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Global Agricultural Productivity: Insights from a Dynamic Gravity Model

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This study estimates an aggregate agricultural industry dynamic structural gravity model with capital accumulation to assess the relationship between capital accumulation and determinants of total factor productivity (TFP) in agricultural trade flows. The Armington elasticity of substitution is 1.47. Institutional variables—government investment, business regulations, legal enforcement of contracts, and communication technology—are key drivers of global agricultural TFP. The capital stock transition parameter is 34.6%. Counterfactual analyses show that increasing all countries' TFP and improving institutional quality in countries with low-quality institutions generally raise exports, imports, output, capital stock, and welfare.

Key words: agricultural trade, capital accumulation, determinants of total factor productivity, dynamic gravity, instrumental variable regression

Introduction

Capital accumulation and productivity growth in the agricultural sector play important roles in determining countries' comparative advantage and trade flows. The evolution of comparative advantage is thus a dynamic process driven by physical capital accumulation and technological progress (Van Berkum and Van Meijl, 2000). Institutions and policies that enhance both capital accumulation and productivity growth can improve agricultural competitiveness. Given these connections, this paper addresses three important questions: (1) What is the relationship between productivity and capital accumulation and their effects on bilateral agricultural trade flows? (2) What are the determinants of agricultural productivity? (3) How does an improvement in agricultural productivity impact the size of the agricultural sector, capital accumulation, bilateral trade flows, and welfare?

Beyond determining trade patterns, the level of productivity and optimal time path of capital impact the volume of agricultural products that exporting countries can sell and importing countries purchase in international markets. For example, a large capital-to-labor ratio and technological advancements have allowed countries, such as the United States (along with a vast land endowment), to be long-time net exporters of major grain crops (corn, soybean meal, wheat, etc). Focusing on US state-level exports, Gopinath and Kennedy (2000) provide evidence that higher growth rates in total factor productivity (TFP) are associated with lower rates of capital decline and higher growth rates in exports. Furthermore, since agriculture is typically a key sector in developing countries, growth in agricultural capital, productivity, and thus production, could help to alleviate food insecurity and lower food prices (Fan and Rosegrant, 2008; Ivanic and Martin, 2008; Sanjuán-López and Dawson, 2010; Fuglie and Rada, 2013). Therefore, understanding the implications of capital accumulation

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and advancement in productivity on agricultural production and trade is important for policymakers, intergovernmental organizations, and international financial institutions. In addition, given the differences in agricultural production, we examine the differential impact of country-level estimates of production function for high-income and low-income countries.

Understanding the determinants of TFP at an international level is important given the role productivity plays in shaping agricultural trade patterns and flows. TFP measures the overall effectiveness of inputs (e.g., labor, capital, and fertilizer) employed in generating agricultural output and is calculated as the ratio of total output to the combination of inputs used in production. TFP thus measures the level of output that is not accounted for by inputs. An expansion in TFP can be achieved, for example, by combining the same quantity of inputs more efficiently to obtain a larger quantity of output. External factors such as climate can help to determine agricultural TFP. However, governments can play a role in improving the overall efficiency of the agricultural sector by investing in public goods such as supporting research, investing in infrastructure, and creating functioning institutions to manage quality and set standards. Most prior studies of agricultural TFP have typically focused on farm-level data from a single country or a homogeneous region (e.g., Rosegrant and Evenson, 1992; Fuglie and Rada, 2013). In contrast, this study contributes to the literature by analyzing the impact of country-level indicators—such as government investment and communication technology—on TFP in aggregate agricultural production across a broad sample of countries.

Several studies have examined the impact of institutional quality—including labor market regulations, market entry barriers, tax levels and efficiency (Borrmann, Busse, and Neuhaus, 2006), as well as the quality of transport and communications infrastructure (Francois and Manchin, 2013)—on trade. Additionally, research has examined how institutional differences (Levchenko, 2007) and contract enforcement (Nunn, 2007) affect comparative advantage and trade flows. Importantly, Hou, Wang, and Xue (2021) show that improvements in institutional quality reduce trade costs for agricultural goods. While these studies make important connections between institutional quality, comparative advantage, and trade, we contribute by examining how institutional quality directly affects agricultural production and, in turn, how changes in institutional quality influence both production and trade.

Focusing specifically on agriculture, Fuglie and Wang (2012) emphasize that, while national investments in agricultural R&D are critical for agricultural growth, "enabling environments"—including policies that enhance producer incentives, effective extension services, and infrastructure that improves market access—can complement research and are key determinants of cross-country differences in TFP. See Fuglie (2018) for a review covering over 40 studies on the relationship between R&D and TFP in agriculture. Furthermore, Zhang and Fan (2004) find that infrastructure development in India significantly enhanced agricultural TFP growth. These findings suggest that government investment and communication technologies are key determinants of agricultural TFP—an issue this study further investegates. This paper links these two strands of literature by examining how institutional quality and communications infrastructure affect agricultural TFP, and how resulting changes in TFP influence agricultural trade.

Anderson (1979) was the first study to connect the empirical gravity equation to trade theory. Anderson and van Wincoop (2003) popularized Anderson's (1979) model by extending the gravity model to include not only bilateral trade costs but also multilateral trade costs. These multilateral costs are widely referred to as inward and outward multilateral resistance terms (MRTs) and generally represent the ease of access of importers and exporters to international markets. Since Anderson and van Wincoop (2003)'s key insight into multilateral trade costs, the development and application of structural gravity models has been extensive (Head and Mayer, 2014; Yotov et al., 2016). In a recent development, Anderson, Larch, and Yotov (2020) embed a multi-country gravity model in a dynamic equilibrium framework with capital accumulation. In this model, trade impacts capital accumulation by influencing both consumer and producer prices, while growth in the capital stock influences trade by increasing the size of the economy (direct channel) and altering trade costs (indirect channel). The theoretical model yields structural econometric equations for trade, the value of production, and capital accumulation. Furthermore, a tight connection between the theory and the econometric model allows for counterfactual analyses. Anderson, Larch, and Yotov (2020) apply their model to the aggregate economy and quantify the dynamic impact of NAFTA. This paper builds on Anderson, Larch, and Yotov (2020) by controlling for factors that impact TFP in the production function and applying the model to study the determinants of agricultural productivity and capital accumulation in the global agricultural sector.

The agricultural trade literature has utilized gravity models to examine a wide range of international and domestic policies (Zahniser et al., 2002; Koo, Kennedy, and Skripnitchenko, 2006; Sarker and Jayasinghe, 2007; Disdier, Fontagné, and Mimouni, 2008; Grant and Lambert, 2008; Jayasinghe and Sarker, 2008; Sun and Reed, 2010; Raimondi and Olper, 2011; Grant and Boys, 2012; Grant, Peterson, and Ramniceanu, 2015; Tong, Pham, and Ulubaşoğlu, 2019; Luckstead, 2022; Kondaridze and Luckstead, 2023). While structural gravity models fully parameterize the underlying theoretical trade model, their implementation for counterfactual simulations in the agricultural trade literature is limited but includes Ridley, Luckstead, and Devadoss (2022, 2024); Ridley and Devadoss (2023); Larch, Luckstead, and Yotov (2024). In contrast to the existing agricultural gravity literature that implements gravity-model simulations that hold capital and output constant, the current paper allows for capital accumulation and output to evolve endogenously. In addition to examining counterfactual scenarios involving improvements in the determinants of agricultural TFP, this study contributes to the agricultural trade literature by estimating structural equations for agricultural trade, the value of production, and capital accumulation. In doing so, this study is the first to quantify the capital stock transition parameter governing agricultural capital accumulation.

Based on the structural model, this study estimates gravity, the value of production, and capital accumulation equations using data from three sources: (i) aggregate bilateral trade flows and agricultural trade policies from the United States International Trade Commission, (ii) capital, land, labor, pesticide, and fertilizer from the Food and Agricultural Organization's FAOStat database, and (iii) productivity-related indicators from the World Bank and Economic Freedom of the World databases. Tariffs are included in the model and estimated from aggregate trade-weighted average MFN and preferential tariff rate data from the World Integrated Trade Solution. With the structural model parameterized, the study then simulates the dynamic impacts of two counterfactual scenarios. First, we consider a 10% increase in agricultural TFP for all countries, driven by international research and potentially resulting from a non-discriminatory breakthrough in agricultural productivity (e.g., the Green Revolution). Second, since institutional quality is vital for an efficient agricultural sector and market, and many countries could improve the quality of their institutions by enhancing laws and regulations that strengthen property rights and contract enforcement, we simulate a 50% increase in the legal enforcement of contracts index for the bottom half of countries.

The Dynamic Gravity Model

We present the dynamic gravity model of Anderson, Larch, and Yotov (2020),[1] which extends the structural gravity model by explicitly accounting for value of production and capital accumulation

[1] While the model implicitly assumes consumers make the capital investments, this is a reasonable assumption in this sectoral specification as consumers, particularly in developing countries, often play a direct role in funding agricultural investments through savings, microcredit, or remittances. In developed countries, consumers may similarly contribute to capital investments indirectly through mechanisms such as agricultural subsidies, government programs, or retail investment opportunities in agricultural assets (e.g., farmland, ag-tech stocks). Moreover, in highly integrated global markets, even households in developed countries can impact investment decisions through their consumption patterns and preferences, which can influence agricultural firms' capital allocation decisions.

(see Appendix for the full model setup):

$$X_{ij,t} = \frac{Y_{i,t}E_{j,t}}{Y_t}\left(\frac{t_{ij,t}}{\Pi_{i,t}P_{j,t}}\right)^{1-\sigma}\tau_{ij,t}^{-\sigma} \tag{1}$$

$$P_{j,t}^{1-\sigma} = \sum_i \frac{Y_{i,t}}{Y_t}\left(\frac{t_{ij,t}}{\Pi_{i,t}}\right)^{1-\sigma} \tag{2}$$

$$\Pi_{i,t}^{1-\sigma} = \sum_j \frac{E_{j,t}}{Y_t}\left(\frac{t_{ij,t}}{P_{j,t}}\right)^{1-\sigma} \tag{3}$$

where $X_{ij,t}$ is nominal bilateral trade exported from country i to j in year t, $Y_{i,t}$ is the value of production, $E_{j,t}$ are expenditures given by the trade balance $E_{j,t} = \phi_{j,t}Y_{j,t}$ with $\phi_{j,t} > 0$ such that aggregate expenditures are equal to the value of production by factor $\phi_{j,t}$, $Y_t = \sum_i Y_{i,t}$ is total value of agricultural production, $t_{ij,t}$ is bilateral friction variables such as distance or common language, $\tau_{ij,t} = 1 + tariff_{ij,t}$ where $tariff_{ij,t}$ are ad valorem tariffs imposed by importer j on exporter i in year t,[2] $\sigma > 1$ is the Armington elasticity of substitution, and $\Pi_{i,t}$ and $P_{j,t}$ are the outward and inward MRTs. The MRTs reflect that bilateral trade depends not only on trade costs between i and j but also on trade costs with all other trading partners. The nominal value of production is

$$Y_{j,t} = p_{j,t}A_{j,t}K_{j,t}^{\alpha}L_{j,t}^{\xi_1}H_{j,t}^{\xi_2}F_{j,t}^{\xi_3}B_{j,t}^{\xi_4} \tag{4}$$

where $p_{j,t} = \frac{\left(\frac{Y_{j,t}}{Y_t}\right)^{1/(1-\sigma)}}{\gamma_j \Pi_{j,t}^{1-\sigma}}$ is the farm price of agricultural production in j at time t, $\gamma_j > 0$ is a positive distribution parameter in the CES utility function, $A_{j,t} = \prod_{a=1} A_{a,j,t}^{\eta_a}$ is TFP, $A_{a,j,t}^{\eta_a}$ are determinants of TFP, $K_{j,t}$ is capital stock, $L_{j,t}$ is labor, $H_{j,t}$ is land, $F_{j,t}$ is fertilizer, $B_{j,t}$ is pesticide, α and $\xi_1,...,\xi_4$ are share parameters. The capital accumulation equation is given by

$$K_{j,t+1} = \left[\frac{\alpha\beta\delta Y_{j,t}}{(1-\beta+\beta\delta)P_{j,t}}\right]^{\delta} K_{j,t}^{1-\delta} \tag{5}$$

where $\delta \in (0,1]$ is the capital stock transition parameter,[3] $\beta \in (0,1)$ is consumers' time discount factor.[4]

The structural gravity model with capital accumulation is fully summarized by equations (1)-(5) where K_0 is given.

In the counterfactual analyses, given the structure of the Armington gravity model, welfare changes are measured by changes in real income from agricultural production:[5]

$$\hat{W}_j = \hat{A}_j^{\frac{\alpha}{1-\alpha}}\hat{\lambda}_{jj}^{\frac{1}{(1-\sigma)(1-\alpha)}} \tag{6}$$

where ^ implies the ratio of the counterfactual variable to the baseline variable and $\lambda_{jj} = \frac{X_{jj}}{Y_j}$ is the share of domestic expenditure. See Appendix for the extension of the welfare measure in Anderson, Larch, and Yotov (2015) to include TFP changes.

[2] For the derivation of the gravity model with tariffs see Appendix B: Structural gravity with tariffs in Yotov et al. (2016).

[3] The capital stock transition parameter includes the depreciation of capital and the costs of adapting embodied investments into new capital. The costs can include the purchase of new capital, adjustment to production practice, training for the new equipment, etc, and incorporate both financial and operational elements of new capital investments. We thus expect the capital stock transition parameter to be larger than the depreciation rate.

[4] See Anderson, Larch, and Yotov (2015) for additional details on the model.

[5] This welfare approach conforms to standard CES gravity models, in which real income is a sufficient statistic for welfare with sector-specific shocks (Arkolakis, Costinot, and Rodríguez-Clare, 2012).

Econometric Model

We transform the structural model into reduced-form equations for econometric estimation and identify the relationship between reduced-form parameters and structural parameters.

Trade

As is now standard in the trade literature, we use the Poisson Pseudo-Maximum- Likelihood (PPML) estimator (Santos Silva and Tenreyro, 2006), which accounts for heteroskedasticity and zeros in trade data. Bilateral trade costs are defined as

$$t_{ij,t}^{1-\sigma} = \exp\left\{\gamma_2 WTO_{ij,t} + \gamma_3 FTA_{ij,t} + F_{ij}\right\},$$

where $WTO_{ij,t}$ is an indicator variable equal to 1 if countries i and j are both members of the WTO, $FTA_{ij,t}$ is an indicator variable equal to 1 if countries i and j are both members of an FTA, and F_{ij} are country-pair fixed effects that controls for all observable (e.g., distance, common language) and unobserved bilateral factors (e.g., political ties) impacting trade between country i and j. Baier and Bergstrand (2007) demonstrate that country-pair fixed effects can control for endogeneity arising from omitted variables (the primary source of endogeneity) in free trade agreements. However, Fontagné, Guimbard, and Orefice (2022) argue that tariffs do not suffer from endogeneity and the inclusion of country-pair fixed effects absorbs the cross-country variation, which is the primary source of variation in tariff data. Furthermore, the cross-country variation is required for accurate estimates of the structural elasticity of substitution parameter. Given these considerations with country-pair fixed effects, we report estimates for models both with and without country-pair fixed effects.

With bilateral trade costs defined, the gravity equation (1) is

$$X_{ij,t} = \exp\left(F_{i,t} + F_{j,t} + F_{ij} + \gamma_1 \log\left(\tau_{ij,t}\right) + \gamma_2 WTO_{ij,t} + \gamma_3 FTA_{ij,t}\right) + \varepsilon_{ij,t} \tag{7}$$

where $F_{i,t}$ controls for all observed (e.g., size of exporters' agricultural sector $Y_{i,t}$) and unobserved (e.g., outward MRT $\Pi_{i,t}^{1-\sigma}$) factors impacting exporter i in year t and $F_{j,t}$ controls for all observed (e.g., size of importers' agricultural sector $E_{j,t}$) and unobserved (e.g., inward MRT $P_{j,t}^{1-\sigma}$) factors impacting importer j in year t. Together, $F_{i,t}$ and $F_{j,t}$ capture all time varying factors. With tariffs included in the model, we can recover the structural elasticity of substitution parameter as $\sigma = -\gamma_1$ (when country-pair fixed effects are excluded). Since we use the structural model to simulate the impacts of changes in TFP factors, the importer-time, exporter-time, and country-pair fixed effects are important for accurate estimation of multilateral resistance and bilateral trade costs. Thus, the model with country-pair fixed effects is the best model for the simulation.

Output

Next, we transform the theoretical specification for nominal production into an econometric equation by substituting farm-gate price $p_{j,t} = \frac{\left(\frac{Y_{j,t}}{Y_t}\right)^{1/(1-\sigma)}}{\gamma_j \Pi_{j,t}^{1-\sigma}}$ into (4) and expressing in log form:

$$\begin{aligned} \log Y_{j,t} \quad = \quad & \kappa_1 \log\left(K_{j,t}\right) + \kappa_2 \log\left(L_{j,t}\right) + \kappa_3 \log\left(H_{j,t}\right) + \kappa_4 \log\left(F_{j,t}\right) + \kappa_5 \log\left(B_{j,t}\right) \\ & + \kappa_6 \log\left(\Pi_{j,t}^{\sigma-1}\right) + \sum_a \kappa_{0,a} \log\left(a_{a,j,t}\right) + \upsilon_t + \vartheta_j + \varepsilon_{j,t}. \end{aligned} \tag{8}$$

Here υ_t are year fixed effects that control for global changes in technology, ϑ_j are country fixed effects that control for observable and unobservable cross-country differences, and $\varepsilon_{j,t}$ is an error term. The relationships between the reduced form parameters and the structural parameters are $\kappa_1 = \alpha\frac{\sigma-1}{\sigma}$, $\kappa_i = \xi_i\frac{\sigma-1}{\sigma}$ $i = 2,\ldots,5$, $\kappa_6 = \frac{1}{-\sigma}$, and $\kappa_{0,a} = \frac{1}{\sigma}\eta_{0,a}$. TFP is defined as $\log\left(A_{j,t}\right) = \sum_a \kappa_0^a \log\left(a_{j,t}^a\right) + \upsilon_t + \vartheta_j$.

Due to concerns about endogeneity in both the input variables and the trade openness term $\log\left(\Pi_{j,t}^{\sigma-1}\right)$, we estimate (8) using an instrumental variable approach. Regarding the inputs to production, we exploit the panel structure of the dataset and construct instruments from two-period lagged values of capital, labor, land, fertilizer, and pesticide. These lagged inputs are plausibly exogenous to current productivity shocks and thus serve as valid instruments. In addition, since natural disasters are exogenous events that may influence farmers' input decisions, we include the occurrence of natural disasters as an additional instrument.

The outward MRT suffers from endogeneity because it is a function of both output $Y_{it} = \sum_j X_{ij,t}$ and expenditure $E_{it} = \sum_i X_{ij,t}$ which are themselves dependent on bilateral trade flows—the dependent variable. Following Anderson, Larch, and Yotov (2020), we construct an instrument that breaks this confounding relationship in two ways. First, we remove each country's own observation when calculating MRT, thereby reducing the direct feedback between a country's trade flows and its MRT. Second, we replace the output and expenditure weights $\frac{Y_{j,t}}{Y_t}$ and $\frac{E_{j,t}}{Y_t}$ with historic population shares $\frac{L_{j,2000}}{L_{2000}}$ from 2000. These shares are exogenous to current shocks but still correlated with production and consumption levels. The resulting instrumental variable are $\Pi_{i,t}^{IV} = \sum_{j\neq i}\left(\frac{t_{ij,t}}{P_{j,t}^{IV}}\right)^{1-\sigma}\frac{L_{j,2000}}{L_{2000}}$ and $P_{j,t}^{IV} = \sum_{j\neq i}\left(\frac{t_{ij,t}}{\Pi_{i,t}^{IV}}\right)^{1-\sigma}\frac{L_{j,2000}}{L_{2000}}$. We also construct a second instrument based on gravity-predicted trade flows. Specifically, we estimate a gravity equation using only bilateral trade costs and population as explanatory variables and exclude exporter-time and importer-time fixed effects, which normally absorb MRT and aggregate supply/demand. The predicted trade flow $X_{ij,t}^{IV}$ are then aggregated to construct an instrument for country-level output: $Y_{i,t}^{IV} = \sum_j X_{ij,t}^{IV}$. By excluding fixed effects related to MRT and aggregate production and consumption, we mitigate the endogeneity of the predicted trade flows with respect to the outcome variable.

Capital

To transform the theoretical specification for capital into an econometric equation, we log linearize (5):

$$\text{(9)} \qquad \log K_{j,t} = \psi_1 \log\left(E_{j,t-1}\right) + \psi_2 \log\left(K_{j,t-1}\right) + \psi_3 \log\left(P_{j,t-1}^{\sigma-1}\right) + \upsilon_t + \vartheta_j + \nu_{j,t},$$

where $\psi_1 = \delta$, $\psi_2 = 1-\delta$, and $\psi_3 = -\frac{\delta}{\sigma-1}$, υ_t are year fixed effects, ϑ_j are country fixed effects, and $\nu_{j,t}$ is an error term. We include year fixed effects to control for observed and unobserved global effects that can impact the capital stock. We also include country fixed effects to control for time-invariant observed and unobserved country-specific characteristics that influence capital accumulation.

Equation (9) relates the current-period capital stock to the previous year's capital stock, which creates dynamic panel bias resulting from $\log K_{j,t}$ being correlated with country-specific effects in the error term. This bias is resolved through the inclusion of country fixed effects (Anderson, Larch, and Yotov, 2020). Expenditures on agricultural production and inward trade openness are also functions of capital, raising concerns about endogeneity in these variables. As a result, we include instruments for three-period lags of capital, land, agricultural expenditure, and inward trade openness. We also include a one-period lag of the structural instrumental variable of trade openness and natural disasters.

Data

Next, we discuss the data and source for bilateral trade flows, production inputs, and TFP determinants. We obtained data for bilateral agricultural trade flows from the International Trade and Production Database for Estimation (ITPD-E) of the US International Trade Commission (Borchert et al., 2021) for the years 2000 to 2019. To ensure a square dataset for the simulation, we keep countries that account for 95% of total agricultural production, which is calculated as $Y_{i,t} = \sum_j X_{ij,t}$ from the bilateral trade data. Then, we keep countries that both import and export agricultural goods. The data include 69 importing countries and 69 exporting countries. Since data for capital (discussed below) is at the aggregate agricultural production level, we add all agricultural commodities (commodity codes 1-26) into one aggregate commodity. The ITPD-E data includes domestic sales in the dataset. We collect data on the joint membership to the WTO and an FTA from the Dynamic Gravity Data of the USITC (Gurevich and Herman, 2018). We collect aggregate trade-weighted average MFN and preferential tariff rate data from the World Integrated Trade Solution, Tariff and Trade Analysis database of the World Trade Organization (The World Bank, b). We combine the MFN and preferential tariff data into one variable by replacing MFN tariffs with preferential tariffs if preferential tariffs exist for a given bilateral country pair.

We collect data for capital (gross fixed capital formation for agriculture, forestry, and fishing), land (agriculture), labor (employment in agriculture, forestry, and fishing by age, total 15+), pesticides (total), and fertilizer (nutrient nitrogen, total) from FAOStat. Natural disasters are constructed as an indicator variable based on data from EmDat that takes the value of one if total deaths from a natural disaster are greater than 100 and zero otherwise.

Various factors, including investments in research and development (e.g., improved seeds and technologies), extension services and education (e.g., farm management training), and rural infrastructure (e.g., roads and market facilities) shape agricultural productivity. However, consistent cross-country data on these inputs are unavailable, particularly for a large panel of countries. To address this limitation, we use proxies derived from global datasets. Furthermore, when estimating TFP at the aggregate level, institutional quality and communication infrastructure emerge as significant determinants. To capture these dimensions, we incorporate data from the EFW database, which provides institutional quality indicators on a 0–10 scale. The government investment index depends on the share of government investment in total investment, with lower values indicating a greater presence of government enterprises and investment. This variable can influence TFP by supporting public infrastructure, funding agricultural research and extension services, and fostering human capital development. The business regulations index includes administrative requirements, bureaucracy costs, the cost of starting a business, impartial public administration (i.e., nepotism, cronyism), licensing restrictions, and the cost of tax compliance. Higher scores indicate less burdensome regulations, which can enhance efficiency, lower transaction costs, and allow for efficient entry and exit of farms. The legal enforcement of contracts index is constructed from the time and cost of collecting debt from the World Bank's Doing Business database and the Enforcement of Contracts database from the Historical Ratings Research Package by Business Environment Risk Intelligence. Higher index values imply that countries have better legal enforcement of contracts, which can enhance TFP by reducing transaction costs, encouraging long-term investments, and supporting market development by reducing the risk of contract breaches in the input and output markets.

Second, from the The World Bank (a), we collect data on the number of Mobile Cellular Subscriptions; Regulatory Quality; Taxes on Income, Profits, and Capital Gains; and the Number of Scientific Articles. Mobile subscriptions serve as a proxy for communication infrastructure and digital access, enabling farmers—particularly in developing countries—to engage more effectively in markets. The Regulatory Quality index indicates the perceptions of governments' capabilities of formulating and implementing policies to allow and develop the private sector by improving investment capabilities, enhancing technological adoption, reducing corruption, and improving

Table 1. Summary Statistics

	Min	Max	Mean	Standard Deviation	*N*
Bilateral Trade (Millions USD)	0.00	914,571.65	428.85	10,139.45	90,459
Tariffs (Percent)	0.00	503.33	11.08	13.27	90,459
Joint WTO Membership (Indicator)	0.00	1.00	0.76	0.43	90,459
FTA (Indicator)	0.00	1.00	0.18	0.38	90,459
Ag. Output (Millions USD)	1,192.50	932,547.72	35,240.66	102,975.86	771
Labor (1000 Number)	6.84	334,420.00	8,936.29	37,829.27	771
Real Capital (Millions USD)	59.87	145,259.52	6,739.39	16,990.71	771
Land (1000 ha)	504.50	528,217.60	58,490.92	112,852.75	771
Fertilizer (Tonnes)	2,790.00	30,981,666.67	1,504,242.26	4,315,037.13	771
Pesticide (Tonnes)	1.00	549,280.44	48,037.65	91,242.85	771
Gov. Inv. (Index 0 to 10)	0.00	10.00	8.24	2.49	771
Bus. Reg. (Index 0 to 10)	2.34	8.85	5.68	1.38	771
Cont (Index 0 to 10)	0.47	9.85	5.40	1.91	771
Cell (Number)	0.20	177.02	96.87	38.20	771
Reg.Quality (Index -2.5 to 2.5)	-1.35	66.72	27.49	13.61	771
Taxes (Percent)	-1.35	66.72	27.49	13.61	771
Number of Sci. Articles	22.23	531,109.87	33,487.18	74,046.53	771

access to inputs and markets. Index values range from -2.5 to 2.5, with larger numbers indicating better regulatory quality. Taxes as a percent of income, profits, and capital gains represent the general level of taxes levied on individuals, corporations, capital, and securities. Higher values indicate higher tax rates could enhance the capacity to finance productivity-enhancing public goods but, in contrast, could also reduce the incentive for farms to grow in size. The number of scientific articles (which reflect the total scientific and technical journal publications by country and over time) serves as a proxy for national research output and innovation capacity. Higher research output can enhance agricultural technologies and farming practices, thereby enhancing productivity. In addition to these variables, we include country and time fixed effects to control for different countries' propensity to provide research and development, extension/education services, and infrastructure development. Table 1 provides the summary statistics for the variables used in the analysis.

Econometric Results

This section discusses the reduced form and structural parameter estimates of the gravity, value of output, and capital equations.

Gravity

For the gravity model defined in equation (7), Table 2 presents the estimated coefficients of the tariffs, WTO, and FTAs for aggregate bilateral agricultural trade. Model 1 and Model 2 report these results based on models with and without country-pair fixed effects, respectively. In Model 1, the country-pair fixed effects control for unobserved heterogeneity between country pairs, which is the main source of endogeneity when estimating the impacts of the WTO and FTAs (Baier and Bergstrand, 2007). For comparison purposes across the three (gravity, output, and capital) equations, we are also interested in accurate estimates of the elasticity of substitution, calculated from the estimated coefficient of tariffs (i.e., the trade elasticity). However, country-pair fixed effects control for all cross-country variation, which is the main source of variation in applied tariffs. Since the Armington elasticity of substitution captures how consumers substitute agricultural goods across countries, accurate estimation of this parameter requires preserving the cross-country variation in

Table 2. Gravity Equation

Variable	Model 1	Model 2
log(Tariffs)	-0.031^{***}	-1.484^{***}
	(0.012)	(0.177)
WTO	0.653^{**}	7.690^{***}
	(0.193)	(0.847)
FTAs	0.039	-2.385^{***}
	(0.035)	(0.718)
Fixed Effects		
it	yes	yes
jt	yes	yes
ij	yes	no
No. of obs.	87,970	90,459

Notes: The dependent variable is unidirectional aggregate agricultural trade. Robust standard errors are in parentheses and clustered at the country-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

trade flows to identify the trade elasticity (Fontagné, Guimbard, and Orefice, 2022).[6] Model 2 reports the coefficient estimates of tariffs without country-pair fixed effects; however, the estimates of WTO and FTA suffer from omitted variable bias in this model. Based on this discussion, Model 1 is the preferred model for the counterfactual analyses because trade frictions play a central role, and the country-pair fixed effects offer the most accurate measure of observed and unobserved trade frictions; however, Model 2 is preferred for identifying the elasticity of substitution σ.

The results for Model 1 provide evidence that MFN and preferential tariffs marginally reduce aggregate agricultural trade for bilateral links over time, with a statistically significant coefficient estimate of −0.031. This small magnitude likely reflects the limited variation in tariff rates between country pairs over time However, Model 2 yields a statistically significant trade elasticity of −1.484, implying an elasticity of substitution of $\hat{\sigma} = -(-1.484) = 1.484$, which indicates low substitutability of agricultural goods across source countries. This low elasticity may reflect the influence of comparative advantage in agricultural production, which depends on country-specific endowments of land, capital, labor, and climate, thereby constraining consumers' ability to substitute among suppliers. The elasticity of substitution (1.484) is lower than the estimate of 2.91 estimated by Fontagné, Guimbard, and Orefice (2022) for the broader category of agriculture, hunting, forestry, and fishing. While both estimates suggest low substitutability, the higher elasticity reported by Fontagné, Guimbard, and Orefice (2022) may stem from their broader sectoral coverage, which includes activities likely to be more easily substituted across countries.

Model 1 indicates that joint membership in the WTO positively impacts aggregate agricultural trade. For example, if both countries are WTO members, they experience a statistically significant 92.130% $(= 100 \times (\exp(0.653) - 1))$ increase in aggregate agricultural trade. Estimates from the literature range between the 44.5% increase reported by Larch, Luckstead, and Yotov (2024) and the 114% increase found by Grant and Boys (2012). However, while we find evidence that FTAs positively impact aggregate trade, the coefficient estimate is statistically insignificant. This somewhat surprising result could imply that the primary impact of the formulation of an FTA on aggregate agricultural trade is tariff reduction. Since the tariff data capture both MFN and preferential tariffs (i.e., tariff rates under FTAs) the FTA coefficient captures the impact of FTAs after controlling for the impact of tariffs. These results further suggest that the primary benefit of FTAs to agriculture is tariff reduction.[7] For instance, since Larch, Luckstead, and Yotov (2024) find that regional trade agreements increase agricultural commodity trade by a modest but statistically

[6] Fontagné, Guimbard, and Orefice (2022) show that the estimates of tariffs do not suffer from endogeneity bias.

[7] Again, we do not dwell on the results of WTO or FTA from Model 2 without country-pair fixed effects because of the known endogeneity bias of these coefficients (Baier and Bergstrand, 2007).

significant 7% on average, but their estimate includes the effects of preferential tariffs, as they do not explicitly control for them.

A key element of the gravity trade model estimation is to provide estimates of the trade costs, which play a pivotal role in the counterfactual analysis (discussed in the subsequent section). For the counterfactual analysis, we thus utilize Model 1 since country-pair fixed effects are the most robust method to capture both observable (e.g., distance, common language, colonial relationship, etc.) and unobservable (e.g., political synergy, etc.) bilateral trade costs, we use Model 1 to calculate trade frictions and policies as

$$\left(\hat{t}_{ij,t}\right)^{1-\hat{\sigma}} \tau_{ij,t}^{-\hat{\sigma}} = \exp\left(\hat{F}_{ij} + \hat{\gamma}_1 \log\left(\tau_{ij,t}\right) + \hat{\gamma}_2 WTO_{ij,t} + \hat{\gamma}_3 FTA_{ij,t}\right).$$

Output

We report the results for the panel estimation of the global production function for all countries in the sample and for high-income and low-income countries separately.

Full Sample

For the value of output defined in equation (8), Table 3 reports the reduced form and structural coefficients of the inputs to production, the outward MRT, and determinants of TFP in the value of output. Given the endogeneity of inputs and the outward MRT, we utilize instrumental variables regression. As discussed in subsection , the instruments are theoretically sound. The instruments are also empirically sound as the F-statistics for the Weak Instruments test range from 14.98 to 182.056, suggesting strong instruments (see Appendix for the first-stage regressions and diagnostic tests). Furthermore, the Wu-Hausman Endogeneity Test yields a statistic of 74.554 (p-value < 0.01), indicating that endogeneity is present in the model, and thus 2SLS estimation is required. Finally, the p-value for Hansen's J-test is 0.741, suggesting that the instruments are valid and do not violate the overidentifying restrictions.

The coefficient estimates under the "Reduced Form" column come from the estimation of equation (8) and the parameter estimates under the "Structural" column result from converting the reduced form parameters to their structural counterparts. The reduced form parameters on capital, labor, land, fertilizer, and pesticides have the expected positive sign and are significant for all parameters except labor. The parameter estimate on the outward MRT is negative as predicted by the theory and is statistically significant. The parameter estimates for the determinants of TFP have the expected signs and are largely statistically significant.

From the Structural column, the share parameters on capital, labor, land, fertilizer, and pesticides are all positive and statistically significant. Recognizing the data are at the country level, these share parameters sum to 2.430, indicating increasing returns to scale. At the aggregate level, this could arise if larger farms contribute proportionately more to output. Also, as scale economies are realized and smaller farms are taken over by more efficient operations, aggregate-level estimates could reflect increasing returns while individual farms display constant returns. From a developing country's perspective, such a pattern may arise because agricultural production takes place on small, household-run plots. For instance, the average farm size in India and Ghana is less than three acres.[8] Scale economics could be taken advantage of by these farms increasing in size. See Hallam (1991); Fafchamps, Gabre-Madhin, and Minten (2005); Coelli, Rahman, and Thirtle (2002) for further evidence of increasing returns in the agricultural sector, particularly in developing countries. We analyze the heterogeneity of factor shares across high versus low-income countries by analyzing subsamples of the data, which is presented in the below subsubsection

[8] This finding aligns with Gollin (2010), who notes that as developing countries grow, the main source of employment shifts from agriculture to nonagricultural sectors, with fewer people operating increasingly larger farms.

Table 3. Value of Output Equation

Reduced Form[1]		Structural[2]	
Variable	**Estimate**	**Variable**	**Estimate**
$\log\left(K_{jt}\right)$	0.135***	$\hat{\alpha}$	0.424***
	(0.038)		(0.11)
$\log\left(L_{jt}\right)$	0.044	ξ_1	0.138*
	(0.031)		(0.08)
$\log\left(H_{jt}\right)$	0.330**	ξ_2	1.036***
	(0.134)		(0.37)
$\log\left(F_{jt}\right)$	0.199***	ξ_3	0.623***
	(0.046)		(0.12)
$\log\left(B_{jt}\right)$	0.067**	ξ_4	0.209***
	(0.030)		(0.07)
$\log\left(\Pi_{j,t}^{\sigma-1}\right)$	−0.681**	$\hat{\sigma}$	1.468***
	(0.314)		(0.56)
asinh(GovtInv)	0.043***	$\hat{\eta}_1$	0.063*
	(0.014)		(0.04)
asinh(BusReg)	0.166**	$\hat{\eta}_2$	0.244*
	(0.065)		(0.14)
asinh(LegalEnfCont)	0.209***	$\hat{\eta}_3$	0.306*
	(0.062)		(0.17)
asinh(CellNo)	0.058***	$\hat{\eta}_4$	0.084*
	(0.020)		(0.05)
asinh(RegQuality)	0.026	$\hat{\eta}_5$	0.04
	(0.041)		(0.06)
asinh(Taxes)	0.051**	$\hat{\eta}_6$	0.08
	(0.021)		(0.06)
asinh(SciJournal)	0.024	$\hat{\eta}_7$	0.04
	(0.022)		(0.03)
Intercept	0.008		
	(2.356)		
Fixed Effect			
j	yes		
t	yes		
Obs	710		
Adj R-Sq	0.9938		

Notes: The dependent variable is the logarithm of aggregate agricultural production. [1]Capital, labor, land, fertilizer, pesticide, and the outward multilateral resistance term are treated as endogenous and the regression is run using *ivreg* function in the *AER* package in R. Robust standard errors are in parentheses. [2]The structural standard errorsÃŕÂ£ÅŞare calculated using the Delta method. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The $asinh$ function is desirable because it is well-defined at zero and approximates the log function, while leaving the interpretation of coefficients largely unaffected.

The elasticity of substitution of 1.468 (calculated from the reduced form coefficient of the outward MRT) is nearly equal in magnitude to that estimated from Model 2 of the gravity equation (1.484). These two estimates of the elasticity of substitution provide evidence of the low elasticity of substitution of agricultural commodities across countries. To the best of our knowledge, this is the first Armington elasticity of substitution estimate in the agricultural trade literature obtained through structural estimation of a value of production equation with the outward multilateral trade resistance term.

Although traditional factors of TFP, such as research and development, extension services, education, and rural infrastructure, could not be included due to the cross-country nature of the

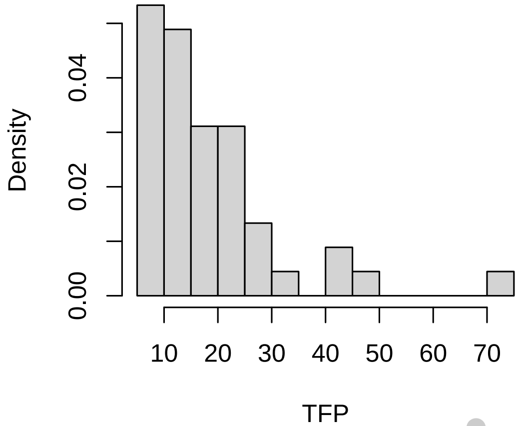

Figure 1. Histogram of TFP

production function estimation, the results emphasize the relevance of the proxies used. These findings offer new insights, emphasizing the role of institutional quality and communication technology in enhancing global agricultural TFP. For instance, the statistically significant structural coefficient estimate for government investment is 0.063, implying that a 1% increase in the government investment index leads to a 0.063% increase in agricultural TFP. Consistent with economic intuition, this result suggests that countries with higher proportions of private investment and enterprises, compared to those run by the government, have more productive agricultural sectors. For business regulation, the statistically significant coefficient indicates that less burdensome business restrictions improve agricultural productivity, as a 1% increase in the regulation index causes a 0.244% increase in agricultural productivity. The coefficient estimate for legal enforcement of contracts reveals that the efficiency of court systems, transparent legal proceedings, and ease of contract enforcement enhance agricultural productivity, with a 1% increase in the contracts index resulting in a 0.306% increase in TFP. Furthermore, a more robust communications infrastructure, proxied by the number of mobile cellular subscriptions, leads to more productive agricultural sectors, as a 1% increase in subscriptions expands agricultural productivity by a statistically significant 0.084%. Finally, the estimated structural coefficients for regulatory quality, taxes, and number of scientific journals are statistically insignificant. These are the first structural estimates of the determinants of global agricultural productivity, derived from a global production equation with cross-country variation, linked to agricultural trade through an outward multilateral trade resistance term.

Figure 1 depicts the histogram of TFP for all the countries in the sample.[9] As expected, the histogram is right skewed meaning more countries are likely to have a low to medium TFP level than a high TFP level. TFPs range from 5.258 to 73.038, and the Netherlands has the highest agricultural TFP followed by Belgium, Korea, and the United States, while Kazakhstan and Belarus have the lowest TFPs.

High-Income Versus Low-Income Countries

To examine heterogeneity in factor shares across high-income versus low-income countries, we estimate production functions separately for each group. High-income and low-income countries are defined using the World Bank income classifications. Table A3 presents both the reduced-form and structural coefficient estimates for the two subsamples. The implications of these results are discussed below; Appendix provides additional details.

[9] TFP is calculated as $TFP = \prod_a \left(\kappa_0^a a_{j,t}^a\right) \upsilon_t \vartheta_j$.

Focusing on the structural estimates, comparing high-income and low-income countries reveals substantial heterogeneity in factor shares. The capital share parameter is similar across both groups, at approximately 0.5. However, the labor share parameter is considerably larger and statistically significant for high-income countries, while it is insignificant for low-income countries. This result may reflect differences in labor use: in high-income countries, labor is typically hired on the market and varies with production, whereas in low-income countries, labor is often provided by household members and may not be adjusted in response to production needs. In contrast, the land share parameter is larger and statistically significant for low-income countries but insignificant for high-income countries. A likely explanation is that land in high-income countries is largely fixed in the short run and exhibits limited variation across farms. The high land share parameter for low-income countries—estimated at 2.195—likely reflects, as discussed above, the small scale of household-run farms, where substantial scale economies could arise by expanding in size. The fertilizer share parameter is statistically significant for both high- and low-income countries, with a larger coefficient in the latter. This underscores the central role of fertilizer in agricultural production, particularly in low-income settings. Finally, the share parameter for pesticides is statistically significant for high-income countries but not for low-income countries, suggesting that pesticide use is a more important component of variable costs in the former.

Noting that these scale economies are at the country level and not the individual farm level, the share parameters sum to 1.98 and 3.60 for high- and low-income countries, respectively, indicating increasing returns to scale in both cases. For high-income countries, this result is somewhat surprising but may reflect fixed costs or technologies that only become viable above a certain scale (e.g., advanced irrigation systems, bulk fertilizer purchases, precision agriculture). It may also reflect aggregation effects if larger, more productive farms disproportionately drive output growth. Moreover, as smaller farms exit and resources are reallocated to larger, more efficient operations, aggregate-level estimates may exhibit increasing returns even if returns at the individual farm level remain constant. For low-income countries, pronounced economies of scale may arise as the farm sectors transform from subsistence to commercial farming, farms expand cultivated land, adopt basic technology (e.g., pesticide or irrigation), and input utilization becomes more efficient as farmers expand production. Overall, these results suggest the presence of scale economies in both high- and low-income countries at the aggregate level, though the underlying margins through which they arise appear to differ systematically across contexts.

Capital

For capital defined in equation (9), Table 4 reports the reduced form and structural coefficients of the lagged values of production, capital, and the inward MRT for the dynamic capital equation. As discussed in subsection , the instruments are theoretically sound. The instruments are also empirically sound as the F-statistics for the Weak instruments test range from 82.926 to 95.395, indicating strong instruments (see Appendix for the first-stage regressions and diagnostic tests). Furthermore, the Wu-Hausman Endogeneity Test yields a statistic of 3.198, with a p-value of 0.023, suggesting endogeneity arises in the model and 2SLS estimation is required. Finally, the p-value for the Hansen's J-statistic is 0.963, suggesting that the instruments are valid and do not violate the overidentifying restrictions.

The coefficient estimate for lagged expenditures is statistically insignificant, indicating that consumer expenditures on agricultural goods do not influence capital accumulation. The coefficient estimate for lagged capital stock is positive and statistically significant, while the estimate for the inward MRT is negative and statistically significant, consistent with *a priori* expectations. The structural coefficient estimate of the elasticity of substitution of 1.471 closely matches the estimates from the gravity equation (1.484) and value of production equation (1.468), further suggesting a low level of substitution of agricultural goods across countries. This estimate is generally lower than the elasticity of substitution for aggregate trade found in Anderson, Larch, and Yotov (2020). The

Table 4. Capital Equation

Reduced Form[1]		Structural[2]	
Variable	**Estimate**	**Variable**	**Estimate**
$\log\left(E_{j,t-1}\right)$	−0.083		
	(0.167)		
$\log\left(K_{j,t-1}\right)$	0.654***	$\hat{\delta}$	0.346**
	(0.071)		(0.142)
$\log\left(\hat{P}^{\sigma-1}_{j,t-1}\right)$	−0.735*	$\hat{\sigma}$	1.471***
	(0.440)		(0.257)
Intercept	5.522**		
	(2.213)		
Fixed Effect			
j	yes		
t	yes		
Obs	710		
Adj R-Sq	0.9912		

Notes: The dependent variable is the logarithm of capital. [1]All covariates are treated as endogenous and the regression are run using *ivreg* function in the *AER* package in R. Robust standard errors are in parentheses. [2]The structural standard errors are calculated using the Delta method. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

capital stock transition parameter, which should be higher than the depreciation rate, is $\hat{\delta} = 0.345$. This value is larger than the value of 0.141 estimated by Anderson, Larch, and Yotov (2020). This result suggests that the transition parameter is larger for agricultural capital than for total capital. This is the first capital stock transition parameter estimate in the agricultural literature.

Counterfactual Analyses

This section considers the dynamic effects of improvements in TFP on bilateral trade, the value of production, capital stock, and welfare. Two scenarios are examined: (1) a uniform 10% increase in TFP across all countries, and (2) a 25% increase in the legal enforcement of contracts index for countries below the median value.

To run the counterfactual analyses, we use the five equations (1), (2), (3), (4), and (5). We solve the baseline steady state, the alternate scenario steady state, and the transition path between the baseline and alternate steady states. To solve the baseline steady-state, we replace $t + 1$ with t in the capital equation (5)[10] and use data for the last year (2018) in the sample. For the alternate scenario, we impose the counterfactual TFP in the equation (4) and iterate over equations (1), (2), (3), (4), and (5) until the difference between the value of production and capital between iterations is less than 1×10^{-8}. To solve the transition path from the baseline to the alternate scenario, we initialize with the baseline steady state and utilize the 2018 capital stock as the initial condition for capital (K_0). We then impose the counterfactual TFP and iterate over the five equations, allowing capital to dynamically update (with $t + 1$ in equation (5)) until production, capital, and bilateral trade converge to within 1×10^{-8} of their counterfactual steady-state levels. The only parameter not estimated in the structural model is the consumers' time discount factor, which is obtained from the literature ($\hat{\beta} = 0.98$ Yao et al., 2012).

Previous counterfactual analyses in the agricultural gravity literature only use (1), (2), and (3) and inherently assume that total production is held constant. However, this study extends the

[10] Replacing $t + 1$ with t, the capital equation (5) becomes $K_{j,t} = \frac{\alpha\beta\delta Y_{j,t}}{(1-\beta+\beta\delta)P_{j,t}}$.

Table 5. Impact of 10% Increase in TFP on Value of Trade, Output, Capital, and Welfare

ISO 3	Total Exp	ISO 3	Total Imp	ISO 3	Output	ISO 3	Capital	ISO 3	Welfare
CHN	6.61	IND	8.11	CHN	128.86	CHN	296.39	USA	7.05
IND	5.46	CHN	7.68	IND	54.91	IND	195.19	ARG	7.05
BLR	4.44	MLI	4.61	USA	35.05	BRA	81.7	AUS	7.05
MEX	3.33	IDN	3.86	IDN	17.95	IDN	25.92	AUT	7.05
IDN	3.07	TUR	2.95	BRA	16.44	USA	13.41	BEL	7.05
USA	2.99	USA	2.83	FRA	9.02	MLI	3.83	BLR	7.05
BRA	2.89	THA	2.65	ESP	7.8	MEX	3.57	BRA	7.05
ESP	2.62	COL	2.44	THA	6.63	THA	3.26	CAN	7.05
RUS	2.6	FRA	2.33	TUR	6.59	MYS	2.21	CHE	7.05
MLI	2.55	ROU	2.25	RUS	6.43	AUS	1.24	CHL	7.05
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
ARG	1.4	PRT	1.34	PRT	0.9	BEL	0.05	PHL	7.05
CHE	1.27	LKA	1.32	ISR	0.86	HUN	0.04	POL	7.05
ISR	1.19	CZE	1.3	LKA	0.84	BLR	0.03	PRT	7.05
LKA	1.17	ISR	1.24	KAZ	0.81	ISR	0.03	PRY	7.05
CZE	1.12	DNK	1.16	CRI	0.73	PRT	0.03	ROU	7.05
AUT	1.09	CHE	1.14	CZE	0.7	AUT	0.02	RUS	7.05
NZL	1.09	ZAF	1.04	AUT	0.68	DNK	0.02	SWE	7.05
SWE	1.08	SWE	1.03	BLR	0.68	SWE	0.02	THA	7.05
CRI	0.93	NZL	0.98	CHE	0.57	CHE	0.01	TUR	7.05
DNK	0.76	CRI	0.86	SWE	0.35	CZE	0.01	ZAF	7.05

Notes: In this scenario, all countries TFP is increased by 10%. Total exports, total imports, output, and capital are calculated as the difference between the counterfactual values and the baseline values and are reported in million USD. Welfare is a percent change from the baseline to the alternate scenario. Each variable reports the countries with the 10 largest increases and the 10 smallest increases.

agricultural gravity literature by running counterfactual analyses while allowing the capital stock and output to respond to external shocks endogenously.

Increase in all countries' TFP

With the ever-increasing global demand for food and the growing threat of climate change, technological advancements that enhance agricultural productivity—by improving crop yields, quality, and resilience to pests, disease, and climate stress—will be crucial for ensuring food security worldwide (Hamdan et al., 2022). In this scenario, we consider a hypothetical, biotechnology-driven 10% increase in TFP for all countries. Table 5 reports the resulting changes in total exports, total imports, output value, capital, and welfare for the ten countries with the largest improvements and the ten with the smallest gains.

Four key results stand out. First, as expected, a uniform increase in TFP across all countries leads to an expansion in all five endogenous variables—exports, imports, output, capital, and welfare—indicating that no country is left behind. Second, while output and capital rise by the same proportion in all countries due to the uniform TFP shock, the absolute changes vary by country size. Larger countries in terms of capital and output—such as China, India, Brazil, and the United States—experience the greatest increases in total exports and imports, output, and capital. Third, several advanced economies appear among the countries with the smallest gains, largely because they have relatively small agricultural sectors (e.g., Sweden, New Zealand, Switzerland). Fourth, welfare (measured by consumers' purchasing power via real income) increases uniformly by 7.05% for all countries which is less than the 10% increase in TFP. Because productivity and production expand by the same proportion across countries, domestic consumption also expands proportionally. Overall, a

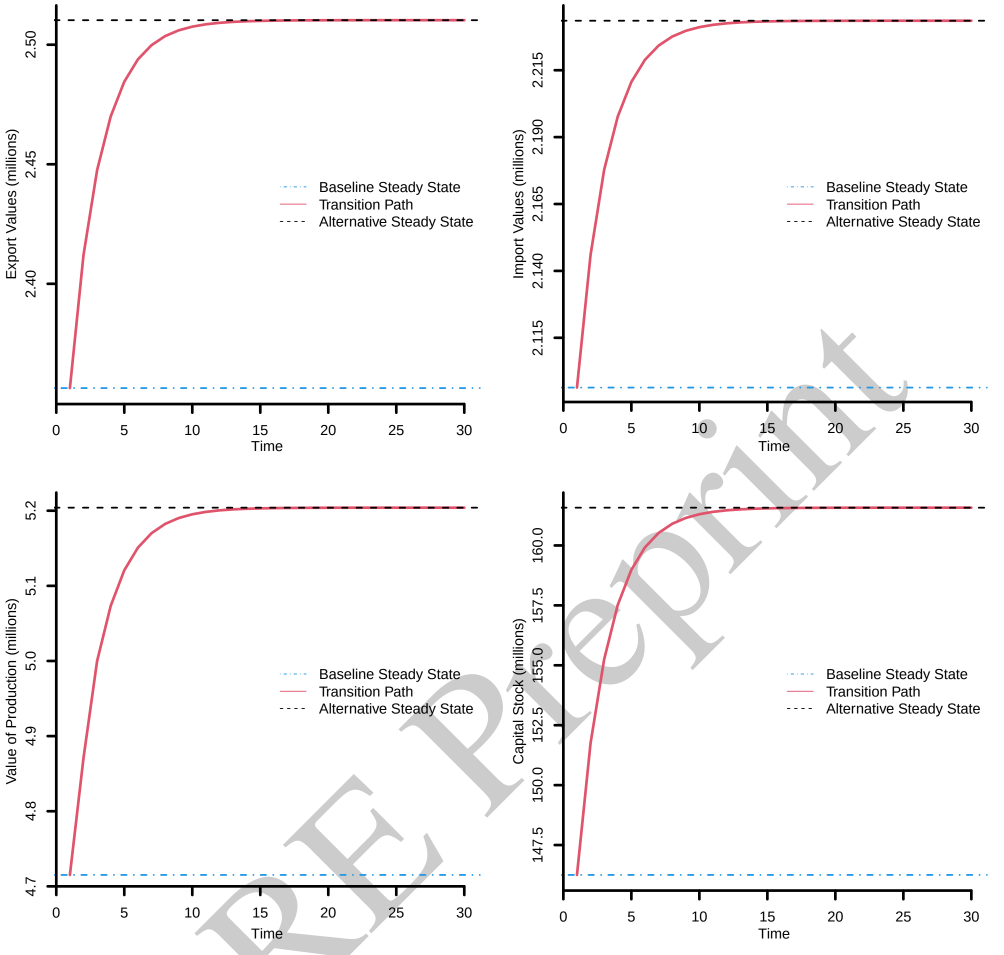

Figure 2. Transition Dynamics for the United States: 10% Increase in TFP

global improvement in agricultural TFP stimulates trade, boosts food production, accelerates capital accumulation, and enhances welfare globally.

Figure 2 depicts the transition dynamics for the United States from the baseline to the alternate scenario resulting from the 10% increase in all countries' agricultural TFP.[11] Two observations are made. First, the transition dynamics monotonically increase from the baseline to the alternate scenario, albeit at a decreasing rate as the transition path progresses. Second, due to the convex relationship between production and capital in equation (5), where $\delta = 0.35$, implying diminishing returns to capital as production expands, the transition path converges to within 90% of the alternate levels by year 18; the full transition from the baseline scenario to the alternate scenario for all four variables then takes about another 30 years to complete.

Increase in TFP via Legal Enforcement of Contracts

The econometric results indicate that institutional quality supports efficient agricultural sectors and well-functioning markets. Since institutional quality is generally linked to economic growth (Glaeser et al., 2004), governments with weaker institutions can promote development by strengthening

[11] While we focus on the United States here, a similar graph could be made for every country in the sample. For the other countries, the transition dynamics are similar but with different magnitudes between the baseline and alternate scenarios.

Table 6. Impact of 25% Increase in Legal Enforcement of Contracts on Value of Trade, Output, Capital, and Welfare

ISO 3	Total Exp	ISO 3	Total Imp	ISO 3	Output	ISO 3	Capital	ISO 3	Welfare
IND	1.81	CHN	1.80	CHN	17.05	IND	68.35	MYS	4.07
BLR	1.34	IND	1.74	IND	16.31	CHN	49.09	AUS	3.82
MEX	1.14	MLI	0.90	IDN	5.34	BRA	32.90	ZAF	3.81
IDN	1.02	IDN	0.83	BRA	5.06	IDN	8.86	THA	3.81
BRA	1.00	USA	0.69	USA	4.34	USA	1.66	SWE	3.79
RUS	0.85	THA	0.64	TUR	1.94	MEX	1.37	NZL	3.65
TUR	0.82	COL	0.60	RUS	1.88	MLI	0.96	CAN	3.60
PHL	0.78	TUR	0.58	ITA	1.82	THA	0.70	ISR	3.33
ITA	0.76	BRA	0.57	MEX	1.78	MYS	0.51	GBR	3.29
MLI	0.75	FRA	0.51	FRA	1.22	PHL	0.46	CHL	3.29
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
ZAF	0.15	CZE	0.28	KAZ	0.24	HUN	0.01	POL	1.01
GBR	0.14	BEL	0.28	CZE	0.21	PRT	0.01	KAZ	0.93
BEL	0.13	PRT	0.28	CRI	0.20	BEL	0.01	RUS	0.90
CHL	0.13	ISR	0.27	BLR	0.20	BLR	0.01	ECU	0.87
NZL	0.11	DNK	0.25	NZL	0.18	ISR	0.01	PRY	0.76
ISR	0.11	CHE	0.24	DNK	0.13	CZE	0.00	BLR	0.73
CHE	0.11	SWE	0.24	ISR	0.12	SWE	0.00	PER	0.72
SWE	0.11	ZAF	0.23	AUT	0.09	AUT	0.00	COL	0.43
AUT	0.10	NZL	0.22	CHE	0.08	DNK	0.00	MLI	-0.02
DNK	0.07	CRI	0.18	SWE	0.05	CHE	0.00	CRI	-0.56

Notes: In this scenario, the legal enforcement of contracts index is increased by 50% for the bottom half of countries. Total exports, total imports, output, and capital are calculated as the difference between the counterfactual values and the baseline values and are reported in billions USD. Welfare is a percent change from the baseline scenario to the alternate scenario. Each variable reports the countries with the 10 largest increases and the 10 smallest increases.

contract laws and enforcement mechanisms. In this scenario, we simulate a 25% increase in the legal enforcement of contracts for countries below the median value of the enforcement index. This policy change leads to an average increase in TFP of 4.6% across all treated countries.[12] Table 6 reports changes in total exports, total imports, output, capital, and welfare for the ten countries with the largest increases and the ten with the smallest gains.

A striking result emerges from increasing the enforcement of contract law in the bottom 50% of countries: exports, imports, agricultural production, and capital stock increase across the board. Treated countries—those experiencing improvements in legal enforcement—show the largest relative gains in output and capital compared to their respective baselines. This outcome appears to stem from a proportionally larger increase in agricultural production, which lowers output prices and enhances competitiveness in international markets. The resulting export expansion reflects this improved market position. Moreover, given that large portions of income in developing countries are derived from agriculture, productivity improvements translate into higher expenditures and consumption. In this CES-based model, higher incomes lead to increased consumption of both domestic and imported goods.

Another notable result is that welfare increases less in treated countries than in untreated countries. With welfare measured as real income, as defined in equation (6), we can decompose it into the direct effect of the productivity change $\hat{A}_j^{\frac{\alpha}{1-\alpha}}$ and the change in the domestic expenditure

[12] The ISO 3 country codes for these treated countries are: ARG, BLR, BRA, COL, CRI, CZE, ECU, GRC, HUN, IDN, IND, ITA, KAZ, LKA, MEX, MLI, PER, PHL, PRT, PRY, RUS, and TUR.

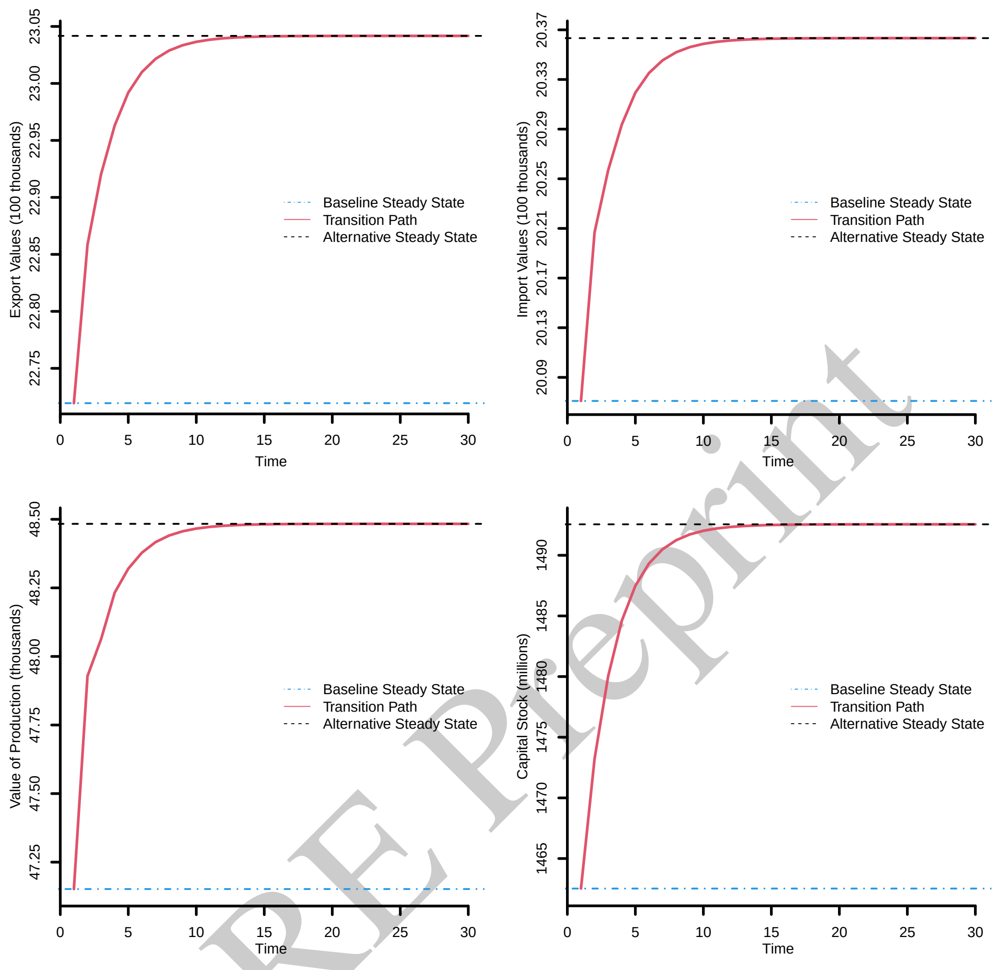

Figure 3. Transition Dynamics for the United States: 25% Increase for Bottom 50% of Countries

share $\hat{\lambda}_{jj}^{\frac{1}{(1-\sigma)(1-\alpha)}}$.[13] Productivity increases for treated countries, leading to higher welfare, but remains unchanged for untreated ones. The results indicate that, in treated countries, the domestic consumption share falls because the increase in productivity and output lowers the price of agricultural goods, making their commodities more attractive in foreign markets and thus boosting exports and lowering the domestic expenditure share. In untreated countries, the domestic consumption share rises: heightened international competition means more goods are sold domestically in a greater proportion. Consequently, in treated countries, while the productivity gain boosts real income, the fall in domestic consumption share dampens the welfare gain. In untreated countries, even though no productivity improvement arises, the relative increase in domestic expenditure share contributes positively to real income.

Figure 3 illustrates the transition dynamics for the United States from the baseline to the alternate scenario resulting from a 25% increase in the legal enforcement of contracts index for the bottom half of countries. In contrast to the results for a 10% increase in all countries' TFP, the transition paths take longer to reach 90% of the alternate levels, which occurs by year 21. The full transition occurs in about 35 years. Furthermore, US production and capital drop slightly in the first period as

[13] Note that $\frac{\alpha}{1-\alpha} > 0$ and $\frac{1}{(1-\sigma)(1-\alpha)} < 0$.

producers adjust to a boost in production by the producers in the treated countries. Treated countries do not experience this initial drop as production and capital monotonically increase.

Conclusions

This study utilizes a dynamic structural gravity model to examine the relationship between capital accumulation and the determinants of productivity in agricultural trade flows. The theoretical model gives rise to three structural econometric equations: bilateral trade, value of production, and capital accumulation. Determinants of productivity are embedded in the value of production equation, while the capital equation is explicitly dynamic. We consider a range of institutional characteristics—including government investment, business regulations, legal enforcement of contracts, mobile cellular subscriptions, government effectiveness, regulatory quality, and taxation—as potential drivers of productivity.

The study contributes to the literature by jointly estimating structural equations for agricultural trade, production, and capital accumulation. It is the first to quantify the Armington elasticity of substitution across trade, production, and capital channels and to estimate the capital stock transition parameter specific to agriculture. By leveraging cross-country variation in aggregate agricultural outcomes, the paper offers new insights into the roles of institutional quality and communication infrastructure in shaping global agricultural TFP. Additionally, the study explores the implications of (i) a global increase in TFP and (ii) improved legal enforcement of property rights among the bottom 50% of countries for agricultural production, capital accumulation, and trade flows.

Applied to aggregate agricultural data, the model yields several key findings. The elasticity of substitution is relatively low and stable across specifications, ranging from 1.468 to 1.484. Estimates of the cross-country agricultural production function indicate increasing returns to scale. This may arise even if individual farms exhibit constant returns, particularly if larger farms contribute disproportionately to output or if small farms consolidate into larger units to take advantage of scale economies, especially in developing countries. Government investment, regulatory quality, contract enforcement, and mobile communication access are consistently associated with higher agricultural productivity. Finally, the estimated capital stock transition parameter of 34.6% indicates a relatively rapid rate of capital adjustment in the sector.

Two counterfactual scenarios are analyzed using the estimated structural parameters and theoretical framework. First, a biotechnology-driven increase in TFP across all countries leads to widespread gains in trade, output, capital accumulation, and welfare. Second, enhanced legal enforcement of contracts among countries below the median institutional quality level results in improved outcomes for the treated countries and the rest of the world through trade and capital channels.

The findings underscore the critical role of institutional quality and communication technology in shaping global agricultural outcomes. Given the positive externalities observed in the results, international organizations such as the FAO, World Bank, and IFAD should support institutional reforms in countries with weak governance by promoting stronger legal frameworks, expanding public investment capacity, and reducing regulatory burdens. Moreover, as mobile connectivity facilitates information flows, market access, and financial inclusion, governments should foster public and private investment in rural digital infrastructure. Since institutional improvements in one country can generate welfare gains abroad, these reforms exhibit the characteristics of a global public good—justifying multilateral cooperation and targeted development support.

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Appendix

Dynamic Gravity Model

We extend the gravity model with capital accumulation presented in Anderson, Larch, and Yotov (2020) to suit agricultural production and introduce determinants of TFP. The model combines the CES-Armington gravity trade model with a capital accumulation model for transition between steady states that assumes perfect foresight and exogenous labor, land, and intermediate input, trade imbalances, and technologies. These assumptions are necessary for a closed-form solution for capital accumulation which is vital for econometric estimation of the structural system of growth, value of production, and trade.

Next, we define the nested two-level optimization problem. In the upper-level, a representative consumers in country j choose the optimal paths for consumption of an aggregate agricultural commodity, $C_{j,t}$, and investment in agricultural capital, $\Omega_{j,t}$, to maximize the present discounted value of lifetime utility

$$\text{(A1)} \qquad \max_{C_{j,t},\Omega_{j,t}} \sum_{t=0}^{\infty} \beta^t \ln\left(C_{j,t}\right)$$

subject to the law of motion of agricultural capital $\left(K_{j,t}\right)$

$$\text{(A2)} \qquad K_{j,t+1} = \Omega_{j,t}^{\delta} K_{j,t}^{1-\delta},$$

where δ is the capital stock transition parameter;[14] nominal production $\left(Y_{j,t}\right)$

$$\text{(A3)} \qquad Y_{j,t} = p_{j,t} A_{j,t} K_{j,t}^{\alpha} L_{j,t}^{\xi_1} H_{j,t}^{\xi_2} F_{j,t}^{\xi_3} B_{j,t}^{\xi_4},$$

where $p_{j,t}$ is the farm price of agricultural production in j at time t, $A_{j,t} = \prod_{a=1} A_{a,j,t}^{\eta_a}$ is TFP, $A_{a,j,t}^{\eta_a}$ are determinants of TFP, $L_{j,t}$ is labor, $H_{j,t}$ is land, $F_{j,t}$ is fertilizer, and $B_{j,t}$ is pesticide; expenditures $\left(E_{j,t}\right)$

$$\text{(A4)} \qquad E_{j,t} = P_{j,t} C_{j,t} + P_{j,t} \Omega_{j,t}$$

where $P_{j,t}$ is the aggregate price index (or inward MRT defined below); and trade balance

$$\text{(A5)} \qquad E_{j,t} = \phi_{j,t} Y_{j,t},$$

where aggregate expenditures are equal to the value of production by factor $\phi_{j,t}$. Solving equations (A1) - (A5) as a dynamic program yields the policy function for capital

$$\text{(A6)} \qquad K_{j,t+1} = \left[\frac{\alpha\beta\delta Y_{j,t}}{(1-\beta+\beta\delta) P_{j,t}}\right]^{\delta} K_{j,t}^{1-\delta}.$$

In the lower-level, we solve for optimal consumption, $c_{ij,t}$, and investment, $I_{ij,t}$, from each country i. The CES aggregate consumption of agricultural goods and investment are

$$\begin{aligned} C_{j,t} &= \left(\sum_i \gamma_i^{\frac{1-\sigma}{\sigma}} c_{ij,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \\ \Omega_{j,t} &= \left(\sum_i \gamma_i^{\frac{1-\sigma}{\sigma}} I_{ij,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \end{aligned}$$

[14] The capital stock transition parameter includes the depreciation of capital and the costs of adapting embodied investments into new capital. The costs can include the purchase of new capital, adjustment to production practice, training for the new equipment, etc, and incorporate both financial and operational elements of new capital investments. We thus expect the capital stock transition parameter to be larger than the depreciation rate.

where γ_i is a positive distribution parameter. The price of agricultural products produced in i and sold in j are defined as $p_{ij,t} = p_{j,t} t_{ij,t} \tau_{ij,t}$ where $t_{ij,t}$ is bilateral trade costs, $\tau_{ij,t} = 1 + tariff_{ij,t}$, and $tariff_{ij,t}$ are ad valorem tariffs imposed by importer j on exporter i in year t.[15] The maximization problem

$$\max \left(\sum_i \gamma_i^{\frac{1-\sigma}{\sigma}} c_{ij,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} + \left(\sum_i \gamma_i^{\frac{1-\sigma}{\sigma}} I_{ij,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

subject to the budget constraint[16]

$$E_{j,t} = \sum_i p_{ij,t} \left(c_{ij,t} + I_{ij,t} \right) = Y_j + \sum_i \left(\tau_{ij,t} - 1 \right) X_{ij,t},$$

yields the structural gravity

$$X_{ij,t} = \frac{Y_{i,t} E_{j,t}}{Y_t} \left(\frac{t_{ij,t}}{\Pi_{i,t} P_{j,t}} \right)^{1-\sigma} \tau_{ij,t}^{-\sigma} \tag{A7}$$

$$P_{j,t}^{1-\sigma} = \sum_i \frac{Y_{i,t}}{Y_t} \left(\frac{t_{ij,t}}{\Pi_{i,t}} \right)^{1-\sigma} \tag{A8}$$

$$\Pi_{i,t}^{1-\sigma} = \sum_j \frac{E_{j,t}}{Y_t} \left(\frac{t_{ij,t}}{P_{j,t}} \right)^{1-\sigma} \tag{A9}$$

where $P_{j,t}$ and $\Pi_{i,t}$ are the inward and outward MRTs.

The structural gravity model with capital accumulation is fully summarized by equations (A3), (A6), (A7), (A8), and (A9) where $p_{j,t} = \frac{\left(\frac{y_{j,t}}{y_t} \right)^{1/(1-\sigma)}}{\gamma_j \Pi_{j,t}^{1-\sigma}}$ and K_0 is given.

First-Stage Regressions

Welfare

In this appendix, we extend the derivation of welfare in Anderson, Larch, and Yotov (2015) to include changes in TFP. If welfare is defined as real income, then the change in welfare is

$$d\ln W_j = d\ln Y_j - d\ln P_j.$$

From the production function, the change in output is

$$d\ln Y_j = d\ln p_j + d\ln A_j + d\ln K_j.$$

Using the price index, the change in price is defined as

$$d\ln P_j = -\frac{1}{1-\sigma} d\ln \lambda_{jj} + d\ln p_j,$$

where $\lambda_{jj} = \frac{x_{jj}}{Y_j} = \left(\frac{\gamma_j p_j t_{jj}}{P_j} \right)^{1-\sigma}$ (Anderson, Larch, and Yotov, 2015). The change in welfare can be defined as

$$d\ln W_j = d\ln A_j + d\ln K_j + \frac{1}{1-\sigma} d\ln \lambda_{jj}.$$

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[15] See Yotov et al. (2016) for the incorporation of tariffs in structural gravity models.

[16] Here tariff revenues $\sum_i \left(\tau_{ij,t} - 1 \right) X_{ij,t}$ are rebated to consumers as part of their income from agricultural production Y_j.

Table A1. First Stage Regressions for Value of Production Equation

	Endogenous Variable					
	Labor	**Capital**	**Land**	**Fertilizer**	**Pest**	**MRjt**
Intercept	3.258	5.653***	1.746**	4.084*	1.929	2.406***
	(4.181)	(1.871)	(0.680)	(2.321)	(4.576)	(0.926)
asinh(Lab_lag)	0.421**	0.019	−0.001	−0.007	0.014	−0.011
	(0.169)	(0.012)	(0.002)	(0.016)	(0.015)	(0.006)
asinh(Cap_lag)	0.006	0.643***	−0.004)	0.019	−0.070	−0.039***
	(0.060)	(0.043)	(0.004)	(0.028)	(0.048)	(0.010)
asinh(Lan_lag)	0.393	−0.215**	0.868***	−0.048	−0.139	−0.082
	(0.347)	(0.105)	(0.057)	(0.158)	(0.363)	(0.060)
asinh(VFer_lago)	−0.195**	−0.026	0.000	0.606***	0.106**	−0.06***
	(0.077)	(0.025)	(0.005)	(0.051)	(0.049)	(0.014)
asinh(Pes_lag)	0.041	−0.026	0.004	0.046	0.63***	−0.024**
	(0.031)	(0.018)	(0.005)	(0.033)	(0.047)	(0.010)
asinh(MRjt_IV)	2.025	0.434	(0.022)	1.846**	0.907	0.963***
	(1.367)	(0.577)	(0.057)	(0.777)	(0.853)	(0.250)
asinh(tij_IV)	−0.501*	−0.054	−0.005	−0.077	0.081	0.029
	(0.264)	(0.081)	(0.010)	(0.085)	(0.122)	(0.035)
asinh(NDist_lag)	(0.001)	0.025	0.008**	−0.018	0.016	−0.007
	(0.018)	(0.016)	(0.004)	(0.022)	(0.027)	(0.007)
asinh(EFGovInv)	0.026	0.036	0.003	−0.035	−0.029	−0.021***
	(0.031)	(0.024)	(0.002)	(0.027)	(0.034)	(0.006)
asinh(EFBusReg)	−0.298*	0.134*	0.009	−0.172*	0.170	−0.057**
	(0.170)	(0.076)	(0.012)	(0.091)	(0.119)	(0.024)
asinh(EFCont)	0.117	0.074	0.007	0.068	0.138	−0.105***
	(0.124)	(0.053)	(0.010)	(0.064)	(0.088)	(0.024)
asinh(Cell)	0.035	0.087***	0.000	0.077**	0.087***	−0.045***
	(0.043)	(0.022)	(0.002)	(0.032)	(0.030)	(0.007)
asinh(GovtE)	−0.185	0.035	0.008	0.081	−0.010	−0.032
	(0.144)	(0.039)	(0.007)	(0.057)	(0.064)	(0.021)
asinh(RegQ)	0.058	0.047	0.001	−0.001	−0.021	−0.021*
	(0.066)	(0.032)	(0.003)	(0.030)	(0.050)	(0.011)
asinh(TaxInc)	0.101***	0.032	0.008	−0.048*	−0.013	−0.022**
	(0.037)	(0.019)	(0.006)	(0.027)	(0.050)	(0.011)
Fixed Effects						
Year	yes	yes	yes	yes	yes	yes
Country	yes	yes	yes	yes	yes	yes
Adj R-Sq	0.977	0.991	0.999	0.990	0.987	0.976
Obs	723	723	723	723	723	723

Integrating between the baseline and counterfactual solutions yields

$$d\ln\hat{W}_j = d\ln\hat{A}_j + d\ln\hat{K}_j + \frac{1}{1-\sigma}d\ln\hat{\lambda}_{jj},$$

Table A2. First Stage Regressions for Capital Equation

	Endogenous Variable		
	Cap_lag1	**E_lag1**	**MRit_lag1**
Intercept	1.616	5.352**	2.879***
	(2.781)	(2.444)	(1.006)
asinh(Cap_lag3)	0.079**	0.518***	−0.033**
	(0.035)	(0.041)	(0.013)
asinh(E_lag3)	0.218**	−0.123	0.016
	(0.098)	(0.079)	(0.029)
asinh(MRit_lag3)	−0.784***	−0.633***	0.531***
	(0.274)	(0.233)	(0.088)
asinh(MRit_IV_lago1)	−1.151*	−0.135	1.206***
	(0.623)	(0.920)	(0.237)
asinh(VLan_lag3)	0.745***	0.29**	−0.264***
	(0.170)	(0.136)	(0.065)
NDist_lago1	−1.881	−1.989***	0.269
	(1.192)	(0.637)	(0.383)
Fixed Effects			
Year	yes	yes	yes
Country	yes	yes	yes
Adj R-Sq	0.970	0.987	0.9874
Obs.	966	966	966

where ^ implies the ratio of the counterfactual variable to the baseline variable. Using the steady state version of the policy function for capital, the change in capital is

$$d\ln K_j = \frac{1}{1-\alpha}\left(d\ln p_j + d\ln A_j - d\ln P_j\right).$$

Plugging in for the price index yields

$$\ln\hat{K}_j = \frac{1}{1-\alpha}\left(\ln\hat{A}_j\hat{\lambda}_{jj}^{\frac{1}{1-\sigma}}\right) \text{ or } \hat{K}_j = \left(\hat{A}_j\hat{\lambda}_{jj}^{\frac{1}{1-\sigma}}\right)^{\frac{1}{1-\alpha}}.$$

Then plugging $\hat{K}_j = \left(\hat{A}_j\hat{\lambda}_{jj}^{\frac{1}{1-\sigma}}\right)^{\frac{1}{1-\alpha}}$ into $\hat{W}_j = \hat{K}_j^{\alpha}\hat{\lambda}_{jj}^{\frac{1}{1-\sigma}}$ yields

$$\hat{W}_j = \hat{A}_j^{\frac{\alpha}{1-\alpha}}\hat{\lambda}_{jj}^{\frac{1}{(1-\sigma)(1-\alpha)}}.$$

Production Function: High Income vs Low Income

Here we examine how factor shares vary across high- versus low-income countries by analyzing subsamples of the data. Specifically, we distinguish high income from low-income countries using the World Bank income classifications. The ISO3 codes for the countries included in the high income subsample are AUS, AUT, BEL, CAN, CHE, CHL, CZE, DEU, DNK, ESP, FRA, GBR, GRC, ISR, ITA, KOR, NLD, NZL, POL, PRT, ROU, RUS, SWE, and USA. The ISO3 code for the countries included in the low and middle income sample include ARG, BLR, BRA, CHN, COL, CRI, ECU, HUN, IDN, IRN, KAZ, MAR, MEX, MYS, PER, PHL, PRY, THA, TUN, TUR, UKR, ZAF, BGD, CIV, CMR, EGY, ETH, GHA, IND, KHM, LKA, MLI, NPL, and TZA. Table A3 reports the estimated coefficients and structural parameter for the two subsamples.

Table A3. Value of Output Equation for High- and Low-Income Countries

	Reduced Form[1]			Structural[2]	
Variable	**High Income**	**Low Income**	**Variable**	**High Income**	**Low Income**
$\log\left(K_{jt}\right)$	0.214***	0.124**	$\hat{\alpha}$	0.502***	0.554**
	(0.059)	(0.053)		(0.12)	(0.23)
$\log\left(L_{jt}\right)$	0.161**	0.002	ξ_1	0.377**	0.01
	(0.079)	(0.024)		(0.17)	(0.12)
$\log\left(H_{jt}\right)$	0.052	0.492*	ξ_2	0.12	2.195**
	(0.199)	(0.266)		(0.39)	(1.11)
$\log\left(F_{jt}\right)$	0.249***	0.205***	ξ_3	0.583***	0.913***
	(0.089)	(0.058)		(0.14)	(0.23)
$\log\left(B_{jt}\right)$	0.17***	−0.016	ξ_4	0.397***	−0.07
	(0.047)	(0.037)		(0.08)	(0.14)
$\log\left(\Pi_{j,t}^{\sigma-1}\right)$	−0.573	−0.776**	$\hat{\sigma}$	1.75	1.289***
	(0.572)	(0.348)		(1.66)	(0.49)
asinh(GovtInv)	0.053	0.042***	$\hat{\eta}_1$	0.09	0.054*
	(0.037)	(0.014)		(0.12)	(0.03)
asinh(BusReg)	0.024	0.149	$\hat{\eta}_2$	0.04	0.19
	(0.079)	(0.091)		(0.16)	(0.14)
asinh(LegalEnfCont)	0.314*	0.128**	$\hat{\eta}_3$	0.55	0.17
	(0.171)	(0.064)		(0.73)	(0.12)
asinh(CellNo)	−0.065	0.027	$\hat{\eta}_4$	−0.11	0.04
	(0.042)	(0.025)		(0.13)	(0.03)
asinh(RegQuality)	0.035	−0.011	$\hat{\eta}_5$	0.06	(0.01)
	(0.081)	(0.050)		(0.17)	(0.06)
asinh(Taxes)	0.038*	0.039	$\hat{\eta}_6$	0.07	0.05
	(0.021)	(0.046)		(0.10)	(0.07)
asinh(SciJournal)	−0.078	0.079**	$\hat{\eta}_7$	−0.14	0.10
	(0.049)	(0.035)		(0.14)	(0.06)
Intercept	1.546	−0.525			
	(4.128)	(4.033)			
Fixed Effect					
j	yes	yes			
t	yes	yes			
No. of obs.	384	343			
Adj R-Sq	0.9942	0.9949			

Notes: The dependent variable is the logarithm of aggregate agricultural production. [1]Capital, labor, land, fertilizer, pesticide, and the outward multilateral resistance term are treated as endogenous and the regression is run using *ivreg* function in the *AER* package in R. Robust standard errors are in parentheses. [2]The structural standard errorsÃŕÂ£ÅŞare calculated using the Delta method. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The $asinh$ function is desirable because it is well-defined at zero and approximates the log function, while leaving the interpretation of coefficients largely unaffected.

Regarding instrument validity, for the high-income countries, the weak instrument test yields F-stats ranging from 11.787 to 101.309 indicating strong instruments. The Wu-Hausman test of endogeneity has a statistic of 21.355 or a p-value less than 0.001, indicating that endogeneity is an issue and IV regression is required. The Sargan Test (Overidentification Test) has a statistics of 1.408 and a p-value of 0.495 indicating that the instruments are valid. For the low-income countries, the weak instrument test yields F-stats ranging from 11.529 to 56.858 indicating strong instruments. The Wu-Hausman test of endogeneity has a statistic of 80.652 or a p-value less than 0.001, indicating that endogeneity is an issue and IV regression is required. The Sargan Test (Overidentification Test) has a statistics of 0.980 and a p-value of 0.613 indicating that the instruments are valid.