We estimate the effects of agricultural technological progress on cropland expansion at various geographical resolutions, from the country level to the world as a whole, while formally accounting for the international interdependence of national supply responses. Evidence for these effects has thus far been scant, contributing to polarized perceptions about the potential for improving agricultural technologies as a means to slow down deforestation. We find that, in most countries of the world, growth in total factor productivity (TFP) is either uncorrelated or is positively associated with cropland expansion. Yet worldwide TFP growth have been an important source of global land savings. The divergence between the country-level and the global results is explained by the changes in production patterns as countries interact in international markets. Our preferred point estimate of the elasticity of global cropland to global TFP growth is -0.34. Moreover, we estimate that satisfying food demand from 1991 to 2010 without observed TFP growth would have necessitated an additional 173 million hectares, or close to 10% of the area covered by tropical rain forests.

Key words: Agricultural technology, deforestation, global agriculture, land use change, international trade, total factor productivity.

JEL codes: Q15, Q16, Q24, Q56.

Technological progress is a central component of any viable strategy to increase the supply of agricultural goods while improving the sustainability of the world food system (Godfray et al. 2010; Tilman et al. 2011). Technological progress has the potential to reduce or slow down deforestation by decreasing the land needed to produce a given amount of agricultural goods. Yet, as we discuss below, under some circumstances technological progress can actually accelerate deforestation (Angelsen et al. 2001; Hertel, Ramankutty, and Baldos 2014). Such seemingly contradictory effects have given rise to skepticism about the desirability of investments in agricultural research and development (R&D) as a way of decreasing the land use footprint of agriculture (Rudel et al. 2009; Ewers et al. 2009; Phelps et al. 2013; Carrasco et al. 2014).

Conceptually, the effects of technological progress on land use are well understood. Technological progress encourages cropland expansion only if the excess demand faced by producers is price elastic (e.g., Chavas and Helmberger 1996; Angelsen et al. 2001); when this condition is met, the extent of land expansion depends on the land scarcity as well as on the available technologies (Chavas and Helmberger 1996; Hertel, Ramankutty, and Baldos 2014). Regardless of whether technological progress leads to increased deforestation in the innovating country, the interdependence of local land use decisions as countries interact in international markets...
may result in decreased deforestation elsewhere (Hertel, Ramankutty, and Baldos 2014).

Notwithstanding the insights provided by theory, we lack solid econometric evidence on the effects of national agricultural technological progress on both domestic and foreign cropland expansion.\(^1\) To be sure, there is a rich body of empirical research on the effects of the adoption of specific technologies in the production of different commodities in different ecosystems (see Villoria, Byerlee, and Stevenson 2014, for a recent review of the literature). For the most part, these studies have found that the introduction of new technologies has not led to increased conservation of the land resources in innovating regions. There are also a number of studies that have looked at correlations between changes in yields and changes in harvested areas across countries (Barbier and Burgess, 2001; Ewers et al. 2009; Rudel et al. 2009). These studies find scant support for the notion that yield growth is associated with reductions in cropland. A difficulty facing some of these studies is the lack of a clear counterfactual against which the effects of crop yields, used as a proxy measure for technological progress, can be measured (Hertel, Ramankutty, and Baldos 2014). In sharp contrast, on a global level, the evidence indicates that most of the world’s growth in cereal output has come fundamentally from technological progress (e.g., Johnson 2000).

The objective of this article is to measure the effects of technological progress in agriculture on cropland expansion at various geographical resolutions, from the country level to the world as a whole, while formally accounting for the international interdependence of supply responses in different countries linked together by international trade. We measure technological progress using the annual growth rates in total factor productivity (TFP) estimated by Fuglie (2012) for decennial periods from 1961 to 2010. Despite various potential weaknesses regarding number index bias and other measurement issues (Alston and Pardey 2014), these data have the virtue of being comparable across a large number of countries.

The current article makes three contributions to the literature. First, it extends the conceptual framework of Villoria and Hertel (2011) by linking a country’s optimal demand for land to changes in domestic TFP as well as to foreign TFP growth. A key implication of the model developed here is that, conditional on the trade elasticity, the effect of TFP on cropland expansion depends solely on the degree to which agricultural producers in any country are exposed to international competition.

Second, we find that under current levels of international trade, in the overwhelming majority of countries in the sample, domestic TFP growth is either uncorrelated with changes in cropland or associated with cropland expansion. It is only in a few countries in developing Asia and sub-Saharan Africa that domestic TFP growth has a statistically significant land saving effect. This results from the fact that these countries are relatively insulated from world markets, so the elasticity of excess demand faced by their producers is less than one. Regardless of whether changes in TFP lead to changes in the cropland area, the increase in production from TFP growth exerts downward pressure on prices, allowing the innovating region to capture larger shares of the markets it serves. This leads to supply and area reductions in other countries that find it difficult to compete with the innovating region. For those countries where TFP growth is associated with land expansion, heightened competition results in market-mediated reductions in area elsewhere, which partially offset their own cropland expansion.

Finally, we explore the role of technology in global land use change in the context of two questions relevant for policy formulation. First, simple regression counterfactuals are used to explore the extent to which TFP growth counteracted the effects of demand growth on cropland expansion from 1991 to

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\(^1\) An expansive body of literature uses numerical partial and general equilibrium models to study the effects of technological progress on land use. In contrast to econometric studies that seek to estimate the effects of technology on land use, the theory in these models already builds in the market-mediating effects of international trade on global land use patterns. These models are useful for \textit{ex-ante} evaluation of future scenarios and policies or for understanding the drivers of historical market outcomes. As examples of the former, Baker et al. (2013) and Havlik et al. (2013) explore the implications of different plausible trajectories of TFP growth on global land use change and associated greenhouse gas emissions. As examples of the latter, studies of the Green Revolution based on partial and general equilibrium simulation models by Evenson and Rosegrant (2003) and Stevenson et al. (2013) find that TFP growth associated with the Green Revolution was a significant source of land savings. Numerical models are also employed to study the indirect land use effects of technology that originate in forest frontiers (Villoria, Byerlee, and Stevenson 2013). Villoria, Byerlee, and Stevenson (2014) offer an in-depth review of the most prominent and well-established partial and general equilibrium models used in this literature and contrast their findings with the econometric evidence on the link between technology and agricultural land use.
2010. The estimates suggest that the pattern of observed TFP growth in this time period offset much of the hypothetical cropland expansion that would have occurred in the absence of TFP growth. These results underscore the role of continued investment in agricultural R&D as a sound strategy for slowing down deforestation rates in the presence of increasing demand for agricultural goods.

Second, we explore the effects of initiatives to boost productivity in some regions of the world. Our estimates suggest that technological progress in developing Asia and sub-Saharan Africa would reduce cropland within these regions as well as in the rest of the world. In contrast, TFP growth in South America is likely to result in the expansion of the region’s cropland, although the net global effect is the reduction of global croplands. From a policy point of view, this suggests that large increases in technology in Africa and developing Asia could have payoffs, not only in terms of food security, but also in environmental protection. Yet as these regions become more integrated into the world economy the benefits associated with reduced local deforestation are likely to dissipate.

**Theoretical Framework**

There are \( N = 1, \ldots, n \) producing countries selling to \( M = 1, \ldots, m \) destination markets, including domestic markets. Unless otherwise noted, producing countries are indexed by \( i \) \((i \in N)\) and destination markets by \( j \) \((j \in M)\). Aggregate agricultural production in any given country \( i \) can be represented by a technology that combines land and a non-land input composite to produce an aggregate agricultural product, \( Q_i \). The agricultural sector in each country operates under constant returns to scale. Therefore, dual to the production technology there is a unit cost function \( C_i \) that depends on land rents, \( R_{ji} \), and the price of a non-land input composite, \( W_i \). The empirical analysis relies on decennial changes in cropland and TFP; therefore, it is natural to assume a long-run equilibrium where the non-land input price is exogenous to the agricultural sector (Hertel 1989). It is also assumed that individual producers seek to maximize profits and that this assumption carries over to the national level. Furthermore, \( Z_i \) is used to denote a region-specific efficiency factor that captures TFP and thereby affects the real cost of production. Under these assumptions, the price \( P \) of agricultural output produced by country \( i \) and delivered to destination market \( j \) can be written as:

\[
P_{ij} = \frac{C_i(R_i, W_i)}{Z_i} T_{ij}
\]

where \( T_{ij} \) are the iceberg trade costs of shipping one unit of agricultural output from origin \( i \) to destination (Eaton and Kortum 2002).

As a proxy for the unobservable TFP shifter \( Z_i \) in (1), this article uses the TFP indices estimated by Fuglie (2012). Since the data on TFP is available in terms of growth rates, it is convenient to express the relationships in this section in terms of relative changes as they naturally bridge the conceptual and empirical frameworks. In order to distinguish the variables in levels from the variables in relative changes, lowercase is used for the latter. For instance, \( z_i = dZ_i/Z_i \) and is the relative change in the TFP of the agricultural sector in country \( i \). Totally differentiating the price in equation (1) obtains the relative change in the price charged by suppliers in country \( i \) in any market \( j \):

\[
p_{ij} = (1 - \lambda_i)r_i + \lambda_i w_i - z_i + t_{ij}
\]

where \( \lambda_i \) is the share of non-land inputs in total production costs, \( r_i \) and \( w_i \) are relative changes in land and non-land input prices, \( z_i \) is the relative change in TFP, and \( t_{ij} \) is the relative change in bilateral trade costs. Notice that increases in TFP reduce supply prices across all the potential destination markets \( j \in M \); meanwhile, changes in trade costs are bilateral and only affect changes in the price of the good produced by country \( i \) in a particular destination market \( j \).

**Demand for Agricultural Output and Competition in International Markets**

Consumers maximize a sub-utility function over agricultural products that is separable from the demand for other goods. This subutility function follows Armington (1969) and has a Constant Elasticity of Substitution (CES) functional form defined over all the potential sources of agricultural products,
either domestic or foreign. Maximization of this sub-utility function subject to a budget constraint yields bilateral demands from agricultural products. After some manipulations, the linearized form of the CES compensated demands can be expressed as follows (see section SA1.1 of the online supplementary appendix for the derivations):

\[
q_{ij} = d_j - \sigma_i \left[ \sum_{k=1}^{n} \delta_{kj}(p_{ij} - p_{kj}) \right],
\]

where \(q_{ij}\) is the relative change in sales from suppliers in country \(i\) to a market \(j\) (so that when \(i=j\), expression \(3\) is domestic sales) and \(d_j\) is the relative change in demand in market \(j\), also known as the expansion effect.

The second term on the right-hand side of expression \(3\) is termed the substitution effect and is composed of the elasticity of substitution among suppliers, \(\sigma_i\); the relative change in the supply price of country \(i\) at the destination market \(j\), \(p_{ij}\), which was defined in equation \(2\); and the relative change in the supply price of a country \(k\) competing with \(i\) at the destination market \(j\), denoted by \(p_{kj}\). The terms \(\delta_{ij} = P_{ij}Q_{ij}(E_j \sum_{i=1}^{n} Q_{ij})^{-1}\) are the budget shares defined as the share of country \(j\)’s consumption budget spent on products supplied by \(i\), including expenditures on products supplied by \(j\) itself.

The substitution effect is useful to understand how any two suppliers affect each other as they compete in different markets. For instance, if the price charged by suppliers in country \(i\) increases while domestic demand and the prices charged by the other suppliers of market \(j\) remain constant (i.e., \(d_j = 0\), and \(p_{kj} = 0\) for any country \(k \neq i\)), market \(j\) would reduce its demand from supplier \(i\) in direct proportion to \(\sigma_i\), but in indirect proportion to the budget shares, \(\delta_{ij}\).

The next step is to aggregate the changes in bilateral demands to the change in overall demand facing producers in country \(i\). Summing the \(m\) bilateral equations \(3\) and rearranging terms yields the total demand for agricultural products facing producers in country \(i\) as a function of income in all the markets to which country \(i\) sells agricultural products (including their domestic market), as well as of the supply prices charged by all the suppliers that compete with country \(i\) in those markets (see SA-1.2 for the derivations):

\[
q^D_i = \sum_{j=1}^{m} \gamma_{ij}d_j - \sigma_i \left[ \sum_{k=1}^{m} \sum_{j=1}^{m} \gamma_{ij}\delta_{kj}(p_{ij} - p_{kj}) \right].
\]

In line with the previous discussion, the first and second terms on the right-hand side of equation \(4\) are the overall expansion and overall substitution effects. Equation \(4\) also introduces a new term, \(\gamma_{ij}\), which is a revenue share calculated as \(\gamma_{ij} = P_{ij}Q_{ij}(P_i \sum_{j=1}^{m} Q_{ij})^{-1}\); in other words, the revenue share is defined as the share of total revenues in country \(i\) that are obtained from the sales in market \(j\), including \(i\)’s own domestic market. In the overall expansion effect, the revenue shares determine the importance of income changes in each of the individual markets served by \(i\). In the overall substitution effect, the revenue shares determine the contribution of the substitution effect in each destination market.

**Competition in International Markets**

The sum of the products of the budget and revenue shares within the overall substitution effect in equation \(4\) is a key piece of information in our analysis. Because of this, we follow Villoria and Hertel (2011), who map this sum onto a new variable, \(\omega_{ik} = \sum_{j=1}^{m} \gamma_{ij}\delta_{kj}\), which is a bilateral competition index between countries \(i\) and \(k\) in each \(j \in m\) market, including \(i\)’s own market and the market of its competitor \(k\) (i.e., \(i, k \in M\) as well.)

There are a few properties of the bilateral competition indices worth noting. First, they are not symmetric (i.e., \(\omega_{ik} \neq \omega_{ki}\)); therefore, their interpretation is directional. By convention, the first subindex refers to the exporter of interest, while the second index denotes a competitor. As a preview of the discussion below, among the largest competition indices in the data is that between Mexico and the United States, \(\omega_{MEX,USA} = 0.34\); however, the bilateral competition index between the United States and Mexico is much lower, \(\omega_{USA,MEX} = 0.06\). These indices suggest that Mexico generates an important part of its agricultural revenues in markets in which the United States has a non-trivial market share; in contrast, most U.S. sales of agricultural products are in markets in which Mexico has a relatively low market share. Domestic
markets tend to weigh heavily in these indices. Indeed, 47% of the bilateral competition index between Mexico and the United States is explained by the competition of Mexico’s producers with U.S producers in Mexico’s markets.

Second, by construction, the bilateral competition indices range from zero to less than one. Two extreme situations give rise to zero-valued bilateral competition indices with the set of all potential competing countries. One extreme would be a country operating in autarky. Under autarky, the share of the domestic markets in total sales is one, that is, \( \gamma_{ii} = 1 \), while the budget shares allocated to potential competitors are zero, that is, \( \delta_{ki} = 0 \) for all countries \( k \neq i \). The other extreme is that of a country that does not produce agricultural products and therefore earns no agricultural revenues in any market.

The upper bound of the bilateral competition indices (a value near one) with a specific competitor \( k \) would arise under two scenarios. One is when a country sells all its agricultural products in the domestic market \( \gamma_{ii} = 1 \), but such sales satisfy only a marginal share of total demand. The other is when the excess demand of a country is supplied by only one country, such that \( \delta_{ki} \rightarrow 1 \). These extreme cases help to give a better understanding of the bilateral competition indices but they are not found in the data. In reality, most of the countries in the sample used for the empirical work below produce agricultural goods and engage in exports and imports with more than one country. In terms of notation, it is useful to replace the innermost summation of the products \( \gamma_{ij} \delta_{kj} \) of equation (4) with \( \omega_{ik} \) to get a more compact form of the total demand facing producers in country \( i \):

\[
q_i^D = \sum_{j=1}^{m} \gamma_{ij} d_j - \sigma_i \sum_{k=1}^{n} \omega_{ik} (p_i - p_k) + \sum_{k=1}^{n} \sum_{j=1}^{m} \gamma_{ij} \delta_{kj} (t_{ij} - t_{kj}) \quad i \neq j.
\]

The Elasticity of Excess Demand

In closing the demand side of the model, it is useful to consider the role of budget and revenue shares in the own-price elasticity of demand faced by producers in country \( i \). A property of the single-nest CES bilateral system is that the own-price elasticity of demand for domestic consumption in country \( i \), \( q_{ii} \), is given by \( \eta_{ii} = q_{ii} / p_i = -\sigma_i(1 - \delta_{ii}) \), which implies that for countries in which domestic purchases represent a small share of their total expenditures, the absolute value of \( \eta_{ii} \) is close to the elasticity of substitution \( \sigma_i \) (Armington 1969).

Broadening the scope to include both domestic and foreign demand for the domestically produced good, as in equation (5), yields the elasticity of excess demand, as \( \eta_i^D = q_i^D / p_i = -\sigma_i \sum_{k=1}^{n} \omega_{ik} \). The term \( \sum_{k=1}^{n} \omega_{ik} \) is an aggregate competition index measuring the extent of aggregate exposure to foreign competitors in foreign markets (note that the domestic market \( i \) is excluded from the sum); therefore, the excess demand elasticity facing producers in country \( i \) will converge to \( \sigma_i \) the larger the producers’ exposure to competition with producers in international markets.

The aggregate competition indices play a prominent role in the derivation of the crop-land elasticities with respect to domestic and foreign TFP as discussed below. Therefore, the cost of introducing yet another notation symbol will be more than compensated for by the convenience of being able to simply refer to the aggregate competition index of country \( i \) as

\[
\Omega_i = \sum_{k=1}^{n} \omega_{ik}.
\]

So, for instance, the elasticity of excess demand is \( \eta_i^D = -\sigma_i \Omega_i \).

Land and Product Market Equilibrium

Analogous to the demand side, the underlying production technology is assumed to be parsimoniously represented by a CES production function that combines land and a non-land input composite to produce a unit of agricultural output. The relative change in the CES-derived demand for land in country \( i \), derived in SA-1.3, is given by

\[
l_i^D = (q_i^S - z_i) - \phi_i \lambda_i (r_i - w_i).
\]

In this equation, the first right-hand side term is the expansion effect. This term reflects the fact that technological progress (\( z_i \)) counteracts
the expansion effect stemming from changes in overall demand for agricultural products, $q_i^S$. The second term is the substitution effect, which depends on the change in land rents ($r_i$) relative to changes in the price of the non-land input. Lastly, $\phi_i$ is the elasticity of substitution between land and non-land inputs.

The land supply is given by $l_i^S = \nu_i r_i$, where $\nu_i$ is the land supply elasticity (Hertel 1989). In the competitive equilibrium, $l_i^S = l_i^D$. From this equilibrium condition, we solve for $r_i$ to obtain the equilibrium land rents: $r_i^* = (q_i^S - z_i + \lambda_i \phi_i w_i) / (\nu_i + \lambda_i \phi_i)^{-1}$. These land rents can in turn be used to eliminate $r$ in equation (7), then solving for $q_i^S$ and thus obtaining the equilibrium supply of agricultural output:

\begin{equation}
q_i^S = l_i^* \frac{\nu_i + \phi_i \lambda_i}{\nu_i} + z_i - \phi_i \lambda_i w_i.
\end{equation}

The supply of agricultural output in equation (8) depends solely on supply factors: non-land input cost shares, land supply and input substitution elasticities, and changes in input prices and TFP. In contrast, the demand for agricultural output in equation (5) depends on both income and supply prices in country $i$ as well as in the other countries linked to $i$ through international trade. The connections among land demand, income, and foreign prices are made by using the fact that in equilibrium, for any country $i$, $q_i^S = q_i^D$, which entails equating (5) to (8). From the resulting equilibrium, the optimal land allocation that satisfies the market equilibrium is given by

\begin{equation}
l_i^* = \left[ \phi_i w_i' - z_i + \sum_{j=1}^m \gamma_{ij} d_j - \sigma_i \right. \\
\times \left( \sum_{k=1}^n \omega_{ik} (z_k - z_i) + \sum_{k=1 \neq i}^n \omega_{ik} (r_k' - r_k') \\
+ \sum_{k=1}^n \omega_{ik} (w_k' - w_k') + \sum_{k=1 \neq i}^n \gamma_{ij} \delta_{kj} (t_{ij} - t_{kj}) \right) H_i
\end{equation}

where $H_i = \nu_i (\nu_i + \lambda_i \phi_i)^{-1}, (1 - \lambda_i) r_i = r_i'$ and $\lambda_i w_i = w_i'$ (detailed derivations are in online supplementary appendix 1.4.).

**TFP Growth and the Equilibrium Demand for Land**

Equation (9) provides useful insights into the question of whether TFP growth in a given country reduces or increases the country’s cropland extent. Because (9) is an equilibrium equation with all the variables transformed to relative changes (i.e., $z_i = dZ_i / Z_i$), comparative statics of the changes in TFP on the equilibrium demand for land are relatively straightforward. The analysis is further facilitated by the fact that $H_i, \phi_i$ and $\sigma_i$ are all positive. It is also helpful to use equation (6) to simplify equation (9) in terms of the elasticity of excess demand

\begin{equation}
l_i^* = \left[ \phi_i w_i' - z_i + \sum_{j=1}^m \gamma_{ij} d_j \
+ |\eta_i^D| (z_i - w_i' - r_i') \
- \sigma_i \left( \sum_{k=1}^n \omega_{ik} (z_k - r_k' - w_k') \right) \\
- \sigma_i \left( \sum_{k=1 \neq i}^n \gamma_{ij} \delta_{kj} (t_{ij} - t_{kj}) \right) H_i \right] H_i.
\end{equation}

In contrast to the derived demand for land in equation (7), in equation (10), domestic TFP growth does not unambiguously reduce the demand for land. Rather, for any country $i$, the elasticity of cropland with respect to TFP is

\begin{equation}
l_i^* (z_i)^{-1} = H_i (|\eta_i^D| - 1)
\end{equation}

which indicates that TFP growth will increase the demand for land if the absolute value of the elasticity of excess demand is greater than one. In what follows, equation (11) is referred to as the cropland elasticity with respect to changes in domestic TFP, or domestic cropland elasticity for short. Another objective of this article is to explore the extent to which TFP growth spillovers result in changes in land use elsewhere. Equation (9) indicates that increases in TFP growth in a foreign country reduce the domestic demand for land in direct proportion to the size of the bilateral competition index, formally, $l_i^* (z_i)^{-1} = -H_i \sigma_i \omega_{ik}$. Throughout the rest of the article, this elasticity is referred to as the bilateral cropland elasticity.

**Empirical Strategy**

The optimal demand for land in equation (9) motivates the regression to estimate the
cropland elasticities with respect to TFP growth. For this, the parameters $\sigma_i$, $\phi_i$, and $\nu_i$ are grouped together and constrained to be equal across countries. We also add a time subscript $t = 1, 2$ as the regression will be estimated using a two-period panel of countries. Country fixed effects are denoted by $\mu_i$. Finally, an error term $\epsilon_{it}$ is added to the equation:

\[
\begin{align*}
I_{it} &= \beta_1 z_{it} + \beta_2 \sum_{k=1}^{n} \omega_{ikt} (z_{kt} - z_{it}) \\
&\quad + \beta_3 w_{it} + \beta_4 \sum_{k=1}^{n} \omega_{ikt} (r_{it} - r_{kt}) \\
&\quad + \beta_5 \sum_{k=1}^{n} \omega_{ikt} (w_{it} - w_{kt}) + \beta_6 \sum_{j=1}^{n} \gamma_{ij} d_{it} \\
&\quad + \beta_7 \sum_{k=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \delta_{kj} (t_{ij} - t_{ki}) \\
&\quad + \beta_8 L_j + \mu_i + \epsilon_{it},
\end{align*}
\]

where $\beta_1 = -H$, $\beta_2 = \beta_4 = \beta_5 = \beta_7 = -H \sigma$, $\beta_3 = \phi H$, $\beta_6 = H$.

Due to the lack of proper data (discussed in the subsection below), two empirical compromises were needed to transform equation (9) into equation (12). First, the estimation is performed using proxy variables for both land rents and non-land input prices without weighting them by their respective cost shares, that is, $w$ and $r$. Second, the changes in domestic trade costs vis-à-vis the changes in the competitor’s costs, that is, $t_{ij} - t_{ki}$, are not included in the summation over the differences in relative changes in bilateral trade costs.

Land-scarce countries may invest more in R&D than land-abundant countries where there are fewer incentives to increase land productivity. This could lead to a reverse causality argument whereby constraints on cropland expansion underlie larger TFP growth. In order to alleviate this concern, we add an additional parameter ($\beta_8$) estimated using several proxy variables discussed below.

### Elasticities of Cropland with Respect to TFP

The parameter estimates $\beta_1$ and $\beta_2$ are used to derive formulas for elasticities ranging from national to global scales (see table 1; detailed derivations of these expressions appear in online supplementary appendix 1.5). The domestic and bilateral cropland elasticities derived from equation (10) are summarized in the two first rows of table 1 (column labeled “Structural Parameters”). The corresponding formulas as functions of the parameter estimates of equation (12) are under the column labeled “Regression Parameters”.

For any single country, there could be up to $N$ non-zero bilateral elasticities, which are difficult to summarize. A more manageable measure is the foreign cropland elasticity; this is the share-weighted sum of bilateral elasticities, which uses as weights the shares of global cropland accruing to each country $k$, denoted by $\theta_k$ in table 1. This elasticity, shown in the third row of table 1, measures the aggregate effect of TFP growth in any country on the rest of the world, and is therefore an aggregate measure of TFP spillovers. Moreover, using the cropland shares to weight own and foreign cropland elasticities yields the total cropland elasticity, which combines in a single measure the global cropland effects of TFP growth in a given country $i$ (fourth row of table 1).

In many instances, the interest is in the direct and indirect land use effects of regional changes in TFP (e.g., Villoria et al. 2013; Hertel, Ramankutty, and Baldos 2014). As shown in the fifth row of table 1, using cropland shares allows for aggregating the own and foreign elasticities of each country within an innovating region, denoted by $O$. This regional elasticity is interpreted as the change in regional cropland, given a 1% increase uniformly distributed across the countries that form the region. A formula for the extra-regional elasticity, which captures the spillover effects of regional innovation into a different region of interest denoted by $D$, is provided in the sixth row of table 1.

Finally, the last row of table 1 shows that $\beta_1$ is the global cropland elasticity, which is defined as the changes in global cropland that would result from a 1% increase in TFP in each country in the world. This is an interesting result that allows for assessing the effects of global, broad-based, and uniformly distributed technological change. In closing, note that all the elasticities discussed here are

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2 For instance, Lusigi and Thirle (1997) show that land scarcity (as measured by labor/land ratios) is correlated with higher rates of TFP growth in a sample of African countries.
functions of cropland shares and competition indices, both treated as constants, and of the estimates of the regression parameters $\beta_1$ and $\beta_2$. This allows for a straightforward calculation of standard errors of the different estimated elasticities.

**Data and Econometric Issues**

Equation (12) is estimated using a two-period panel ($t=1991–2000$ and 2001–2010) covering 70 countries (listed in the appendix). These countries represent 74% of worldwide cropland, and they account for 91% of global production, 86% of global imports, and 91% of global exports. The focus on these periods is dictated by data availability as well as by the evolution of international agricultural trade. Prior to the 1990s, international markets for agricultural products were extremely thin and unstable due to high levels of protection in developed countries (Johnson 1975, 1987). After the mid 1990s, partial trade liberalization following the signature of the WTO Agreement on Agriculture have contributed to sustained growth in traded volumes of agricultural goods as well as in both the number of countries involved and the agricultural and food products being traded (Aksoy and Ng 2010). As the intensity of competition among countries depends on both the size of the trade flows and the number of countries served by each exporter, the period after 1990 offers a more robust basis for identifying the effects of competition on land use changes.

Summary statistics for the variables used in the regression are in Table 2. With the exception of the shares at the bottom of Table 2, all the variables are average annual growth rates from 1991 to 2000 and from 2001 to 2010 (see note to Table 2 for details). Using annual growth rates over decades facilitates comparisons with the agricultural TFP indices from Fuglie (2012), described just below, and allows for direct interpretation of the parameter estimates as elasticities. The robustness of the results to alternative transformations capturing decennial changes are discussed in online supplementary appendix 3.

**Cropland, TFP growth rates, and simultaneity concerns.** The dependent variable, $l_{it}$, is the decade-specific average annual growth rate in a country’s cropland. Cropland is defined as the sum of arable land and permanent crops, both of which are available from FAOSTAT (FAO 2018).

TFP growth indices ($z_{it}$) come from Fuglie (2012), who estimated average annual growth rates of agricultural TFP over 10-year periods from 1961 to 2009, and from Fuglie (2017b), who provided updates to 2010 and beyond. These data are subject to some important limitations. Alston and Pardey (2014) warn about the likely bias of these indices arising from

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**Table 1. Elasticities of Cropland with Respect to TFP Growth at Various Geographical Scales**

| Elasticity           | Structural Parameters                                                                 | Regression Parameters                                                                 |
|----------------------|----------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|
| Domestic ($\xi_{ii}$) | $l_i'/z_i = -H_i | (\eta_i^P - 1)$                                                                | $\beta_1 - \beta_2 \sum_{k \neq i} o_{ik}$                                                |
| Bilateral ($\xi_{ik}$) | $l_i'/z_k = -H_i | \sigma_k o_{ki}$                                                                | $\beta_2 o_{ki}$                                                                        |
| Foreign ($\xi_{IF}$)  | $(1 - \theta_i)^{-1} \sum_{k \neq i} o_{ik}$                                          | $(1 - \theta_i)^{-1} \sum_{k \neq i} \theta_k o_{ki}$                                   |
| Total ($\xi^{T}$)     | $\theta_i \xi_{ii} + (1 - \theta_i) \xi_{IF}$                                         | $\theta_i \beta_1 + \beta_2 \sum_{k \neq i} (\theta_k o_{ki} - \theta_{i} o_{ik})$   |
| Intra-Regional ($\xi_{OO}$) | $\theta_{oo}^{-1} \left( \sum_{i \in O} \theta_{ii} + \sum_{i \in O} \sum_{(k \neq i) \in O} \theta_{ki} \right)$ | $\beta_1 - \theta_{oo}^{-1} \sum_{i \in O} \sum_{k \neq O} \theta_{ik}$  |
| Extra-Regional ($\xi_{OD}$) | $\theta_{od}^{-1} \sum_{k \in O} \sum_{i \in D} \theta_{ki}$ | $\theta_{od}^{-1} \beta_2 \sum_{k \in O} \sum_{i \in D} \theta_{ik}$                |
| Global ($\xi^{W}$)    | $\sum_{i} \theta_{ii} + \sum_{k \neq i} \xi_{ki}$                                   | $\beta_1$                                                                              |

**Note:** $\theta_i$ is country $i$’s share of global cropland. $H_i = \nu_i (\nu_i + \lambda_i) |^{1/2}$, where $i$ is a country index, $\nu_i$ is the land supply elasticity, $\lambda_i$ is the share of non-land inputs in total costs, and $\phi_i$ is the elasticity of substitution between land and non-land inputs. $\eta_i^P < 0$ is the elasticity of excess demand, which takes into account both domestic and foreign demand as well as domestic and foreign supply responses. $O$ is the innovating region and $D$ is any region outside the innovating region. The set $C^O = N - O$ is all the countries outside the innovating region.
errors in measuring capital and material inputs. These indices may also suffer from index number biases associated with the use of relatively constant cost structures over time. The biases arise because constant cost structures may mask input substitution due to changing relative prices (Fuglie 2012). But despite the weaknesses of the TFP indices, and in the absence of better data, these indices remain the only source of publicly available, globally comparable data on changes in agricultural total factor productivity patterns across countries.

An important econometric issue is that the data on cropland that is used to construct \( l_{it} \) is also used to construct \( z_{it} \) (Fuglie 2017b).\(^3\) This introduces the possibility of inconsistent parameter estimates due to the simultaneous determination of cropland changes and the TFP growth rates. We address this concern by examining the sensitivity of our results to alternative estimates of \( \beta_1 \) and \( \beta_2 \) using data on past public investments in agricultural R&D as instrumental variables (IV) of the regressors involving \( z_{it} \).

**Public R&D expenditures.** The data on R&D comes from Fuglie (2017a) who assembled historical data on public R&D spending for 150 countries from the 1960s to mid-2000s. Fuglie (2017a) calculated R&D capital stocks using different lag structures (25, 35, and 50 years) that capture the life cycle—from the gestation of new ideas, to the diffusion of technology, to the eventual depreciation of the knowledge capital stock—of a dollar invested in agricultural R&D. Past R&D plausibly meets the exclusion restrictions as an IV for contemporaneous TFP growth because there is a conceptually clear path of causality from past R&D investments to contemporaneous TFP growth (Evenson and Fuglie 2010). Moreover, given the long lags separating R&D investments from the realization of TFP gains (Fuglie 2012; Wang et al. 2013; Fuglie 2017a), it seems plausible to assume that any effect of past R&D investments on contemporaneous cropland expansion operates solely through its effects on contemporaneous TFP growth. This satisfies the main identification condition of zero covariance between the IV and the residuals \( e_{it} \).

Although the evidence of TFP growth being the product of past investments on R&D is reasonably strong, a major difficulty for the use of these data is the lack of guidance about the differences in the actual lag structures among different countries, an area that remains under-researched (Fuglie 2017a). Lacking this guidance, we resort to a somewhat ad hoc approach that seeks to maximize the explanatory power of the R&D data on TFP growth rates by looking at the F-statistics of bivariate regressions.\(^4\)

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\(^3\) The TFP growth rates are the difference between the growth rates in aggregate output and input. Formally, for country \( i \), \( z_{it} = q_{it} - \left(1 - \delta_i \right) l_i t + \varepsilon_{it} \), where \( l_i t \) is the growth in quality-corrected cropland and \( l_i t \) is the growth of the non-land inputs. The data underlying both \( l_i t \) and \( l_i t \) is cropland from FAOSTAT. Therefore, by construction, the terms involving \( z_{it} \) on the RHS of equation (12) are simultaneously determined with \( l_i t \).

\(^4\) This is an informal approach motivated in the prescribed use of first-stage F-tests to assess the strength of IV on applied work (e.g., Cameron and Trivedi 2005). Despite the widespread use of F-tests, recent work by Young (2017) presents comprehensive evidence that this technique is fundamentally flawed. We take these concerns into account below, when interpreting the IV estimates of equation (12).
As a result of this exploratory work, to estimate $\beta_1$, we use 25-year lag capital stocks in 1980 and 1990 as instruments for the TFP growth rates observed from 1991 to 2000 and 2001 to 2010, respectively (regression slopes and F-statistics of R&D expenditures on decennial TFP growth are displayed in figure 1). For $\beta_2$, we use relative differences in the rates at which countries spend on agricultural R&D. Analogous to the term $\sum_{k=1}^{m} \omega_{Kk} (z_{kt} - z_{t})$ in equation (12), for each country $i$, we construct sums of the competition-index weighted differences between growth rates in past R&D expenditures in country $i$ as well as in each competitor country $k$. Exploratory analysis indicates that the F-statistic is largest when we use the growth rates during 1960–2000 and 1991–2010 for 1991–2000 and 2001–10, respectively (regression slopes and F-statistics of these relative changes in R&D expenditures on relative changes in decennial TFP growth are displayed in figure 1.) Again, the lack of actual knowledge on the time it takes for investments to translate into TFP growth is a major limitation of this IV strategy. Nevertheless, the IV estimates provide useful information about the direction of bias stemming from the fact that changes in cropland area are an input in the TFP calculations.

Market shares and competition indices. The competition indices used to weight the relative change in TFP growth of a given country relative to its trading partners, that is, $z_{it} - z_{kt}$, are the product of the budget and revenue shares, $\delta_{ij}$ and $\gamma_{ij}$, from the linearization of the CES bilateral demand functions (3) and their aggregation across destinations (4). In practice, the budget and revenue shares are calculated using the following expressions (time subscripts are omitted for clarity):

\[
\delta_{ij} = P_{ij} Q_{ij} (E_i \sum_{j=1}^{n} Q_{ij})^{-1},
\]

\[
\gamma_{kj} = P_{ij} Q_{ij} (P_i \sum_{j=1}^{m} Q_{ij})^{-1},
\]

\[
\sum_{j=1}^{m} \delta_{ij} = \sum_{i=1}^{n} \gamma_{ij} = 1.
\]

The denominator in the budget shares is total consumption of agricultural goods in country $i$ valued using the CES price index $(E_i)$ of the underlying utility function. As a proxy of total consumption, the value of net
agricultural exports is subtracted from the gross value of agricultural production, both from FAOSTAT. The denominator in the budget shares is total agricultural production valued at domestic prices, $P_i$, for which FAOSTAT’s gross production values are used as a proxy variable.

The numerators of both budget and revenue shares are source-specific purchases of agricultural goods. These include domestic purchases or sales (i.e., $P_{ii}Q_{ii}$) and also the value of import and export transactions with various foreign countries (i.e., $P_{ij}Q_{ij}$ for $i \neq j$ is the value of exports from country $i$ to country $j$). Domestic purchases $P_{ii}Q_{ii}$ are calculated as the difference between the gross value of agricultural production and the value of total agricultural exports, both from FAOSTAT.

Bilateral trade in the FAOSTAT database is not available in value terms. The value of bilateral flows is readily available from Gehlhar (2012, GTAP database) and other sources based on UN-COMTRADE. In most cases, UN-COMTRADE’s bilateral trade values do not add up to FAOSTAT’s total trade values. Because FAOSTAT total export values were used to calculate both total consumption in the denominator of the budget shares and domestic sales for the numerators of both budget and revenue shares, any discrepancy in the total trade values violates the condition that the shares add to one inequality (13). As an alternative, FAOSTAT’s total trade values were shared-out using bilateral trade value shares from Gehlhar (2012), aggregated over all the food sectors in the GTAP classification (listed in the appendix); this procedure preserves the observed pattern of bilateral trade flows while matching FAOSTAT aggregate trade values.6

The budget and revenue shares are calculated using total decennial values. This avoids the extreme sensitivity of annual swings in production and trade while reflecting the geographic pattern of trade in the decennial scale used to estimate the parameters of equation (12). As shown at the bottom of table 2, the domestic shares are negatively skewed: Only one-quarter of the countries in the sample have domestic revenue shares of less than 46%, while for half of the countries, domestic revenue shares are greater than 74%. Likewise, only one-quarter of the countries in the sample have domestic budget shares of less than 51%, while for half of the countries, domestic budget shares are greater than 76%. This implies that domestic purchases and revenues tend to dominate the total sales and consumption.

The bilateral competition indices $\omega$ are the product of the budget and revenue shares. Table 3 shows the country pairs with the ten largest bilateral competition indices. In five of these cases, the largest competition index is with the United States. The other four cases involve countries with large agricultural sectors, such as France, Italy, Spain, and Portugal. The interpretation of these indices is that Canada, Mexico, Costa Rica, Panama, and Honduras face intense competition from the United States; the Netherlands faces intense competition from France, Italy, and Spain; and Namibia faces intense competition from South Africa. The bilateral competition indices are used to weight the relative differences in TFP growth, non-land input prices, and land rents.

**Table 3. Ten Highest Competition Indices in 2001–2010**

| Exporter (i) | Competitor (k) | $\omega_{ik}$ | $\omega_{ki}$ |
|-------------|---------------|---------------|---------------|
| Canada | United States | 0.50 | 0.04 |
| Netherlands | France | 0.37 | 0.06 |
| Mexico | United States | 0.33 | 0.06 |
| Costa Rica | United States | 0.31 | 0.00 |
| Panama | United States | 0.30 | 0.00 |
| Netherlands | Italy | 0.30 | 0.07 |
| Netherlands | Spain | 0.26 | 0.06 |
| Honduras | United States | 0.26 | 0.00 |
| Portugal | Spain | 0.25 | 0.03 |
| Namibia | South Africa | 0.25 | 0.01 |

Input prices. The next variables in equation (12) are decennial changes in land rents and non-land input prices, $r_{it}$ and $w_{it}$, used to estimate the parameters $\beta_3$–$\beta_5$. Land rents and non-land input prices are mostly unobserved at the country level. In their absence, implicit land rents and non-land input prices are derived using the shares of total costs of agricultural production accruing to fertilizer and land (see online supplementary appendix 2.

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6 Agricultural final products dominate global agricultural trade (i.e., 41% of global agricultural trade during 2006–2007 was in final goods (Aksoy and Ng 2010; table12)). Therefore, leaving the final products out of the trade shares would omit an important channel of transmission of land use effects (e.g., exports of vegetable oil by one nation could reduce the need for planting oilseeds in another nation).
for data sources, formulas used, and an expanded discussion of the caveats discussed below).\footnote{The author thanks Keith Fuglie for advice on deriving country-level measures of land and non-land input prices using the data in the USDA-ERS database on International Agricultural Productivity (Fuglie 2017b). The empirical choices made here are the sole responsibility of the author.}

An important caveat of this strategy is that the available data on input cost shares are time invariant, and available only for a handful of regions, most of them encompassing many countries. For the calculations of the data values \( r \) and \( w \) used in the regression this is a minor issue because, due to the time invariance of the cost shares, they get eliminated when the data is expressed in relative changes over decennial periods.

While the time invariance of the cost shares alleviates the concerns about their high level of geographical aggregation in the calculation of \( r \) and \( w \), imputing constant cost shares to weight these data to get \( r' \) and \( w' \), as the theory embedded in equation (9) indicates, introduces an additional source of uncertainty in the statistical analysis below. To the extent that the main message from equation (9) is that identifying the effects of domestic and foreign TFP growth on cropland dynamics requires controlling for the difference in relative changes in farm returns and input costs between countries, the most natural empirical compromise is to use the measures \( r \) and \( w \) instead of their weighted counterparts \( r' \) and \( w' \).

The scope for simultaneity bias also arises from the term \( \sum_{k=1}^{n} \omega_{ikt}(r_{it} - r_{kt}) \), as the land rents proxy also depends on changes in croplands (see online supplementary appendix 2). To deal with this additional concern, we examine the sensitivity of our results to the use of lagged values of this term, which are predetermined out of the system.

**Demand and bilateral trade costs.** The data for estimating \( \beta_6 \) is the ratio of constant gross domestic product (GDP) to population counts, both from the World Bank Development Indicators (WDI 2017). In addition, in order to control for the dependence of a country’s economy on agricultural production, the ratio of agricultural value added to national GDP (from FAOSTAT) is also incorporated in the regressions discussed below.

The bilateral trade costs in the theoretical model are comprehensive measures of all the costs incurred by the partner countries engaged in international trade. These include both trade frictions imposed by policy (i.e., tariffs and non-tariff measures,) and non-policy factors, such as transportation costs and geographic and cultural barriers to trade. The ESCAP-World Bank Trade Cost Database (ESCAP-WB 2017) provides trade costs consistent with this definition for the aggregated agricultural sector for the period 1995–2010, using Novy (2013)’s method of inverse gravity. These trade costs are relative to domestic trade costs, which are normalized to unity. For this reason, we are prevented from including changes in domestic trade costs, as alluded to at the beginning of this section.

**Constraints to cropland expansion.** Several alternative variables are considered to capture constraints to cropland expansion. In particular, we use the share of a country’s total area suitable for agriculture that is used as cropland; this variable is constructed as FAOSTAT\textsubscript{ct} cropland at the beginning of each decade over the total land that is suitable for agriculture as defined in Ramankutty et al. (2002) (details available in the appendix). Legal restrictions to land expansion are captured by the share of a country’s total area that is under protected areas WDI (2017). We also include a dummy variable that indicates whether the country was a recipient of monetary transfers for REDD projects during 2001–2010 (see list of countries in the appendix), using the “International Database on REDD” from Simonet et al. (2016). We also incorporate the share of a country’s area that is covered by forests as a gross proxy to land conversion costs (sourced from WDI 2017).

**Results and Discussion**

Table 4 reports the parameter estimates of equation (12) using the data discussed above. All equations are estimated using country fixed effects. Column 1 reports the ordinary least squares (OLS) estimates. These estimates assume that both the TFP terms as well as the relative land rents are uncorrelated with the error terms \( \epsilon_{it} \) in equation (12). Columns 2–5 report two-stage least squares IV estimates that attempt to control for the potential endogeneity of these regressors. At
a glance, all the parameter estimates have the expected signs and most of them are statistically significant, at least at a 90% confidence level. There are also sizable differences between the OLS estimates in column 1 and the IV estimates in columns 2–5. Such differences suggest that, indeed, the simultaneity between cropland and TFP, as well as between cropland and land rents, is potentially important.

Relative to the IV estimates, the OLS estimates of the effects of TFP on cropland appear to be biased downward, underestimating the effects of TFP growth on cropland expansion. The large difference between the OLS and IV estimates warrants further discussion.

All the IV regressions in table 4 are just identified; hence, the main concern is whether the correlation of the instrumental variables with the exogenous regressors is strong enough so that the IV estimates remain unbiased and useful to provide valid inference (e.g., Angrist and Pischke 2008). In the model in column 2, the 25-year capital R&D stocks and the relative change in the growth rates of R&D expenditures are used as instruments for the terms \( z_{it} \) and \( \sum_{k=1}^{n} \omega K_{it} (z_{kt} - z_{it}) \), respectively; the lag of relative change land rents is used as an instrument for the relative change in land rents. A first piece of evidence on the strength of these three instruments is the conditional F-test for weak instruments due to Sanderson and Windmeijer (2016) (reported in the lower part of the table). The low value of the F-statistics for the relative TFP terms and the lagged land rents (\( F_{2|13} \) and \( F_{3|12} \)) suggest that these instruments are weak, thus compromising inference.

Given our focus on the TFP elasticities, land rents are dropped from the model in column 3. In this model, the resulting conditional F-statistics as well as the Kleibergen-Paap’s Wald F
statistics are large enough to reject the null hypothesis of weak instruments. Although F-tests for detecting weak instruments are widely used, recent work by Young (2017) concludes that they are “largely uninformative.” Moreover, their widespread use often produces IV estimates with exceedingly wide empirical confidence intervals, which are inadequate for hypothesis testing (Young 2017). The emerging skepticism about F-tests to support instrument validity, together with the large difference between our OLS and IV estimates, confronts us with an interesting empirical choice: do we rely on IV estimates that are potentially too distorted to conduct any valid inference? Or do we use the more conservative OLS estimates even though we have clear evidence of the scope for simultaneous equation bias? Our strategy is to consider both. As it will become apparent, both the OLS and IV tell essentially the same story, although the IV estimates amplify the land-saving effects of TFP growth.

**Cropland Elasticities to TFP**

To get a perspective on the differences between the estimates, recall that $\beta_1$ has a direct interpretation as the global elasticity of cropland following a 1% increase in TFP uniformly distributed across the world. The OLS point estimate for this elasticity is -0.34, while the IV estimate is three times as large, -1.2 (columns 1 and 3 in table 4). Moreover, using standard error robust to heteroskedasticity, both appear statistically significant at a 95% confidence level.

As an illustrative counterfactual, if annual TFP growth rates in each country in the sample were to match the global average observed from 2001 to 2010 (1.82%), the global cropland would decline by a point estimate of 6.14% as per the OLS estimate, and 19% as per the IV estimate. In terms of physical area, the OLS estimate translates into 69.95 Mha (CI: 11.9-128.4 Mha) while the IV estimate translates into 215 Mha (95% CI between 122 and 309 Mha). To put these results in perspective, consider that in 2010, Indonesia, a major hot spot of deforestation, had 47.3 Mha under primary forests, while Brazil, which hosts two-thirds of the Amazon forest, had nearly 477 Mha under primary forests (Mongabay 2017). This suggests that using the biased OLS estimates is effectively a way of erring on the side of caution as the estimate is more conservative. Next, we first discuss the OLS estimates of domestic, foreign, and total cropland elasticities, and then contrast them with the IV estimates.

In a focus on individual countries, the size of the domestic cropland elasticity with respect to TFP growth (using the OLS estimates) is $-0.345 + 1.368 \Omega_i$, where, to reiterate, $\Omega_i$ captures the exposure of the producers in country $i$ to international competition (see expression 6). In light of (11), the ratio $\beta_1 / \beta_2$ indicates that $\Omega_i \approx 0.25$ (95% CI: 0.11-0.39), which is the threshold that separates countries facing a price-inelastic from a price-elastic excess demand. As per our previous discussion, this is the threshold that separates countries in which domestic TFP growth is cropland-saving from those in which TFP growth is associated with cropland expansion.

The upper panels of figures 2 and 3 display 95% CI for the domestic cropland elasticities for each country and decade in the sample using the OLS estimates. Three patterns in figures 2 and 3 deserve special mention. First, it is only in a handful of countries—Nigeria in Africa, and China, India, and Nepal in Asia—that growth in domestic TFP leads to cropland reductions under 2001–2010 trade patterns. Second, from 1991–2001 to 2001–2010, a number of countries in Africa, South America, and Asia (e.g., Senegal, Ecuador, and Sri Lanka) transitioned from regimes in which TFP had a neutral or negative effect on cropland expansion to regimes in which domestic TFP growth actually incentivized cropland expansion. Such transitions indicate the fact that these countries have become more engaged in international trade, and therefore, their competition indices have increased. Third, large exporters of commodities and other foods and beverages such as Cote d’Ivoire in Africa, Argentina, Canada, Costa Rica, and Chile in the Americas, and Australia, Malaysia, and Thailand in Asia display relatively large, positive domestic cropland elasticities with respect to TFP. Many of the countries in Europe also display large, positive domestic cropland elasticities.

The next effect of interest is that of growth in a country’s TFP on land use abroad. This

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8 The conditional F-statistics reject the null hypothesis of weak instruments in the sense that the size distortion of the regression’s Wald test is not greater than 10%. Similarly, the KP statistic rejects the null hypothesis of weak instruments for a size distortion of at most 25%.
effect, dubbed the foreign cropland elasticity, is obtained by aggregating the bilateral elasticities of country $i$ (OLS estimate of $-1.368 \sigma_{ki}$) over the competing countries indexed by $k$ (see Table 1). Confidence intervals for the foreign cropland elasticities are displayed in the middle panels of figures 2 and 3. Across the board, the foreign elasticities are negative and statistically significant. The largest foreign cropland elasticity in the sample accrues to the United States. As displayed in the middle panel labeled “Americas” in figure 2, a 1% increase in U.S. TFP reduces cropland expansion in the rest of the world by a point estimate of 0.7%, with a 95% CI bound by -0.11% and -0.04%. As is evident from the figure, the other countries with relatively large foreign cropland elasticities are Canada, Brazil, Argentina, and Mexico.

The largest foreign elasticities in Africa—those of Egypt and South Africa—are a fraction of those found in the Americas. This is explained by the fact that the foreign elasticities are weighted by both global cropland shares and the degree to which a country is exposed to international trade (Table 1), both of which are larger in most of the countries in the Americas than in the countries in Africa. In figure 3, China and Japan display the largest foreign cropland elasticities in Asia, yet their magnitudes are similar to those found in Africa. Finally, in Europe the largest foreign elasticities are those of France, Germany, Italy, the Netherlands, Spain, and Russia, although the magnitude of these elasticities is

Figure 2. Estimated decennial elasticities of cropland expansion with respect to total factor productivity for all the countries in the sample (using OLS estimates in column 1 of table 4)

Note: The confidence intervals (90% identified by notches, and 95% by the interval extent) are arranged in increasing order from 1991–2000 to 2001–2010.
moderate, and is in line with countries in the Americas (excluding the United States).

The bottom panels of figures 2 and 3 show that, for most countries, the negative foreign cropland elasticities compensate for the land expansion effects associated with domestic cropland elasticities, yielding negative total cropland elasticities. The most notable exceptions to this pattern are Canada and Australia, countries in which TFP growth is associated with both domestic and foreign land expansion.

**Excess Demand Elasticities: OLS vs. IV Estimates**

Not surprisingly, the IV estimates in column 3 yield a much higher threshold ($\Omega \approx 0.59$) that must be crossed before the association between TFP growth and cropland shifts from negative to positive. Using this higher threshold, we find a much stronger association between TFP growth and cropland savings, particularly in Africa, and the developing countries of Asia and the Americas (see online supplementary figures SA2 and SA3). Although the differences between the estimates do not change the main point of the article, it is still interesting to question how reasonable these results are. As a back-of-the-envelope check, the OLS parameters imply that the excess demand elasticity consistent with the threshold for shifting the sign of the association between cropland expansion and TFP growth is roughly one for the OLS estimates, and

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Figure 3. Estimated decennial elasticities of cropland expansion with respect to total factor productivity for all the countries in the sample (using OLS estimates in column 1 of table 4)

Notes: The confidence intervals (90% identified by notches and 95% by the interval extent) are arranged in increasing order from 1991-2000 to 2001-2010.
around two for the IV. As mentioned in the introduction, the condition for TFP to increase land supply is that the elasticity of excess demand is price elastic ($\eta = 1$); the fact that the OLS estimates align with this fundamental insight add support to their use as preferred estimates.

**Variables Other than TFP**

Using the OLS estimates in column 1, the marginal effect of changes in domestic fertilizer prices on cropland expansion is $0.085 - 0.170\Omega$, confirming that, empirically, land and non-land inputs are substitutes in production. Turning abroad, the marginal effect of foreign fertilizer prices on domestic cropland expansion is $0.170\omega_{ik}$, thus making foreign fertilizers and domestic cropland substitutes, although the parameter estimate is not statistically different from zero in any of the specifications.

The next coefficient, $\beta_6 = 0.212$, measures a significant and sizable positive effect of changes in revenue-share weighted GDP per capita on cropland expansion. As predicted by the theory, increases in trade costs relative to other suppliers reduce cropland expansion through the reduction in the demand for output. The effect, however, is not statistically significant. The estimate of the share of suitable land for agriculture under cropland at the beginning of each decade is negative ($\beta_5 = -0.073$ in column 1 of table 4), indicating that countries where most of the suitable land is already under cropland tend to have lower decennial changes in cropland.

The specification in column 4 of table 4 explores the robustness of the parameter estimates to the inclusion of additional variables that impose restrictions to land expansion. The larger the share of national territory that is within protected areas, the smaller the changes in the decennial cropland extent. This finding is consistent with other studies, most recently Blankespoor, Dasgupta, and Wheeler (2017), who find that protected areas are associated with lower land conversion. The significant estimate on the REDD dummy variable indicates that the countries with REDD projects have, on average, larger rates of cropland expansion, suggesting that REDD projects are being targeted at countries with recent large amounts of land expansion. As in the case of the constraints imposed by land suitability, interaction terms of the protected area shares and the REDD indicator with the TFP variable add no further explanatory power to the models without interactions (see table SA-4.) Finally, the effects of forest cover within a country’s territory, a gross proxy for the costs of land conversion, and the ratio of agricultural value added to total GDP, which captures the dependence of a country’s economy on agricultural production, appear to be uncorrelated with changes in cropland (column 4 in table 4). Notice that the effects of own TFP growth ($\beta_1$) and foreign TFP growth ($\beta_2$) are robust to the inclusion of these additional variables.

**Implications: Demand, Technology, and Regional Innovation**

An interesting question is whether technological improvements in agriculture have been large enough to counteract the cropland expansion caused by growing demand (e.g., Byerlee, Stevenson, and Villoria 2014). This section uses the parameter estimates discussed above to explore this question using in-sample predictions that isolate the effects of growth in TFP and per capita GDP as well as their interaction. The land use effects of regional initiatives to improve agricultural technology are discussed next.

**Demand vs. Technology**

We use our estimates to assess the effects of TFP growth in counteracting the cropland expansion driven by increases in demand for agricultural products as follows. First, the combined effect of TFP and per capita GDP growth on cropland changes is isolated by assuming that trade costs, as well as land and non-land input prices, remain unchanged over time. Second, the TFP terms are also set equal to zero, thus isolating the effect of per capita GDP growth on cropland growth. In order to eliminate the effect of potentially inconsistent country fixed effects associated with short panel data (Cameron and Trivedi 2005), we subtract the predicted cropland without the effect of TFP from the predicted

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9 That is, $\eta^D = -\eta^T$. Using the estimate of the elasticity of substitution for food products of 4.08 reported by Feenstra et al. (2018, table 3), $\eta^T = -1.02$ and $\eta^D = -2.41$.

10 While the size of the TFP terms sharply differs from the OLS to the IV estimates, the rest of the parameter estimates are relatively homogeneous across specifications.
cropland that considers both TFP and demand growth. The sum of these differences across countries is the counterfactual cropland that would have been needed to satisfy growth in demand in the absence of technological progress. Prediction intervals (PI) inclusive of parameter uncertainty and country level prediction errors are elicited using the approach of Gelman and Hill (2007; see SA-4).

Using the OLS estimates in column 1 of table 4, the median estimate of the difference during 1991–2000 is 76 Mha with a 90% aggregated prediction interval of 9-153 Mha (figure 4). The actual observed change in cropland during this period for the countries in the sample was 10.5 Mha, suggesting that keeping production constant in the absence of TFP would have required around seven times more land than actually used. For the period 2001–10, the model predicts a counterfactual cropland expansion of 97 Mha (90% PI 17-186 Mha), which, against the actual global cropland contraction of 2 Mha during this period, suggests a counterfactual need of nine times more land than actually used. Aggregating over these two periods, the OLS estimates predict that in order to satisfy the growth in demand during 1991–2010, we would have needed an additional 172 Mha (90% PI: 27-344 Mha). This is equivalent to approximately 10% of the area covered by tropical rain forests (Elias and May-Tobin 2011; FAO 2016). The IV estimates also indicate important counterfactual savings, although, consistent with the discussion above, they are about three times larger than the OLS estimates (e.g., the median counterfactual land use for 1991–2010 is 601 Mha).

Admittedly, fixing land and non-land input prices to isolate the effects of TFP and per capita GDP is a very simplistic counterfactual that assumes no response in the land and input markets to changes in TFP. This counterfactual also assumes a perfectly inelastic demand curve in which consumers demand a fixed amount of output. Because of these assumptions, the results are an upper bound of the potential effects of TFP in counteracting cropland growth due to increased demand.

**Land Use Effects of Asymmetric Regional Innovation**

At a global level, the remaining lands with untapped potential for agriculture are in Africa, Latin America, Eastern Europe, and Central Asia (Deininger and Byerlee 2011). The effects of TFP growth in some of these regions have been the center of much attention due to the trade-offs involved in increasing agricultural productivity to improve food security and economic development while minimizing the impacts on the natural resource base. Ceddia et al. (2013) and Hertel, Ramankutty, and Baldos (2014) provide recent examples of these concerns in South America and Africa, both focusing on whether technological progress is associated with land savings or land expansion.

The results developed above can be used to shed light on the land use effects of focusing increases in R&D investments in some of
the remaining land-abundant regions of the world. These effects are of particular interest for global actors such as the agencies of the Consultative Group in International Agricultural Research and private donors encouraging the direction of agricultural R&D in sub-Saharan Africa (AGRA 2017). We therefore focus on sub-Saharan Africa and contrast the results with innovations originating in either South America or developing Asia (see the appendix for countries in each region).

Intra- and extra-regional TFP cropland elasticities using the OLS estimates in column 1 of table 4 are estimated using the relevant expressions in table 1.11 Expected values (50th percentile) and 95% CI for these elasticities are reported in table 5. For instance, if TFP grows by 1% in developing Asia as a whole, the expected change in cropland within the region will be −0.19%. In sub-Saharan Africa, regional TFP growth is associated with an expected reduction in the regional cropland (−0.09%), which is about half of the effect in developing Asia. In sharp contrast, the expected change in South America’s cropland following a 1% increase in regional TFP is an expansion of the cropland area by 0.20%. Notice, too, that TFP growth in any of the three innovating regions will lead to cropland contraction in other regions of the world, and in the world as a whole. These elasticities reflect the extent to which each region is integrated in world markets. South America is the region with more exposure to foreign competition, with a cropland-weighted average competition index of 0.52 (from 0.38 in 1991–2000); sub-Saharan Africa follows, with a competition index of 0.21 (from 0.14 in 1991–2000); the countries of developing Asia are the least integrated, with a competition index of 0.17 (from 0.11 in 1991–2000).

A better appreciation of the effects of asymmetric regional innovation is achieved by translating the elasticities into the changes in cropland (in Mha) that would occur if TFP in the focus regions were to increase by 1% (figure 5). The changes in land use are conditional on 2001–2010 bilateral trade patterns. The point estimate of the land use effect of a 1% uniform increase of TFP in sub-Saharan Africa is negative, although, reflecting the wide confidence intervals of the intraregional elasticities, the land use effects within sub-Saharan Africa are quite uncertain. However, the effects of TFP growth in sub-Saharan Africa are associated with statistically significant cropland contraction in every other region, for an overall, global cropland contraction of 54 Mha (95% CI: −88, −19 Mha). A 1% increase in TFP in South America would entice an expansion of existing cropland within the region, a finding which is qualitatively consistent with the findings of Ceddia et al. (2013). However, such land expansion would be more than offset by cropland reduction in the rest of the world, for a global land contraction of around 84 Mha (95% CI: −138, −30 Mha). If similar growth happened in developing Asia, there would be much larger land savings, a point estimate of 140 Mha (95% CI: −258, −23 Mha). The IV estimates largely confirm these

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11 For five aggregated regions: The United States and Canada, Europe (includes the countries in the upper right panel of figure 3.) Australasia, and the rest of the world.

| Destination                  | Developing Asia | South America | Sub-Saharan Africa |
|------------------------------|-----------------|---------------|--------------------|
|                              | 2.5% 50% 97.5%  | 2.5% 50% 97.5% | 2.5% 50% 97.5%  |
| U.S. & Canada                | −0.12 −0.08 −0.04 | −0.18 −0.12 −0.06 | −0.02 −0.02 −0.01 |
| Developing Asia              | **−0.42** −0.19 0.04 | −0.07 −0.05 −0.02 | −0.02 −0.01 −0.01 |
| Europe                       | −0.12 −0.08 −0.04 | −0.18 −0.12 −0.06 | −0.07 −0.05 −0.02 |
| Australasia                  | −0.23 −0.16 −0.08 | −0.08 −0.05 −0.03 | −0.03 −0.02 −0.01 |
| South America                | 0.08 −0.06 −0.03  | **−0.05** **0.20** **0.45** | −0.03 −0.02 −0.01 |
| Sub-Saharan Africa           | −0.05 −0.03 −0.02  | −0.04 −0.03 −0.02  | **−0.31** **−0.09** **0.13** |
| Rest of the World            | −0.27 −0.18 −0.09  | −0.21 −0.14 −0.07  | −0.04 −0.02 −0.01 |
| World (as a whole)           | −0.19 −0.11 −0.02  | −0.10 −0.06 −0.02  | −0.07 −0.04 −0.01 |

Note: Intra-regional (in boldface) and extra-regional cropland elasticities with respect to TFP growth in the regions in the columns. Median values and 95% confidence intervals were calculated using the formulas in table 1 and the parameter estimates in column 1 of table 4.
results, but tend to produce much higher land savings due to lower intra-regional cropland elasticities to TFP growth (online supplementary table SA2 and figure SA4).

From a policy point of view, these results suggest that large increases in technology in Africa and developing Asia could have payoffs, not only in terms of food security, but also in environmental protection. Over time, increased exposure to foreign producers in countries that are currently closed is likely to result in more elastic excess demands for producers in these regions, with an eventual shift from a negative to a positive correlation between TFP growth and land expansion at the country level, and eventually, at the regional level. However, globally, the demand for food staples is likely to remain inelastic, so, as in the past, technological progress will probably play an important role in slowing down global cropland expansion, even if in some countries TFP growth leads to cropland expansion.

Conclusions

This study estimates the effects of agricultural technological progress on cropland expansion at various geographical resolutions, from the country level to the world as a whole, while formally accounting for the international interdependence of national supply responses. For this, we build a stylized model of bilateral trade that motivates a regression of cropland changes on domestic and foreign TFP growth, along with other demand and supply shifter. The key implication of this model is that, conditional on the trade elasticity, the intensity of competition between domestic producers with foreign producers, in both domestic and foreign markets, is a summary measure sufficient to determine the size of the excess demand elasticity faced by producers. In turn, an inelastic (elastic) excess demand implies negative (positive) correlation between cropland changes and TFP growth.

We focus on decennial growth rates (1991–2000 and 2001–2010) in the cropland area and agricultural TFP of 70 countries home to three-quarters of the world’s croplands and responsible for most of the global agricultural production and food trade. An important empirical issue is that changes in cropland are an input in the calculation of TFP growth rates done by Fuglie (2012). This is likely to result in biased parameter estimates due to simultaneous determination of the two variables. We explore the direction of this bias by estimating the effects of TFP growth using past public R&D expenditures as IV. We find that, relative to the IV estimates, the OLS estimates underestimate the effects of TFP growth on cropland savings by a factor of three. Due to the congruence of the OLS estimates with fundamental insights from the theory of production, together with increasing concerns about the use of first-stage F-tests to determine the validity of IV, we use the more conservative, downward biased, but probably
more efficient, OLS estimates as our preferred specification. The IV estimates do not change the fundamental conclusion of the study; on the contrary, they overstate the land-saving effects of TFP growth.

We find that, in most countries of the world, domestic TFP growth does not have a distinguishable effect on cropland expansion. However, in countries with large commodity exporting sectors, TFP growth is strongly associated with increased land expansion. It is only in the few countries in Asia and Africa that remain relatively closed to international trade that growth in domestic TFP is land-saving. The heterogeneity of country-level outcomes disappears when we look at the global level. According to our estimates, the elasticity of global cropland with respect to changes in global TFP is negative and precisely estimated (the preferred OLS point estimate equals -0.34).

According to Fuglie (2008), TFP growth was the main source of increased production in recent decades. Counterfactual analysis using our parameter estimates suggest that, had TFP growth remained stagnant from 1991 to 2010, an (upper bound) estimate of 173 Mha (95% CI of 60–288 Mha) of additional cropland—around one-third of the Brazilian Amazon, or around one-tenth of the extant tropical forests—would have been needed to satisfy observed demand. Looking at regional levels, we find that, under current trade patterns, technological progress in developing Asia and sub-Saharan Africa would reduce cropland within those regions as well as in the rest of the world. In contrast, further TFP growth in South America is likely to result in expansion in regional cropland, even as the net global effect is to reduce global croplands. As these regions become more integrated into the world economy the benefits associated with reduced local deforestation are likely to dissipate.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics online.

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Appendix

GTAP Sectors

The bilateral trade flows are from the GTAP database V.8. These were aggregated over all the agricultural sectors in the GTAP database. All the primary sectors, as well as food sectors, are included. These are the following: Paddy rice (PDR), Wheat (WHT), Cereal grains nec (GRO), Vegetables fruit and nuts (V_F), Oil seeds (OSD), Sugar cane and sugar beet (C_B), Plant-based fibers (PFB), Crops nec (OCR), Bovine and other cattle (CTL), Animal products nec (OAP), Raw milk (RMK), Wool (WOL), Bovine meat products CMT, Meat products nec (OMT), Vegetable oils and fats (VOL), Dairy products (MIL), Processed rice (PCR), Sugar (SGR), Food products nec (OFD), Beverages and tobacco products (B_T).

Countries

Argentina*, Australia, Austria, Bangladesh++, Bulgaria, Bolivia*, Brazil**, Canada, Switzerland, Chile**, China***, Cote d’Ivoire, Cameroon*, Colombia***, Costa Rica**, Germany, Denmark, Ecuador*, Egypt, Spain, Finland, France, United Kingdom, Ghana*, Greece, Honduras**, Hungary, Indonesia***, India****, Ireland, Iran, Israel, Italy, Japan, Kenya*, Korea, Laos People’s Democratic Republic***, Sri Lanka,,, Morocco, Madagascar*, Mexico**, Mozambique*, Malawi*, Malaysia++, Namibia, Nigeria, Nicaragua**, Netherlands, Norway, Nepal**, Pakistan**, Panama**, Peru**, Philippines***, Poland, Portugal, Paraguay**, Saudi Arabia, Senegal*, El Salvador*, Sweden, Thailand++, Tunisia, Turkey, Tanzania*, Uruguay**, United States, Venezuela**, Viet Nam***, South Africa*.

Note: Asterisk * denotes countries with at least one REDD project during 2001–2016 (Simonet et al. 2016); † indicates South America; ++ indicates developing Asia.

Cropland as a Share of the Total Area Suitable for Cultivation

The area of each country that is suitable for cultivation comes from the land suitability index from Ramankutty et al. (2002). The land suitability index is the fraction of a half-degree raster pixel that is suitable for agriculture, based on the temperature and soil conditions of each pixel. The fraction of suitable land is multiplied by the hectares in each pixel, and then all the pixels within the boundaries of each country are added up to obtain the number of hectares that are suitable for agriculture.