Geography Matters: International Trade Patterns and the Indirect Land Use Effects of Biofuels

Nelson B. Villoria and Thomas W. Hertel

This article investigates the relationship between international trade patterns and the global distribution of coarse grain production responses to market developments in the United States. Our null hypothesis is that world markets are fully integrated, rendering the geographic persistence of bilateral trade flows irrelevant in the global production response to a change in U.S. prices. The alternative hypothesis allows price transmission to vary along with the intensity of competition among countries in specific markets. Using data from 1975 to 2002, we reject the null hypothesis. Our work has direct implications for the analysis of the global land use impacts of biofuel mandates.

Key words: area response, Armington model, biofuels, indirect land use, integrated world market, international trade, law of one price.

JEL codes: F14, F18, Q17.

Growing concerns about global environmental issues have brought renewed interest in the interdependence of global agricultural supply responses. A good example of this interest is the debate surrounding greenhouse gases (GHG) emissions due to indirect land use changes (iLUCs) associated with biofuel expansion in the United States and elsewhere. iLUCs are the consequence of adjustments in global agricultural production in response to higher crop prices resulting from an increase in demand for biofuel crops in a given region. When the GHG emissions of iLUCs are taken into account, there is some indication that current-technology crop-based biofuels may be more damaging than conventional fossil fuels (Hertel et al. 2010; Searchinger et al. 2008). Given their importance in the policy debate over biofuels, estimates of iLUCs are the subject of considerable debate, which has been further heightened by the considerable uncertainty involved in their estimation (Wang and Haq 2008; ACE 2009). A particularly contentious point is where these iLUCs will take place (Hertel et al. 2010; Keeney and Hertel 2009). The geography of iLUCs matters due to differences in yields, which determine how much land conversion is necessary to achieve a given level of production, as well as differences in current land cover, which determine the GHG emissions of the newly converted land. Therefore, the geography of international agricultural trade is a critical issue for better understanding the environmental effects of biofuel policies.

In the agricultural economics literature, there are two traditional paradigms guiding the modeling of international trade flows. One paradigm assumes the existence of an integrated world market (IWM) cleared by a single price. This paradigm is widely used in agricultural policy analysis (Fabiosa et al. 2008; Westhoff 2010) as well as in the analysis of long-run issues affecting the agricultural sector (Nelson et al. 2009). Under this assumption, when the relative prices charged by different suppliers change, countries readily adjust their trading patterns by shifting to the lowest cost provider. Such arbitrage ensures a single world market price for each commodity. However, in the near term, it is common to observe that trade patterns do not respond to changes in relative prices as would be expected under the IWM hypothesis (Abbott, Paarlberg, and

Nelson B. Villoria and Thomas W. Hertel are, respectively, a research assistant professor and a distinguished professor in the Department of Agricultural Economics at Purdue University.
The authors thank Dr. David Hennessy and three anonymous referees for helpful comments on the article. The authors acknowledge the support from the U.S. Environmental Protection Agency's Office of Transportation and Air Quality (contract no. SP09H000962).

Amer. J. Agr. Econ. 93(4): 919–935; doi: 10.1093/ajae/aar025
Received January 2010; accepted January 2011; published online July 15, 2011

Patterson 1988; Hillberry et al. 2005; Thursby, Johnson, and Grennes 1986). On the contrary, because of institutional ties, transport infrastructure, and underlying preferences, we observe a significant degree of persistence in trade flows, a phenomenon that we refer to as the "geography of trade." For agricultural commodity markets, this view of the world is typically implemented using the so-called Armington (1969) assumption, which assumes that goods are differentiated by their place of origin (Grennes, Johnson, and Thursby 1978; Johnson, Grennes, and Thursby 1979).

Under the IWM hypothesis, markets clear with a single world price, so the resulting spatial equilibrium is not dependent on the source of the initial market disturbance.[1] In contrast, under the product differentiation hypothesis, the intensity with which supply and demand shocks are transmitted to different regions varies with the degree of trade linkage to the country from which the shock emanates. The specific question we ask concerns which of the two trade assumptions better explains the historical response of coarse grains areas across countries to changes in the U.S. market. The significance of this research question extends beyond the issue of iLUCs from biofuels. Any national policy that alters production patterns in agriculture can modify global land use patterns in unintended ways. Indeed McCarl (2009) suggests that the iLUC impacts of U.S. climate policy could also be significant. Hence, the ability to understand how supply and demand shocks propagate globally is vital for analysis of agricultural markets.

Our empirical strategy is to nest the two alternative models outlined above within a standard land demand equation. Using three decades of country-level data on harvested area, grain consumption, and bilateral trade flows, we test the null hypothesis, in which the IWM view is an appropriate way of modeling the global transmission of a shock in the supply/demand of coarse grains. Motivated by the literature examining the iLUCs associated with U.S. biofuel policy, we focus on the transmission of price changes in the U.S. coarse grains sector to the coarse grains sectors of other countries. We reject the IWM hypothesis in favor of a model that explicitly takes into account the geographic patterns of trade flows. We show that adoption of this alternative model has important implications in terms of international area and production responses to U.S. biofuel policies, as well as the ensuing levels of GHG emissions associated with iLUCs.

Trade Assumptions and Global Land Use Predictions

Searchinger et al. (2008) offer the most widely cited study of global iLUCs associated with biofuels expansion. These authors utilize the model of global agriculture from the Food and Agricultural Policy Research Institute (FAPRI), which embeds the IWM hypothesis. Out of the new 10.817 million hectares (26.729 million acres) needed to accommodate a 55.92 billion liter (14.77 billion gallon) increase in U.S. corn ethanol, they conclude that 21% is in the United States, 26% in Brazil, 10% in China, and 11% in India. Since the FAPRI model takes into account cross-country differences in supply elasticities as well as in border price transmission due to policies (Fabiosa et al. 2008), it is possible that the ensuing pattern of land use change could deviate from simple proportionality to current production levels. Nonetheless, these authors report that the greatest land use change is predicted to arise in the largest producing countries of the world, with the pre-shock geography of trade playing little role in determining the final outcome. By way of example, India has historically been relatively closed to agricultural trade, yet it shows some of the largest land use changes in response to the biofuels shock in the Searchinger et al. (2008) analysis.

As mentioned in the introduction, observed trade patterns tend to be highly persistent over time and space. Armington (1969) rationalizes this persistence by assuming that changes in quantities (consumed, produced, and traded) of each product following a change in relative prices will depend on the ease with which consumers can substitute among the different origins of a given good, as captured by a constant elasticity of substitution (CES). Recent econometric estimates from Hertel et al. (2007), based on cross-country variability in bilateral trade costs, give a CES value for coarse grains of 2.6 (standard error = 1.1),

[1] Naturally, such a unique spatial equilibrium lacks realism; thus, modelers introduce border frictions and differences in supply elasticities that condition local supply responses. However, even after correcting for border frictions and differences in supply elasticities, the assumption of a single world price still tends to cause countries with the largest areas to have the greatest changes in land use, given a change in relative prices.

suggesting that coarse grains do indeed behave as differentiated products. (This estimate is much lower than the estimates obtained by the same authors for other commodities, such as rice, wheat, and oilseeds.) Drawing on these estimated trade elasticities, a recent analysis of the importance of the different assumptions employed in assessing the iLUCs of biofuels by Keeney and Hertel (2009) reports that out of the total land needed to satisfy an increase of 1 billion gallons of U.S. ethanol, 56% is located in the United States, 4% in Brazil, 6% in China, and a negligible amount in India. While these results are not directly comparable to those of Searchinger et al. (2008), the sharp difference between these geographic patterns is enough to suggest that the IWM and Armington models of competition lead to very different conclusions about global iLUC changes.[2]

The GHG releases from the iLUC of biofuels are a function of existing land cover (which in turn determines GHG emissions) and crop yields (which determine the amount of new land needed to make up for the U.S. output diverted to biofuel production). To the extent that both yields and land cover vary widely across countries, the differences in the location of the predicted supply response can translate into sharp differences in the size of the estimated GHG emissions. For example, Searchinger et al. (2008) calculated that a possible increase in U.S. corn ethanol of 56 billion liters above projected levels for 2016 would need 167 years to allow GHG savings from corn ethanol to "pay back" carbon emissions from land use change. Meanwhile, Hertel et al. (2010) modeled the impact of an expansion of U.S. maize ethanol from 2001 levels to 56.7 gallons per year by 2015, obtaining values that suggest a 28-year payback period. One factor contributing to these differences is the use of different trade assumptions: IWM in the case of Searchinger et al. (2008) and Armington in the case of Hertel et al. (2010).

Conceptual Framework

To see which of the two trade paradigms has better support in the historical data, this section develops a land demand equation that links land use decisions to the price of coarse grains and then develops an alternative price transmission mechanism driven by the intensity of competition in international markets. This model serves to formalize the differences between the IWM and the Armington assumptions and provides a formal test of the IWM hypothesis.

The Derived Demand for Land

The profit maximizing allocation of a fixed amount of land to a set of crop choices depends on the full vector of output and input prices, the total endowment of land $\bar{A}$, and a vector of exogenous shifters, $\mathbf{Z}$ (Shumway, Pope, and Nash 1984). We index countries by i and denote the land allocations to coarse grains in country i at time t by A_{it}. Cross-country input and output prices are not available over the time period of our analysis.[3] Therefore, we substitute a world reference price for the domestic price of coarse grains in each country i, P_{it}. Our interest is in the cross-country land allocations to coarse grains production in response to a shock in the demand for coarse grains in the U.S. market; thus, we use as a reference world price the U.S. market price, $P_{us,t}$[4]. The relationship between domestic prices and the world reference price can be formalized using:

$$(1) \qquad P_{it} = RER_{it} P_{us,t} \tau_{it}$$

where RER_{it} is the real exchange rate in local currency units per U.S. dollar (LCU/$) in country i, and τ_{it} is a term (in power-of-the-tax form) that collects the myriad transaction costs that foreign products face when entering i's market. Expression (1) is a classical price transmission equation of the type used to study the law of one price Richardson (1978), which has been

[2] These results are not directly comparable because of the differences in shock sizes as well as the differences in other fundamental assumptions of the FAPRI and Global Trade Analysis Project (GTAP) models. Besides the differences in trade assumptions, these models have different data bases as well as different assumptions regarding yield responses to prices. They also differ in the type of economic linkages included. The FAPRI model is partial equilibrium, while the GTAP model is general equilibrium. In order to better isolate the effect of the trade assumption keeping other differences constant, the online supplementary materials report the results using the GTAP model to compare the effects of the IWM and the Armington models on supply and export behavior. The comparison reinforces the points made in this section.

[3] FAO has some data on domestic producer prices; however, the series is available only for limited periods of time and its measurement is a continuing area of controversy.

[4] Allen and Lutman (2009) indicate that corn is by far the largest globally traded product in the coarse grains category. These authors also point out that the United States is the largest world corn exporter and that world corn prices are determined largely by supply-and-demand relationships in the U.S. market. We use as world reference price the U.S. price because of both the U.S. influence in determining global coarse grains prices and our interest in the link between cross-country land responses to changes in the U.S. prices of coarse grains.

widely tested in agricultural and commodity markets (e.g., Mundlak and Larson 1992).

We also allow for sluggish adjustment by including a lagged area term A_{it-1}. This adjustment reflects the presence of crop rotation considerations, fixed costs associated with the clearing of new land, and other year-to-year adjustment costs. We further assume that farmers' price expectations in the current year are based on the price of the previous year.[5] The relationship between optimal land allocations and its determinants is assumed to be log-linear, giving rise to the following relationship:

$$(2) \qquad \ln(A_{it}) = \ln(P_{it-1})\beta + \mathbf{Z_{it}}\boldsymbol{\Gamma}$$

where P_{it-1} is the price of coarse grains defined in equation (1), β is the elasticity of area with respect to changes in P_{it-1}, and $\boldsymbol{\Gamma}$ is the vector of parameters of the exogenous variables contained in matrix $\mathbf{Z}$, which now contains the exogenous variables lagged and total area, denoted by $\ln(A_{it-1})$ and $\ln(\bar{A}_i)$, respectively.

Substituting equation (1) into equation (2) yields the land response equation in terms of the one-year lagged reference price:

$$(3) \qquad \ln(A_{it}) = \ln(P_{us,t-1})\beta + [\mathbf{Z_{it}}, \mathbf{Z_{it\text{-}1}}]\boldsymbol{\Gamma}$$

where the matrix of exogenous covariates $\mathbf{Z}$ and its corresponding parameter vector $\boldsymbol{\Gamma}$ now include the one-year lagged real exchange rate and the trade cost terms from equation (1).

Equation (3) is consistent with an integrated world market in which farmers uniformly respond, other things being held constant, to a unique world price. This equation forms the basis of the econometric estimation below. To accomplish the goal of contrasting the IWM with the alternative Armington hypothesis, an alternative theory of international price formation based on product differentiation is developed next.

International Trade and Price Transmission

At any point in time t, the disposition of *domestically produced* output of coarse grains in country i, X_i, is destined either for the domestic market, X_{ii}, or for exports to country j, X_{ij}. Consumption of coarse grains in country j is defined as $C_j = \sum_k X_{kj}$, where j's domestic production (net of exports) is included in the summation term. With n countries, there are $m = n - 1$ potential foreign partners.

Following the widely used Armington model, we have the following linearized version of the *compensated* CES demand facing country i in each market j (including i itself)[6]:

$$(4) \qquad x_{ij} = c_j - \sigma\left(p_{ij} - p_j\right)$$

where σ is the elasticity of substitution that we assume here to be equal for substitution between domestic products and imports and among import sources. x_{ij} is the percentage change in exports from country i to market j. c_j is the percentage change in total demand in market j, also known as the expansion effect. p_{ij} is the percentage change in the price charged by country i's suppliers in market j, and p_j is the percentage change in the average price level in market j. Collectively, the second term on the right-hand side (RHS) of equation (4) is termed the substitution effect, capturing the extent to which foreign suppliers displace, for example, U.S. coarse grains, as U.S. prices rise in the wake of biofuels growth.

Note that the larger the elasticity of substitution σ, the smaller the difference in price changes needed to cause a large swing in x_{ij}. In the limit, when a product is completely homogeneous such that $\sigma \to \infty$, any increase in country i's prices relative to the price index of country j drives exporter i entirely out of importer j's market. This case is equivalent to the IWM hypothesis, whereby regions readily change their suppliers if prices deviate from the single market-clearing world price.

With a finite value of σ, there is some stickiness in the trade relationship. In this case, the ability of consumers to substitute away from a given supplier is a function not only of σ, but also of budget shares (Armington 1969, pp.174–175). To see why, we use the fact that, at the optimal shares, the percentage change in the CES price index in market j equals the weighted sum of the prices charged by each of its suppliers, using as weights j's budget shares.

[5] We focus on the effects of changes in the U.S. price. Thus, we do not try to fully model country-specific price expectations. Instead, we simply use one-year lagged U.S. prices. This is a convenient assumption backed up by empirical work such as that of Gardner (1976), Chavas, Pope, and Kao (1983), and Chavas and Holt (1990), who use adaptive expectations based on previous year prices.

[6] The reader can find the derivation of the CES demand in the Armington context and the algebraic details of the derivation of the competition indices discussed below in the online supplementary materials. In the rest of this article, percentage changes are denoted using the variable names in lower case (i.e., $x_{ij} = \frac{dX_{ij}}{X_i}$).

Algebraically, $p_j = \sum_i^n \delta_{ij} p_{ij}$, where $\delta_{ij} = \frac{P_{ij} X_{ij}}{P_j C_j}$ is the budget share that market j expends on products from supplier i. Substituting the linearized price index p_j in equation (4), taking the domestic price i out of the summation, and using the fact that $(1 - \delta_{ij}) = \sum_{k \neq i}^m \delta_{kj}$, yields:

$$(5) \qquad x_{ij} = c_j - \sigma \left[\sum_{k \neq i}^{m} \delta_{kj} (p_{ij} - p_{kj}) \right].$$

In other words, given fixed aggregated consumption in market j ($c_j = 0$), the percentage change in i's sales to market j is a function of the weighted sum of the changes in the prices charged by i relative to those charged by its competitors (indexed by k), using as weights the market share of producer k in market j. Thus, for a given change in relative prices favoring supplier i (e.g., Argentina), relative to k (i.e., the United States), the larger the participation of k in market j (e.g., Japan), the more pronounced the rise in Argentina's exports to Japan.

Summing equation (5) over all the markets j, expanding terms and rearranging them, yields:

$$(6) \qquad x_i = \sum_{j}^{n} \theta_{ij} c_j - \sigma \sum_{k}^{m} \sum_{j}^{n} \theta_{ij} \delta_{kj} (p_{ij} - p_{kj}),$$

where $\theta_{ij} = \frac{P_{ij} X_{ij}}{P_i X_i}$ is the revenue share that producer i obtains from its sales to market j. Now the expansion effect (the first term on the RHS) is the revenue-share weighted sum of the growth in each of the individual markets j served by producers from country i. The second RHS term, or substitution effect, now reflects i's revenue shares as well as the consumption shares in each market. This substitution effect indicates that the percentage change in country i's total output will depend both on the market share of its competitors in the destination market (δ_{kj}) and on the importance that the destination market has for i's total production of coarse grains (θ_{ij}).

The first term on the RHS of equation (6) can be further decomposed into country i's own expansion as well as the expansion in the markets that it sells to, i.e., $\sum_j^n \theta_{ij} c_j = \theta_{ii} x_i + \sum_{j \neq i}^m \theta_{ij} c_j$. Moreover, to focus on the effects of competition between the United States and producer i, we break down the double summation in equation (6) to separate competition between exporter i and the United States from competition with the other k exporters:

$$(7) \qquad x_i = \theta_{ii} x_i + \sum_{j \neq i}^{m} \theta_{ij} c_j - \sigma \sum_{j}^{n} \theta_{ij} \delta_{us,j} \times (p_{ij} - p_{us,j}) - \sigma \sum_{k \neq US}^{m} \sum_{j}^{n} \theta_{ij} \delta_{kj} \times (p_{ij} - p_{kj}).$$

We can further decompose the second term in equation (7) into competition between the United States and country i in third markets, $\sum_{j \neq (i,US)}^{n-2} \theta_{ij} \delta_{us,j}$; in the U.S. market, $\theta_{i,us} \delta_{us,us}$; and in country i's own market, $\theta_{ii} \delta_{us,i}$. Finally, if we treat coarse grains yields as exogenous, then we can translate changes in output into changes in area; i.e., $x_i = a_i$. Equation (7) can then be rewritten as follows:

$$(8) \qquad a_i = \theta_{ii} x_i + \sum_{j \neq i}^{m} \theta_{ij} c_j - \sigma \left[\sum_{j \neq (i,US)}^{n-2} \theta_{ij} \delta_{us,j} (p_{ij} - p_{us,j}) + \theta_{i,us} \delta_{us,us} (p_{i,us} - p_{us,us}) + \theta_{ii} \delta_{us,i} (p_{ii} - p_{us,i}) \right] - \sigma \sum_{k \neq US}^{m} \sum_{j}^{n} \theta_{ij} \delta_{kj} (p_{ij} - p_{kj}).$$

In what follows, the product shares within the bracketed term in equation (8) are referred to as competition indices. They are denoted by ω_j, ω_{us}, and ω_i for competition between the United States and country i in third markets, in the U.S. market, and in country i's own market, respectively. An important feature of the ω_j-values is that they capture the variability of trade costs across partners (and over time). This can be seen by writing the price that country i charges in market j as the product of the market price in i times bilateral trade costs τ_{ij}, so $P_{ij} = P_i \tau_{ij}$ where τ_{ij} is a comprehensive measure of tariffs, sanitary barriers, shipping costs, etc. This allows rewriting ω_j as $\sum_{j \neq (i,US)}^{n-2} \frac{\tau_{ij} X_{ij}}{X_i} \frac{\tau_{us,j} X_{us,j}}{X_{us}}$. By the same logic, the indices ω_i and ω_{us} capture the barriers faced by the United States when entering country i and the barriers faced by country i when entering the United States.

Hypotheses to Be Tested

Given our interest in the iLUCs associated with biofuels expansion in the United States, and the fact that national prices for most countries are unobserved, we focus only on changes in the U.S. price. Thus, we impose on equation (8) the restriction $p_{ij} = 0$ for all $i \neq$ United States. Moreover, we observe U.S. prices at only U.S. markets; thus, $p_{us,j} = p_{us}$ for all j. Using the definitions of the ω indices, these two restrictions simplify equation (8) to the following expression:

$$(9)\quad a_i = \theta_{ii} x_i + \sum_{j \neq i}^{m} \theta_{ij} c_j + \sigma p_{us} \left(\omega_j + \omega_{us} + \omega_i\right).$$

Expression (9) highlights that keeping the prices of other competitors fixed, the transmission of changes in the U.S. coarse grains price to area decisions in country i depends on competition intensity with the United States, and also on whether such competition takes place in the domestic or international markets. In contrast, equation (3) postulates a unique channel of transmission between the U.S. price and the area decisions.

The empirical model is obtained by adding to equation (3) interaction terms that combine the ω indices in equation (9) with the U.S. price. The augmented equation thus nests the IWM hypothesis within a model that allows price transmission along the lines suggested by the Armington model. Formally:

$$\begin{aligned}(10)\quad \ln(A_{it}) = {} & \beta \ln(P_{us,t-1}) \\ & + \alpha_1[\omega_{it} \ln(P_{us,t-1})] + \alpha_2[\omega_{us,t} \\ & \times \ln(P_{us,t-1})] + \alpha_3[\omega_{jt} \ln(P_{us,t-1})] \\ & + [\mathbf{Z_{it}}, \mathbf{Z_{it\text{-}1}}]\mathbf{\Gamma} + \eta_{it},\end{aligned}$$

where β, α_1, α_2, α_3, and $\mathbf{\Gamma}$ are parameters to be estimated. The error term η_{it} is a disturbance that is further decomposed in a country-specific fixed effect (μ_i) and a remainder disturbance ε_{it} assumed to be identically and independently distributed, centered around zero, uncorrelated over time, and with constant variances. The matrices $\mathbf{Z}_{it}$ and $\mathbf{Z}_{it-1}$ contain all the covariates from the structural equations behind the empirical model (i.e., total land endowment $\bar{A}_i$, lagged area $\ln(A_{it-1})$, exogenous shifters such as temperature and precipitation, real exchange rates $\ln(RER_{it-1})$, the expansion terms from equation (8), $\theta_{iit} X_{it}$ and $\sum_{j \neq i}^{m} \theta_{ijt} X_{jt}$, and the ω indices that also capture trade costs τ_{it}.)

The null hypothesis is that geography does not matter. In other words, the IWM hypothesis is an accurate depiction of how harvested areas around the world respond to U.S. price changes. The alternative hypothesis is that geographic patterns of trade influence cultivation decisions in individual countries. Formally:

$$(11)\quad \begin{aligned} H_0 &: [\alpha_1, \alpha_2, \alpha_3] = 0 \\ H_A &: [\alpha_1, \alpha_2, \alpha_3] \neq 0. \end{aligned}$$

Data and Empirical Implementation

Table 1 presents summary statistics for all the variables used in the regressions. The dependent variable is the sum of the annual area harvested for barley, oats, maize, and sorghum for 35 countries for the period 1975–2002, sourced from the UN Food and Agriculture Organization (FAO 2009). These countries, including the United States, cover approximately 75% (average 1975–2002) of the global harvested area of coarse grains and are responsible for 90% of global exports (of which almost half come out of the United States), and 64% of global imports (average 1975–2002).

Key variables for this study are the competition indices based on the market shares of exporters in different importing countries. From the modeling framework, two types of shares are needed. When a given country is seen as an exporter (and thus indexed by i), the relevant share is θ_{ijt}: the share of country i's exports of coarse grains to country j in country i's total coarse grains output at time t. We will refer to this share as a sales share. When the same country is seen as an importer (and thus indexed by j), the needed share is δ_{ijt}, the share of coarse grains originating in country i in the total consumption of coarse grains in country j at time t—a budget share.

In both cases, domestic sales are also considered, so we must augment the trade data with domestic consumption data in order to obtain the own-sales shares θ_{iit} and own-budget shares δ_{jjt}. The production and consumption data come from FAO (2009), and the bilateral trade data come from Gehlhar (2005). Additional details about the procedures and sources used

Table 1. Descriptive Statistics

	Mean	Std.Dev.	Min	Q1	Median	Q3	Max
Area (mill ha)	3.96	7.28	0.03	0.49	1.52	4.27	43.88
Temperature (C)	19.06	5.55	5.70	16.13	19.97	23.08	28.05
Precipitation (ml)	91.53	78.39	0.00	28.44	69.65	138.78	420.72
GDP (billion 2000 US$)	282.10	653.09	2.12	31.13	89.40	263.22	4680.00
U.S. price (index)	0.95	0.16	0.63	0.84	0.94	1.00	1.46
ω_i	0.05	0.12	0.00	0.00	0.00	0.03	0.86
ω_{us}	0.00	0.01	0.00	0.00	0.00	0.00	0.12
ω_j	0.01	0.04	0.00	0.00	0.00	0.00	0.41

Note: Q1 and Q3 are the first and third quartiles of the distribution of each variable. The terms ω are competition indices between any country i in the sample and the United States in country i's own market, the United States market, or in third markets (j).

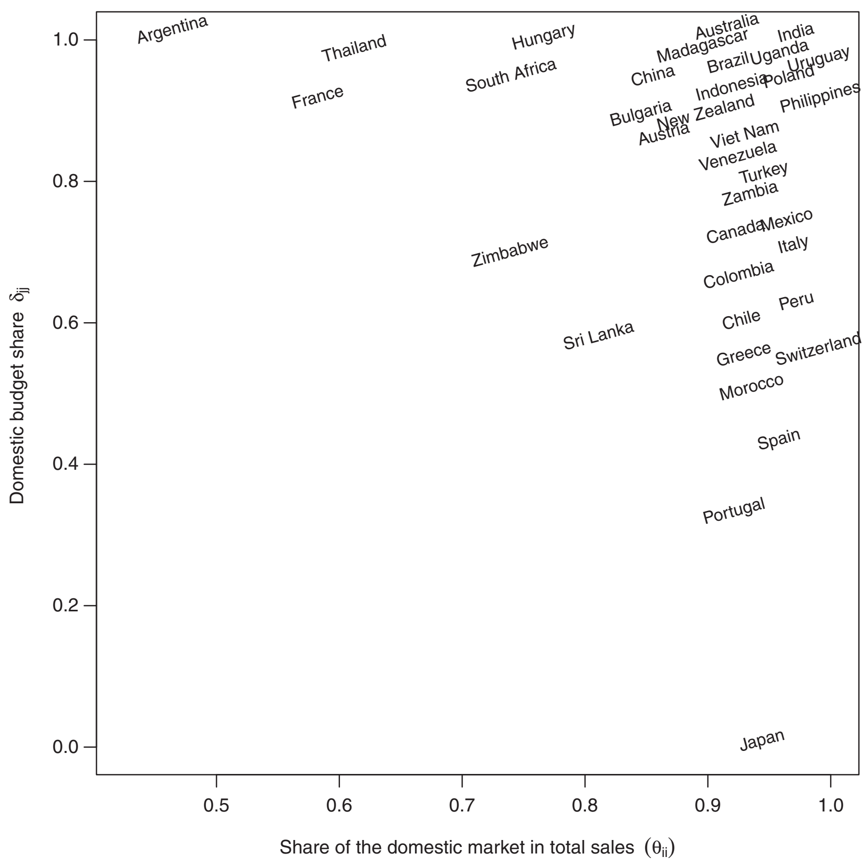

Figure 1. Domestic budget and sales shares, average 1975–2002

to build these shares and the competition indices discussed below are reported in the online supplementary materials. Figure 1 plots the domestic budget shares θ_{ii} (horizontal axis) against the domestic sales shares δ_{jj}. In the upper left corner is Argentina, whose domestic needs are largely satisfied by domestic output, but for which the domestic market is just a small fraction of total sales. In the opposite corner (bottom right) of figure 1 is Japan. This country has a very large demand for coarse grains relative to production. At the upper right corner, we find countries that are largely self-sufficient, such as India.

The market shares just described are used to calculate the competition indices between a given country i with the United States in third markets (ω_{jt}), in country i's own market (ω_{it}),

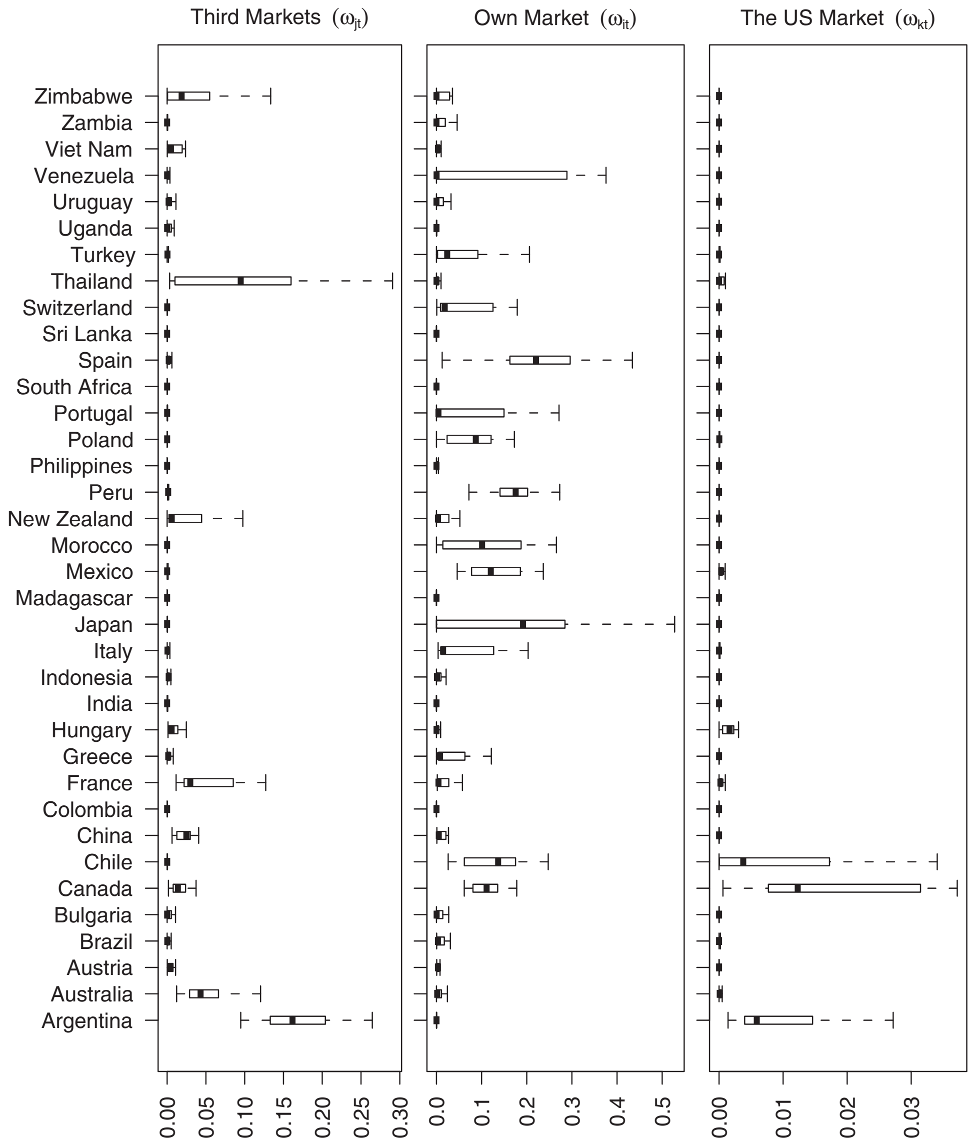

Figure 2. Competition of the sample countries with the U.S. in third markets, in their own markets, and in the U.S. market, period 1975–2002

and in the U.S. market (ω_{kt}). These variables are bounded by $[0, 1]$, as they are the product of two shares which are themselves bounded by 0 and 1. The competition indices are displayed in the three panels of figure 2, which show for each country a box plot describing the temporal distribution of the three types of competition indices. Each boxplot summarizes five statistics: maximum and minimum values (vertical bars at the extremes of the whiskers), first and third quartiles (left and right bounds of the box), and the median (thick bar within the box).

The leftmost panel of figure 2 shows that only a few countries compete intensively with the United States in third markets. These include (judging by the median values) Argentina, Thailand, Zimbabwe, Australia, France, and Germany. The second panel gives similar information, but this time the interest is in competition with U.S. imports in each country's own market. Based on median values of this index, Japan's domestic coarse grains producers face the highest competition of imports from the United States. Finally, the third panel (rightmost) shows competition with the United

States in the U.S. market. This factor is only important for Canada, Argentina, and Chile, and even then, the value of the index is low. The time variation of the indices is a potential source of endogeneity (current market shares may influence land decisions); thus, in the estimation, one-year lags of a three-year moving average are used.

Another potential source of endogeneity bias is the presence of a lagged dependent variable on the right-hand side of equation (10). This is because the dependent variable A_{it} is itself a function of $\eta_{it} = \mu_i + \varepsilon_{it}$, where μ_i is a country-specific fixed effect. As μ_i does not change over time, the lagged area term A_{it-1} is also a function of μ_i, thus inducing a correlation between A_{it-1} and η_{it}. Using a fixed-effect estimator alleviates this problem by explicitly controlling for μ_i. However, the underlying fixed-effect (i.e., within) transformation is based on the differences in A_{it-1} and ε_{it} from their respective means. In calculating the mean value, $\varepsilon_{i.}$, ε_{it-1} is used, and thus, by construction, A_{it-1} is correlated with $\varepsilon_{i.}$ Nickell (1981). The bias induced by the correlation between A_{it-1} and $\varepsilon_{i.}$ decreases with the time dimension of the dataset. Our panel consists of 36 countries during 1975–2002 with observations ranging from 8 years (in 1 country) to 28 years (in 29 countries) due to missing values of the real exchange rate; thus, it is sensible to assume the time dimension of the panel to be fixed. To deal with this potential bias, several suggestions have been offered (Baltagi 2008, pp.147–148). Our method of choice is a bootstrap correction due to Everaert and Pozzi (2007). This is because, with the small sample in both the time-series and cross-sectional dimensions, the bootstrap correction satisfactorily approximates the analytical corrections, and as shown in the Monte Carlo experiments of Everaert and Pozzi (2007), it is more efficient than commonly used generalized method of moments estimators.

To control for differences in total land endowment, we include country-specific fixed effects. These also capture cross-country differences in agricultural policies that are relatively sluggish over time. The U.S. price index is constructed using export prices and export quantities obtained from USDA (2009); weather is controlled for by including country-specific mean temperature (TMP_{it}), and precipitation (PRE_{it}) is sourced from Mitchell and Jones (2005) for globally defined growing seasons (Lobell and Field 2007); changes in demand are considered by including the GDP of both exporters and importers. Following the Armington specification in equation (8), the own and partner GDPs are weighted by revenue and bilateral market shares, respectively. The GDP and exchange rates used to construct the real exchange rates come from the World Bank (2009) and Heston, Summers, and Aten (2006). The reader can find more details about the data sources and procedures in the supplementary online materials.

The final equation to be estimated takes the following form:

$$
\begin{aligned}
(12)\quad \ln(A_{it}) = {} & \mu_i + \gamma_0 \ln(A_{it-1}) + \beta \ln(P_{us,t-1}) \\
& + \alpha_1[\omega_{it-1}^{3-yr-ma} \ln(P_{us,t-1})] \\
& + \alpha_2[\omega_{us,t-1}^{3-yr-ma} \ln(P_{us,t-1})] \\
& + \alpha_3[\omega_{jt-1}^{3-yr-ma} \ln(P_{us,t-1})] \\
& + \gamma_1 \ln(TMP_{it}) + \gamma_2 \ln(PRE_{it}) \\
& + \gamma_3 \theta_{iit-1} \ln GDP_{it-1} \\
& + \gamma_4 \sum_{j \neq i}^{m} \theta_{ijt-1} \ln GDP_{jt-1} \\
& + \gamma_5 \ln RER_{it-1} + \gamma_6 \omega_{it-1}^{3-yr-ma} \\
& + \gamma_7 \omega_{us,t-1}^{3-yr-ma} + \gamma_8 \omega_{jt-1}^{3-yr-ma} \\
& + \varepsilon_{it}.
\end{aligned}
$$

Results and Discussion

To test the null hypothesis (that the geography of trade does not matter for production decisions), the restrictions $\alpha_1 = \alpha_2 = \alpha_3 = 0$ are imposed on equation (12). Then, both the restricted and unrestricted models are estimated using least squares with country-specific dummy variables (LSDV estimation), and a Lagrange multiplier (LM) test is used to compare them. The estimates of the restricted model, along with traditional standard errors, are shown in the first column of table 2 under the heading IWM.

The traditional standard errors assume that the regression residuals have a constant variance (within and across countries) and are serially uncorrelated. In general, homoskedasticity is rejected at the 1% significance level, while the null hypothesis of non-autocorrelation cannot be rejected (with the exceptions of models A and D, which will be discussed shortly). In principle, it would make sense to fix the standard errors to be robust to the presence of heteroskedasticity. However, in panels

Table 2. Regression Results

Variable, Parameter	IWM	A	B	C	D
$\ln(A_{it-1})\ \gamma_0$	0.786	0.783	0.783	0.788	0.784
	(0.021)**	(0.021)**	(0.021)**	(0.021)**	(0.021)**
$\ln(TMP_{it}), \gamma_1$	−0.115	−0.097	−0.090	−0.117	−0.120
	(0.082)	(0.083)	(0.083)	(0.082)	(0.082)
$\ln(PRE_{it}), \gamma_2$	0.015	0.016	0.015	0.015	0.016
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$\theta_{iit-1} \ln GDP_{it-1}, \gamma_3$	−0.026	−0.025	−0.026	−0.026	−0.025
	(0.010)*	(0.012)*	(0.010)**	(0.010)*	(0.012)*
$\sum_{j\neq i}^{m} \theta_{ijt-1} \ln GDP_{j,t-1}, \gamma_4$	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*
$\ln RER_{it-1}, \gamma_5$	0.009	0.008	0.007	0.009	0.009
	(0.005)*	(0.005)	(0.005)	(0.005)*	(0.005)*
$\ln(P_{us,t-1}), \beta$	0.044	0.018	0.048	0.033	0.025
	(0.020)*	(0.026)	(0.024)*	(0.021)	(0.022)
$\omega_{it-1}^{3-yr-ma}, \gamma_6$		0.001	0.001		
		(0.001)*	(0.001)*		
$\omega_{us,t-1}^{3-yr-ma}, \gamma_7$		0.008		0.008	
		(0.010)		(0.010)	
$\omega_{jt-1}^{3-yr-ma}, \gamma_8$		0.001			0.001
		(0.002)			(0.002)
$\omega_{it-1}^{3-yr-ma} \ln(P_{us,t-1}), \alpha_1$		−0.001	−0.001		
		(0.002)	(0.002)		
$\omega_{us,t-1}^{3-yr-ma} \ln(P_{us,t-1}), \alpha_2$		0.059		0.066	
		(0.033)*		(0.033)*	
$\omega_{jt-1}^{3-yr-ma} \ln(P_{us,t-1}), \alpha_3$		0.011			0.012
		(0.005)*			(0.005)*
SSR	8.463	8.330	8.423	8.418	8.404
Adj R^2	0.656	0.659	0.657	0.657	0.657
Log likelihood	814.511	821.574	816.601	816.894	817.637
VIF of β	1.016	1.286	1.174	1.047	1.092
LM test (p-values)	0.000	0.029	0.124	0.093	0.044
LR test (p-values)	1.000	0.028	0.124	0.092	0.044

Note: The dependent variable is the log of annual area harvested of coarse grains in each country (FAO 2009). Regressions based on 894 observations. Information is for 36 countries, of which 29 countries have information for 28 years (1975–2002). The distribution of available years is as follows (countries, years): (29,28), (1,23), (1,21), (2,18), (1,17), (1,13), and (1,8). Traditional standard errors are underneath each parameter estimate. Also shown are the variance inflation factors (VIFs) of the U.S. price coefficients. The last two rows show the probability (p-values) of not rejecting the null hypotheses that the omitted terms in the "Base" model, but present in models A to D, add no explanatory power to the former equation. ** $p \leq 0.01$, * $p \leq 0.10$.

with fixed T and large N, the conventional White estimator is inconsistent (Stock and Watson 2008), so it is advised to use errors that are robust to both heteroskedasticity and serial autocorrelation. Interestingly, in many of these regressions, these robust errors tend to overstate the degree of significance of the parameter estimates relative to their traditional counterparts, perhaps because of small-sample bias. This is particularly worrying in the case of the unrestricted model A, for which the robust errors of $\hat{\alpha}_2$ and $\hat{\alpha}_3$ are less than half the traditional ones. In the case of $\hat{\alpha}_2$, the robust standard errors make the coefficient appear statistically significant. It is preferable to err on the conservative side of less significance, so we present only the traditional standard errors and refer the reader to the supplementary online materials for details on the regression diagnostics.

In table 2, the coefficient of the lagged area term ($\hat{\gamma}_0$) is large and highly significant, evidencing the persistence of harvested areas over time. The coefficient on temperature ($\hat{\gamma}_1$) is negative and large, but the precision of the estimate is low. The coefficient on precipitation ($\hat{\gamma}_2$) is small and insignificant. The terms associated with country size—own GDP weighted by output consumed at home and the revenue share weighted average of the GDPs of the trading partners—are significant and negative. A possible explanation for this is that the income variables are acting as trend variables, thus capturing the downward trend of global harvested areas as yields trend higher (see Bruinsma 2009 for evidence of global production trends). In line with expectations, a depreciation of the real exchange rate ($\hat{\gamma}_5$) has a positive effect on output (doubling the real exchange rate leads to ~1% increase in harvested area). The elasticity of area with respect to the U.S. price, $\hat{\beta}$, is statistically significant and of reasonable size. With a value of 0.044, this elasticity implies that if the U.S. price were to double, areas harvested in non-U.S. regions would increase by 4.4%.

The next column shows the unrestricted model labeled "A." The models under IWM and A are similar, with two important exceptions. First, the coefficient on the real exchange rate loses its significance in model A due to a slight reduction in the size of the estimate. More importantly, the coefficient on the U.S. price, $\hat{\beta}$, is no longer significant. However, the new interaction term between degree of competition overseas (ω_j) and the U.S. price is highly significant. This suggests that a price increase in the United States will affect areas harvested by the proportion $0.011 \times \omega_{j,t-1}^{3-yr-ma}$, and thus, the size of the national elasticity is contingent on the importance of the output of country *i* exposed to markets where the United States is an important supplier.

To investigate whether model A explains the temporal cross-country variability of area harvested better than the IWM model, we use an LM test (Wooldridge 2002, p. 186). The null hypothesis is that the excluded parameters, α_1, α_2, α_3, and the parameters on the ω terms, are uncorrelated with the residuals of the restricted model; if they were, the restricted parameter estimates would be inconsistent. The penultimate row in table 2 ("LM test") shows the probability (p-values) of rejecting this null hypothesis given that the excluded restrictions are indeed zero. This probability is 2.9% in the comparison of models A and IWM, so the null hypothesis of the LM test is rejected at the 5% level of significance. In other words, the inclusion of the interaction terms represents a model improvement relative to the IWM model.

Before further exploring what is driving the apparent superiority of model A over the IWM model, we assess how severe is the so-called Nickell bias mentioned before. As indicated, we use a bootstrap correction due to Everaert and Pozzi (2007). The results for the restricted (IWM) and unrestricted (Armington) models—available to the interested reader in the supplementary online materials—yield three general conclusions. First, the LSDV parameter $\hat{\gamma}_0$ is severely biased downward in both models. Second, the rest of the parameter estimates are virtually identical. Third, the pattern of significance based on the bootstrap sample confirms the pattern of significance observed using traditional standard errors (as opposed to the robust ones), thus supporting the earlier decision to use them as the basis for inference.

The most consequential finding of the bootstrap correction relates to the estimation of long-run elasticities, $(1-\gamma_0)^{-1}\beta$ for the IWM model or its counterpart for the Armington model, which will be biased if the LSDV estimates are employed in their calculation. Pesaran and Zhao (1998) point out that simply using the bootstrap corrected parameter will not solve the problem due to the nonlinearities involved in the long-run elasticity. They compare four different methods, including a bootstrap correction, and conclude that "none of the estimators seem to be effective when the coefficient of the lagged dependent variable is around 0.8." Due to this limitation, this article will not pursue the calculation of long-run elasticities. Moreover, due to the similarity between the bootstrap-corrected and the LSDV estimates, the rest of the discussion will continue focusing on the latter.

A puzzling feature of model A, as presented in table 2, is that, although the addition of the interaction terms is an improvement over the restricted model, the exclusion restrictions—with parameters $\hat{\gamma}_7$, $\hat{\gamma}_8$, $\hat{\alpha}_1$, and $\hat{\alpha}_2$—are statistically no different from zero. To investigate whether they are zero because of interactions with the other price terms or simply because they do not add any additional explanatory power to the restricted model, columns B, C, and D report regressions keeping one price interaction at a time. As before, table 2 shows LM and likelihood ratio (LR) tests for the pairwise comparison of the IWM model against these alternative models. This exercise gives evidence that neither competition in country *i*'s own market (model B including ω_i and its interaction with the U.S. price) nor competition in the U.S. market (model C including ω_{us} interacting with the U.S. price) improve the IWM formulation (with a p-value of 0.085, the LM test rejects the IWM model only marginally in the case of model B). In contrast, model D, which retains competition in third markets, reiterates the significance of the interaction term and also rejects, albeit in a weaker fashion than model A, the IWM model.

The fact that $\hat{\beta}$ is statistically insignificant in model A prompts the question of whether this is because of multicollinearity with the interaction terms. To investigate this possibility, table 2 (bottom) shows the variance inflation factors (VIFs) of $\hat{\beta}$ for all the estimated models. The VIF indicates the proportion by which the variance of $\hat{\beta}$ is inflated due to the addition of the exclusion restrictions. In model IWM, the VIF is 1.016, indicating that there are no other variables collinear with the U.S. price term. When all the exclusion restrictions are added, the VIF jumps to 1.286, and as noted before, $\hat{\beta}$ loses its significance. This is a relatively low VIF. If, for example, the standard error of $\hat{\beta}$ in model A were reduced by 30%, the parameter estimate would still not be significant. In model B, the VIF reduces to 1.174, and $\hat{\beta}$ regains its significance. In model D, the VIF is even lower (1.09), and $\hat{\beta}$ is once again insignificant. This seems to reinforce the notion that in these regressions, higher VIFs are disconnected from the significance of $\hat{\beta}$.

The results discussed thus far suggest that only a reduced number of countries truly compete with the United States in the global coarse grains market. The online supplementary materials report the results of a robustness test in which the restricted and unrestricted model are estimated by dropping one country at a time. It was found that the parameter values were virtually unchanged. This robustness check also involves redoing the LM test in the absence of individual countries. Here, we reject the IWM model in favor of the Armington specification in all cases, except for the case where Argentina is dropped. This is not surprising given the large degree of competition between Argentina and the United States in third markets.

The Aggregation Problem

An important question is whether the results discussed above are an artifact of aggregating heterogeneous crops such as barley, oats, maize, and sorghum into a coarse grains composite. If the composition of the exported bundle varies across countries, and these crops are not perfect substitutes in production or consumption, importers will appear to differentiate their demands for the composite by national origin due to differences in the composition of the aggregate. This could explain why the Armington model fits the data better than the IWM model.

To explore whether this is the case, we estimated the restricted and unrestricted models using harvested areas of maize, competition indices based solely on maize trade (from Gehlhar 2005), and U.S. prices for corn (USDA 2009). Of course, using maize does not entirely solve the problem of aggregation, as different qualities or varieties of maize may also be functionally distinct. Nevertheless, this is the narrowest definition for which data on bilateral trade with comprehensive country and time coverage (i.e., UN #Comtrade) are available.

The IWM model performs poorly on the maize-only dataset, with $\hat{\beta} = 0.038$ and $p = 0.1242$. However, in the Armington formulation, α_3, the parameter on the degree of competition between a given exporter and the U.S. in third markets is significant at conventional levels ($\alpha_3 = 0.08$ with $p = 0.03$). Hence, the maize-only model supports the notion that the country-level elasticity of area to changes in the U.S. price depends on the degree of exposure to competition with the United States.

It is surprising to find support for the IWM hypothesis in coarse grains but not in a more disaggregated product such as maize.[7] However, the U.S. prices of maize and of the coarse grains composite are practically indistinguishable (see supplementary online materials for more details). Therefore, the main difference between the maize and coarse grains models is the dependent variable, harvested area. A likely explanation of the weaker evidence for the IWM model when using maize only, as opposed to the coarse grains aggregate, relates to the broader range of countries growing coarse grains. To the extent that the individual coarse grains crops are close substitutes in consumption and production (as evidenced by the high correlation in prices mentioned above), what responds to changes in the U.S. price is the coarse grains area as a whole, not just the maize area.

Without a more complete model that considers supply, demand, and cross price elasticities of the individual coarse grains, it is impossible to disentangle the responsiveness of individual crops to U.S. prices. Such a model is well beyond the scope of this paper and, given

[7] Thursby, Johnson, and Grennes (1986) and Abbott, Paarlberg, and Patterson (1988) compared observed and simulated bilateral trade data for wheat, a product perhaps more narrowly defined than maize, and found no support for the IWM hypothesis.

current data availability, it would appear to be infeasible in an econometric cross-country setting. In contrast, by focusing on the coarse grains aggregate, we can capture broad changes in the harvested area of products that are close substitutes in production and consumption, albeit subject to the aggregation concerns raised above.

Implications for Land Use Changes and Emissions from Biofuels

Are the differences in the prediction of harvested areas, at the national and global levels, large enough to matter? More specifically, do they have consequences for the estimates of the iLUC-induced GHG emissions? We address these questions here.

One approach to answering the questions of significance would be to compare historical changes over the recent biofuels boom period to predictions based on a model excluding the biofuels effect. However, to do so would entail decomposing the price impact of biofuels from that of all the other forces at work over this period, including weather, economic growth, etc. As Abbott, Hurt, and Tyner (2008) suggest, this is a daunting task. Instead, we choose to focus on a natural experiment which occurred in 1993 and which rivals the impact of biofuels in magnitude. Specifically, Babcock (2007) reports that the year 1993 was a year of excess rain and limited heat. As a consequence, corn production in the United States fell significantly. According to USDA data from 1992 to 1993, area harvested for coarse grains fell by 14% (−5.46 million hectares); production of coarse grains fell by 32% (corn output fell from 9,476.7 to 6,337.7 million bushel—240 to 160 million metric tons [MT]); exports of coarse grains fell by 22% (corn exports decreased from 1,663.28 to 1328.32 million bushel—41.58 to 33.21 million MT); and the coarse grains index price increased by 15%. This shock to U.S. coarse grains excess supplies to the world market is comparable in size to that induced by recent U.S. biofuels expansion (Allen and Lutman 2009).

To appreciate the effect of a 15% increase in the U.S. price from 1992 to 1993, we use the data values of 1994. Recall that producers in our model base their planting decisions on one year lagged prices. So in our model, the effects of a price shock in 1993 are realized only in 1994. For each model, we predict two sets of harvested areas by country. The first set of predictions uses the data as observed and thus captures the price increase from 1992 to 1993. The second set of predictions presents a counterfactual solution in which the U.S. price does not change between 1992 and 1993. For each country and model, the difference between these two predictions provides an estimate of how much additional area is incorporated by a 15% increase in the U.S. price, relative to a scenario in which the U.S. price does not change. Because these values are based on model predictions, they inherit the uncertainty attached to the underlying estimated parameters. We take account of this uncertainty by bootstrapping confidence intervals around the land use predictions. These confidence intervals, in turn, allow us to examine whether the mean values of the two sets of predictions are statistically distinct.

Figure 3 plots the area predictions for the estimated IWM and Armington models. The countries are sorted by the predicted changes in area. Dots are used to represents the mean prediction of the IWM model, while squares are used for the Armington model. The line segments depict the 95% confidence interval. If the confidence intervals of the two models do not overlap, we conclude that the models have statistically different predictions. Three conclusions can be drawn from figure 3. First, for 22 of the 35 countries, we find no significant difference between the predictions from the IWM and the Armington models. Second, in 8 of the 13 countries where we detect significant differences, the IWM model tends to predict larger changes in area than does the Armington model. Note that these countries include India, Brazil, and Mexico, which are large countries in terms of harvested area. Conversely, for China, Canada, Argentina, and Australia, the IWM predictions are lower than in the Armington model. The latter three countries, in particular, are large exporters with high yields. These differences in the geographic pattern of response to U.S. prices could well translate into differences in global area changes, a question to which we now turn.

Summing each bootstrapped vector of predictions gives an average of 1,018,030 hectares for the IWM model and an average of 985,436 hectares for the Armington model. The confidence intervals around these predictions reveal that they are not statistically different. To see how this translates into production, we combine country-level yields (index for coarse grains taken from FAO) with the predicted harvested areas. The IWM predicts 2.66 million MT, while the Armington model

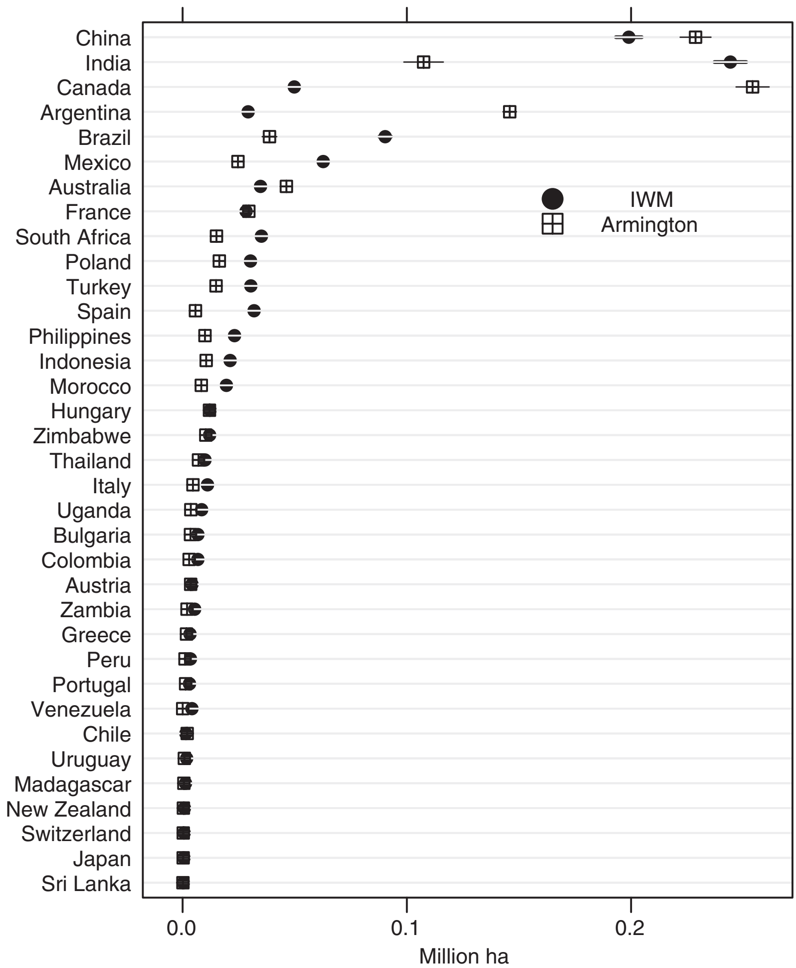

Figure 3. Bootstrapped confidence intervals (95%) for the differences between the mean changes in harvested areas predicted by the IWM and the Armington models, by country

predicts 3.16 million MT; this time, these means are statistically different. This suggests that, for the same amount of land, the Armington model predicts a larger quantity produced. Intuitively, if yields were randomly distributed across countries, we should expect no differences in total production. However, because the countries that are more productive are also the ones that are more exposed to U.S. prices in international markets, the Armington model predicts significantly larger changes in production for a given U.S. price shock. Alternatively, this implies that, for a given reduction in U.S. supplies to the world market, fewer areas in the rest of the world must be converted to "fill the gap."

Finally, we use carbon dioxide equivalent (CO_2e) estimates for the biomass in forests, savannas, and grassland from Dumortier and Hayes (2009) to estimate the GHG emissions from land use change. Assuming that expanded coarse grains area translates into expansion in total cropland,[8] we combine these emissions with the country-level area predictions to obtain average emissions. These GHG releases due to land use change amount to 506 $MTCO_2$e/ha (metric tons of carbon dioxide equivalent per hectare) under the IWM model and 216 $MTCO_2$e/ha under the Armington model (as in the case of production, these averages are statistically different). Thus, for roughly the same area expansion, the IWM model predicts more than twice the level of

[8] The assumption that the new coarse grains area comes from unused lands is a simplification that likely overstates the size of potential GHG emissions from land use change.

emissions predicted by the Armington formulation. This is due to the fact that countries more exposed to competition with the United States, and therefore, more responsive to U.S. supply shocks, tend to have higher yields and lower average GHG emission factors. This finding underscores the point that the international trade specification used for global carbon lifecycle analysis of policies with global production effects has a critical effect on the size of the obtained GHG emission estimates.

Conclusions

The analysis of indirect land use change owing to biofuels programs in the United States and Europe has become an important policy issue generating significant demand for agricultural economic analysis. Large-scale economic models have been used for this task; however, such models have resulted in widely differing predictions of where the land-use changes will occur, partly because of differences in the treatment of the interaction between bilateral trade and supply behavior. This article investigates which of the two competing views of global agricultural trade—IWM vs. product differentiation by place of origin—has better grounding in the historical data.

We use a reduced form land demand equation that nests the two pricing mechanisms, characterizing the aforementioned trade assumptions. The focus is on changes in the harvested areas of coarse grains triggered by changes in the U.S. price of these products. We derive competition indices that combine the share of a country's output in a given market with the importance of the United States as a supplier of that market. Using data for a cross section of countries representative of global production and trade covering the period 1975–2002, we reject the IWM model in favor of the Armington model. Our main results are robust to correction of the bias generated by the presence of a lagged dependent variable, to potential multicollinearity of price terms, and to variation in the countries included in the sample.

The dominance of the differentiated products model has important consequences for the global distribution of land area response following a shock to the U.S. coarse grains price. Predictions using the parameter estimates of the two competing models show that allowing competition in third markets leads to dramatic differences in the predictions of area changes, especially for the largest producers of the world. Moreover, the results highlight that by taking competition into account, the total estimates of production, land conversion, and GHG emissions of the two models are quite different due to differences in productivity and emission factors across countries. Our results support the notion that the geography of trade is an important factor explaining the global distribution of agricultural production and global GHG emissions responses to national biofuels programs.

References

Abbott, P., C. Hurt, and W. Tyner. 2008. What's Driving Food Prices? Issue Report. The Farm Foundation, Oak Brook, IL, July.

Abbott, P. C., P. L. Paarlberg, and P. M. Patterson. 1988. Supplier Substitutability by Importers: Implications for Assessing the 1980 U.S. Grain Embargo. *Southern Journal of Agricultural Economics* 20(2): 1–14.

Allen, E., and H. Lutman. 2009. ERS USDA Briefing Room—Corn: Trade. http://www.ers.usda.gov/Briefing/corn/trade.htm. (accessed August 8, 2009).

American Coalition for Ethanol. 2009. Statement on House Agreement Calling for Scientific Review Before EPA Imposes International Land Use Effects on Biofuels. Press Release. http://www.ethanol.org. (accessed June 24, 2009).

Armington, P. S. 1969. A Theory of Demand for Products Distinguished by Place of Production. *Staff Papers - International Monetary Fund* 16(1): 159–178.

Babcock, B. 2007. Corn Shortfalls: Historical Patterns and Expectations. Center for Agricultural and Rural Development, Iowa Ag Review, Vol.7-2, Iowa State University, Ames, IA.

Baltagi, B. H. 2008. *Econometric Analysis of Panel Data*, 4th ed. New York: John Wiley.

Bruinsma, J. 2009. The Resource Outlook to 2050. By How Much Do Land, Water Use and Crop Yields Need to Increase by 2050? Paper presented at FAO Expert Meeting on How to Feed the World in 2050. Rome, Italy, 24-26 June.

Chavas, J., and M. T. Holt. 1990. Acreage Decisions Under Risk: The Case of

Corn and Soybeans. *American Journal of Agricultural Economics* 72(3): 529–538.

Chavas, J., R. D. Pope, and R. S. Kao. 1983. An Analysis of the Role of Futures Prices, Cash Prices and Government Programs in Acreage Response. *Western Journal of Agricultural Economics* 8(01): 27–33.

Dumortier, J., and D. J. Hayes. 2009. Towards an Integrated Global Agricultural Greenhouse Gas Model: Greenhouse Gases from Agriculture Simulation Model (GreenAgSiM). Working Paper 09-WP 490, Center for Agricultural and Rural Development, Iowa State University, Ames, May.

Everaert, G., and L. Pozzi. 2007. Bootstrap-Based Bias Correction for Dynamic Panels. *Journal of Economic Dynamics and Control* 31(4): 1160–1184.

Fabiosa, J. F., J. C. Beghin, F. Dong, A. Elobeid, S. Tokgoz, and T. E. Yu. 2008. Land Allocation Effects of the Global Ethanol Surge: Predictions from the International FAPRI Model. Working Paper 08005, Department of Economics, Iowa State University, Ames, IA, March.

FAO 2009. FAOSTAT. http://faostat.fao.org/.

Gardner, B. L. 1976. Futures Prices in Supply Analysis. *American Journal of Agricultural Economics* 58(1): 81–84.

Gehlhar, M. 2005. Reconciling Merchandise Trade Data. In Betina Dimaranan, ed. *Global Trade, Assistance, and Production: The GTAP 6 Data Base*, chapter 15-B. GTAP Center, Purdue University, West Lafayette, IN, pp. 1-11.

Grennes, T., P. R. Johnson, and M. Thursby. 1978. Insulating Trade Policies, Inventories, and Wheat Price Stability. *American Journal of Agricultural Economics* 60(1): 132–134.

Hertel, T., A. Golub, A. Jones, M. O'Hare, R. Plevin, and D. Kammen. 2010. Global Land Use and Greenhouse Gas Emissions Impacts of U.S. Maize Ethanol: The Role of Market-Mediated Responses. *BioScience* 60(3): 223–231.

Hertel, T., D. Hummels, M. Ivanic, and R. Keeney. 2007. How Confident Can We Be of CGE-based Assessments of Free Trade Agreements? *Economic Modelling* 24(4): 611–635.

Heston, A., R. Summers, and B. Aten. 2006. Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania. http://pwt.econ.upenn.edu/php_site/pwt_in. (accessed August 14, 2009).

Hillberry, R. H., M. A. Anderson, E. J. Balistreri, and A. K. Fox. 2005. Taste Parameters as Model Residuals: Assessing the "Fit" of an Armington Trade Model. *Review of International Economics* 13(5): 973–984.

Johnson, P. R., T. Grennes, and M. Thursby. 1979. Trade Models with Differentiated Products. *American Journal of Agricultural Economics* 61(1): 120–127.

Keeney, R., and T. W. Hertel. 2009. The Indirect Land Use Impacts of United States Biofuel Policies: The Importance of Acreage, Yield, and Bilateral Trade Responses. *American Journal of Agricultural Economics* 91(4): 895–909.

Lobell, D., and C. Field. 2007. Global Scale Climate-Crop Yield Relationships and the Impacts of Recent Warming. *Environmental Research Letters* 2(1): 1–7.

McCarl, B. A. 2009. Estimating the Intensive and Extensive Margins of Crop Land Yields in the United States. Presented at AAEA/AERE Annual Meeting. Milwaukee, Wisconsin, 25–28 July.

Mitchell, T. D., and P. D. Jones. 2005. An Improved Method of Constructing a Database of Monthly Climate Observations and Associated High-Resolution Grids. *International Journal of Climatology* 25(6): 693–712.

Mundlak, Y., and D. F. Larson. 1992. On the Transmission of World Agricultural Prices. *World Bank Economic Review* 6(3): 399–422.

Nelson, G. C., M. W. Rosegrant, J. Koo, R. Robertson, T. Sulser, T. Zhu, C. Ringler, S. Msangi, A. Palazzo, M. Batka, M. Magalhaes, R. Valmonte-Santos, M. Ewing, and D. Lee. 2009. *Climate Change: Impact on Agriculture and Costs of Adaptation*. Food Policy Report 21, International Food Policy Research Institute, Washington, DC.

Nickell, S. 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica* 49(6): 1417–1426.

Pesaran, M. H., and Z. Zhao. 1998. Bias Reduction in Estimating Long-run Relationships from Dynamic Heterogenous Panels. In *C. Hsiao, K. Lahiri, L. Lee and H. Pesaran, Editors, Analysis of Panels and Limited Dependent Variables: A Volume in Honour* *of G.S. Maddala*, ed. C. Hsiao, K. Lahiri, L. Lee and H. Pesaran, 297–321. Cambridge: University Press.

Richardson, J. D. 1978. Some Empirical Evidence on Commodity Arbitrage and the Law of One Price. *Journal of International Economics* 8(2): 341–351.

Searchinger, T., R. Heimlich, R. A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T. Yu. 2008. Use of U.S. Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change. *Science* 319(5867): 1238–1240.

Shumway, C. R., R. D. Pope, and E. K. Nash. 1984. Allocatable Fixed Inputs and Jointness in Agricultural Production: Implications for Economic Modeling. *American Journal of Agricultural Economics* 66(1): 72.

Stock, J. H., and M. W. Watson. 2008. Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression. *Econometrica* 76(1): 155–174.

Thursby, M. C., P. R. Johnson, and T. J. Grennes. 1986. The Law of One Price and the Modelling of Disaggregated Trade Flows. *Economic Modelling* 3(4): 293–302.

USDA 2009. ERS/USDA Data—Feed Grains Database. http://www.ers.usda.gov/data/. (accessed August 14, 2009).

Wang, M., and Z. Haq. 2008. Ethanol's Effects on Greenhouse Gas Emissions (E-letter to Searchinger et al.). http://www.sciencemag.org/cgi/eletters/319/5867/123. (accessed August 14, 2009).

Westhoff, P. 2010. Impacts of Climate Change Legislation on US Agricultural Markets: Sources of Uncertainty. FAPRI-MU Report 06-10, Food and Agricultural Policy Research Institute, University of Missouri, Columbia, MO, July.

Wooldridge, J. M. 2002. *Introductory Econometrics: A Modern Approach*. Mason, OH: Thomson South-Western.

World Bank 2009. World Development Indicators Online. http://go.worldbank.org/6HAY. (accessed August 14, 2009).