Aggregate Agricultural Intensive and Extensive Land Supply Response to Price and Non-Price Factors

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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 generalized method of moments (GMM) or instrumental variables 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.

JEL codes: Q110, Q150, Q180

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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 appendix A). 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 (2015), and Miao, Khanna, and Huang (2015). Except for Miao, Khanna, and Huang (2015) 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)[2]. The second group provides empirical evidence that shows supply response to prices is the result of response both at the extensive and intensive margin[3]. 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 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

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

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[4]. 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-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.

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

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[5]. 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 generalized method of moments (GMM) panel estimator. The FD estimator addresses country-specific omitted fixed effects bias. The dynamic GMM panel estimator exploits the time-series variation in dependent and explanatory variables within each cross-country observation, accounts for unobserved country-specific omitted fixed effects bias, allows for the inclusion of lagged dependent variable as explanatory variable, controls for measurement

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

error in the lagged endogenous (dependent) variable and expectation error or endogeneity of explanatory variables as 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 an 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 GMM panel 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 2 provides a conceptual framework on how we decompose total supply (harvested) response into the extensive and intensive margin. Section 3 describes the data and presents descriptive analysis. Section 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 5 presents the empirical results. Finally, section 6 concludes.

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 yikeld, 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[6]; 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

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

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

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, θ_1 measures land use change at the extensive margin whereas the other two, change in cropland used for second crop planting, θ_2 and the change in unharvested land, λ measures land use change at the intensive margin. From this expression, we can make the following two statements

Statement 1: Given θ_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 λ>0 (λ <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.

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

[6] 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.

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

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

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

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

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

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

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

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

where, $\alpha_1 (= H_1Y_1 / HY)$ and $\alpha_2 (= H_2Y_2 / HY)$ 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.

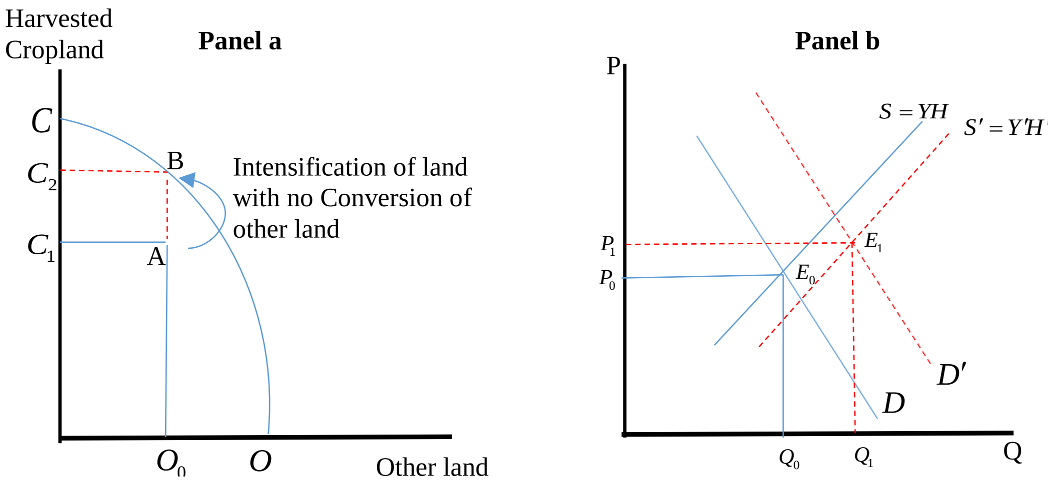

Figure 1. The response of output to higher crop prices without any change in extensive margin and yield rate.

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.

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, θ_{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[7].

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 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

[7] 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).

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[8]. 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

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

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) 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.

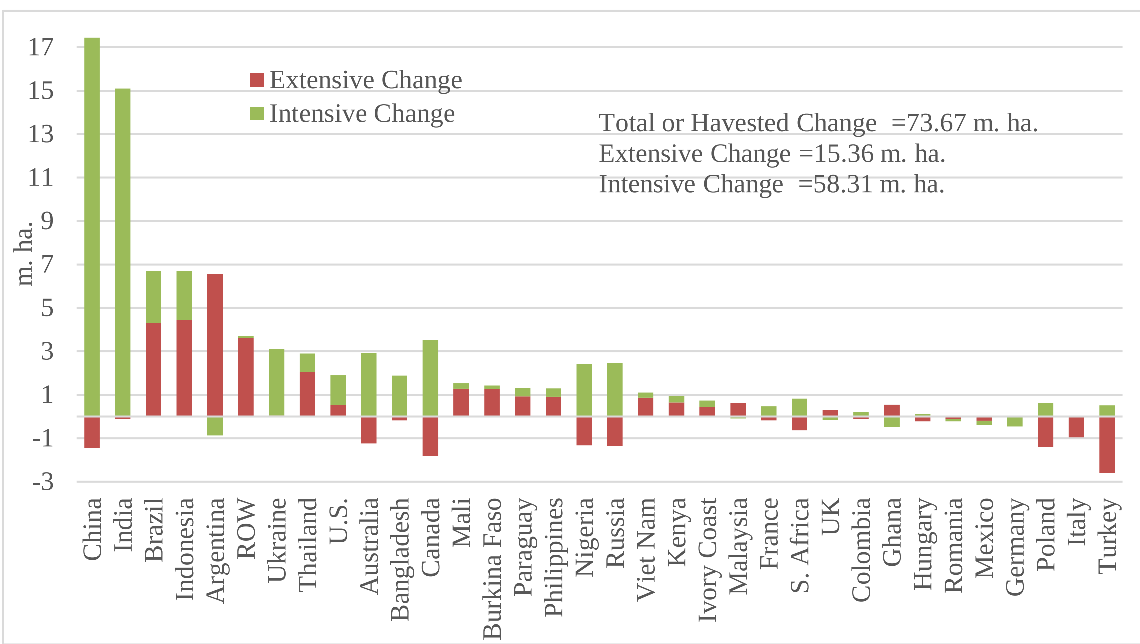

Figure 2. Decomposition of total land (harvested) use changes in extensive and intensive margin: an average of 2011-2013 relative to the average of 2004-2006.

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).

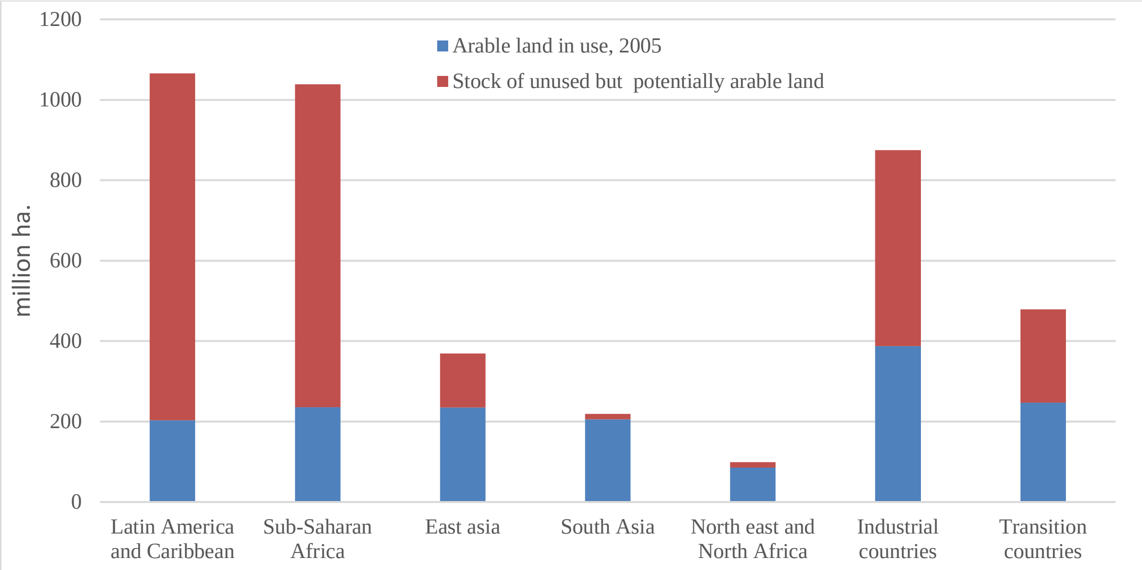

Figure 3. Arable land in use and potentially available arable land for future crop production.
Source: Bruinsma (2011).

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. 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.

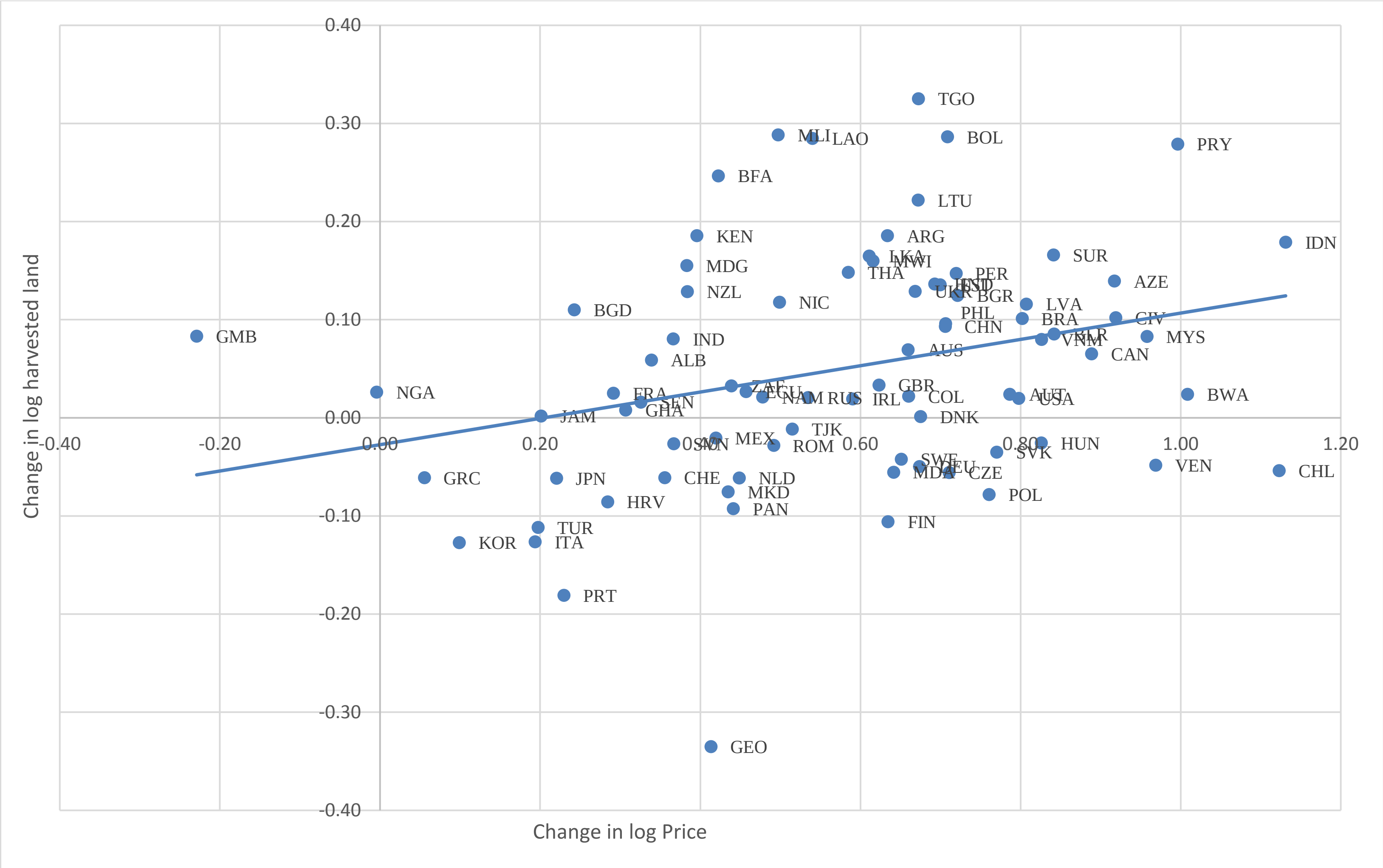

Figure 4. Change in harvested land use to change in crop price: average of 2011-2013 relative to average of 2004-2006

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

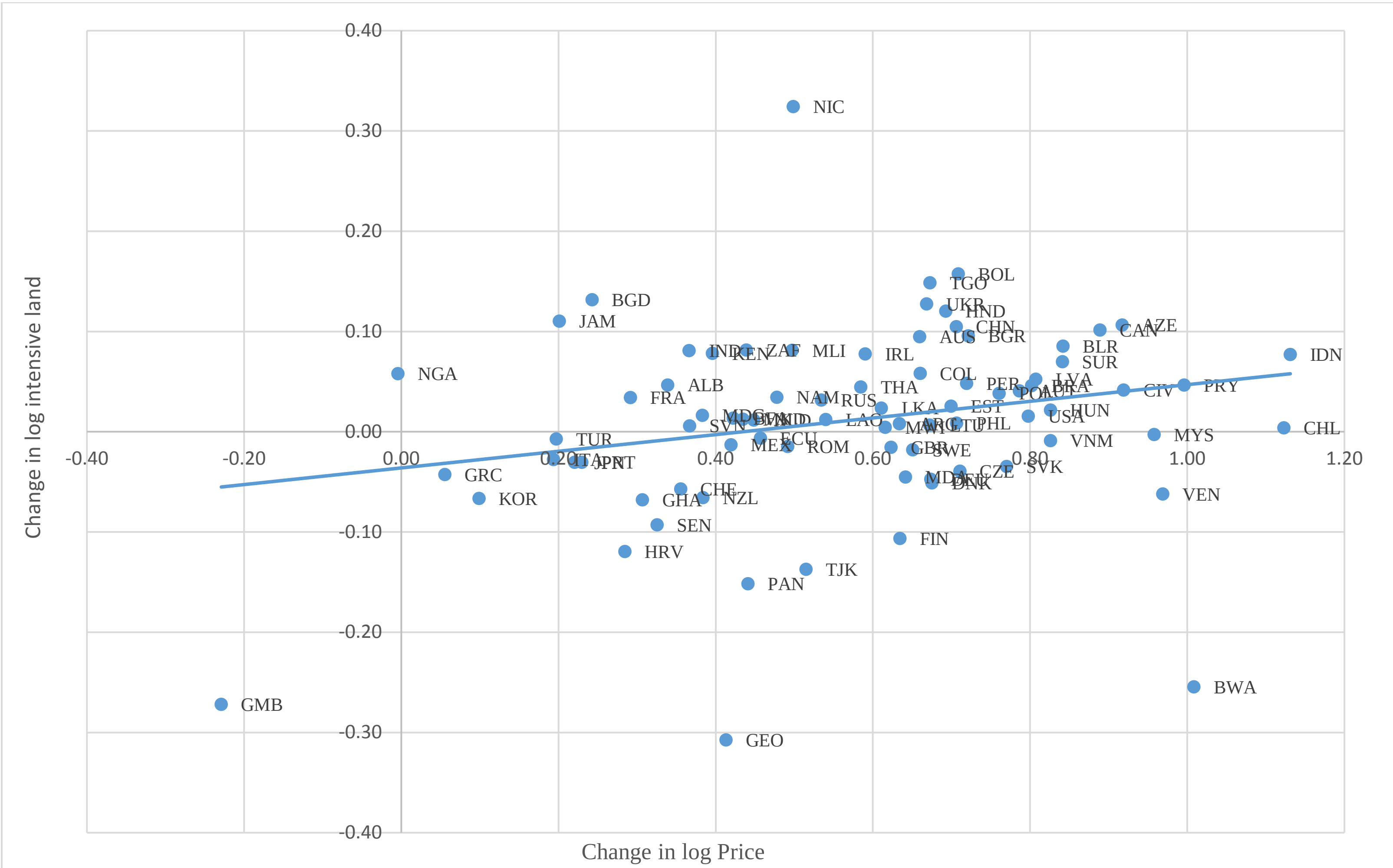

Figure 5. Change in intensive land use to change in crop price: average of 2011-2013 relative to average of 2004-2006

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

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 Econometric Methods

4.1 Static Panel and Cross-Sectional Estimation

We start using a static supply model[9]. 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 α_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.

[9] 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 α_i is likely correlated with P_{it} and Z_{it} because it is likely that factors in α_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[10]. 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 α_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) $A_{i2} = (\beta_0 + \delta_0) + \beta_1 P_{i2} + Z'_{i2}\beta_2 + \alpha_i + e_{i2}$ (t=2:2011-2013)

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

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

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

where Δ 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.

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[11]. As long as the strict exogeneity assumption on the explanatory variables is held, i.e. Δe_i is uncorrelated with ΔP and ΔZ_i, the estimates from the FD estimator are unbiased and consistent. Equation

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

[11] We derive the equivalency of both estimators in appendix B.

(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 α_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 α_i has disappeared.

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 heterogeneity in adjustment dynamics between different types of panel units. Thus, we now consider the following dynamic panel specification of a supply model[12]

(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 ρ is a measure of the speed of adjustment, β 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

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

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.

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[13], we subtract time mean of (11) from (11) itself and we obtain

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

Or

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

[13] 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 α_i now has disappeared. A pooled OLS estimator based on this type of equation (14) is known as FE or WG estimator[14]. 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)[15]. 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 ρ will be asymptotically downward-biased when ρ 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 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.

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[14] 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.
[15] We discuss Nickell bias in details in appendix C.

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[16]. Suppose, instead of observing P_{it}^{e}, we observe $P_{it}^{*} = P_{it}^{e} + w_{it}$, where w_{it} represents expectation error or errors of measurement in P_{it}^{e}. Therefore, instead of estimating equation (11), we estimate[17]

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

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

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

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

where $dA_{it} = A_{it} - A_{it-1}$ and similarly for the other variables; σ_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 β will underestimate the true β 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. 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[18].

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

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

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 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 π_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 π_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 (2015) and Miao, Khanna, and Huang (2015).

The basic steps of a dynamic GMM panel estimator are the following[19]. 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) $$A_{it} - A_{i,t-1} = \rho(A_{i,t-1} - A_{i,t-2}) + \beta(P_{it}^{e} - P_{i,t-1}^{e}) + (Z'_{it} - Z'_{i,t-1})\delta + \phi_i\,(f_t - f_{t-1}) + (u_{it} - u_{i,t-1}), \text{ or}$$
$$\Delta A_{it} = \rho\Delta A_{i,t-1} + \beta\Delta P_{it}^{e} + \Delta Z'_{it}\,\delta + \phi_i\,\Delta f_t + \Delta u_{it}$$

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 $u_{i,t-1}$ in Δu_{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 $$E(A_{i,t-s}\Delta u_{it}) = 0 \text{ for } t = 3, \ldots\ldots, T \text{ and } 2 \le s \le t-1$$

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

[19] Appendix D provides mathematical details of dynamic panel GMM estimators.

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

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

(22) $E(x'_{i,t-1}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \le s \le t-1$; 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 ρ approaches unity, or as the variance of the fixed effects α_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 α_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 ΔA_{it} and ΔX_{it} are uncorrelated with α_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 Δu_{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. 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 Δu_{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. It can weaken the Hansen test to the point where it generates 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[20]. Second, exclusion of longer lags as instruments 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.

5 Empirical Results and Discussion

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),

[20] 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).

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.

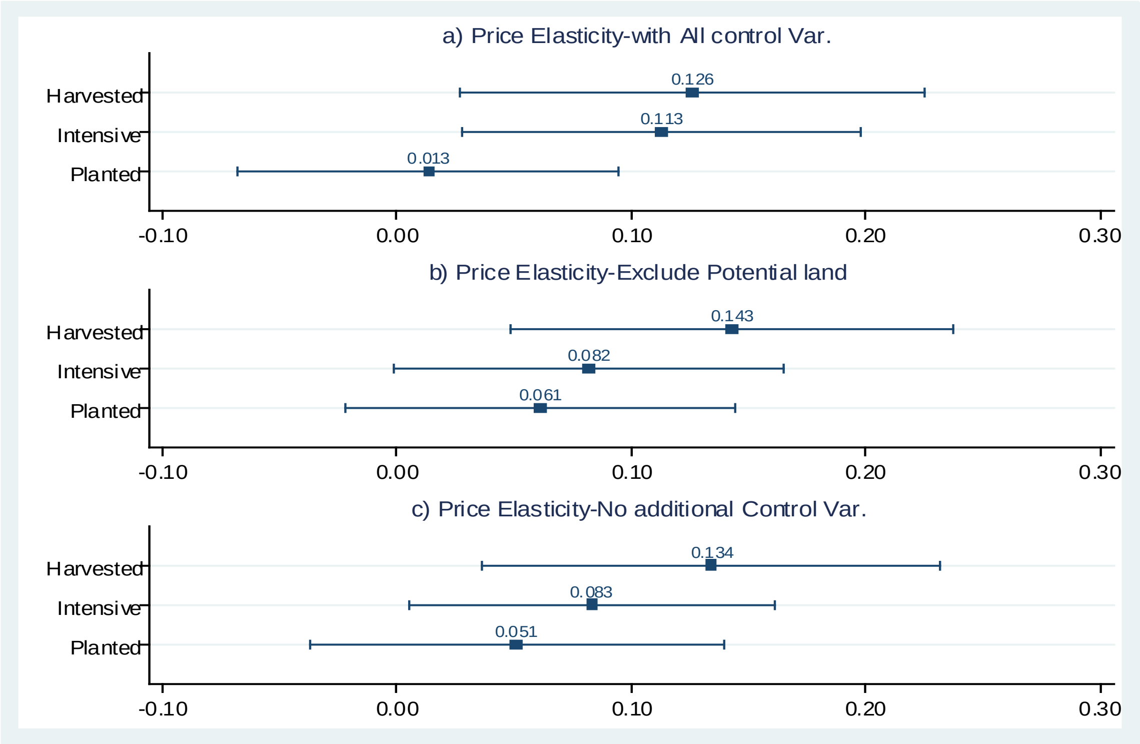

Figure 7. Elasticity estimates and 95% confidence interval for different measures of land use from first difference estimator

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.

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[21]. 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 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%.[22] 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

[21] 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

[22] 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.

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.

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						
ρ 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 D1 in appendix D, 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[23]. 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[24]. 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.

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

[24] 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 E1 in appendix E shows the results.

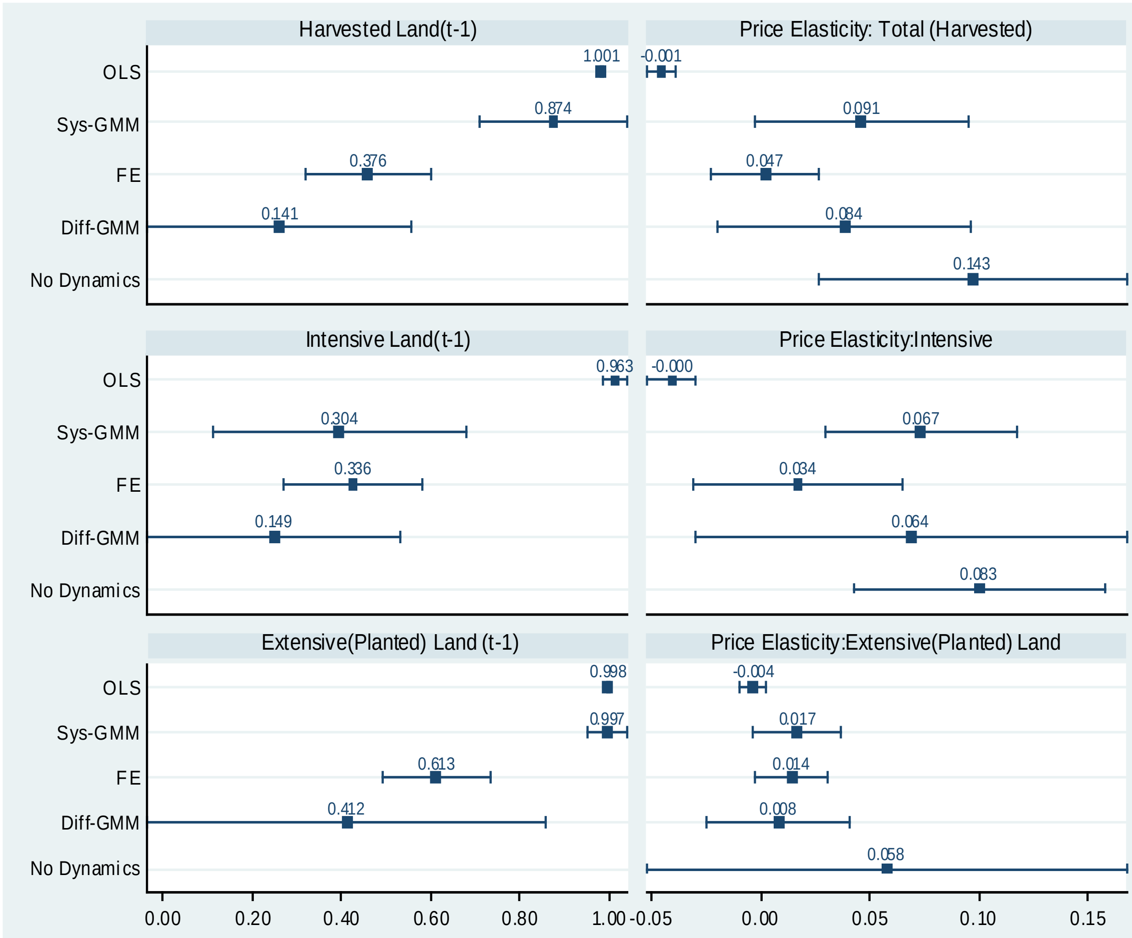

Figure 8. Coefficient estimates and 95% confidence interval using alternative estimators

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[25]. 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 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

[25] 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.

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 ρ and the bias in ρ gets larger when ρ increases. In a special case, he finds that when exogenous variables are highly autocorrelated (autocorrelation coefficient is close to one), the bias in β 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 coefficient on the output price 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 coefficient in the no dynamics model is much higher than the model with dynamics. These upward biases are perhaps because of the positive correlation between output 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[26]. 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 planted (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 three land use 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 ρ and the corresponding confidence intervals are relatively

[26] Figure E2 in appendix E 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.

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 two important diagnostic tests required for the validity of GMM. In our preferred specification, neither the Arellano and Bond test detects any problem with second-order autocorrelation of residuals nor does the Hansen test detect any problem with instrument validity at the 5% level of significance (see table 3).

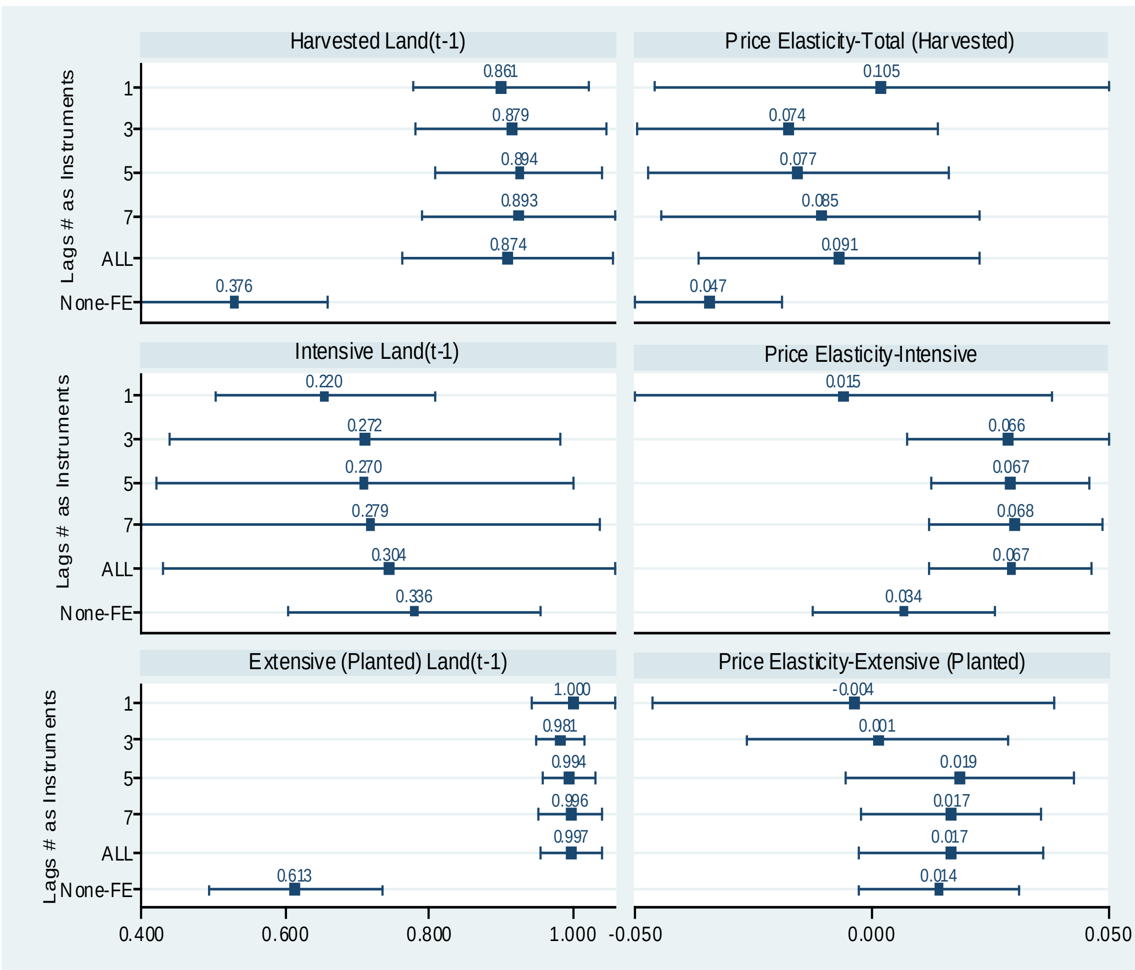

Figure 9. Coefficient estimates and 95% confidence interval with alternative maximum lag lengths

7 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

A Data Description

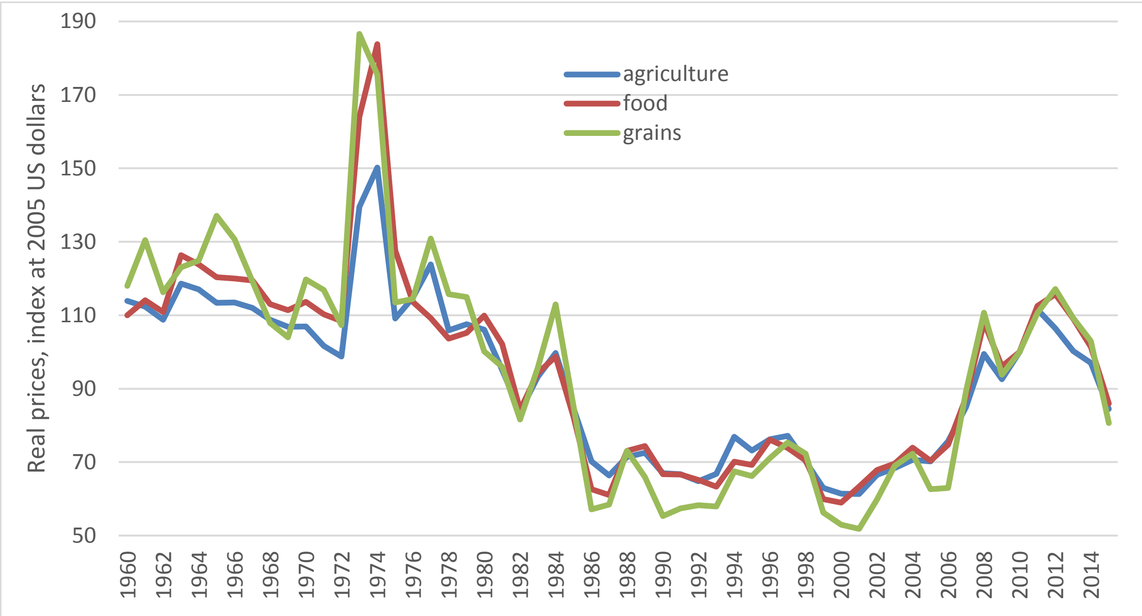

Figure A1. The trend of real commodity prices, index (2010=100). ***Source: The World Bank***

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. Countries in the sample (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

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

B 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

(B1) $$A_{i2} - A_{i1} = \delta_0 + (x'_{i2} - x'_{i1})\theta + (e_{i2} - e_{i1}), \text{ or}$$
$$\Delta A_i = \delta_0 + \Delta x'_i\ \theta + \Delta e_i, \quad i = 1,\ldots\ldots\ldots.., N$$

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

(B2) $$\theta_{FE_{T=2}} = [(x_{i1} - \bar{x}_i)(x_{i1} - \bar{x}_i)' + (x_{i2} - \bar{x}_i)(x_{i2} - \bar{x}_i)']^{-1}[(x_{i1} - \bar{x}_i)(A_{i1} - \bar{A}_i) + (x_{i2} - \bar{x}_i)(A_{i2} - \bar{A}_i)]$$

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 (B2) as

(B3)
$$\begin{aligned}
\theta_{FE_{T=2}} &= \left[\sum_{i-1}^{N} \frac{(x_{i1} - x_{i2})}{2}\frac{(x_{i1} - x'_{i2})}{2} + \frac{(x_{i2} - x_{i1})}{2}\frac{(x_{i2} - x'_{i1})}{2}\right]^{-1}\left[\sum_{i-1}^{N} \frac{(x_{i1} - x_{i2})}{2}\frac{(A_{i1} - A_{i2})}{2} + \frac{(x_{i2} - x_{i1})}{2}\frac{(A_{i2} - A_{i1})}{2}\right] \\
&= \left[\sum_{i-1}^{N} 2\frac{(x_{i2} - x_{i1})}{2}\frac{(x_{i2} - x'_{i1})}{2}\right]^{-1}\left[\sum_{i-1}^{N} 2\frac{(x_{i2} - x_{i1})}{2}\frac{(A_{i2} - A_{i1})}{2}\right] \\
&= 2\left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(x_{i2} - x_{i1})'\right]^{-1}\left[\sum_{i-1}^{N} \frac{1}{2}(x_{i2} - x_{i1})(A_{i2} - A_{i1})\right] \\
&= \left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(x_{i2} - x_{i1})'\right]^{-1}\left[\sum_{i-1}^{N} (x_{i2} - x_{i1})(A_{i2} - A_{i1})\right] = \theta_{FD_{T=2}}
\end{aligned}$$

C Dynamic Panel or Nickell Bias and Inconsistency of the FE Estimator

We write the equation (11) as

(C1) $A_{it} = \rho A_{i,t-1} + x'_{it}\beta + \alpha_i + u_{it}, \; i = 1,\ldots\ldots..,N, \; t = 1,\ldots\ldots..,T$

After FE transformation. i.e., averaging equation (C1) over time for each panel group and subtracting it from the original equation (C1), we obtain

(C2) $$\begin{aligned} A_{it} - \overline{A}_{i.} &= \rho(A_{i,t-1} - \overline{A}_{i.-1}) + (\mathrm{x}'_{it} - \overline{x}'_{i.})\beta + (u_{it} - \overline{u}_{i.}), \text{ or} \\ \tilde{A}_{it} &= \rho\tilde{A}_{i,t-1} + \beta\tilde{x}'_{it} + \tilde{u}_{it} \end{aligned}$$

where dots indicate time averages. $\overline{A}_{i.} = 1/T\sum_{t=1}^{T} A_{it}$, $\overline{A}_{i.-1} = \sum_{t=2}^{T} A_{i,t-1}/(T-1)$, and so on. $\tilde{A}_{it} = A_{it} - \overline{A}_{i.}$ is the time-demeaned value of A. The other variables are defined similarly. The FE transformation wipes out the fixed effects, α_i .Therefore, it is likely that the FE estimator as applied to equation (C2) are unbiased and consistent. But, that is not necessarily true for the dynamic model because $(A_{i,t-1} - \overline{A}_{i.-1})$ is correlated with $(u_{it} - \overline{u}_{i.})$ 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 $\overline{u}_{i.}$. The disturbances average $\overline{u}_{i.}$ 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 (B1). Assuming x'_{it} is exogenous, we write the probability limit of FE estimator as

(C3) $$\mathrm{plim}_{N\to\infty}(\hat{\rho} - \rho) = [\underbrace{(\mathrm{plim}_{N\to\infty}\frac{1}{NT}\tilde{A}'_{-1}M\tilde{A}_{-1})^{-1}}_{B}][\underbrace{\mathrm{plim}_{N\to\infty}\tilde{A}'_{-1}\tilde{u}}_{C}]$$

and

(C4) $$\mathrm{plim}_{N\to\infty}(\hat{\beta} - \beta) = -\mathrm{plim}_{N\to\infty}[(\tilde{x}'\tilde{x})^{-1}\tilde{x}'\tilde{A}_{-1})^{-1}]\;\mathrm{plim}_{N\to\infty}(\hat{\rho} - \rho)$$

where $M = I - \tilde{x}(\tilde{x}'\tilde{x})^{-1}\tilde{x}'$. Now, from the equation (C4) we can calculate

(C5) $$\text{plim}_{N\to\infty}\,\tilde{A}'_{-1}\tilde{u} = -\frac{\sigma_u^2}{T(1-\rho)}\left(1 - \frac{1}{T}\frac{(1-\rho^T)}{1-\rho}\right)$$

Now, we can derive the direction of bias. When ρ 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 ρ will be asymptotically downward-biased. The bias on β depends on the relationship between price and $\tilde{A}_{-1}$. If price is positively related (in regression sense) with $\tilde{A}_{-1}$, then equation (C4) indicates that the coefficient β 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.

D Dynamic Panel Estimation with GMM

Again, we write the equation (11) as

(D1) $A_{it} = \rho A_{i,t-1} + x'_{it}\beta + \alpha_i + u_{it}$, $i = 1, \ldots\ldots\ldots.., N;\ t = 1, \ldots\ldots.., T$

where ρ is a scalar and $|\rho| < 1$, x'_{it} is $1\times K$ a row vector of control variables and β 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 α_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 (D1), we obtain inconsistent estimates of the parameters of interest because both $A_{i,t-1}$ and x'_{it} are correlated with α_i and therefore violates strict exogeneity of explanatory variables. In order to get consistent estimates of

ρ and β, we take first differences of the equation (D1), which removes country-specific fixed effects α_i

(D2) $$A_{it} - A_{i,t-1} = \rho(A_{i,t-1} - A_{i,t-2}) + (x_{it} - x_{i,t-1})'\beta + (u_{it} - u_{i,t-1}), \text{ or}$$
$$\Delta A_{it} = \rho(\Delta A_{i,t-1}) + (\Delta x_{it})'\beta + \Delta u_{it}$$

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

(D3) $$A_{i3} - A_{i2} = \rho(A_{i2} - A_{i1}) + (x_{i3} - x_{i2})'\beta + (u_{i3} - u_{i2})$$

Now, from equation (D3) 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

(D4) $$A_{i4} - A_{i3} = \rho(A_{i3} - A_{i2}) + (x_{i4} - x_{i3})'\beta + (u_{i4} - u_{i3})$$

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 (D2) estimable. Moreover, Arellano (1989) and Kiviet (1995) obtain results that suggest that the estimator based on levels is more efficient[27].

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 (D2), 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

(D5) $$W_i^{\text{DIF}} = \begin{bmatrix} A_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & A_{i1} & A_{i2} & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{i1} & A_{i2} & A_{i3} & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & A_{i1} & A_{i2} & \cdots & A_{i,T-2} \end{bmatrix}$$

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

(D6) $$W_i^{\text{DIF:Exo}} = \begin{bmatrix} A_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & x'_{i3} \\ 0 & A_{i1} & A_{i2} & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & x'_{i4} \\ 0 & 0 & 0 & A_{i1} & A_{i2} & A_{i3} & \cdots & 0 & 0 & 0 & x'_{i5} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & A_{i1} & \cdots & A_{i,T-2} & x'_{i,T} \end{bmatrix} \begin{matrix} t=3:2006 \\ t=4:2007 \\ t=5:2008 \\ \\ t=T:2013 \end{matrix}$$

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

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[27] 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.

(D7) $$W_i^{\text{DIF:Endo}} = \begin{array}{cl} \begin{bmatrix} A_{i1}, x'_{i1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & A_{i1}, x'_{i1} & A_{i2}, x'_{i2} & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & A_{i1}, x'_{i1} & \cdots & A_{i,\mathrm{T}-2}, x'_{i,T-2} \end{bmatrix} & \begin{array}{l} t=3:2006 \\ t=4:2007 \\ t=5:2008 \\ \\ t=T:2013 \end{array} \end{array}$$

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 (D7) corresponds to the following orthogonality conditions which are linear in the ρ and β parameters

(D8) $E(A_{i,t-s}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \le s \le t-1$

(D9) $E(x'_{i,t-1}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $2 \le s \le t-1$; when x' is endogenous

When x' is predetermined (D8) turns out to be

(D10) $E(x'_{i,t-s}\Delta u_{it}) = 0$ for $t = 3,......,T$ and $1 \le s \le t-1$;

The estimator that fits the model (D2) using linear GMM and the instrument matrix (D5) and (D6) or (D7) 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 (D1)

(D11) $A_{it} = \rho A_{i,t-1} + \alpha_i + u_{it}, |\rho| < 1$, 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

(D12) $\Delta A_{i2} = \pi A_{i1} + r_i$

where the second-stage is $\Delta A_{i3} = \rho \Delta A_{i2} + \Delta u_{i3}$. For a very high value of ρ or variance of α_i, the OLS estimator of π tends to be zero, because $\pi \cong 1-\rho$. In this case, the instrument A_{i1} is only weakly correlated with ΔA_{i2}. To see this, manipulating equation (D11) we have (T=2)

(D13) $$\begin{aligned} &A_{i2} - A_{i1} = (\rho - 1)A_{i1} + \alpha_i + u_{i2}, \text{ or} \\ &\Delta A_{i2} = (\rho - 1)A_{i1} + \alpha_i + u_{i2} \end{aligned}$$

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 (D13) is only weakly correlated with ΔA_{i2} and the DIF-GMM estimator in equation (D11) 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

(D14) $A_{i3} = \rho A_{i2} + (\alpha_i + u_{i3})$

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

(D15) $A_{i2} = \pi \Delta A_{i2} + r_i$

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 (D14) 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

(D16) $\begin{pmatrix} \Delta A_{i2} \\ A_{i2} \end{pmatrix} = \begin{pmatrix} \pi^1 A_{i1} \\ \pi^2 \Delta A_{i2} \end{pmatrix} + \begin{pmatrix} r_i^1 \\ r_i^2 \end{pmatrix}$

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

$$\text{(D17)}\quad W_i^{\text{Level}} = \begin{array}{c} \begin{pmatrix} \Delta A_{i2} & 0 & 0 & \cdots & 0 \\ 0 & \Delta A_{i3} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1} \end{pmatrix} \end{array} \begin{array}{c} 2005 \\ 2006 \\ \vdots \\ 2013 \end{array}$$

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

$$\text{(D18)}\, W_i^{\text{Level:Exo}} = \begin{pmatrix} \Delta A_{i2} & 0 & 0 & \cdots & 0 & \Delta x'_{i2} \\ 0 & \Delta A_{i3} & 0 & \cdots & 0 & \Delta x'_{i3} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1} & \Delta x'_{i,T-1} \end{pmatrix} \begin{array}{c} 2005 \\ 2006 \\ \vdots \\ 2013 \end{array}$$

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

$$\text{(D19)}\, W_i^{\text{Level:Endo}} = \begin{pmatrix} \Delta A_{i2}, \Delta x'_{i2} & 0 & 0 & \cdots & 0 \\ 0 & \Delta A_{i3}, \Delta x'_{i3} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \Delta A_{i,T-1}, \Delta x'_{i,T-1} \end{pmatrix} \begin{array}{c} 2005 \\ 2006 \\ \vdots \\ 2013 \end{array}$$

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

(D20) $w_i^{\text{SYS}} = \begin{pmatrix} W_i^{\text{DIF}} & 0 \\ 0 & W_i^{\text{Level}} \end{pmatrix}$, when no x' is included.

(D21) $w_i^{\text{SYS:Exo}} = \begin{pmatrix} W_i^{\text{DIF:Exo}} & 0 \\ 0 & W_i^{\text{Level:Exo}} \end{pmatrix}$, when x' is strictly exogenous variables.

(D22) $w_i^{\text{SYS:Endo}} = \begin{pmatrix} W_i^{\text{DIF:Endo}} & 0 \\ 0 & W_i^{\text{Level:Endo}} \end{pmatrix}$, when x' is endogenous variables.

The corresponding moment conditions for (D22) in addition to (D8) and (D9) are

(D23) $E[(\alpha_i + u_{it})\Delta A_{i,t-1}] = 0$ for $i = 1, \ldots., N$ and $t = 3, 4, \ldots.., T$

(D24) $E[(\alpha_i + u_{it})\Delta x'_{i,t-1}] = 0$ 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 (D7) and (D19) as

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

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

We can collapse other instruments matrices as we have shown earlier in similar ways. We now present formulas for instruments count in table D1.

Table D1. 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.

E Further Empirical Results

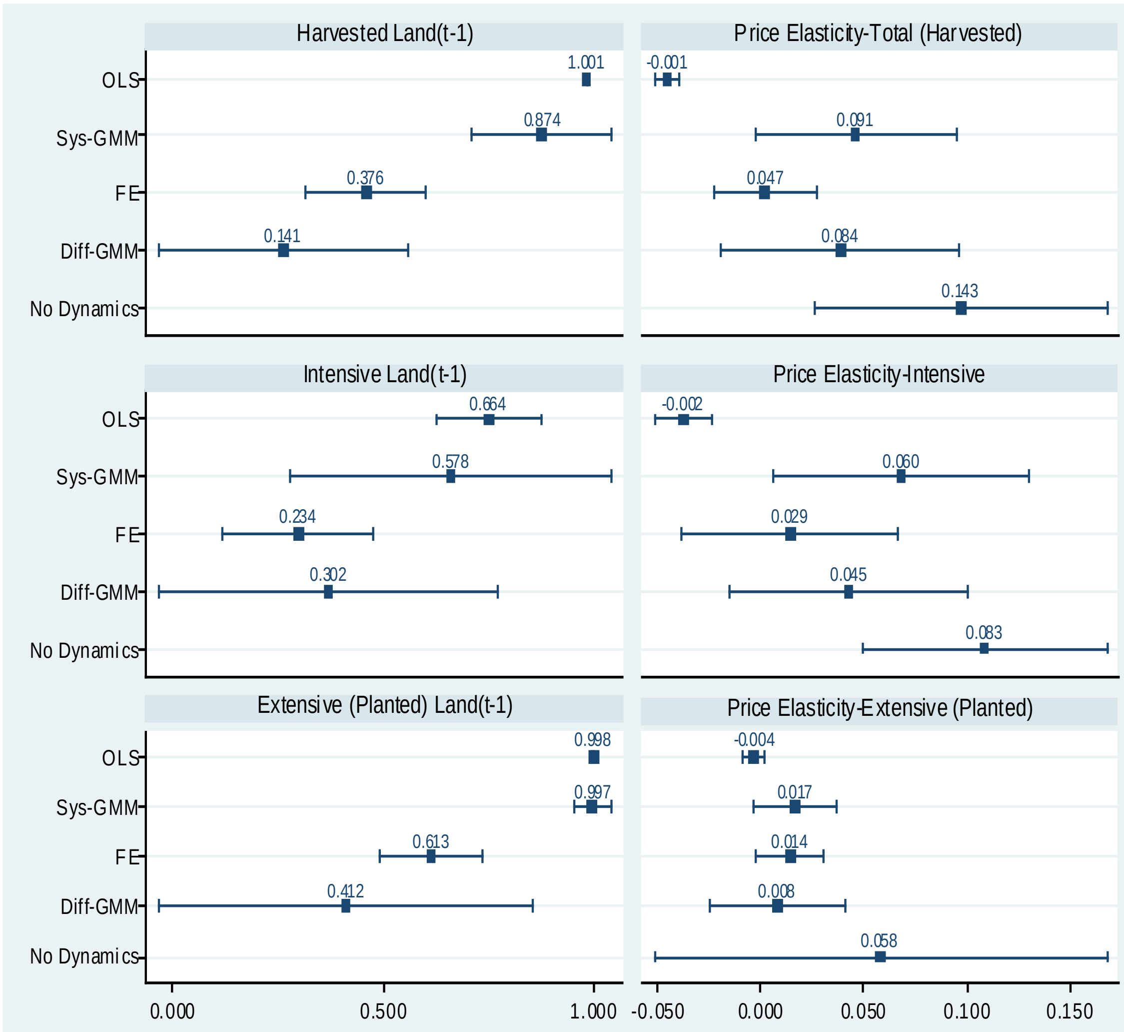

Figure E1. Coefficient estimates and 95 % confidence interval using alternative estimators—we include first and second lag of the dependent variable as controls for intensive land use model.

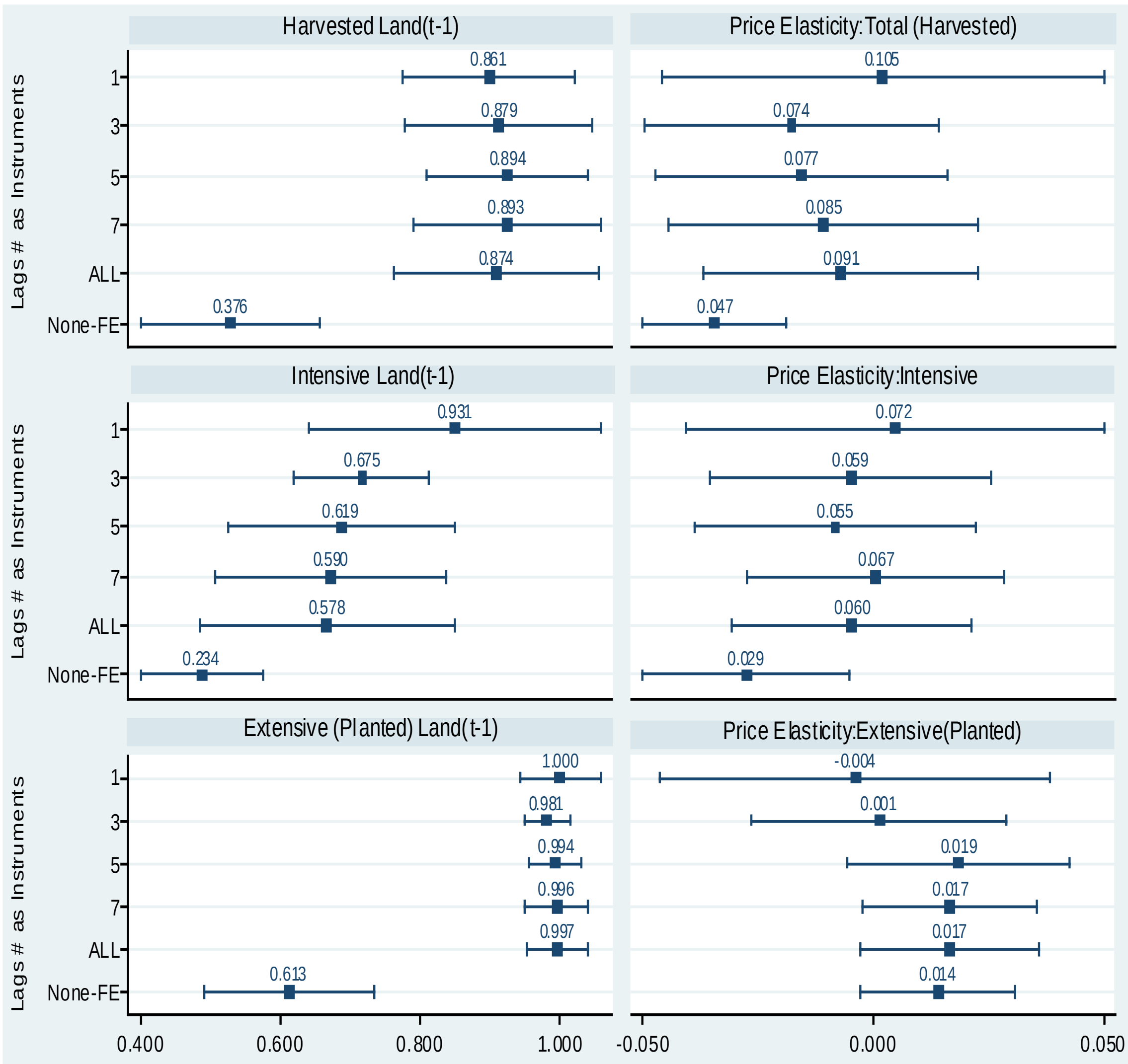

Figure E2. Coefficient estimates and 95 % confidence interval with alternative maximum lag lengths—we include first and second lag of the dependent variable as controls for intensive land use model.