was the result of both extensive and intensive margin changes. The third group represents countries for which land use has increased mainly at the extensive margin. Countries of this group mostly include African countries such as Mali, Burkina Faso, Kenya, and Ivory Coast. Finally, Hungary, Romania, UK, Colombia, Mexico, and Germany are countries where neither intensive nor extensive margin changes were noticeable between 2004-2006 and 2011-2013. The lack of responses both at the extensive and intensive margin in these countries was perhaps due to a slower growth in the overall economy.

In summary, the observed changes in extensive and intensive land use changes suggest that developing countries with a long farming history have expanded at the intensive margin. China and India, the two leading developing countries, have expanded at the intensive margin because agricultural arable land is limited in these two countries. Agricultural growth in India and China has risen in the past decade, supported by crop yields, increased cropping intensity, increased input use through large subsidies, favorable terms of trade, and higher economic growth (OECD-FAO Outlook 2013, 2014). Emerging countries like Brazil and Indonesia have expanded both at the intensive and extensive margin while Argentina has expanded only at the extensive margin. Countries in Africa have expanded at the extensive margin because these countries mainly rely on traditional technologies for their crop production and have potentially arable cropland. Deininger and Byerlee (2011) note that that Sub-Saharan African countries are slow in adopting improved technology so that increasing food production depends on area expansion rather than increasing yields. Both countries in Latin America and Africa have a large stock of unused arable land compared to other countries and therefore have provided a significant opportunity for extensive margin expansion in response to higher crop prices (figure 3).

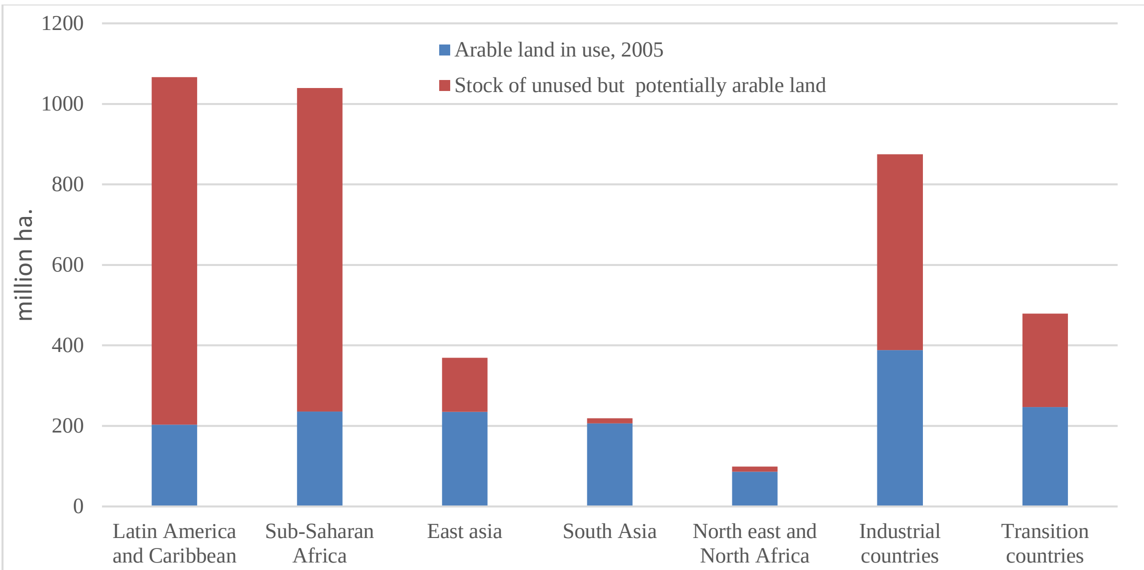


**Figure 3. Arable land in use and potentially available arable land for future crop production.**
*Source:* Bruinsma (2011).

Figure 4, 5, and 6 link countries' land use changes to crop price changes after controlling for fixed effects. In each figure, we plot a regression line for a different measure of land use against crop price (all variables are in changes in natural log). The slope of each regression line provides estimates of the average land supply elasticity with respect to price because it measures the mean ratio of percentage changes in land use to percentage changes in price.

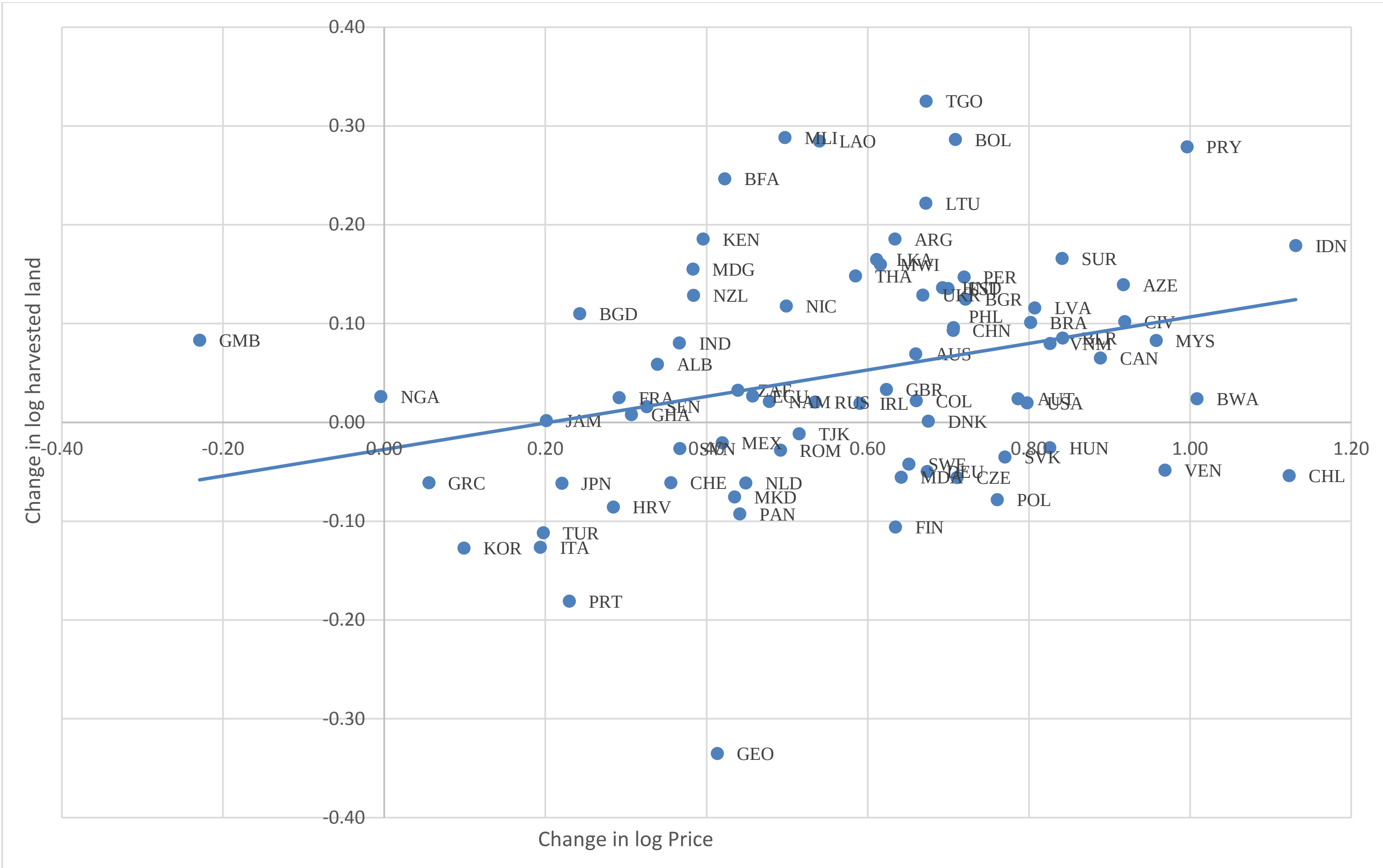


**Figure 4. Change in harvested land use to change in crop price: average of 2011-2013 relative to average of 2004-2006**

*Notes:* The regression represented by fitted line yields a coefficient of 0.134 (standard error=0.049), N=79. See table A2 in section A1 of appendix for country definition.

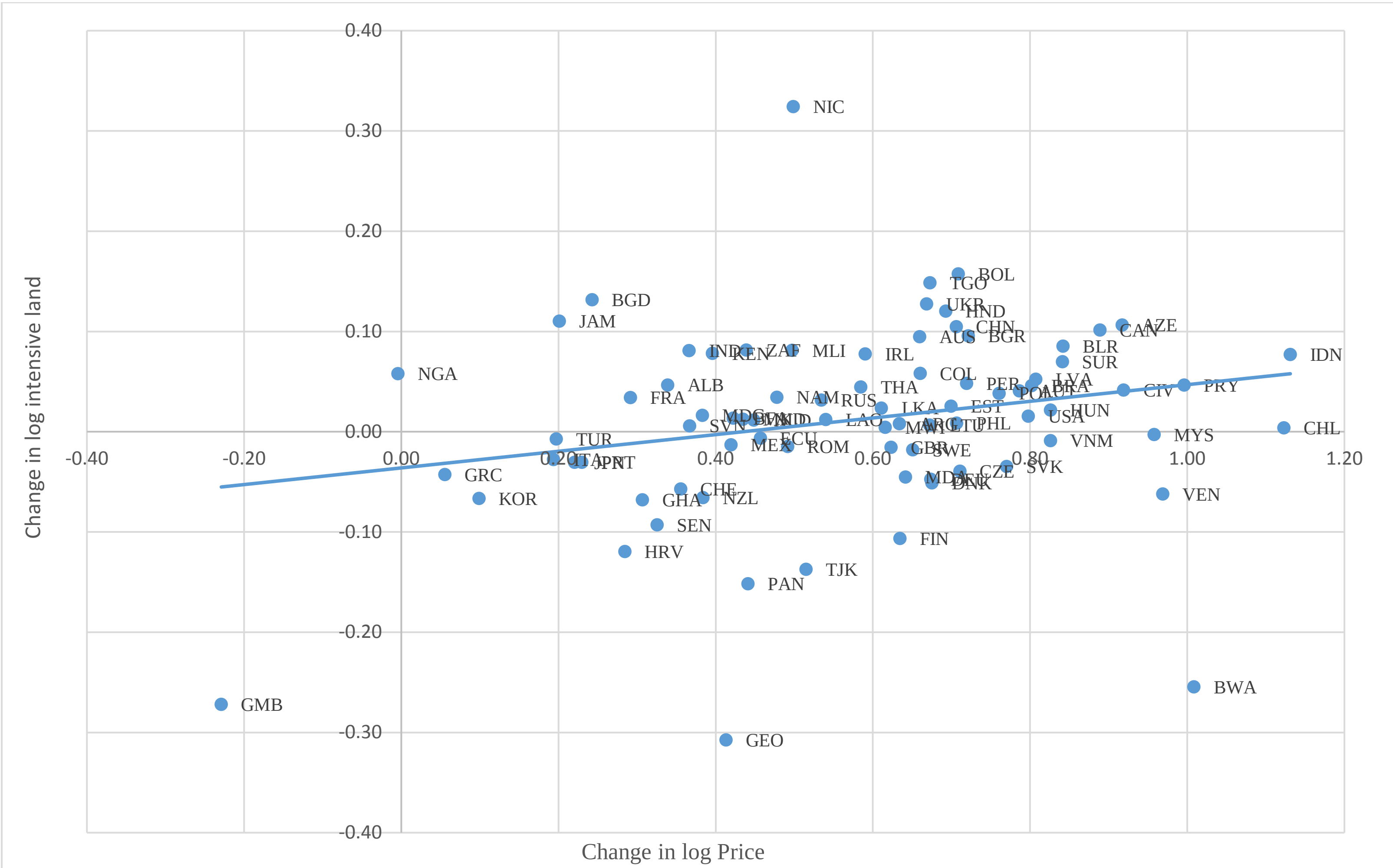


**Figure 5. Change in intensive land use to change in crop price: average of 2011-2013 relative to average of 2004-2006**

*Notes:* The regression represented by fitted line yields a coefficient of 0.083 (standard error=0.039), N=79. See table A2 in section A1 of appendix for country definition.


**Figure 6. Change in extensive land use to change in crop price: average of 2011-2013 relative to average of 2004-2006**

*Notes:* The regression represented by fitted line yields a coefficient of 0.051 (standard error=0.044), N=79. See table A2 in section A1 of appendix for country definition.

From figure 4, we find that the estimate of total land use response to a price change is 0.134. Existing literature often interprets this total land use response to price as the land use response at the extensive margin. However, our plots in figures 5 and 6 indicate a different story. When we decompose total land use response into intensive and extensive margin changes, we find that about 62% of the total land response to price is due to more intensive use of existing land. The estimated elasticities of intensive and extensive land use are about 0.083 and 0.051, respectively (figures 5 and 6). These results indicate that since 2004 world's agricultural land use response to price was more due to increased intensive use of existing land rather the expansion onto new land.

Our simple descriptive analysis suggests that the land use response that has occurred over the last decade is mainly because of greater intensive use of existing land through a reduction of unharvested land and an increase of double or triple cropping. If a higher price is the key factor for these observed changes, then we find that the land use response at the intensive margin to price is higher than response at the extensive margin. To complement our descriptive analysis, we now carry out a formal empirical analysis.

## 4.4 Econometric Methods

### 4.4.1 Static Panel and Cross-Sectional Estimation

We start using a static supply model.[26] As discussed in the previous section, we construct two periods of data for 79 countries around the world by taking an average of all variables and dividing the whole sample into data from the pre-boom commodity price era and data from the boom or post-boom commodity price era. Thus, we have the simplest form of panel data where each panel unit (country) has two data points. Letting i denote the country and t the time period, we can write a panel data model for supply response as follows

(7) $A_{it} = \beta_0 + \delta_0 D_t + \beta_1 P_{it} + Z'_{it}\beta_2 + \alpha_i + e_{it}$ , $t$=1, 2 and $i$=1, 2,…………,79

where i denotes the country and t denotes the time period. The variable $D_t$ is a dummy variable that equals zero when $t$ = 2004-2006 and one when $t$ = 2011-2013. The parameter $\alpha_i$ is individual fixed effects used for the proxy of country-specific observed or unobserved heterogeneity. The source of this heterogeneity may be land quality, production culture, managerial capacity of farmers, human capital of farmers, or the amount of agricultural land. The variable $Z_{it}$ is time varying non-price factors such as income and population density that affect land use. The variable $e_{it}$ is called the idiosyncratic error or time varying error, which is in general unobservable.

[26] The static model is a variant of the Nerlovian partial adjustment supply model, which does not include a lagged dependent variable. We discuss the problem of disregarding the dynamics in the next section.

Equation (7) can be estimated pooling two data points and applying simple OLS, which is called pooled OLS estimate. But, the estimated coefficients from pooled OLS are biased and inconsistent even if we assume that idiosyncratic error $e_{it}$ is uncorrelated with $P_{it}$ and $Z_{it}$. This is because $\alpha_i$ is likely correlated with $P_{it}$ and $Z_{it}$ because it is likely that factors in $\alpha_i$ affect supply decisions. For example, a country which practices improved production culture will typically make different supply decisions than a country which practices traditional production culture[27]. Ignoring these fixed effects while estimating supply response may lead to biased estimates of the parameters of interest. The resulting bias is sometimes called heterogeneity bias caused by omitting country-specific fixed effects and estimating the model using pooled OLS. Thus, we need an alternative estimator which accounts for correlation between $\alpha_i$ and $P_{it}$ or $Z_{it}$ but provide unbiased and consistent estimates of the parameters of interest. We write the equation (7) for a country i and for each of the two years as

$$(8) \qquad A_{i2} = (\beta_0 + \delta_0) + \beta_1 P_{i2} + Z'_{i2}\beta_2 + \alpha_i + e_{i2} \quad \text{(t=2:2011-2013)}$$

$$(9) \qquad A_{i1} = \beta_0 + \beta_1 P_{i1} + Z'_{i1}\beta_2 + \alpha_i + e_{i1} \quad \text{(t=1:2004-2006).}$$

and then subtracting (9) from (8) we obtain

$$(10) \qquad \begin{aligned} &A_{i2} - A_{i1} = \delta_0 + \beta_1 (P_{i2} - P_{i1}) + (Z'_{i2} - Z'_{i1})\beta_2 + (e_{i2} - e_{i1}), \text{ or} \\ &\Delta A_i = \delta_0 + \beta_1 \Delta P_i + \beta_2 \Delta Z'_i + \Delta e_i \end{aligned}$$

where $\Delta$ denotes the change from t=1 to t=2. The intercept in equation (10) is the change in intercept from t=1 to t=2.

[27] We expect production culture is constant for a short period of time.

Equation (10) is the FD equation and is a single cross-sectional equation, but each variable is differenced over time. A pooled OLS estimator that is based on equation (10) is called the FD or FE estimator and both estimators are equivalent[28]. As long as the strict exogeneity assumption on the explanatory variables is held, i.e. $\Delta e_i$ is uncorrelated with $\Delta P$ and $\Delta Z_i$ , the estimates from the FD estimator are unbiased and consistent. Equation (10) explicitly show how changes in the price over time affect the change in land use over the same period and remove the fixed effects omitted variable bias. The key advantage of using equation (10) is even if we assume that $\alpha_i$ is correlated with the explanatory variables in equation (8) and (9), a pooled OLS estimator to the equation (10) produces unbiased and consistent estimates because $\alpha_i$ has disappeared.

**4.4.2 Dynamic Panel Estimation**

"Economic behavior is inherently dynamic so that most econometrically interesting relationship are explicitly or implicitly dynamic" (Nerlove 2002). Examples include growth models, partial adjustment models of firm investment, labor demand and supply models, household consumption, and labor supply models with habits, including many others. Statistically, even when the dynamics themselves are not of direct interest, if we allow dynamics in an equation or in a process we can recover consistent estimates of other parameters (Bond 2002). Moreover, Nickell (1987) and Bond (2002) note that use of aggregate time series data does not reveal true microeconomic dynamics due to aggregation bias and therefore limits the ability for panel data to provide an opportunity to investigate

[28] We derive the equivalency of both estimators in section A2 of appendix.

heterogeneity in adjustment dynamics between different types of panel units. Thus, we now consider the following dynamic panel specification of a supply model[29]

(11) $A_{it} = \rho A_{i,t-1} + \beta P_{it}^{e} + Z_{it}' \delta + \phi_i \; f_t \; + \alpha_i \; + u_{it}$ , $t$=2004 to 2013 and $i$=1, 2,…………, 79.

where $\rho$ is a measure of the speed of adjustment, $\beta$ is a short-run supply response to price, $f_t$ is a year fixed effect (one dummy for each year), which control for cross-sectional dependence in the random error $u_{it}$ caused by common shocks such as random weather shock (el Niño or La Niña) , growth in demand, or biofuel production. The error $u_{it}$ has zero mean and is uncorrelated across countries. All other variables are as defined before.

Unlike the static model, the dynamic model incorporates aspects of supply related to the fixity of resources (Nerlove 1958). More importantly, the dynamic panel specification of supply provides opportunities to address several methodological problems and challenges that we encounter while identifying the effects of price and non-price factors on supply. We now turn our discussion to the problems and challenges with estimating supply models and on how they are recognized by our empirical dynamic panel model. We also discuss how traditional estimators such as OLS or FE estimator as applied to the dynamic panel model lead to bias and inconsistent estimates of the parameters of interest. Then, we propose an instrumental variables estimation strategy to address those challenges and problems.

[29] This model is based on the Nerlovian (1958) supply model which assumes partial adjustment of supply in modeling supply response to output price.

*Omitted-variable Bias from the Omission of Fixed Effects*

If we ignore country-specific fixed effects and assume $\alpha_i = \alpha$ , then the OLS estimator as applied to the equation (11) produces biased and inconsistent estimates of the parameters of interest in a similar way to that of the static panel model. Trognon (1978) shows that the pooled OLS as applied to the dynamic panel data model produces asymptotically upward biased estimate of the coefficient on the lagged dependent variable and downward biased (toward zero) estimates of the coefficients on the strictly exogenous variables. Anderson and Hsiao (1981) also show that the pooled OLS regression estimates in a dynamic panel model are biased and inconsistent for small T and large N (ours is similar to this). These biases and inconsistency arise because of the correlation between lagged dependent variable and country fixed effects, which can be expressed as

(12) $E[\alpha_i, A_{i,t-1}] = E[\alpha_i (\alpha_i + \rho A_{i,t-2} + \beta P^e_{i,t-1} + u_{i,t-1})] \neq 0$

The standard procedure to avoid the above bias is the use of FE estimator. Following the standard FE transformation[30], we subtract time mean of (11) from (11) itself and we obtain

(13) $A_{it} - \bar{A}_{i.} = (\phi_i - \bar{\phi})' f_t + \rho(A_{i,t-1} - \bar{A}_{i.-1}) + \beta(P^e_{it} - \bar{P}^e_{i.}) + (Z'_{it} - \bar{Z}_{i.})\delta + (u_{it} - \bar{u}_{i.})$

Or

(14) $\tilde{A}_{it} = (\phi_i - \bar{\phi})' \tilde{f}_t + \rho \tilde{A}_{i,t-1} + \beta \tilde{P}^e_{it} + \tilde{Z}'_{it}\delta + \tilde{u}_{it}$

[30] The FE transformation is also called the within-group (WG) transformation.

where dots indicate time averages. $\bar{A}_{i.} = 1/T\sum_{t=1}^{T} A_{it}$ , $\bar{A}_{i.-1} = \sum_{t=2}^{T} A_{i,t-1}/(T-1)$, and so on. $\tilde{A}_{it} = A_{it} - \bar{A}_{i.}$ is the time-demeaned value of $A$ . The other variables are defined similarly. The country-specific fixed effects $\alpha_i$ now has disappeared. A pooled OLS estimator based on this type of equation (14) is known as FE or WG estimator[31]. We know a FE estimator as applied to a model after FE transformation produces unbiased and consistent results as long as the random error, $u_{it}$ is uncorrelated with each explanatory variable across all time periods. This lack of correlation likely holds when the model is static. In a dynamic panel model, the pooled OLS estimates based on FE transformation are biased even though the speciation in equation (14) avoids heterogeneity bias caused by omitting country-specific fixed effects. This is because of the correlation between $A_{i,t-1}$ and $\bar{u}_{i.}$ , which is known as dynamic panel bias or Nickell bias (Nickell 1981)[32]. The correlation arises because by construction $A_{i,t-1}$ is correlated with $\bar{u}_{i.}$ . The disturbances average $\bar{u}_{i.}$ contains $u_{i,t-1}$ which is obviously correlated with $A_{i,t-1}$. Nickell (1981) shows that for small T and large N ( $N \to \infty$ ), the FE estimate of $\rho$ will be asymptotically downward-biased when $\rho$ is positive (likely to be in our case). He also shows that the bias of $\hat{\beta}$ depends on the relationship between the strictly exogenous variable and $\tilde{y}_{i,t-1}$. If the strictly exogenous variable is positively related to $\tilde{y}_{i,t-1}$, the estimated coefficient $\hat{\beta}$ will be asymptotically upward-biased and vice versa. However, this bias will be asymptotically zero when T goes

[31] Then name “within-group" comes from the fact that the OLS on equation (14) uses the time variation of all variables within each cross-sectional observation.
[32] We discuss Nickell bias in details in section A3 of appendix.

to infinity. We also note here that the random effects estimator that assumes country-specific random error terms are uncorrelated with the explanatory variables, is inconsistent in a dynamic panel model because country-specific fixed effects are always correlated with the lagged dependent variable. This inconsistency will not disappear even when T tends to infinity.

In summary, what we can say is that the OLS estimator as applied to a dynamic panel model with unobserved country-specific fixed effects produces upward-biased estimate of the coefficient on the lagged dependent variable and downward-biased estimates of the coefficients on the strictly exogenous regressors. The estimates from the FE estimator, in this case, run in opposite direction—estimates of the coefficient on the lagged dependent variable are downward-biased and estimates of the coefficients on the strictly exogenous regressor are upward-biased.

*Expectation Error in Prices*

Expected crop prices are one of the key factors for land use decisions. We can observe crop prices after harvest. As a result, there may be expectation error in prices. The difference between expected crop prices and observed (actual) prices is the expectation error and is a type of measurement error. Because of the presence of potential measurement error in the prices, the OLS estimator as applied to the equation (11) is asymptotically biased[33]. Suppose, instead of observing $P_{it}^{e}$, we observe $P_{it}^{*} = P_{it}^{e} + w_{it}$, where $w_{it}$ represents

[33] This bias is also known as attenuation bias caused by expectation or measurement error in explanatory variable.

expectation error or errors of measurement in $P_{it}^{e}$. Therefore, instead of estimating equation (11), we estimate[34]

$$(15)\quad \begin{aligned} A_{it} &= \alpha_i + \rho A_{i,t-1} + \beta P_{it}^{*} + u_{it} - \beta w_{it} \\ &= \alpha_i + \rho A_{i,t-1} + \beta P_{it}^{*} + v_{it} \end{aligned}$$

where $v_{it} = u_{it} - \beta w_{it}$. Even though we assume $Cov(P_{it}^{e}, \mathrm{w}_{it}) = 0$, the composite error term $v_{it}$ in equation (15) is correlated with the realized prices, i.e. $Cov(P_{it}^{*}, v_{it}) = -\beta\sigma_{w_{it}}^{2}$. Because of this non-zero correlation between prices and random error, the OLS or FE estimator will be biased and inconsistent. Taking the first differences of equation (15) and applying FD estimator to the differenced equation does not solve this problem rather it worsens the problem. For a static panel model which assumes stationary and uncorrelated measurement errors, Griliches and Hausman (1986) show the plim of the FD estimator as

$$(16)\quad \mathrm{plim}(\hat{\beta}) = \beta\left[1 - \frac{2\sigma_{w}^{2}}{\mathrm{var}(dP^{*})}\right]$$

where $dA_{it} = A_{it} - A_{it-1}$ and similarly for the other variables; $\sigma_{w}^{2}$ and $\mathrm{var}(dP^{*})$ are the variances of $w_{it}$ and $P_{it}^{*}$, respectively. As $\frac{2\sigma_{w}^{2}}{\mathrm{var}(dP^{*})} > 0$, the estimates of $\beta$ will underestimate the true $\beta$ if the effect of price on land use is positive, which we expect. An instrumental variable strategy can overcome this bias. Maravall and Aigner (1977) and Maravall (1979) discuss that a static model that is unidentified in the presence of serially uncorrelated measurement errors could be identifiable if the model has a dynamic form.

[34] For simplicity, we only include price as a control variable other than lagged land use.

This could be possible by using internal instruments from lags of the dependent and other explanatory variables. In general, the availability of panel data helps to solve the problem of measurement error bias by providing internal instruments from the system as long as we assume measurement errors are serially uncorrelated[35].

*Presence of Endogenous Control Variable*

A potential problem in estimating supply response is the endogeneity of expected prices. Past production shocks may be part of the error term in equation (11) and affect expected prices, i.e. $E[u_{it}, P_{it}^{e}] \neq 0$. Then, both the pooled OLS as applied to the equation (11) and FE estimator as applied to the equation (14) will be biased and inconsistent. The direction of biases of supply elasticity estimates varies depending on the correlation between prices and the unobserved error term. In our model, we use lagged crop prices as the proxy of expected crop prices. Crop prices are serially correlated, it is likely that these prices are correlated with past production shocks or anticipated production shocks that are part of the error term and therefore may affect current-year land use decisions. This indicates a potential endogeneity in the crop prices. The standard approach to address such problem is the use of the instrumental variable (IV) approach.

*Inertia*

The dynamic specification has at least two advantages over the static supply model. First, it helps to eliminate serial correlation of the residuals. Second, it addresses underlying dynamic nature of agricultural production processes. Usually, there is a delayed adjustment

35 Arellano (2009) mentions this point in his lecture notes: available at http://www.cemfi.es/~arellano/static-panels-class-note.pdf

in converting new land to agricultural land due to fixed inputs, so past land use decisions affect today's land use choice. But if we omit lagged land use from equation (11) and estimate a static supply model similar to the model as estimated by Hendriks, Janzen, and Smith (2015), then we will have usual omitted variable bias problem. To explain this bias, for simplicity we assume that the true model is $A_{it} = \alpha_i + \rho A_{i,t-1} + \beta P_{it}^e + u_{it}$. But, instead, if we estimate the model $A_{it} = \alpha_i + \beta P_{it}^e + v_{it}$. Then the error term $v_{it} = u_{it} + \rho A_{i,t-1}$ and the explanatory variable $P_{it}^e$ will be correlated, i.e. $Cov(\mathrm{P}_{it}^e, v_{it}) = \rho Cov(\mathrm{P}_{it}^e, \mathrm{A}_{i,t-1}) \neq 0$ caused from omitting lagged land use. As a result, the OLS estimates will be biased and inconsistent. The omitted variable bias formula takes the form

$$(17) \quad p\lim(\hat{\beta}) = \beta + \rho \frac{Cov(A_{i,t-1}, P_{it}^e)}{Var(P_{it}^e)} = \beta + \rho\pi_2$$

where $\pi_2$ is the OLS estimate of the regression equation $A_{i,t-1} = \pi_{1,it} + \pi_{2,it} P_{it}^e + \eta_{it}$. As $\pi_2$ and $Var(P_{it}^e)$ are positive, the sign of the bias will depend on the sign of the correlation between past-year land use and current-year expected prices. If $\pi_2 > 0 (< 0)$, then the true effects of price on land use will be overestimated (underestimated).

We summarize the above discussion as follows. There are well known problems with estimating agricultural supply models. They are: i) omitted variable bias caused by omitting panel specific fixed effects, ii) expected prices are measured with an error or are endogenous to supply analysis, and iii) omitted variable bias problem from ignoring underlying dynamic nature of production process. The pooled OLS or FE estimator that is usually used in the literature to address the above problems does not produce unbiased and consistent estimates of the parameters of interest. The pooled OLS estimator as applied to the dynamic panel model is inconsistent because of the correlation between country-specific fixed effects and lagged land use. Although the FE estimator avoids bias caused by omitting fixed effects, it is biased and inconsistent because the lagged dependent variable is correlated with the mean error term—a bias known as a dynamic panel or Nickell bias. The pooled OLS or the FE estimator also does not provide unbiased and consistent estimates of the parameters of interest in the presence of measurement error or endogeneity of prices. Thus, we need an estimator that addresses problems or challenges associated with estimating supply regression and provides consistent estimates of land use response to prices. To this end, we use an application of the generalized methods of moments (GMM) or instrumental variables estimator developed for dynamic panel data model for fixed T and large N, where T is small relative to N. The estimators are called dynamic panel GMM (dynamic GMM) when they are applied to the dynamic panel data model. The dynamic GMM estimators were introduced by Anderson and Hsiao (1981, 1982), Holtz, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The GMM estimators use internal instruments from the system to address potential problems associated with dynamic panel model estimation. In our application, we deal with worldwide data on several key variables related to land use response. Hence, it is almost impossible to obtain valid external instruments both from a theoretical and empirical point of view. Thus, the dynamic GMM is an appropriate tool.

The dynamic GMM estimators or methods have been widely used in the empirical literature across different fields of economics. Examples include i) growth (Caselli, Esquivel, and Lefort 1996; Levine, Loayza, and Beck 2000; Acemoglu et al. 2014, among many others, ii) production functions (Blundell, Bond, and Windmeijer 2001), iii) money demand functions (Bover and Watson 2005 and many others), and iv) wage equations and Philips curve (Alonso-Borrego and Arellano 1999 and others). Recently, dynamic GMM estimators have been used in agricultural supply literature to investigate supply response to prices. Examples of such works are Subervie (2008), Haile, Kalkuhl, and von Braun (2016) and Miao, Khanna, and Huang (2016).

The basic steps of a dynamic panel GMM estimator are the following.[36] First, we take first differences of a dynamic panel data model (equation 11) to eliminate country-specific fixed effects (unobserved or observed). Second, we then instrument the explanatory variables in the FD equations using levels of the series lagged two periods or more. The number of instruments depends on time-period and it varies for each period. While instrumenting, we assume that the time-varying disturbances in the original levels equations are serially uncorrelated. This estimation procedure is mainly based on Arellano and Bond (1991). To explain these steps, consider the following first difference of equation (11)

$$(18)\quad \begin{aligned} &A_{it} - A_{i,t-1} = \rho(A_{i,t-1} - A_{i,t-2}) + \beta(P^e_{it} - P^e_{i,t-1}) + (Z'_{it} - Z'_{i,t-1})\delta + \phi_i\,(f_t - f_{t-1}) + (u_{it} - u_{i,t-1}), \text{ or} \\ &\Delta A_{it} = \rho\Delta A_{i,t-1} + \beta\Delta P^e_{it} + \Delta Z'_{it}\,\delta + \phi_i\,\Delta f_t + \Delta u_{it} \end{aligned}$$

Equation (18) removes omitted country-specific fixed effects bias but the lagged land use is still potentially endogenous because the $A_{i,t-1}$ term in $\Delta A_{i,t-1}$ is correlated with the

[36] Section A4 in appendix provides mathematical details of dynamic panel GMM estimators.

$u_{i,t-1}$ in $\Delta u_{it}$. But, longer lags of the dependent variable are orthogonal to the error term and available as instruments, which was not the case with the FE transformation (equation 14). The estimator that use lag levels of the endogenous explanatory variables as instrumental variables in the first difference equation is known as Arellano-Bond dynamic DIF-GMM estimator. The instrumental variables matrix used by this estimator can be expressed through the following orthogonality condition

(19 $\quad E(A_{i,t-s}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \leq s \leq t-1$

where $\Delta u_{it} = u_{it} - u_{i,t-1}$. While studies commonly use the orthogonality condition in equation (19) for lagged dependent variable to address dynamic panel bias, they also use additional orthogonality conditions for other control variables depending on whether the variables are strictly exogenous, or predetermined, or endogenous. Let $x'$ denote a vector of control variables $P_{it}^{e}$ and $Z_{it}'$, then we write additional orthogonality or moment conditions used by dynamic DIF-GMM estimator as

(20) $\quad E(x_{it}'\,\Delta u_{it}) = 0$ for $t = 1,......,T$ ; when $x'$ is strictly exogenous

(21) $\quad E(x_{i,t-s}'\Delta u_{it}) = 0$ for $t = 3,......,T$ and $1 \leq s \leq t-1$; when $x'$ is predetermined

(22) $\quad E(x_{i,t-1}'\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \leq s \leq t-1$; when $x'$ is endogenous

The dynamic DIF-GMM estimator uses the moment conditions (19) and either conditions (20) and (21) or all three conditions depending on the nature of additional explanatory variables. The estimator provides consistent estimates of the parameters of interest. However, the dynamic DIF-GMM estimator may suffer from finite sample bias due to weak instrument problems caused by the presence of persistent time-series data.

Blundell and Bond (1998) show that the dynamic DIF-GMM estimator suffers from weak instruments problem for moderately short panels when the autoregressive parameter $\rho$ approaches unity, or as the variance of the fixed effects $\alpha_i$ increases relative to the variance of the random shocks $u_{it}$. As a result, the dynamic DIF-GMM estimator is expected to have poor finite sample properties, in terms of bias and efficiency. An additional statistical problem is that when variables (in our case price) are measured with error, differencing may exacerbate the bias and make things worse rather than better (Griliches and Hausman 1986). Moreover, theoretically, we would also like to study the response of land use to the price at the level or log-level form, which gets eliminated when we take first differences of equation (11).

The above features are typically present in an empirical supply response model, where in general, the coefficient of the lagged dependent variable (output or land use) approaches unity. As a result, weak instrument results are likely when using dynamic DIF-GMM estimator, which potentially biases the results. To reduce this potential bias and to achieve more plausible results, we use an alternate dynamic GMM estimator called dynamic SYS-GMM developed by Arellano and Bover (1995) and Blundell and Bond (1998). Dynamic SYS-GMM estimates a system of equations that combines the standard set of equations in first-differences with suitably lagged levels as instruments and an additional set of equations in levels with suitably lagged first differences as instruments (Arellano and Bover 1995). The validity of these instruments depends on the validity of a stationary assumption about the initial conditions process generating $A_{i1}$ as discussed in Blundell and Bond (1998). The stationarity assumption implies that although the levels of explanatory variables in equation (11) are necessarily correlated with the country-specific fixed effects $\alpha_i$ , there will be no correlation between the first differences of the variables and the country-specific fixed effects. This assumption will hold if the means of each explanatory variable when differing across countries are constant through time periods $t = 1, 2, ......, T$ for each country. Thus, when both $\Delta A_{it}$ and $\Delta X_{it}$ are uncorrelated with $\alpha_i$ , the additional orthogonality moment conditions for the dynamic SYS-GMM estimator are

(23) $E[\Delta A_{i,t-1}(\alpha_i + u_{it})] = 0$ for $i = 1, ....., N$ and $t = 3, 4, ......, T$

and

(24) $E[\Delta x'_{i,t-1}(\alpha_i + u_{it})] = 0$ for $i = 1, ....., N$ and $t = 3, 4, ......, T$

in the case where $x'_{it}$ is endogenously determined or is measured with error; or

(25) $E[\Delta x'_{it}\ (\alpha_i + u_{it})] = 0$ for $i = 1, ....., N$ and $t = 2, 4, ......, T$

when $x'_{it}$ is strictly exogenous or predetermined. The estimator based on moment conditions as we showed in equations (19) and (23) as well as combination of equations (21)-(23) and (24-(25) is known as dynamic SYS-GMM estimator and it produces consistent and efficient estimates of the parameters of interests compared to DIF-GMM.

Though the dynamic GMM estimator or more specifically our preferred dynamic SYS-GMM estimator provides consistent and efficient estimation, its consistency depends on the validity of the instruments, i.e. whether (1) the lagged values of land use and other explanatory variables are valid instruments in the supply response regression and (2) serial correlation is absent in errors, $u_{it}$ . To address these issues, we consider three specification tests i) Arellano- Bond test for autocorrelation as suggested by Arellano and Bond (1991),

ii) the Sargan/Hansen test of over-identifying restrictions as suggested by Arellano and Bover (1995) and Blundell and Bond (1998), and iii) the difference-Sargan\Hansen test as presented in Blundell and Bond (1998). The Arellano-Bond autocorrelation test examines the null hypothesis that the error term, $u_{it}$ is not serially correlated. This test is applied to residuals in differences because $\Delta u_{it}$ is mathematically related to $\Delta u_{i,t-1}$ via the shared $u_{i,t-1}$ term, a negative first-order serial correlation is expected in differences and evidence of it is uninformative (Roodman 2009b). Thus, to check for first-order serial correlation in levels, we look for second-order correlation in differences, on the idea that this will detect a correlation between the $u_{i,t-1}$ in $\Delta u_{it}$ and the $u_{i,t-2}$ in $\Delta u_{i,t-2}$ (Roodman 2009b). The Sargan or Hansen test of over-identifying restrictions evaluates the overall validity of the instrument sets by analyzing moment conditions with their sample analog as exploited in the estimation procedure. The difference-Sargan or -Hansen test examines the null hypothesis that the lagged differences of the explanatory variables are uncorrelated with the residuals, which are the additional restrictions imposed in the SYS-GMM estimator with respect to the DIF-GMM estimator.

Although the GMM estimator has advantages over the usual OLS or FE estimator with respect to the estimation challenges and problems as discussed in this section, the results from these estimators might be suspicious because of instrument proliferation, especially when T rises relative to N. Instrument proliferation can cause several problems in finite samples. First, Roodman (2009a) notes that a large instrument count overfits endogenous variables (i.e. fails to correct for endogeneity). Intuitively, if the number of instruments equals the number of observations, then the first-stage regressions of a 2SLS regression will achieve a $R^2$ value of 1.0. The second stage will then be equivalent to OLS, which we know to be biased. Second, because of a large number of instruments count, the optimal weighting matrix that makes a SYS-GMM estimator asymptotically efficient, becomes imprecise, which can lead SYS-GMM far from the theoretically efficient ideal. Although this does not make the two-step SYS-GMM estimator inconsistent, it does bias the SYS-GMM standard errors (Roodman 2009a). When the instrument count is high, the usual formula for coefficients standard errors in SYS-GMM tends to be severely downward biased. As a result, the coefficients which should not be statistically significant in the usual sense, are found to be significant. Third, a high instrument count can weaken the Hansen test of instrument validity, which may produce implausibly good p-values of 1.00 (Andersen and Sørensen 1996; Bowsher 2002).

The econometric literature does not provide any rule of thumb on the optimal number of instruments required for avoiding overfitting bias, or downward-biased standard errors or, weaken Hansen test of instrument validity. However, there are some practical suggestions in the existing literature to address these issues. Arellano and Bond (1998) note that N is the key threshold for safe estimation. Moreover, Roodman (2009a) recommends two strategies to avoid the problems associated with high instrument count. First, the instrument matrix can be collapsed by only constructing instruments for each additional lag—substituting zeros where those lags are not available—rather than constructing an instrument for each lag in each period.[37] Second, exclusion of longer lags as instruments

[37] The "collapsed" matrix contains one instrument for each lag depth instead of one instrument for each period and lag depth as in the conventional dynamic panel GMM instrument matrix (Bazzi and Clemens 2013).

reduce the number of lags used as instruments. Roodman (2009a) suggests varying the number of lags chosen and analyzing the sensitivity of the coefficient estimates and the value of the Hansen test. We check the robustness of our results by varying the number of instruments while estimating supply response using a SYS-GMM. Moreover, we also use the Windmeijer (2005) two-step error bias correction to take care of downward biased standard errors caused from imprecise estimates of optimal weight matrix. The Windmeijer corrected standard errors are also robust in the presence of any pattern of heteroscedasticity and autocorrelation within panels.

## 4.5 Empirical Results and Discussion

### 4.5.1 Results from First-Differenced (FD) and Cross-Sectional Estimators

Our primary interest is in how and to what extent land use responds to crop output prices. We also try to determine what other factors explain supply response or to what extent the estimates of price elasticity change once we control for time-varying variables such as per capita real income and population density.

Table 2 reports the pooled OLS estimates of the coefficients on prices, per capita real income, population density, and potential cropland. Except for columns (1c), (2c), and (3c), we obtain all estimates by estimating regression equation (10). Those latter three columns are from a pure cross-sectional regression, where we do not control for the unobserved country-specific fixed effects. This is because we have only single year's data on potentially arable cropland. Columns (1a)-(1c) show results for harvested land use response. Columns (2a)-(2c) show results for intensive land use response and columns (3a)-(3b) report supply responses at the extensive margin. As we mentioned earlier, total land use response equals the sum of the intensive and extensive land use response. Figure 7 displays estimates and 95% confidence intervals for the price variable across alternative model specification. Panel a in figure 7 shows estimates on the price variable using all control variables whereas panel c shows elasticity estimates without any control variable. Panel b displays result without controlling for potentially arable cropland.

Columns (1a), (2a), and (3a) show estimates of supply response to price without any additional control variables. The results indicate that the impact of price on harvested land and intensive land use are positive and statistically significant. The response of land use at the extensive margin is positive but statistically insignificant. The estimated elasticities for harvested, intensive, and extensive land use are 0.134, 0.083, and 0.051 respectively. Thus 62% of land use response is more intensive use of existing land. These findings imply that the significant increase in harvested land that have occurred around the world over the last decade in response to higher crop prices was mainly caused by more intensive use of existing land rather than expanding land use at the extensive margin (converting forest or pasture land to cropland). When per capita income and population density are added to the regression equation (in columns (1b), (2b), and (3b) of table 2), the results are similar with a small change in the price elasticities and the composition of the source of total (harvested) supply response. When we control for potentially arable cropland in the regression equation (columns (1c), (2c), and (3c) of table 2), the estimated price elasticities change significantly. The estimates of price elasticity for intensive land use goes up and the extensive land use elasticity decreases. Approximately 90% of land use change in response to price comes from more intensive use of existing land once we control for the amount of arable land a country has. This suggests that much of the conversion of land that we have seen since 2006 would have occurred even if prices had not risen.

**Table 2. Estimates of Supply Response using FD Estimator**

| | Harvested land | | | Intensive land | | | Extensive (Planted) land | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3c) |
| Price elas. | 0.134** | 0.143** | 0.126* | 0.083* | 0.082+ | 0.113* | 0.051 | 0.061 | 0.013 |
| | (0.049) | (0.047) | (0.050) | (0.039) | (0.042) | (0.043) | (0.044) | (0.042) | (0.041) |
| Income | | 0.070 | 0.099 | | 0.005 | -0.046 | | 0.065 | 0.145* |
| | | (0.079) | (0.083) | | (0.069) | (0.071) | | (0.069) | (0.068) |
| Pop. Density | | 0.597** | 0.552** | | -0.011 | 0.072 | | 0.609** | 0.481** |
| | | (0.161) | (0.166) | | (0.141) | (0.142) | | (0.142) | (0.135) |
| Potential land | | | 0.020 | | | -0.036* | | | 0.055** |
| | | | (0.018) | | | (0.016) | | | (0.015) |
| Constant | -0.027 | -0.085** | -0.062 | -0.036 | -0.036 | -0.078* | 0.009 | -0.050+ | 0.016 |
| | (0.031) | (0.032) | (0.039) | (0.025) | (0.028) | (0.033) | (0.028) | (0.028) | (0.032) |
| *N* | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 |
| F | 7.496 | 7.944 | 6.259 | 4.482 | 1.459 | 2.488 | 1.326 | 7.159 | 9.776 |
| Adjusted R-square | 0.077 | 0.211 | 0.212 | 0.043 | 0.017 | 0.071 | 0.004 | 0.192 | 0.310 |

Note: All variables are in natural log form. Standard errors in parentheses, $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$

With regard to the other control variables, we find that in general income has a positive but statistically insignificant effect on the land use across all models. Higher per capita income could mean a higher public investment or more national research across different sectors. Assuming investment happens equally across economic sectors, we would then expect a technological improvement in the agricultural sector, which might increase the possibility of inventing higher-yielding seeds, or improved harvesting technologies, or high-quality fertilizer. The invention of quality inputs likely creates an opportunity for farmers to intensify their use of existing land. As a result, we should see a negative effect of income on extensive land use and a positive effect on intensive use.

Income may also affect land use changes positively. When income rises due to an increase in crop output, then countries who have agricultural frontiers might tend to convert noncropland into cropland because unlike the long-term investment/research required for intensification (yield gains), this process does not require much time to obtain an investment return. Perhaps, this latter effect is stronger than the former, which produce a positive impact of the income on extensive land use change.

We also find that in general population density has a positive effect on land use across all three indicators of land supply (table 2). The effect of population density on harvested and intensive land use is statistically significant. This is not unexpected. A likely explanation for the positive correlation between the land use and population density is that higher growth in population increases the demand for food, which in turn raises the prices and thereby farmers increase the production through increasing input (land) use.

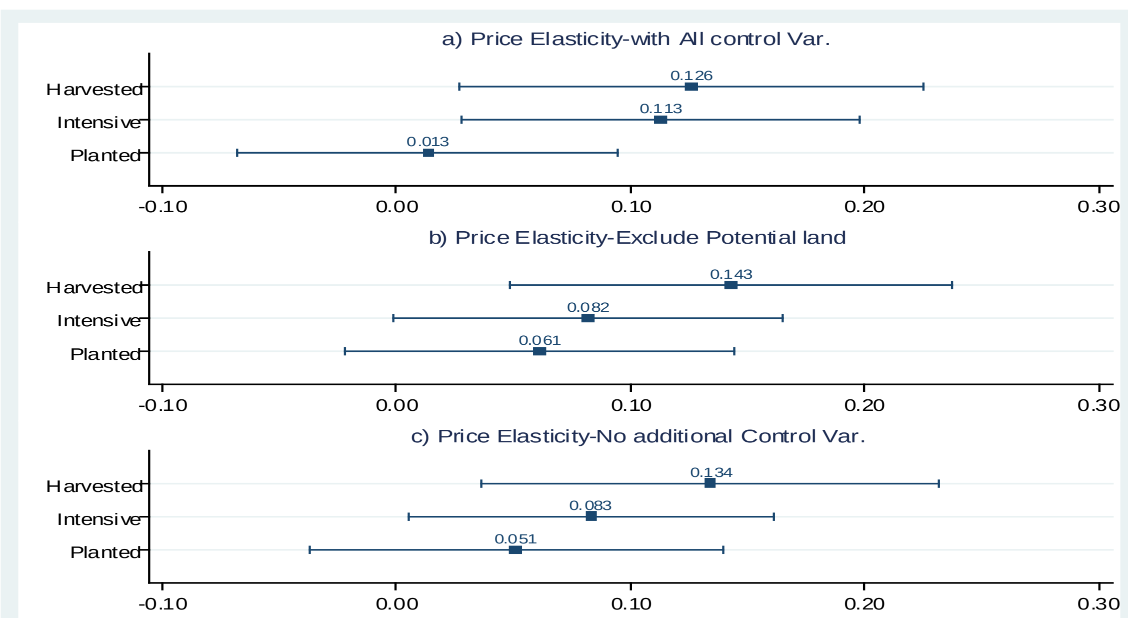


**Figure 7. Elasticity estimates and 95% confidence interval for different measures of land use from FD estimator**

Finally, we find a negative effect of potentially arable cropland on the intensive use and a positive effect on extensive land use (columns (2c) and (3c)). Both are statistically significant. These results indicate that countries with a large amount of potentially arable cropland have expanded more at the extensive margin than at the intensive margin. This is a common sense result because countries with a large amount of cropland will tend to expand at the extensive margin more than countries that have less arable land. Availability of land likely lowers the cost of extensive expansion relative to intensive expansion. The estimated results also show that when potentially arable cropland enters as a control in the regression equation (in columns (2c) and (3c) of table 2), the estimated price coefficient changes substantially. From a statistical viewpoint, this is expected because of the omitted variable bias. The positive correlation (estimated coefficient =0.072) between price and omitted potentially arable land together with the  negative effects of omitted potentially arable land on intensive land use explain why price elasticity of intensive land use is lower when potential land is not controlled for (column 2b). The positive effect of potentially arable cropland on extensive land use help to explain why the effect of price on extenive land use is higher when potentially arable cropland is not controlled for (column 2c).

In summary, our findings are as follows. First, the effects of output price on land use are positive across all three land use categories. Second, of the total supply response to prices, the response at the intensive margin accounts for between 62 and 90% of the total increase in harvested land. Not surprising, these findings are consistent with the results we obtain from scatter plots, which once again confirms since 2004 the world's land supply response to prices changes was mainly due to intensive use of existing cropland. The main factors helped to intensify agricultural land use are an increase of multiple-cropped land and reduction of unharvested land. Third, omitted variable bias caused by omitting potentially arable cropland from the supply model produces downward-biased price elasticity estimates for the intensive land use and upward-biased estimates for the extensive land.

### 4.5.2 Results from Dynamic Model and GMM Estimators

Table 3 reports estimates from equation (11) using harvested, intensive, and planted land as the dependent variable. Results are obtained applying a dynamic GMM, FE, and OLS estimators. The first three columns (1a)-(1c) report results using the dynamic GMM estimator[38]. The dynamic GMM is a two-step SYS-GMM estimator of equation (11) that uses a maximum of nine lags (all available time-periods) as instruments. The estimator accounts for the possibility that price suffers from expectation error and treats price as a potentially endogenous variable. The SYS-GMM estimator also assumes that both population density and per capita income are endogenous variables. Columns (2a)-2(c) provide results from the FE estimator. The last three columns (3a)-(3c) present estimates from the OLS estimator. Table 3 also presents results from the three distinct specification tests required for investigating the validity of dynamic SYS-GMM estimator: (1) the Hansen test, where the null hypothesis is that the instrumental variables are uncorrelated with the residuals, (2) the serial correlation test, where the null hypothesis is that the errors in the differenced equation exhibit no second-order serial correlation, and (3) the

[38] The GMM estimates of the parameters have been obtained using the xtabond2 command in Stata; see Roodman, D., 2015. xtabond2: Stata module to extend xtabond dynamic panel data estimator. Statistical Software Components from Boston College, Department of Economics. http://econpapers.repec.org/software/bocbocode/s435901.htm

difference-in-Hansen test for the levels equation, where the null hypothesis is that the lagged differences of all explanatory variables are uncorrelated with the residuals.

First, we start with the discussion of results obtained from our preferred dynamic SYS-GMM estimator. The dynamic panel estimates suggest that short-run price elasticities of land use are positive and statistically significant across all three land use categories. More specifically, if crop output price increases by 10%, harvested land rises by 0.91%, intensive land by 0.67%, and extensive land by 0.17%.[39] These results indicate that output price increases have a larger impact on land use changes at the intensive margin than at the extensive margin. From columns (1a)-(1c), we see that 74% of the total (harvested) land use response is due to changes in land use at the intensive margin (0.067/0.091=0.74), with the remaining due to changes in land use at the extensive margin. This means the existing literature that uses total land use to predict global land use changes caused by price changes are in error and provides an upward bias. For example, studies such as Searchinger et al (2008) and Hertel et al (2010), which consider harvested land use changes as extensive margin changes and do not account for double cropping when estimating the land use effects of corn ethanol production, significantly overestimate the indirect land use change caused by corn ethanol production. For example, Brazil, one of the top-five corn producer, exhibits about 16% increase of average corn area harvested in 2011-2013 relative to 2004-2006—which was because of an increase in second-crop corn area rather than an increase in land use at extensive margin.

[39] In carrying out the estimation we do not impose the restriction that the sum of intensive and extensive land use elasticities equals the elasticity of total land use. In a small sample there is no reason to the equality to hold.

**Table 3. Determinants of Aggregate Land Use**

| | SYS-GMM | | | FE | | | OLS | | |
|---|---|---|---|---|---|---|---|---|---|
| | Harvest | Intense. | Planted | Harvest | Intense. | Planted | Harvest | Intense. | Planted |
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) | (3a) | (3b) | (3b) |
| Lagged dep. | 0.874$^{**}$ | 0.304$^{*}$ | 0.997$^{**}$ | 0.376$^{**}$ | 0.336$^{**}$ | 0.613$^{**}$ | 1.00$^{**}$ | 0.963$^{**}$ | 0.998$^{**}$ |
| | (0.097) | (0.150) | (0.022) | (0.085) | (0.082) | (0.061) | (0.001) | (0.014) | (0.001) |
| Price Elast. | 0.091$^{**}$ | 0.067$^{**}$ | 0.017$^{+}$ | 0.047$^{**}$ | 0.034$^{*}$ | 0.014$^{+}$ | -0.001 | -0.000 | -0.004 |
| | (0.024) | (0.013) | (0.010) | (0.013) | (0.014) | (0.008) | (0.003) | (0.003) | (0.003) |
| Pop. Density | 0.106 | 0.071 | 0.016 | 0.300$^{*}$ | -0.039 | 0.199$^{*}$ | -0.002 | 0.004 | -0.002$^{*}$ |
| | (0.124) | (0.096) | (0.019) | (0.118) | (0.098) | (0.077) | (0.002) | (0.003) | (0.001) |
| Income | -0.050 | -0.060$^{*}$ | -0.007 | 0.026 | 0.012 | 0.007 | -0.006$^{**}$ | -0.005$^{**}$ | -0.004$^{**}$ |
| | (0.046) | (0.024) | (0.006) | (0.031) | (0.029) | (0.018) | (0.001) | (0.002) | (0.001) |
| Observation | 711 | 711 | 711 | 711 | 711 | 711 | 711 | 711 | 711 |
| N | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 |
| T | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 |
| Year Dummy[a] | Yes | Yes | Yes | | | | | | |
| $\rho$ in AR(1) model: GMM[b] | 0.885** | 0.584** | 0.975** | | | | | | |
| Number of Instrument[c] | 41 | 41 | 41 | | | | | | |
| Hansen test: p-value | 0.074 | 0.126 | 0.379 | | | | | | |
| Test for AR (1): p-value | 0.030 | 0.043 | 0.009 | | | | | | |
| Test for AR (2): p-value | 0.161 | 0.619 | 0.317 | | | | | | |
| Diff-in-Hansen test: p-value | 0.191 | 0.366 | 0.218 | | | | | | |
| Lag instrument count | 9 | 9 | 9 | | | | | | |

*Notes:* All variables are in natural log form. Heteroscedasticity-robust standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$. All control variables are assumed endogenous. The SYS-GMM uses the lagged levels and lagged differences of endogenous right-hand side variables as the instruments in the respective difference and levels equations of the dynamic system of equations. [a]We include year dummy for year 2009, 2010, 2011, 2012, and 2013 as additional control variables. Other year dummies were not statistically significant so we drop those. Year dummies are strictly exogenous variables. [b]The estimated coefficient of AR (1) model indicates that the land use series is highly or moderately persistent. [c]Instruments are collapsed. Based on the formulas as shown in table A1 in section A4 of appendix, we calculate number instrument equals 41 for each model.

In addition to the impact of crop output price on land use, we also report results of the effects of population density and per capita income on land use changes (table 3). In columns (1a)-(1c) of table 3, we find that population density has a positive impact on land use across all three categories, although not statistically significant. This means that an increase in population growth which increases the demand for food could induce a farmer response by producing more through increasing land use. Unlike the FD estimates as shown in table 2, the coefficient of per capita income is negative across all three land use categories. This may indicate that the greater a country's income the more resources available for overall and agricultural investment purposes, which create an opportunity to invent improved seed and thereby reduces land use.

The dynamic SYS-GMM estimates satisfy all specification tests. The Hansen test does not reject the validity of the over-identifying restriction, which implies that the instruments are valid and instrumental variables are uncorrelated with the residuals. The difference-in-Hansen test also supports the validity of the instruments. Neither the Hansen nor the Difference-in-Hansen rejects the null hypothesis of instrumental validity at the 5% level of significance. The results also satisfy the Arellano-Bond test for autocorrelation. The autocorrelation test suggests that in all three categories of land use we fail to reject the null hypothesis of second order serial correlation. This once again implies that lagged values of land use and other explanatory variables are valid instruments in the all supply response models.

We now turn our discussion to explain why we prefer results from dynamic SYS-GMM over results from other estimators. Figure 8 displays the coefficient estimates and 95% confidence interval for the parameters of lagged land use and output price across several methods. First, we compare estimates of the coefficients on the lagged land use among SYS-GMM, DIF-GMM, FE, and OLS. As expected in the presence of the country-specific fixed effects, the OLS estimator provides upwards-biased estimates of the coefficients on the lagged land use in all three land use categories, whilst the FE method provides downwards-biased estimates of these coefficients. Bond, Hoeffler, and Temple (2001) and Bond (2002) note that for a well specified AR (1) model, a candidate consistent estimate of the lagged autoregressive coefficient is likely to lie between the OLS and FE estimates, or at least not higher than the former or not significantly lower than the latter. This pattern is also likely to hold with additional exogenous regressors in the AR (1) model.[40] From table 3 and figure 8, we see that except for the coefficients of lagged intensive land use, the SYS-GMM estimates of the coefficients on the lagged land use fall between FE and OLS estimates. The SYS-GMM estimate of the coefficient on the lagged intensive land use is slightly below the FE estimate. All these estimates of the coefficients on the lagged land use indicate that our SYS-GMM models are well specified[41]. From figure 8, we also observe that the DIF-GMM estimates are well below the FE estimates, which indicate that the difference GMM estimates are biased downwards or towards FE estimates in all three land use models. These results suggest that the DIF-GMM estimates suffer from finite sample bias caused by weak instruments, which we address using SYS-GMM.

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[40] The coefficients of the lagged dependent variable will remain biased in the same direction even the additional regressors are predetermined or endogenous.

[41] We also run an AR (2) model for the intensive land use model keeping the same right-hand side variables to check whether our AR (1) dynamic specification is well specified. Bond (2002) suggest that in the cases where AR (1) model does not seem well specified, one can compare the sum of the estimated coefficients on the lagged values of the dependent variable from GMM with OLS and FE estimates. We find that the GMM estimate lies between OLS and FE estimates. Figure A2 in section A5 of appendix shows the results.

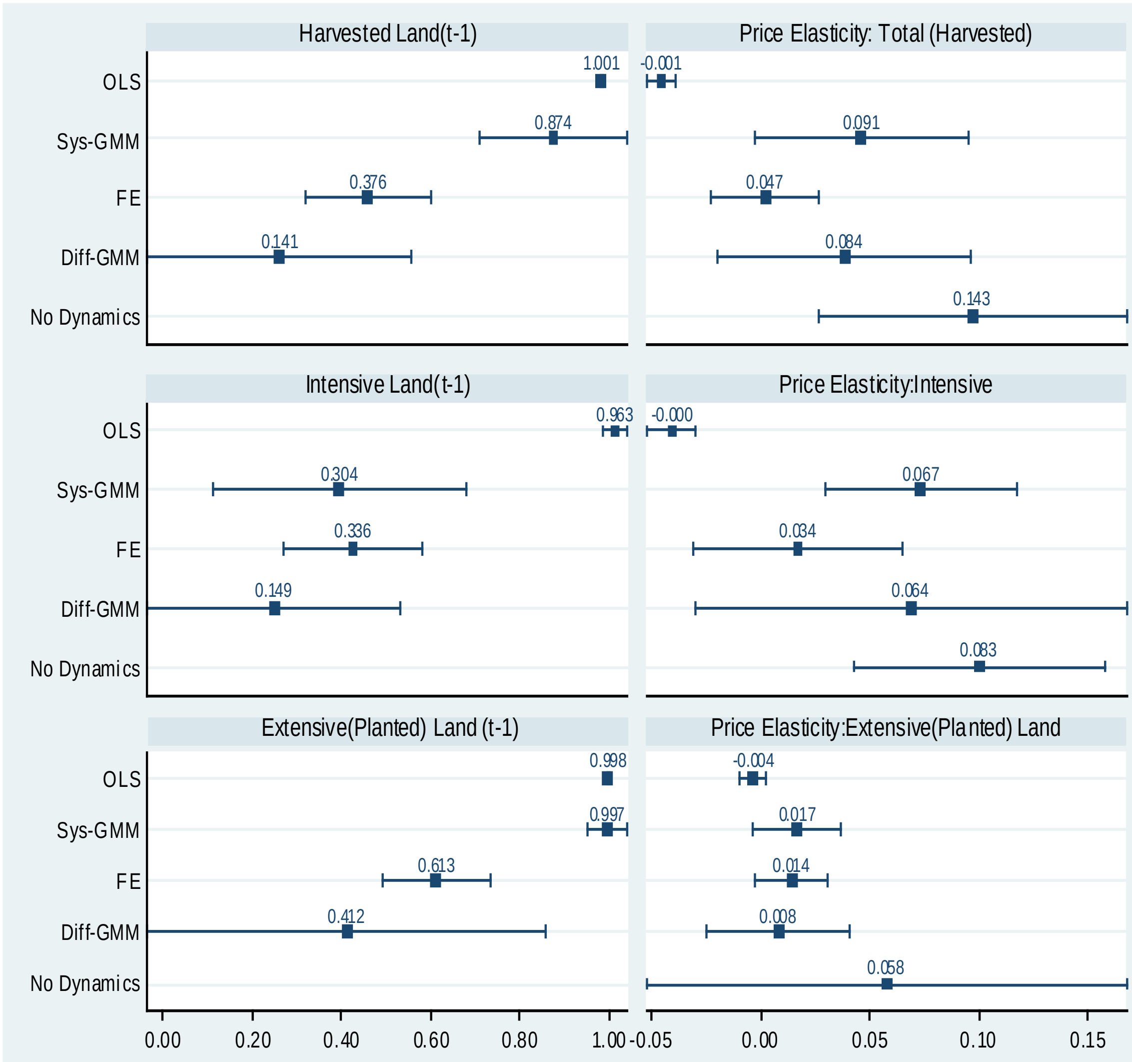


**Figure 8. Coefficient estimates and 95% confidence interval using alternative estimators**

Next, we compare the estimated coefficients on the crop output price among SYS-GMM, DIF-GMM, FE, and OLS estimators. As expected, the OLS estimates are biased toward zero[42]. The OLS estimates are also statistically insignificant. The FE estimates of the coefficient on price for harvested, intensive, and planted land use are 0.047, 0.034, and

[42] Trognon (1978) provide formulas for the asymptotic bias of the OLS estimator for AR (p) model and for a model also containing exogenous variables. Hsiao (2003) also notes this point.

0.014, respectively—all three estimates are statistically different from zero. As we discussed earlier, Nickell (1981) shows that when strictly exogenous variables are introduced in the AR (1) model, the FE estimate of the coefficient on an exogenous variable will be biased upward if the estimated coefficient on the lagged dependent (endogenous) variable is positive as well as exogenous variable is positively related to lagged dependent variable (in the regression sense). Kiviet (1995) notes that formulas, as shown by Nickell (1981), are not very helpful in providing a clear-cut insight into the asymptotic bias, and they may even be very inaccurate as far as the actual magnitude of the bias of the FE estimator in small samples is concerned. In a simulation for T=6 and N=100, Kiviet (1995) find that in general, OLS has a very high bias and the FE estimator has a moderate bias in the coefficient of exogenous variables with an increase in $\rho$ and the bias in $\rho$ gets larger when $\rho$ increases. In a special case, he finds that when exogenous variables are highly autocorrelated (autocorrelation coefficient is close to one), the bias in $\beta$ is relatively high compared to a very low or insignificant bias when autocorrelation coefficient is not close to one. Thus, a theoretically valid estimate of price elasticity should lie between the OLS and FE estimates or close to the FE estimate. However, this should be the case only if explanatory variables are strictly exogenous. We do not expect that to be held in our application as we suspect price may suffer from expectation error or that price is endogenous. Theoretically, expectation error and endogeneity (when the price is correlated with past shocks that are part of the current-year error term) should bias both OLS and FE coefficient estimates downward. Thus, theoretically, valid estimates of price elasticities for all three land use models should be larger than the OLS and FE estimates. The dynamic

SYS-GMM estimates of the coefficient on price for harvested, intensive, and planted land use are 0.091, 0.064, and 0.017, respectively and all three are statistically different from zero. Our estimates indicate that expectation error or endogeneity in price leads to a substantial bias for the coefficient on price, because except for the extensive margin, the point estimates from FE are half of the dynamic SYS-GMM estimates. The OLS estimates are biased toward zero and negative because it suffers from both omitted fixed effects bias and expectation error or endogeneity problem.

We next turn to the results of a SYS-GMM estimate that do not include a lagged dependent variable and compare with the results from dynamic SYS-GMM. This comparison provides an opportunity to assess the effect of omitted dynamics for the coefficient on output price. As we noted previously, we do not have any prior expectations about the sign of this omitted variable bias. From figure 8, we find that the model without dynamics creates substantial upward bias in the coefficient estimate for all land use models. When harvested land use is the proxy of supply, the estimated price elasticity in the model with no dynamics is 0.143 compared to 0.091 in the dynamic SYS-GMM. We also observe similar patterns for intensive and extensive land use model—the estimated elasticity in the no dynamics model is much higher than the model with dynamics. These upward biases are perhaps because of the positive correlation between prices and omitted lagged land use.

*Sensitivity Analysis*

To test the robustness of results from our preferred dynamic SYS-GMM estimator, we conduct a sensitivity analysis by varying the number of lags used as instruments. Figure 9 reports how the estimates of the coefficients on the lagged dependent variable and output price vary with an alternative number of lags.[43] In each estimate, we collapse the instrument matrix so that we can keep the instrument count below the number of panel units. From figure 9, we find that when we use only one lag as an instrument, the point estimate of price elasticities for extensive and intensive land use are biased towards zero and they approach the OLS estimates in table 3. For harvested land use, this pattern is not evident. The corresponding confidence intervals are very large in all models. These results are expected because a limited number of instruments produce less efficient estimates with higher confidence intervals (Roodman 2009a). On the contrary, when we use the maximum available lags (i.e. nine) as instruments, the point estimates of price elasticities are meaningful across all models with lower confidence intervals. Figure 9 shows that changing the number of lags from the maximum value of 9 to a lower number does not change substantially the magnitude of the coefficients on the lagged dependent variable and the price. Moreover, except for the intensive land use model, the estimates of the autoregressive coefficients $\rho$ and the corresponding confidence intervals are relatively stable across an alternate number of lags. Therefore, given the importance of the point estimate of price elasticity for the present study, our preferred dynamic SYS-GMM uses all the available lags as instruments, which passes the three important diagnostic tests required for the validity of SYS-GMM. They are: i) the Arellano and Bond test does not detect any problem with second-order autocorrelation of residuals ii) the Hansen test at

[43] Figure A3 in section A5 of appendix reproduces the plot similar to figure 9, where we include first and second lag of the dependent variable as controls for intensive land use model.

level passes the instrument validity at the 5% level of significance, and iii) The diff-in-Hansen test also passes the instrument validity at the 5% level of significance (see table 3).

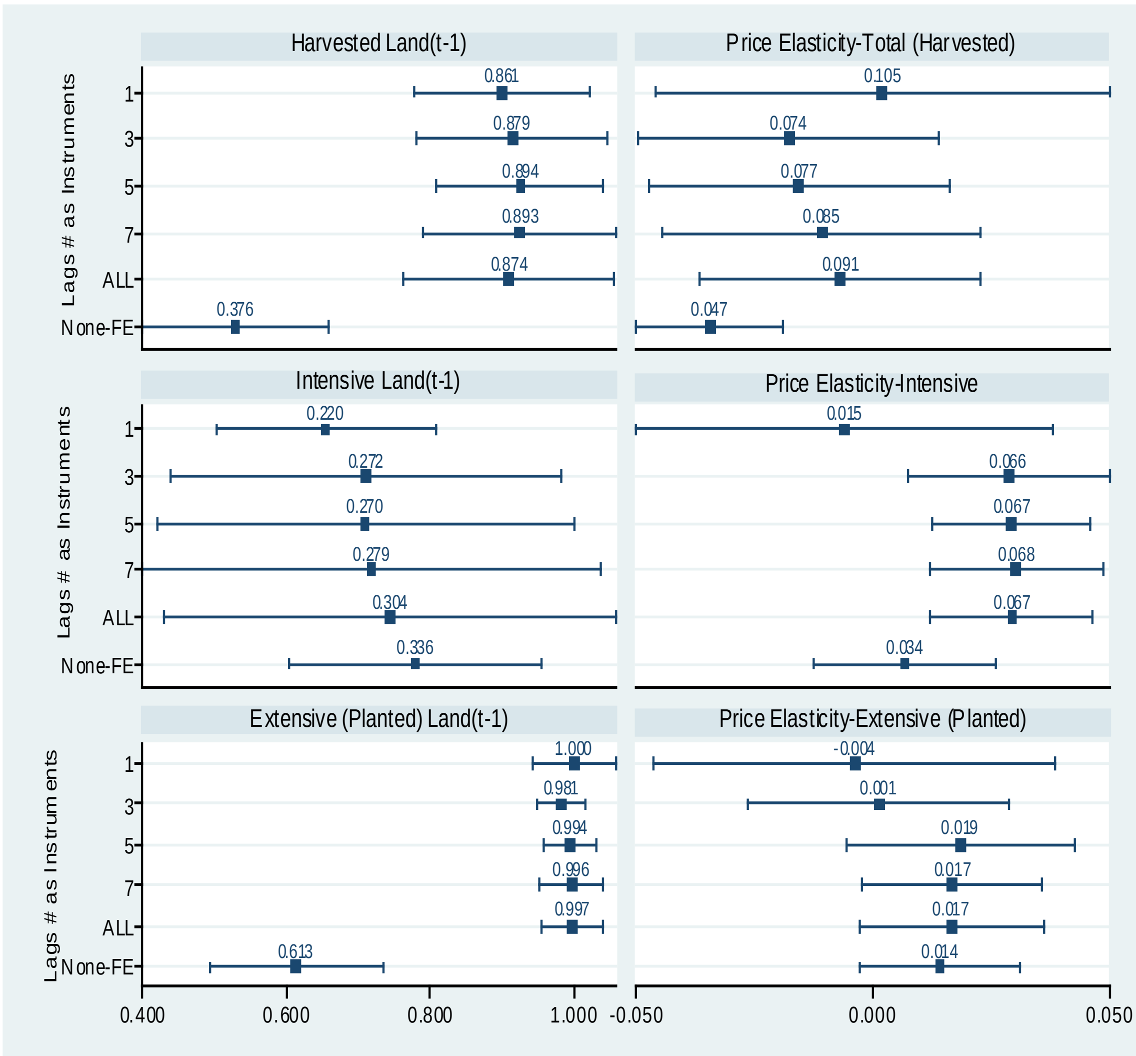


**Figure 9. Coefficient estimates and 95% confidence interval with alternative maximum lag lengths**

## 4.6 Conclusions

We examine world aggregate agricultural crop land use response to prices while controlling for the effects of per capita income, population density, and potentially arable cropland. We use country-level panel data from 2004 to 2013 that cover about 80 percent of total cropland harvested globally. The analysis is conducted in the context of the recent debate over land use change at the extensive margin around the globe caused by the significant increase in crop prices during the period 2006 to 2013.

To estimate the effects of price and non-price factors, we first decompose total land use response at the extensive and intensive margin. Then, we propose a two-period static supply model and a dynamic supply model. When we use a two-period static panel model, we construct two three-year periods from the sample data: they are 2004-2006 and 2011-2013. The 2004-2006 is the pre-boom commodity price period and 2011-2013 is the boom or post-boom commodity price period. When we adopt the dynamic supply model, we use the full sample annual data. We estimate the models using two econometric methods. FD or FE estimator is utilized to estimate the two-period supply model whereas a dynamic SYS-GMM estimator is used to estimate the dynamic supply model. The FD estimator accounts for bias due to omitted country-specific fixed effects and provides estimates for the consistency check of dynamic GMM estimator. The dynamic GMM estimator accounts for bias due to omitted country-specific fixed effects, bias due to lagged dependent variable, errors of measurement in the explanatory variables, expectation error, and endogeneity in prices.

Except for the effects of per capita real income on land use, we generally find similar patterns of estimates of the coefficients on the all explanatory variables from both FD and dynamic GMM estimators. However, the magnitude of price elasticity estimates varies between FD and dynamic GMM estimators. Our main findings are as follows. First, if higher crop prices are the key factors for the large increases in land use that have occurred around the globe over the period 2004 to 2013, then we find that of the total response, between 62 and 90% is at the intensive margin with the remaining at the extensive margin. The FD estimator produces a total land use elasticity of 0.134—of this, intensive and extensive margin elasticities equal 0.093 and 0.042, respectively. The elasticity estimates from the dynamic GMM estimator at the total, intensive margin, and extensive margin equal 0.091, 0.067, and 0.017, respectively. Second, the impact of potentially arable cropland on extensive land use is positive as opposed to a negative impact on land use at the intensive margin. This implies that over the last decade countries with higher potentially arable cropland have expanded at the extensive margin. We expect that this pattern is likely to continue because the world has some 1.4 billion hectares of prime land (class very suitable in the GAEZ classifications) and good land (classes suitable and moderately suitable) that could be brought into cultivation if needed. Most of this land is available in countries of Sub-Saharan Africa and Latin America (Alexandratos and Bruinsma 2012). Third, the impact of population density is found to be positive across all three land use categories. These results imply that higher population growth increases the demand for food and therefore producers respond by producing more through increasing land use. Fifth, expectation error or endogeneity of output prices lead to the downward biased estimation of price elasticity when we use traditional FE estimator to estimate supply response. Sixth, the incorrect specification of land use model such as ignoring dynamics of lagged land use overestimates supply response to prices. Last, omitted variable bias caused by omitting potentially arable cropland produces a downward-biased estimate of price elasticity for the land use response at the intensive margin and upward-biased estimate for the extensive margin.

Our supply elasticity estimates have important implications for the ongoing debates on negative environmental effects caused by an increase in land use at the extensive margin (more land from non-cropland). The results imply that most of the world's agricultural land growth from 2004 to 2013 resulted from intensification rather than conversion of non-cropland. The main factors that helped to intensify agricultural land use are an increase of multiple cropping and reduction of unharvested land. The results suggest that use of harvested land as an indicator of extensive land use does not provide the true magnitude of response at the extensive margin. If global economic models such as GTAP and FAPRI-CARD model continue to use the total (harvested) land use response as the response at the extensive margin, then the resulting negative environmental effects from the higher response at the extensive margin due to higher prices will be higher than the actual.

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## Appendix. Additional Materials

### A1. Data Description

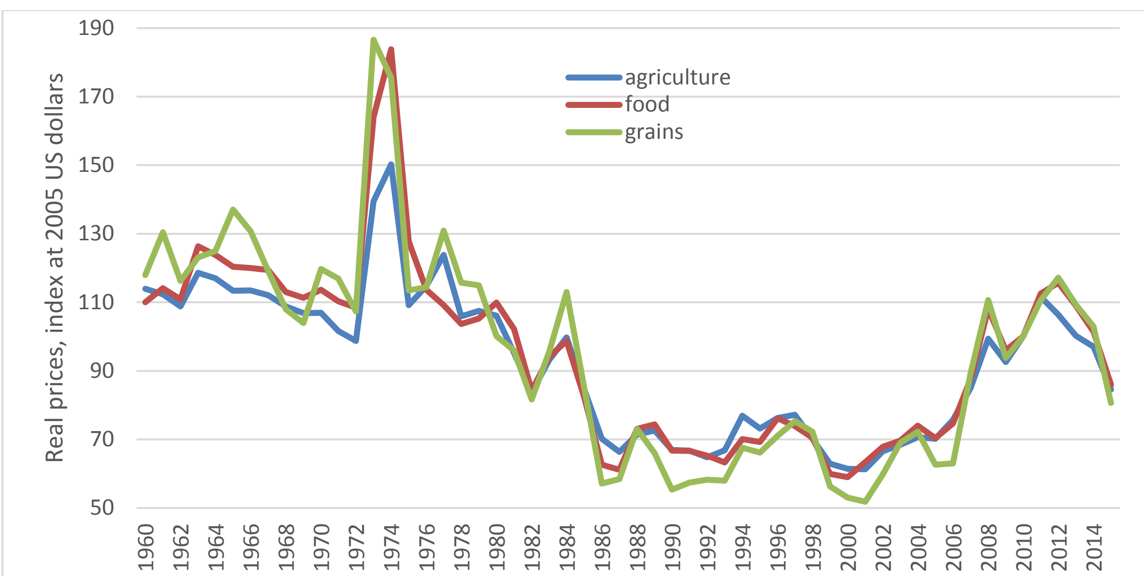


**Figure A1. The trend of real commodity prices, index (2010=100).** ***Source: The World Bank***

**Table A1. Summary Statistics: Two-period Data**

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | **2004-2006** | | |
| Area harvested (ha.) | 79 | 12600 | 30100 | 56.14 | 182000 |
| Area Planted (ha.) | 79 | 15038.92 | 31491.44 | 56.33 | 169675.70 |
| Price Index lagged | 79 | 273.68 | 271.90 | 78.19 | 1812.08 |
| Price Index | 79 | 293.30 | 292.98 | 86.63 | 1814.49 |
| Population Density (people per sq. km of land area) | 79 | 114.97 | 152.71 | 2.46 | 1097.57 |
| Per Capita Real GDP (US $) | 79 | 11749.66 | 15330.28 | 275.88 | 55171.93 |
| | | | **2010-2013** | | |
| Area harvested (1000 ha.) | 79 | 13500 | 32500 | 66.27 | 197000 |
| Area Planted (1000 ha.) | 79 | 15233.38 | 31505.24 | 62.00 | 169571.70 |
| Price Index lagged | 79 | 460.66 | 333.06 | 208.28 | 2219.64 |
| Price Index | 79 | 471.01 | 331.53 | 201.06 | 2175.89 |
| Population Density ( people per sq. km of land area) | 79 | 122.24 | 163.44 | 2.78 | 1192.85 |
| Per Capita Real GDP (US $) | 79 | 12547.06 | 15489.84 | 270.45 | 58716.90 |
| Proportion of arable land already in use in 1996-1999 | 79 | 0.39 | 0.21 | 0.01 | 0.89 |

**Table A2. Countries in the sample**

| Continent | Region | Country | Country Code |
|---|---|---|---|
| Africa | Eastern Africa | Malawi | MWI |
| Africa | Eastern Africa | Madagascar | MDG |
| Africa | Eastern Africa | Kenya | KEN |
| Africa | Southern Africa | Botswana | BWA |
| Africa | Southern Africa | Namibia | NAM |
| Africa | Southern Africa | South Africa | ZAF |
| Africa | Western Africa | Ghana | GHA |
| Africa | Western Africa | Togo | TGO |
| Africa | Western Africa | Burkina Faso | BFA |
| Africa | Western Africa | Ivory Coast | CIV |
| Africa | Western Africa | Mali | MLI |
| Africa | Western Africa | Senegal | SEN |
| Africa | Western Africa | Gambia | GMB |
| Africa | Western Africa | Nigeria | NGA |
| Americas | Caribbean | Jamaica | JAM |
| Americas | Central America | Nicaragua | NIC |
| Americas | Central America | Mexico | MEX |
| Americas | Central America | Honduras | HND |
| Americas | Central America | Panama | PAN |
| Americas | Northern America | United States | USA |
| Americas | Northern America | Canada | CAN |
| Americas | South America | Venezuela | VEN |
| Americas | South America | Argentina | ARG |
| Americas | South America | Paraguay | PRY |
| Americas | South America | Colombia | COL |
| Americas | South America | Chile | CHL |
| Americas | South America | Bolivia | BOL |
| Americas | South America | Brazil | BRA |
| Americas | South America | Suriname | SUR |
| Americas | South America | Peru | PER |
| Americas | South America | Ecuador | ECU |
| Asia | Central Asia | Tajikistan | TJK |
| Asia | Eastern Asia | Japan | JPN |
| Asia | Eastern Asia | South Korea | KOR |
| Asia | Eastern Asia | China | CHN |
| Asia | South-Eastern Asia | Malaysia | MYS |
| Asia | South-Eastern Asia | Philippines | PHL |
| Asia | South-Eastern Asia | Viet Nam | VNM |

**Table A2. Continued**

| Continent | Region | Country | Country Code |
|---|---|---|---|
| Asia | South-Eastern Asia | Indonesia | IDN |
| Asia | South-Eastern Asia | Thailand | THA |
| Asia | South-Eastern Asia | Laos | LAO |
| Asia | Southern Asia | Bangladesh | BGD |
| Asia | Southern Asia | India | IND |
| Asia | Southern Asia | Sri Lanka | LKA |
| Asia | Western Asia | Azerbaijan | AZE |
| Asia | Western Asia | Turkey | TUR |
| Asia | Western Asia | Georgia | GEO |
| Europe | Eastern Europe | Romania | ROM |
| Europe | Eastern Europe | Moldova | MDA |
| Europe | Eastern Europe | Slovakia | SVK |
| Europe | Eastern Europe | Bulgaria | BGR |
| Europe | Eastern Europe | Hungary | HUN |
| Europe | Eastern Europe | Czech Republic | CZE |
| Europe | Eastern Europe | Poland | POL |
| Europe | Eastern Europe | Belarus | BLR |
| Europe | Eastern Europe | Russia | RUS |
| Europe | Eastern Europe | Ukraine | UKR |
| Europe | Northern Europe | Finland | FIN |
| Europe | Northern Europe | United Kingdom | GBR |
| Europe | Northern Europe | Estonia | EST |
| Europe | Northern Europe | Denmark | DNK |
| Europe | Northern Europe | Latvia | LVA |
| Europe | Northern Europe | Lithuania | LTU |
| Europe | Northern Europe | Ireland | IRL |
| Europe | Northern Europe | Sweden | SWE |
| Europe | Southern Europe | Albania | ALB |
| Europe | Southern Europe | Italy | ITA |
| Europe | Southern Europe | Croatia | HRV |
| Europe | Southern Europe | Greece | GRC |
| Europe | Southern Europe | Macedonia | MKD |
| Europe | Southern Europe | Slovenia | SVN |
| Europe | Southern Europe | Portugal | PRT |
| Europe | Western Europe | Austria | AUT |
| Europe | Western Europe | Netherlands | NLD |
| Europe | Western Europe | Germany | DEU |
| Europe | Western Europe | France | FRA |
| Europe | Western Europe | Switzerland | CHE |

**Table A2. Continued**

| Continent | Region | Country | Country Code |
|---|---|---|---|
| Oceania | Australia and New Zealand | Australia | AUS |
| Oceania | Australia and New Zealand | New Zealand | NZL |

## A2. Equivalency of FE and FD Estimators When T=2

We derive equivalency of FF and FD estimator for the especial two period case (T=2). Let's write equation (10) as

(A2.1)
$$A_{i2} - A_{i1} = \delta_0 + (x'_{i2} - x'_{i1})\theta + (e_{i2} - e_{i1}), \text{ or}$$
$$\Delta A_i = \delta_0 + \Delta x'_i\ \theta + \Delta e_i,\ \ i = 1, \ldots\ldots\ldots.., N$$

where $x'_i$ is a row vector of control variables and $\theta = (\beta_1\, \beta_2)'$. After demeaning each variable over two periods for each cross-sectional unit, we derive that the FE estimator is

(A2.2)
$$\theta_{FE_{T=2}} = [(x_{i1} - \bar{x}_i)(x_{i1} - \bar{x}_i)' + (x_{i2} - \bar{x}_i)(x_{i2} - \bar{x}_i)']^{-1}[(x_{i1} - \bar{x}_i)(A_{i1} - \bar{A}_i) + (x_{i2} - \bar{x}_i)(A_{i2} - \bar{A}_i)]$$

where $\bar{x}_i = (x_{i1} + x_{i2})/2$ and $\bar{A}_i = (A_{i1} + A_{i2})/2$. Using this we show the equivalency by rewriting equation (A2.2) as

(A2.3)
$$\theta_{FE_{T=2}} = \left[\sum_{i-1}^{N} \frac{(x_{i1} - x_{i2})}{2}\frac{(x_{i1} - x'_{i2})}{2} + \frac{(x_{i2} - x_{i1})}{2}\frac{(x_{i2} - x'_{i1})}{2}\right]^{-1}\left[\sum_{i-1}^{N} \frac{(x_{i1} - x_{i2})}{2}\frac{(A_{i1} - A_{i2})}{2} + \frac{(x_{i2} - x_{i1})}{2}\frac{(A_{i2} - A_{i1})}{2}\right]$$
$$= \left[\sum_{i-1}^{N} 2\frac{(x_{i2} - x_{i1})}{2}\frac{(x_{i2} - x'_{i1})}{2}\right]^{-1}\left[\sum_{i-1}^{N} 2\frac{(x_{i2} - x_{i1})}{2}\frac{(A_{i2} - A_{i1})}{2}\right]$$
$$= 2\left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(x_{i2} - x_{i1})'\right]^{-1}\left[\sum_{i-1}^{N} \frac{1}{2}(x_{i2} - x_{i1})(A_{i2} - A_{i1})\right]$$
$$= \left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(x_{i2} - x_{i1})'\right]^{-1}\left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(A_{i2} - A_{i1})\right] = \theta_{FD_{T=2}}$$

### A3. Dynamic Panel or Nickell Bias and Inconsistency of the FE Estimator[44]

We write the equation (11) as

(A3.1) $A_{it} = \rho A_{i,t-1} + x'_{it}\theta + \alpha_i + u_{it}$, $i = 1,\ldots\ldots\ldots, N$, $t = 1,\ldots\ldots\ldots, T$

where $\rho$ is a scalar and $|\rho| < 1$, $x'_{it}$ is $1\times K$ a row vector of control variables and $\theta$ is $K\times 1$ a column vector of coefficients. After FE transformation. i.e., averaging equation (A3.1) over time for each panel group and subtracting it from the original equation (A3.1), we obtain

$$\text{(A3.2)}\quad \begin{aligned} &A_{it} - \bar{A}_{i.} = \rho(A_{i,t-1} - \bar{A}_{i.-1}) + (x'_{it} - \bar{x}'_{i.})\theta + (u_{it} - \bar{u}_{i.}),\ \text{or} \\ &\tilde{A}_{it} = \rho\tilde{A}_{i,t-1} + \tilde{x}'_{it}\theta + \tilde{u}_{it} \end{aligned}$$

where dots indicate time averages. $\bar{A}_{i.} = 1/T\sum_{t=1}^{T} A_{it}$, $\bar{A}_{i.-1} = \sum_{t=2}^{T} A_{i,t-1}/(T-1)$, and so on. $\tilde{A}_{it} = A_{it} - \bar{A}_{i.}$ is the time-demeaned value of $A$. The other variables are defined similarly. The FE transformation wipes out the fixed effects, $\alpha_i$ .Therefore, it is likely that the FE estimator as applied to equation (A3.2) are unbiased and consistent. But, that is not necessarily true for the dynamic model because $(A_{i,t-1} - \bar{A}_{i.-1})$ is correlated with $(u_{it} - \bar{u}_{i.})$ even if $u_{it}$ are not serially correlated. This violates the strict exogeneity assumption of explanatory variables required for consistency of the FE estimator. The correlation arises because by construction $A_{i,t-1}$ is correlated with $\bar{u}_{i.}$. The disturbances average $\bar{u}_{i.}$ contains $u_{i,t-1}$ which is obviously correlated with $A_{i,t-1}$. Nickell (1981) shows that the FE estimator will be biased of order $(1/T)$ and its consistency will depend upon T being large. If $T \to \infty$, the bias will go away but for small T and large N ( $N \to \infty$ ), this bias will not disappear. This bias is known as Nickell bias or dynamic panel bias. Nickell (1981) drives the asymptotic bias of FE parameters for a model similar to equation (A3.1). Assuming $x'_{it}$ is exogenous, we write the probability limit of FE estimator as

[44] Based on Nickell (1981).

$$\text{(A3.3)}\quad \text{plim}_{N\to\infty}(\hat{\rho}-\rho)=[\underbrace{(\text{plim}_{N\to\infty}\frac{1}{NT}\tilde{A}'_{-1}M\tilde{A}_{-1})^{-1}}_{B}][\underbrace{\text{plim}_{N\to\infty}\tilde{A}'_{-1}\tilde{u}}_{C}]$$

and

$$\text{(A3.4)}\quad \text{plim}_{N\to\infty}(\hat{\theta}-\theta)=-\text{plim}_{N\to\infty}[(\tilde{x}'\tilde{x})^{-1}\tilde{x}'\tilde{A}_{-1})^{-1}]\,\text{plim}_{N\to\infty}(\hat{\rho}-\rho)$$

where $M=I-\tilde{x}(\tilde{x}'\tilde{x})^{-1}\tilde{x}'$. Now, from the equation (A3.4) we can calculate

$$\text{(A3.5)}\quad \text{plim}_{N\to\infty}\tilde{A}'_{-1}\tilde{u}=-\frac{\sigma_u^2}{T(1-\rho)}\left(1-\frac{1}{T}\frac{(1-\rho^T}{1-\rho}\right)$$

Now, we can derive the direction of bias. When $\rho$ is positive, $\text{plim}_{N\to\infty}(\hat{\rho}-\rho)$ is negative as $\text{plim}_{N\to\infty}\tilde{A}'_{-1}\tilde{u}$ is negative. Therefore, the FE estimate of $\rho$ will be asymptotically downward-biased. The bias on $\theta$ depends on the relationship between price and $\tilde{A}_{-1}$. If price is positively related (in regression sense) with $\tilde{A}_{-1}$, then equation (A3.4) indicates that the coefficient $\theta$ will be upward-biased. Hence, the FE estimators are inconsistent for small T and large N when we apply the estimator to a dynamic panel model. However, the inconsistency will disappear if T tends to infinity.

### A4. Dynamic Panel Estimation with GMM

To explain this, we write the equation (11) as

$$\text{(A4.1)}\quad A_{it}=\rho A_{i,t-1}+x'_{it}\theta+\alpha_i+u_{it},\ i=1,\ldots\ldots\ldots.,N;\ t=1,\ldots\ldots.,T$$

where $\rho$ is a scalar and $|\rho|<1$, $x'_{it}$ is $1\times K$ a row vector of control variables and $\theta$ is $K\times 1$ a column vector of coefficients. $v_{it}\equiv\alpha_i+u_{it}$ is the usual fixed effects decomposition of the error term in which $\alpha_i$ is a country-specific fixed effect and $u_{it}$ is the time-varying idiosyncratic shocks. We assume that $\alpha_i\sim\text{IID}(0,\sigma_\alpha^2)$ and $u_{it}\sim\text{IID}(0,\sigma_u^2)$ independent of each other and among themselves. We also assume the lack of serial correlation in the idiosyncratic shocks, i.e. $E(u_{it})=E(u_{it}u_{is})=0$ for $t\neq s$. $T$ is small (fixed) and $N$ is large. If we apply pooled OLS to estimate equation (A4.1), we obtain inconsistent estimates of the parameters of interest because both $A_{i,t-1}$ and $x'_{it}$ are correlated with $\alpha_i$ and therefore violates strict exogeneity of explanatory variables. In order to get consistent estimates of $\rho$ and $\theta$, we take first differences of the equation (A3.1), which removes country-specific fixed effects $\alpha_i$

(A4.2) $$A_{it} - A_{i,t-1} = \rho(A_{i,t-1} - A_{i,t-2}) + (x_{it} - x_{i,t-1})'\theta + (u_{it} - u_{i,t-1}), \text{ or}$$
$$\Delta A_{it} = \rho(\Delta A_{i,t-1}) + (\Delta x_{it})'\theta + \Delta u_{it}$$

Now, we see that $x'_{it}$ is exogenous given we assume it is uncorrelated with $u_{it}$. But, the lagged dependent variable is still potentially endogenous, because the $A_{i,t-1}$ term in $\Delta A_{i,t-1}$ is correlated with the $u_{i,t-1}$ term in $\Delta u_{i,t-1}$. As a result, the OLS estimator based on first differences will be inconsistent. As we have shown earlier, the FE transformation also does not solve the endogeneity problem because of the dynamic panel bias. Thus, we need an instrument that is correlated with the $\Delta A_{i,t-1}$ but not the $\Delta u_{i,t-1}$. Finding an external suitable instrument that is orthogonal to the error term is challenging. However, Anderson and Hsiao (1981, 1982) show that such instrumental variable is available within the structure of the first difference model when t equals at least 3. To explain this for t=3 we write

(A4.3) $$A_{i3} - A_{i2} = \rho(A_{i2} - A_{i1}) + (x_{i3} - x_{i2})'\theta + (u_{i3} - u_{i2})$$

Now, from equation (A4.3) we see that $A_{i1}$ is orthogonal to the error term $\Delta u_{i3} = (u_{i3} - u_{i2})$, so it can serve as an instrumental variable for the endogenous variable $\Delta A_{i2} = (A_{i2} - A_{i1})$. Similarly, when t=4, we have

(A4.4) $$A_{i4} - A_{i3} = \rho(A_{i3} - A_{i2}) + (x_{i4} - x_{i3})'\theta + (u_{i4} - u_{i3})$$

and we see that $A_{i2}$ or $\Delta A_{i2} = (A_{i2} - A_{i1})$ can be used as instrumental variables for $\Delta A_{i3} = (A_{i3} - A_{i2})$ because they are uncorrelated with the error term $\Delta u_{i4} = (u_{i4} - u_{i3})$. This is the Anderson and Hsiao's (1981) approach to using IV estimation for the dynamic panel model and basic foundation of GMM estimator. Therefore, we can use either lagged level dependent variable or the change in lagged dependent variable between two periods as the instrumental variable. Use of lagged level has the advantage over the change in lag as the former require t=3 compared to later which require t=4 to make the equation (A4.2) estimable. Moreover, Arellano (1989) and Kiviet (1995) obtain results that suggest that the estimator based on levels is more efficient.[45]

Based on this idea or observation, Arellano and Bond (1991) show that a large number of instruments are available within the model and these increases with the increase of t. Now for the model in equation (A4.2), we can write the number of valid instruments for different time period t as

- For t=3, $A_{i1}$
- For t=4, $A_{i1}$ , $A_{i2}$
- For t=5, $A_{i1}$, $A_{i2}$, $A_{i3}$

and so on. For each individual *i*, the instrument matrix is then

$$\text{(A4.5)}\quad W_i^{\text{DIF}} = \begin{bmatrix} A_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & A_{i1} & A_{i2} & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{i1} & A_{i2} & A_{i3} & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & A_{i1} & A_{i2} & \cdots & A_{i,T-2} \end{bmatrix}$$

when no exogenous variable is included. If we add exogenous variables $x'$ and they are strictly exogenous, i.e., $E(X_{it}, u_{it}) = 0$, then the instrument matrix is

$$\text{(A4.6)}\quad W_i^{\text{DIF:Exo}} = \begin{array}{cl} \begin{bmatrix} A_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & x'_{i3} \\ 0 & A_{i1} & A_{i2} & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & x'_{i4} \\ 0 & 0 & 0 & A_{i1} & A_{i2} & A_{i3} & \cdots & 0 & 0 & 0 & x'_{i5} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & A_{i1} & \cdots & A_{i,T-2} & x'_{i,T} \end{bmatrix} & \begin{array}{l} t=3:2006 \\ t=4:2007 \\ t=5:2008 \\ \\ t=T:2013 \end{array} \end{array}$$

If $x'$ are endogenous variables, i.e., $E(x'_{it}, u_{it}) \neq 0$, then the instrument matrix is

[45] Arellano (1989) shows that standard errors are much larger for the estimator that use $\Delta A_{i,t-2}$ as instruments than the standard errors for the estimator that use $A_{i,t-2}$ as instruments, indicating that the former estimator is not useful for a dynamic panel data model for a sample with small T and large N.

$$\text{(A4.7)}\quad W_i^{\text{DIF:Endo}} = \begin{array}{c} \begin{bmatrix} A_{i1}, x'_{i1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & A_{i1}, x'_{i1} & A_{i2}, x'_{i2} & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & A_{i1}, x'_{i1} & \cdots & A_{i,T-2}, x'_{i,T-2} \end{bmatrix} \end{array} \begin{array}{l} t=3:2006 \\ t=4:2007 \\ t=5:2008 \\ \\ t=T:2013 \end{array}$$

This is the use of the instrument for equations of different time periods as suggested by Arellano and Bond (1991) compared to conventional IV estimation which uses the same instrument for all endogenous variables. The matrix (A4.7) corresponds to the following orthogonality conditions which are linear in the $\rho$ and $\beta$ parameters

(A4.8) $E(A_{i,t-s}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \le s \le t-1$

(A4.9) $E(x'_{i,t-1}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \le s \le t-1$; when $x'$ is endogenous

When $x'$ is predetermined (A4.8) turns out to be

(A4.10) $E(x'_{i,t-s}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $1 \le s \le t-1$;

The estimator that fits the model (A4.2) using linear GMM and the instrument matrix (A4.5) and (A4.6) or (A4.7) is called the difference GMM (DIF-GMM) estimator developed by Arellano and Bond (1991). The DIF-GMM estimator provides consistent estimates of the parameters of interest in a dynamic panel model. However, it can have poor finite sample properties in terms of bias and precision when the series (here land use) is highly persistent or when the variance of the individual time-invariant unobserved effects is large relative to the variance of the purely idiosyncratic error component (Blundell and Bond 1998). This characteristic of the series makes the instruments weak as the lagged level of the series will only weakly correlated with the subsequent differences. To explain this, let's consider the AR (1) specification of model (A4.1)

(A4.11) $A_{it} = \rho A_{i,t-1} + \alpha_i + u_{it}, |\rho| < 1$, for $i = 1,.....,N$

where $u_{it}$ have the same characteristics as we mentioned previously. For simplicity consider the case with T=3, where we have only one orthogonality conditions or one instrument for the DIF-GMM estimator. The first-stage of the IV regression then will be

(A4.12) $\Delta A_{i2} = \pi A_{i1} + r_i$

where the second-stage is $\Delta A_{i3} = \rho \Delta A_{i2} + \Delta u_{i3}$. For a very high value of $\rho$ or variance of $\alpha_i$, the OLS estimator of $\pi$ tends to be zero, because $\pi \cong 1-\rho$. In this case, the instrument $A_{i1}$ is only weakly correlated with $\Delta A_{i2}$. To see this, manipulating equation (A4.11) we have (T=2)

(A4.13) $$\begin{aligned} A_{i2} - A_{i1} &= (\rho - 1)A_{i1} + \alpha_i + u_{i2}, \text{ or} \\ \Delta A_{i2} &= (\rho - 1)A_{i1} + \alpha_i + u_{i2} \end{aligned}$$

where the plim of $\hat{\pi}$ is given by $\text{plim}\hat{\pi} = (\rho\text{-}1)\dfrac{k}{(\sigma_\alpha^2/\sigma_u^2)+k}$ with $\dfrac{(1-\rho)^2}{(1-\rho^2)}$. When $\rho \to 1$ or $(\sigma_\alpha^2/\sigma_u^2) \to \infty$, we find that $\text{plim}\,\hat{\pi} \to 0$. As a result, the instrument $A_{i1}$ in equation (A4.13) is only weakly correlated with $\Delta A_{i2}$ and the DIF-GMM estimator in equation (A4.11) performs poorly. This problem is addressed by an alternate estimator called system GMM (SYS-GMM) estimator developed by Arellano and Bond (1995) and Blundell and Bond (1998). The SYS-GMM estimator uses lagged differences of dependent (endogenous) variables as instruments for the equation in levels to address weak instrumental problem suffered by DIF-GMM estimator. To explain this, we again consider the equation in levels. For T=3, we have

(A4.14) $A_{i3} = \rho A_{i2} + (\alpha_i + u_{i3})$

for which the instrument is $\Delta A_{i2} = A_{i2} - A_{i1}$, and the first-stage of the IV regression is

(A4.15) $A_{i2} = \pi \Delta A_{i2} + r_i$

where the plim of $\hat{\pi}$ is given by $\text{plim}\hat{\pi} = \dfrac{1}{2}\left(\dfrac{1-\rho}{1-\rho^2}\right)$. In this case, like the DIF-GMM estimator, the OLS estimator as applied to equation (A4.14) does not tend to zero when $\rho \to 1$ or $(\sigma_\alpha^2/\sigma_u^2) \to \infty$. Rather it performs better. The estimator that uses these additional instruments along with the instruments used by DIF-GMM is called the SYS-GMM estimator. The SYS-GMM estimator estimate the following system of equations at the first-stage

(A4.16) $$\begin{pmatrix} \Delta A_{i2} \\ A_{i2} \end{pmatrix} = \begin{pmatrix} \pi^1 A_{i1} \\ \pi^2 \Delta A_{i2} \end{pmatrix} + \begin{pmatrix} r_i^1 \\ r_i^2 \end{pmatrix}$$

The instrument matrix for each $i$ for the level equation can be written as

(A4.17) $$W_i^{\text{Level}} = \begin{array}{cc} \begin{pmatrix} \Delta A_{i2} & 0 & 0 & \cdots & 0 \\ 0 & \Delta A_{i3} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1} \end{pmatrix} & \begin{matrix} 2005 \\ 2006 \\ \vdots \\ 2013 \end{matrix} \end{array}$$

When we add strictly exogenous variables as controls, the instruments matrix for the level equation is then

(A4.18) $$W_i^{\text{Level:Exo}} = \begin{array}{cc} \begin{pmatrix} \Delta A_{i2} & 0 & 0 & \cdots & 0 & \Delta x'_{i2} \\ 0 & \Delta A_{i3} & 0 & \cdots & 0 & \Delta x'_{i3} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1} & \Delta x'_{i,T-1} \end{pmatrix} & \begin{matrix} 2005 \\ 2006 \\ \vdots \\ 2013 \end{matrix} \end{array}$$

If $x'$ is endogenous variables, i.e., $E(x'_{it}, u_{it}) \neq 0$, then the instrument matrix for the level equation is

(A4.19) $$W_i^{\text{Level:Endo}} = \begin{array}{cc} \begin{pmatrix} \Delta A_{i2}, \Delta x'_{i2} & 0 & 0 & \cdots & 0 \\ 0 & \Delta A_{i3}, \Delta x'_{i3} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1}, \Delta x'_{i,T-1} \end{pmatrix} & \begin{matrix} 2005 \\ 2006 \\ \vdots \\ 2013 \end{matrix} \end{array}$$

Combining instrument matrix for levels and for the difference equation, we have the following series of instrument matrices for the SYS-GMM estimator

(A4.20) $w_i^{\text{SYS}} = \begin{pmatrix} W_i^{\text{DIF}} & 0 \\ 0 & W_i^{\text{Level}} \end{pmatrix}$, when no $x'$ is included.

(A4.21) $w_i^{\text{SYS:Exo}} = \begin{pmatrix} W_i^{\text{DIF:Exo}} & 0 \\ 0 & W_i^{\text{Level:Exo}} \end{pmatrix}$, when $x'$ is strictly exogenous variables.

(A4.22) $w_i^{\text{SYS:Endo}} = \begin{pmatrix} W_i^{\text{DIF:Endo}} & 0 \\ 0 & W_i^{\text{Level:Endo}} \end{pmatrix}$, when $x'$ is endogenous variables.

The corresponding moment conditions for (A4.22) in addition to (A4.8) and (A4.9) are

(A4.23) $E[(\alpha_i + u_{it})\Delta A_{i,t-1}] = 0$ for $i = 1, \ldots\ldots, N$ and $t = 3, 4, \ldots\ldots, T$

(A4.24) $E[(\alpha_i + u_{it})\Delta x'_{i,t-1}] = 0$ for $i = 1,.....,N$ and $t = 3,4,......,T$

*Collapsing the Instrument Matrix*

The results from the DIF- and SYS-GMM estimators as described above can suffer from finite sample problems caused by instrument proliferations. When T rises relative to N, then we will have large number of instrument or instrument proliferations. Large instrument count weakens test results of instrument validity, overfits endogenous variables, and makes SYS-GMM results inefficient. Usually, the instrument count in the GMM methods is quadratic in T. Though econometric literature does not provide any rule of thumb on the optimal number of instruments required for avoiding finite sample biases, Roodman (2009a) suggests to collapse instruments matrix, which makes instrument count linear in T as well as improves the performance of GMM estimators. Therefore, following Roodman (2009a), we collapse the instrument matrix of (A4.7) and (A4.19) as

$$W_{collapse}^{\text{DIF:Endo}} = \begin{pmatrix} A_{i1}, x'_{i1} & 0 & \cdots & 0 \\ A_{i2}, x'_{i2} & A_{i1}, x'_{i1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{i,\text{T}-2}, x'_{i,T-2} & A_{i2}, x'_{i2} & \cdots & A_{i1}, x'_{i1} \end{pmatrix}$$

$$W_{collapse}^{\text{Level:Endo}} = \begin{pmatrix} \Delta A_{i2}, \Delta x'_{i2} \\ \Delta A_{i3}, \Delta x'_{i3} \\ \vdots \\ \Delta A_{i,T-1}, \Delta x'_{i,T-1} \end{pmatrix}$$

We can collapse other instruments matrices as we have shown earlier in similar ways. We now present formulas for instruments count in table A3.

**Table A3. Formulas for Instrument Count**

| | | DIF-GMM | | SYS-GMM | |
|---|---|---|---|---|---|
| | Model | Non-collapse | Collapse | Non-collapse | Collapse |
| | | (a) | (b) | (c) | (d) |
| 1 | AR(1) | (T-1)(T-2)/2 | (T-2) | (a)+(T-2) | (b)+1 |
| 2 | AR(1)+ Exogenous var. | (T-1)(T-2)/2+k | (T-2)+k | (a)+(T-2)+k | (b)+1+k |
| 3 | AR(1)+ Endogenous var. | (T-1)(T-2)/2+m*(T-1)(T-2)/2 | (T-2)+m*(T-2) | (a)+ m*(T-2) | (b)+ m |
| 4 | AR(1)+ predetermined var. | (T-1)(T-2)/2+q*(T+1)(T-2)/2 | (T-2)+q*(T-1) | (a)+ (T-2)+ q*(T-1) | (b)+1+q |

*Notes:* k is no. of strictly exogenous variables, m is no. of endogenous variable other than lagged dependent variable, q is no. of predetermined variables.
*Source:* Author's calculation

## A5. Further Empirical Results

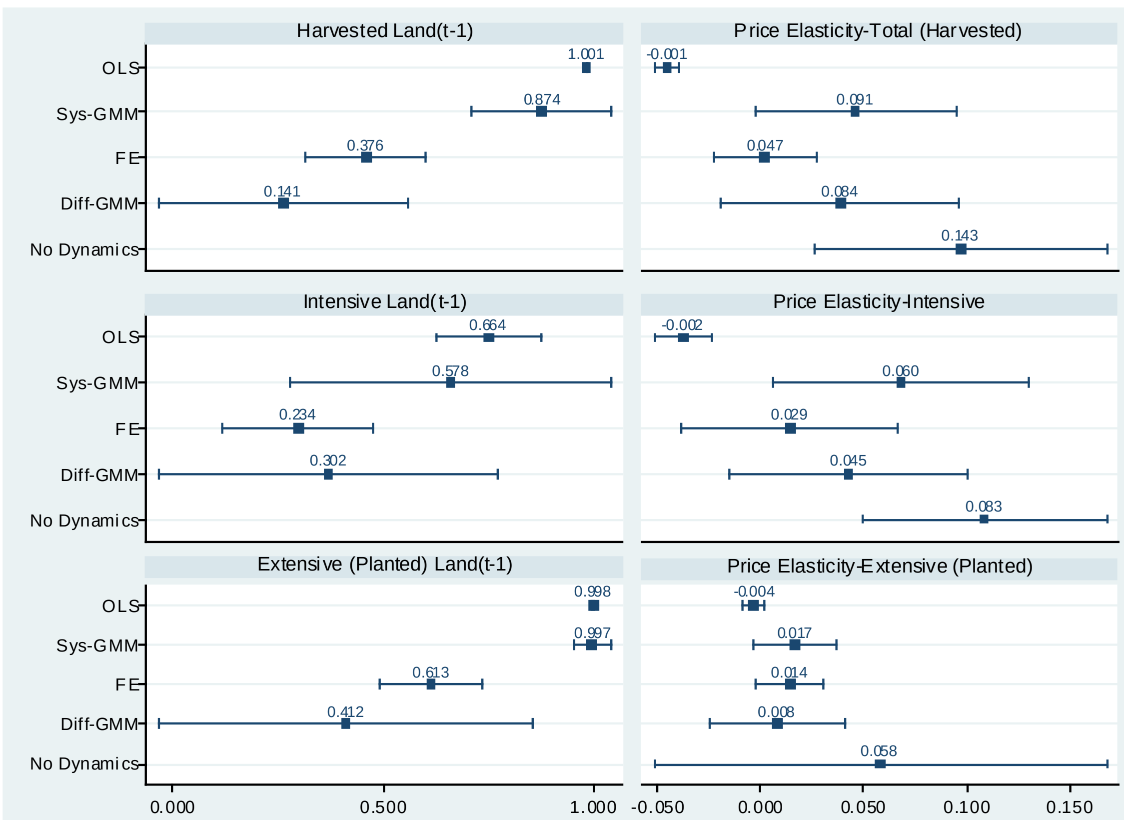


**Figure A2. Coefficient estimates and 95 % confidence interval using alternative estimators—we include first and second lag of the dependent variable as controls for intensive land use model.**

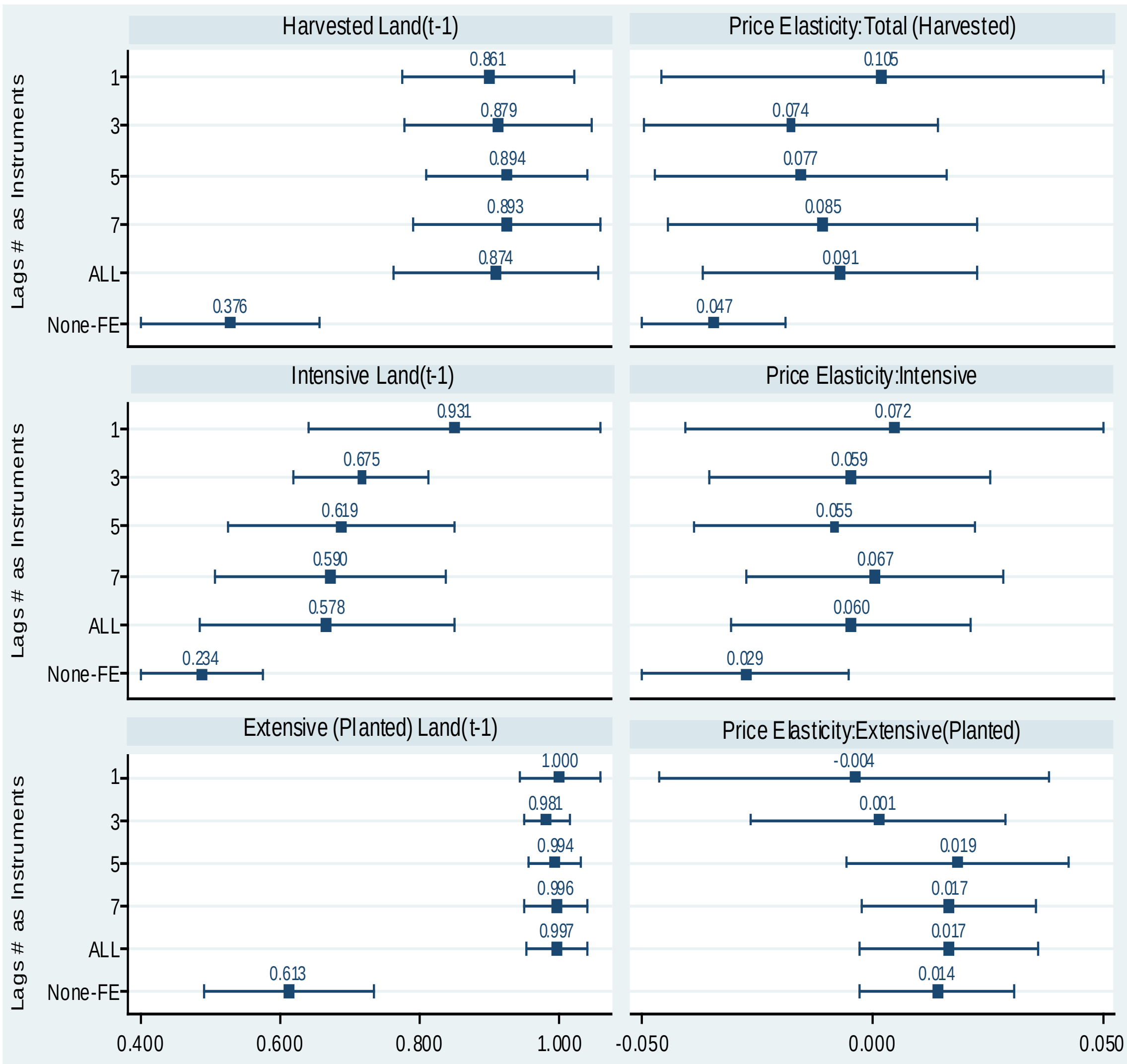


**Figure A3. Coefficient estimates and 95 % confidence interval with alternative maximum lag lengths—we include first and second lag of the dependent variable as controls for intensive land use model.**