# Agricultural Productivity, International Trade, and Structural Change*

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**Abstract**

Agricultural productivity growth has two opposing effects on structural change. On the one hand, it increases income; given non-homothetic preferences, this pushes labor into non-agriculture. On the other hand, it shifts comparative advantage toward agriculture. The relative strength of these two forces depends on trade openness. We provide reduced-form evidence consistent with heterogeneous effects of agricultural productivity by levels of openness. Exploiting plausibly exogenous variation in agricultural productivity induced by the Green Revolution, we find that for over 15% of the countries in our sample there are negative effects of agricultural productivity on structural change. Moreover, due to increases in openness, this fraction increases over time. We develop an Eaton-Kortum model with non-homothetic preferences that features heterogeneous effects of agricultural productivity by levels of openness. We calibrate the model and show that it can explain a non-trivial portion of the observed changes in countries' sectoral labor shares during the Green Revolution. We also calibrate the model for 1995 to analyze the effects of further increases in agricultural productivity, and find that such increases would have negative effects on structural change over 35% of countries in our sample.

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# 1 Introduction

Agricultural productivity growth has two opposing effects on structural change. On the one hand, it releases labor from the agrictural sector, inducing structural change. On the other hand, it shifts comparative advantage toward agriculture. The relative strength of these two forces depends on trade costs.

Both classic and recent contributions emphasize *positive* effects of agricultural productivity on industrialization (the *labor push* effect). Nurkse (1953) and Rostow (1960) emphasized that significant increases in agricultural productivity were a pre-condition for industrialization and the take-off into modern economic growth. Schultz (1953) emphasized that many developing countries' experiences were so close to subsistence that large fractions of their populations inevitably had to be employed in agricultural production—"the food problem." A number of recent contributions also argue that improvements in agricultural productivity are a key driver of industrialization (see Gollin et al., 2002, 2007; Ngai and Pissarides, 2007; Alvarez-Cuadrado and Poschke, 2011; Herrendorf et al., 2014).

However, Matsuyama (1992) shows that for a small open economy, agricultural productivity has *negative* effects on industrialization because of the comparative advantage effect. He thus argued, "the openness of an economy should be an important factor when planning development strategy and predicting growth performance." While Matsuyama's paper became a well-known classic in macro-development, both development policies and research often assume that agricultural productivity can only have positive effects. Even if the small open economy with free trade case is an extreme case that is not directly applicable to the real world, Matsuyama's insight may still be relevant.

Real world economies are intermediate cases lying between the polar extremes of Matsuyama's model—free trade and autarky—and in such cases both the labor push effect and the comparative advantage effect are relevant. Moreover, the relative magnitude of these depends on the degree of openness, implying a source of heterogeneity in the effects of agricultural productivity on structural change that has not received much attention.

In this paper we start by documenting heterogeneity in the effects of agricultural productivity on structural change, depending on trade openness. We provide reduced-form evidence consistent with such heterogeneous effects, exploiting the Green Revolution as a source of plausibly exogenous variation in agricultural productivity. The estimates imply that for level of openness in 1961, about 15% of the countries in our sample would experience negative effects of agricultural productivity on structural change.

We then show that an Eaton-Kortum model with non-homothetic preferences can capture the heterogeneous effects of agricultural productivity depending on levels of openness. Our model is a multi-country, two-sector (agriculture and non-agriculture) Ricardian model of trade. The structure of the model follows Eaton and Kortum (2002) ("EK"), but with non-homothetic CES preferences over two sectors, following Comin et al. (2017) ("CLM"). This model structure allows us to go beyond the two extreme cases analyzed by Matsuyama (1992) and analyze intermediate cases. We start with a simple two-country numerical simulation of the model to show that the relative strength of the labor push effect and the comparative advantage effect vary in a continuous way with openness, thus confirming and extending Matsuyama's insight.

We then take the model to data, exploiting the Green Revolution as a natural experiment, in order to quantify the relative strength of the labor push effect and comparative advantage effect. During the Green Revolution, when many different countries were simultaneously experiencing increases in agricultural productivity − with the size of this increase varying from country to country − and these countries were trading with each other subject to a complex network of trade costs varying at the country-pair level, our structural model makes a rich set of predictions regarding how the Green Revolution changed the global trading equilibrium, in particular how much each country's sectoral labor shares changed.

We evaluate these predictions of the model based on a calibration exercise. We use 1961 data to calibrate the model, then feed into the model the plausibly exogenous changes in agricultural productivity that occurred from 1961 to 1995 during the Green

Revolution, and then compute the new equilibrium of the model. The model matches a small but non-trivial share of observed changes from 1961 to 1995 in countries' sectoral labor shares, and it captures how agricultural productivity affected countries differently depending on their degree of openness.

Finally, we analyze the effects of agricultural productivity growth in more recent times, after the period of the Green Revolution. In a set of counterfactual experiments, we use our model to predict the effects of further increases in agricultural productivity from 1995 onward. The predicted effects on structural change vary significantly with countries' openness to trade. Our results indicate that at the turn of the century, 36% of countries would experience negative effects of agricultural productivity growth on structural change.

Our paper contributes to a large literature on the impact of agricultural productivity on development (e.g. Gollin, 2010; de Souza, 2015; Marden et al., 2015; McArthur and McCord, 2017)), including recent contributions with novel identification strategies (Gollin et al., 2019; Moscona, 2018). Most of the literature suggests positive effects of agriculture on development, suggesting that Matsuyama's predictions for a small open economy with frictionless trade may just not be relevant in the real world. Moscona (2018), however, finds heterogeneity in the effects of agricultural productivity on structural change depending on openness in line with Matsuyama. We confirm this finding, and show that our estimates imply that the overall effect of agricultural productivity growth is negative for a non-trivial share of countries. Moreover, as openness has increased over time, this share has increased as well.

We add to the bourgeoning literature in international trade that follows EK in using quantitative, multi-country, multi-sector models of trade for a wide variety of empirical applications (see Eaton and Kortum, 2012; Costinot and Rodríguez-Clare, 2014, for overviews). While the EK framework has become a workhorse in international trade, this is the first paper using this framework to demonstrate the empirical relevance of Matsuyama's classic insight on the heterogenous effects of agricultural productivity growth.

Our model is similar to Uy et al. (2013) ("UYZ"), but has a key difference in the specification of preferences. The extent of non-homotheticity implied by the preferences in UYZ (Stone-Geary preferences) varies substantially by income level. As income goes to infinity, preferences are asymptotically homothetic. In contrast, we model preferences following Comin et al. (2017) (CLM), whose specification is consistent with their evidence that the extent of non-homotheticity is roughly constant across income levels.

One of the motivations for examining structural change is its implications for economic growth. In the theoretical model of Matsuyama (1992), the non-agricultural sector experiences endogenous growth from learning-by-doing, while the agricultural sector does not, hence movement of labor into the non-agricultural sector causes an increase in aggregate economic growth, while the pulling of labor into agriculture retards it. McMillan and Rodrik (2011) document cases of labor reallocation from higher- to lower-productivity sectors (e.g. Nigeria and Zambia, whose employment share in agriculture increased), and conjecture that this may have been partly driven by a comparative advantage effect. While these theoretical and empirical findings are interesting and closely related to our paper, our paper does not directly speak to these issues. We focus on the (heterogeneous) effects of agricultural productivity on structural change. The implications of our findings for aggregate productivity growth are beyond the scope of our paper.

The paper is organized as follows. The next section provides evidence on the heterogeneous effects of agricultural productivity on structural change depending on an economy's trade openness. Section 3 presents our two-sector Ricardian model, which features both a labor push effect and a comparative advantage effect of agricultural productivity. Section 4 offers a simple numerical illustration that shows how the overall effects depend on trade openness. Section 5 presents our calibration of the model and quantitative analyisis of the effects of agricultural productivity growth on structural change during the Green Revolution and in a more recent period. This analysis highlights the heterogeneous effects of agricultural productivity across countries, and across time periods. Section 6 concludes.

# 2 The heterogeneous effects of agricultural productivity

## 2.1 Data and Empirical Framework

This section provides reduced-form evidence on the effect of higher agricultural productivity on structural change, allowing for heterogeneous effects by level of openness to trade. The estimating equation has the following form:

$$Y_{it} = \beta_0 + \beta_2 \text{ Ag.Productivity}_{it} + \beta_1 \text{ Openness}_{it} + \beta_3 \text{Ag.Productivity}_{it} \times \text{ Openness}_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{1}$$

where $Y_{it}$ is a measure of the non-agricultural share of the economy in country $i$ at date $t$, $\text{Ag.Productivity}_{it}$ is a measure of agricultural productivity, $\text{Openness}_{it}$ is a measure of openness to trade, and $\delta_t$ and $\gamma_i$ are year and country fixed effects, respectively. As discussed in the introduction, and as will be made precise in section 3, theory predicts that $\beta_1 > 0$, $\beta_2 > 0$, and $\beta_3 < 0$.

We consider two measures of the non-agricultural share: the non-agricultural share of GDP and the non-agricultural share of employment. For non-agricultural shares of GDP, we use sectoral shares of value added as measured by the World Bank's World Development Indicators (WDI). For non-agricultural shares of employment, we use data from Wingender (2014).

Both of these measures of the non-agricultural share are informative about the impacts of agricultural productivity and openness on structural change. When the outcome is the non-agricultural share of GDP, there is a certain mechanical effect of agricultural productivity: if agricultural productivity increases, even if no other variables in the economy (including prices) endogenously respond at all, the non-agricultural share of GDP will decrease mechanically. When using shares of employment, the effect of agricultural productivity growth might depend not only on openness, but also on the labor intensity of the new agricultural technology compared to the oldtechnology. This is not captured in our one-factor model, hence this is an important caveat when mapping between the empirics and our theory.

There are, of course, potential endogeneity issues regarding the effects of agricultural productivity and openness on sectoral GDP and labor shares. To address this, we consider an instrumental variables specification that relies on plausible variation in agricultural productivity (induced by the Green Revolution) as well as in openness (using the distance-weighted GDP of trading partners).

Our primary measure of agricultural productivity is caloric yields per acre, calculated following Moscona (2018). We use FAO GAEZ estimates of each country's production of each crop, combined with USDA tables that estimate kilocalories per kilogram for each crop, in order to compute the implied caloric yield per acre. That is, total productivity in calories per acre is given by $\sum_K \frac{c_{i,k,t}}{a_{i,k,t}} \left( \frac{a_{k,i,t}}{\sum_K a_{k,i,t}} \right)$, where $c_{i,k,t}$ is the caloric yield of crop $k$ in country $i$ in year $t$ and $a_{k,i,t}$ is the acreage of crop $k$ in country $i$ at time $t$. We use data on the caloric productivity of rice, wheat, maize, sorghum, potato, groundnut, dry beans and millet.

Our IV for agricultural productivity exploits plausibly exogeneous variation created by the Green Revolution. In particular, we follow Moscona (2018) by measuring the predicted productivity, HYV $\text{Ag.Prod}_{i,t}$ as the average (across crops) of the maximum agro-climatic productivity of crop $k$ at time $t$ in country $i$, based on the availability of high-yield variety (HYV) crops of type $k$ at time $t$ combined with the climatic conditions of country $i$:

$$\text{HYV Ag.Productivity}_{i,t} = \frac{\sum_k \left( (1 - I_{k,t}) P^L_{i,k} + I_{k,t} P^H_{i,k} \right)}{N_{i,t}}, \tag{2}$$

where $I_{k,t}$ is an indicator of the presence of HYVs for crop $k$ at time $t$, $P^L_{i,k}$ and $P^H_{i,k}$ are the potential yields for crop $k$ in country $i$ under the low- and high-input measures respectively and $N_{i,t}$ is the total number of crops[6].

During the Green Revolution, starting in the early 1960's, high-yield varieties were developed for different crops at different points in time, and tended to quickly dif-

[6] Moscona (2018) argues that the FAO data are structured such that the low- versus high-input potential yields correspond to the HYV technology difference.

fuse across the world. Hence, as soon as a new HYV was discovered, it soon became available for usethroughout the world, but countries varied in how useful this was depending on their climactic suitability for that crop.

A possible concern is that research and development of HYVs was targeted to crops that grew particularly well in particular countries. However, for the most part the Green Revolution was the result of highly centralized philanthropic research efforts rather than country-specific profit-motivated R&D. Furthermore, note in equation (2) that $P_{i,t}$ is an *unweighted* average across crops, hence it is not affected by the endogenous selection of crops in different countries in either the high- or low- productivity states.

We measure openness as the Exports/GDP ratio, using data from the *World Development Indicators*. Following Helliwell (2000), our IV for a country's openness is a measure of market potential, the distance-weighted average GDP of every country besides that country. The logic here may be associated to a gravity equation, since we identify expected changes in trade via changes in the GDP of a country's trading partners. We construct this measure as follows:

$$\text{Market Potential}_{i,t} = \sum_{j \neq i} \Big( GDP_{j,t} / dist_{i,j} \Big), \tag{3}$$

where $GDP_{j,t}$ is the GDP of country $j$ in year $t$ and $dist_{i,j}$ is the physical distance between countries $i$ and $j$, using data from Feyrer (2019). This measure satisfies the relevance requirement given the logic of gravity equations; that is, the higher the GDP of nearby countries (or alternatively, the closer high-GDP countries are), the higher a country's trade share will be.

The exclusion restriction is satisfied under the assumption that changes in partner GDP are exogenous. That is, the identification assumption is that changes in other countries' GDP affect a country's sectoral shares only through trade with that country. Although this assumption almost certainly does not hold perfectly, the distance-weighted average GDP of other countries is likely much less endogenous to a country's sectoral shares than within-country drivers of a country's openness, e.g. the quality of a country's institutions.

## 2.2 Results

Table 1 displays OLS and IV estimates of equation for both key outcome, the non-agricultural share of GDP and the non-agricultural share of the labor force. First stage results of the IV estimation are shown in Appendix 7.

**Table 1:** Agricultural Productivity, Openness, and Structural Change

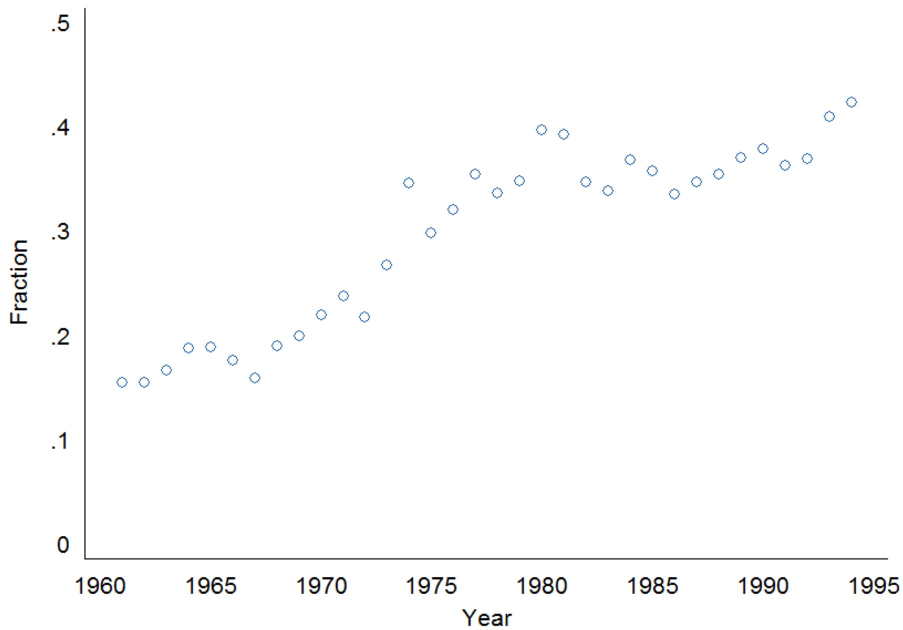
| | OLS | | IV | |
|---|---|---|---|---|
| Dep.Var.: | Non-Agri. Share of GDP (1) | Non-Agri. Share of LF (2) | Non-Agri. Share of GDP (3) | Non-Agri. Share of LF (4) |
| Agri.Productivity | 0.151*** | 0.0577*** | 0.228** | 1.233*** |
| | (0.0185) | (0.0185) | (0.110) | (0.346) |
| Openness | 0.192*** | 0.0572*** | 0.349 | 1.089** |
| | (0.0182) | (0.0138) | (0.272) | (0.543) |
| Agri.Productivity × Openness | -0.00380*** | -0.00182*** | -0.0126*** | -0.0394*** |
| | (0.000389) | (0.000387) | (0.00452) | (0.00949) |
| Year FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Observations | 6,339 | 5,817 | 4,124 | 3,979 |

*Notes:* Outcome measures: percent non-agricultural GDP and percent non-agricultural labor force. Openness measure: trade share. Productivity measure: caloric productivity. Panel Regression, 1961-2016. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

For both measures of structural change, we find a positive association with both openness and productivity, and a negative association with the interaction term. In this simple reduced-form analysis, taking the estimates from the specification in column (4), the overall effect of agricultural productivity changes on structural changes is $1.233 - 1.089 \times$ Openness. The overall effect is positive or negative depending on whether a country's openness is above or below a cutoff, which for these estimates is an exports/GDP ratio of 31 percentage points.

Due to increasing trade openness across the world over time, the share of countries for which we would expect a negative total effect of agricultural productivity on structural change is negative is increasing over time. Figure 1 shows the evolution of this share of time, calculated with the estimated coefficientes obtained before and the openness measures for each country in each year. In 1961, 15.5% of the countries in the sample were above that threshold, and this share rose significantly over time.

**Figure 1:** Share of countries with negative effects of agri.productivity on structural change




# 3 Model

Our reduced-form analysis shows that the effect of agricultural productivity growth on structural change depends crucially on a country's openness to trade. However, one limitation of the reduced-form analysis is that it treats each country as a separate observation. That is, it supposes that the effects of agricultural productivity and openness on a country's structural change are simply a matter of the amount of agricultural productivity growth in that country itself and the country's overall level of openness.

In reality, it potentially matters not only how much agricultural productivity is growing in that country itself but also in other countries, and it potentially matters not only how open to trade that country is overall, but also which specific countries it is trading with. The only way to explore this intricate web of effects is through a structural model. To that end, we turn our attention now to a structural model of international trade and structural change. In this section we describe the model, then in section 4 we simulate the model to show how the effects of agricultural productivity growth on sectoral labor shares vary with openness. In section 5 we take the model to data in order to quantify the effects of the Green Revolution on each country's structural change, depending on where each country is in the global trading network.

Our model is a multi-country, two-sector (agriculture and non-agriculture) Ricardian model of trade. The structure of the model follows Eaton and Kortum (2002) ("EK"), but with non-homothetic CES preferences over two sectors, following Comin et al. (2017) ("CLM").[7]

### 3.1 Production and trade

There is a continuum of goods in the agriculture ($A$) and non-agriculture ($M$) sectors. Each country has the technology to produce all goods in all sectors, but with different levels of productivity. The production function for good $z \in [0, 1]$ in sector $k \in \{A, M\}$ in country $i$ is

$$Y_{ik}(z) = A_{ik}(z)L_{ik}(z) \tag{4}$$

where $Y_{ik}(z)$ denotes output, $A_{ik}(z)$ denotes exogenous productivity, and $L_{ik}(z)$ denotes labor.

Following EK, $A_{ik}(z)$ is the realization of a random variable $Z_{ik}$, with each $A_{ik}(z)$ drawn independently from a Fréchet distribution with cumulative distribution function $F_{ik} \equiv Pr[Z_{ik} \leq A] = e^{-T_{ik}A^{-\theta}}$, where $T_{ik} > 0$ and $\theta > 1$. The larger $T_{ik}$ is, the higher is country $i$'s mean productivity in sector $k$. The higher $\theta$ is, the less dispersion there is in productivity across goods within a sector within a country.

Trade between countries is subject to iceberg trade costs. That is, if one unit of good $z$ in sector $k$ is shipped from country $j$ to country $i$, then only $1/\tau_{ijk}$ units arrive in

[7] Note that CLM's model is a closed-economy model; we embed it in the EK model of trade. Our model is also similar to Uy et al. (2013) ("UYZ"), except that preferences in UYZ are such that the extent of non-homotheticity varies substantially by income level (in particular, as income goes to infinity, preferences are asymptotically homothetic). CLM find evidence in both international data and sub-national data that the extent of non-homotheticity is roughly constant across income levels, which their preference structure rationalizes. Given that our analysis looks at a much broader range of countries than UYZ, this is important for our purposes.

country $i$, where $\tau_{ijk} \geq 1$. We assume zero trade costs within a country, i.e., $\tau_{iik} = 1$ $\forall i, k$.

Markets are perfectly competitive, and prices are therefore determined by marginal costs of production. The price at which country $j$ can supply good $z$ in sector $k$ to country $i$ is $p_{ijk}(z) = \tau_{ijk} w_j / A_{jk}(z)$, where $w_j$ is the wage in country $j$. Consumers buy each good from the cheapest source, hence the price of good $z$ in sector $k$ in country $i$ is $p_{ik}(z) = \min\{p_{ijk}(z)\}$.

The composite good in sector $k$ consumed by country $i$, denoted $C_{ik}$, is a CES aggregate of the individual goods $C_{ik}(z)$:

$$C_{ik} = (\int_0^1 C_{ik}(z)^{\frac{\eta-1}{\eta}} dz)^{\frac{\eta}{\eta-1}} \tag{5}$$

where $\eta > 0$ is the elasticity of substitution across goods within a sector.

Given the Fréchet distribution of productivities, EK show that the price of the composite good $C_{ik}$ is $P_{ik} = \Gamma(\Phi_{ik})^{-\frac{1}{\theta}}$, where the constant $\Gamma$ denotes the Gamma function evaluated at $(1 - \frac{\eta-1}{\theta})^{\frac{1}{1-\eta}}$, and $\Phi_{ik} = \sum_j T_{jk}(w_j \tau_{ijk})^{-\theta}$ captures country $i$'s access to global production in sector $k$.[8]

The share of country $i$'s expenditure on sector $k$ sourced by country $j$ equals the probability that country $j$ is the lowest-cost supplier of a good $z$ in sector $k$ to country $i$. This equals

$$\pi_{ijk} = \frac{T_{jk}(w_j \tau_{ijk})^{-\theta}}{\Phi_{ik}} \tag{6}$$

### 3.2 Preferences

Following CLM, the representative household in country $i$ has non-homothetic CES utility $U_i$ implicitly defined by the equation

$$\sum_k (\Omega_k U_i^{\epsilon_k})^{\frac{1}{\sigma}} C_{ik}^{\frac{\sigma-1}{\sigma}} = 1 \tag{7}$$

[8] Under the assumption $\eta - 1 < \theta$, this price index is well-defined, and the elasticity of substitution $\eta$ can be ignored because it only appears in the constant term $\Gamma$.

where $\sigma$ is the elasticity of substitution between the two sectors, $\Omega_k$ is a sector-$k$ utility weight, and $\epsilon_k$ governs the income elasticity of demand for sector $k$. As utility $U_i$ rises, the weight given to the consumption of sector $k$ varies at a rate controlled by $\epsilon_k$. More specifically,

$$\frac{\partial \log(C_{iA}/C_{iM})}{\partial \log U_i} = \epsilon_A - \epsilon_M \tag{8}$$

As discussed in CLM, $\Omega_k$ and $\epsilon_k$ can be normalized to 1 for one sector without loss of generality; we normalize $\Omega_M$ and $\epsilon_M$ to 1.[9]

The representative household is endowed with a unit of labor, which it supplies inelastically, and it spends all of its labor income. It maximizes its utility $U_i$ in (7) subject to its budget constraint

$$\sum_k P_{ik} C_{ik} = w_i \tag{9}$$

### 3.3 Equilibrium

Labor is perfectly mobile across sectors within a country, but immobile across countries. The labor market clearing condition in country $i$ is

$$\sum_k L_{ik} = L_i \tag{10}$$

where $L_i$ is the total labor endowment in country $i$, and $L_{ik}$ is the labor employed in country $i$ in sector $k$.

[9] Non-homothetic CES (NHCES) preferences were, to our knowledge, first formulated by Hanoch (1975), who studied them in a partial equilibrium setting. To our knowledge, CLM were the first to embed NHCES preferences in a general equilibrium, multi-sector model of economic growth. In addition to their important feature that non-homotheticity does not counterfactually taper off at high incomes, another attractive feature of NHCES preferences is that they do not impose any parametric restriction on the relationship between the elasticity of substitution across sectors and the income elasticities of demand for each sector. This allows one to decompose the effects of sectoral productivity growth into price and income effects. See CLM for more discussion of NHCES preferences, in particular for a characterization of the Hicksian and Marshallian demand functions. Matsuyama (2019) uses NHCES preferences in a unified theoretical analysis of the role of Engel's Law (that is, differences across sectors in their income elasticities of demand) in structural change, international trade, innovation, and product cycles from rich to poor countries.

Trade between countries is balanced:

$$w_i L_i = \sum_j \sum_k \pi_{jik} \omega_{jk} w_j L_j \tag{11}$$

where $\omega_{jk} \equiv \frac{P_{jk} C_{jk}}{\sum_k P_{jk} C_{jk}}$ is the share of country $j$'s expenditure on sector $k$.

**Definition of equilibrium.** Given a set of parameters $\{L_i, T_{ik}, \theta, \tau_{ijk}, \eta, \Omega_k, \epsilon_k, \sigma\}_{i,j,k}$, an equilibrium of the economy is a set of prices $\{P_{ik}, w_i\}_{i,k}$, allocations $\{Y_{ik}, L_{ik}, C_{ik}\}$, and trade shares $\{\pi_{ijk}\}_{i,j,k}$ such that: (i) given prices, the allocations solve the firms' profit-maximization problem associated with technologies (4) and households' utility-maximization problem given by (7) and (9); and (ii) the allocations satisfy the market clearing conditions (10) and (11), with trade shares given by (6).

# 4 Numerical illustration

Suppose a country has an increase in its agricultural productivity. What effect does this have on structural change − in particular, does this increase or decrease the share of the country's labor force working in the agricultural sector? Our model captures two opposing effects. On the hand, higher agricultural productivity raises the country's income, which shifts demand toward non-manufacturing, which thereby causes a *decrease* in the equilibrium share of the country's labor force in agriculture. This is the *labor push effect*. On the other hand, higher agricultural productivity means the country now has a larger comparative advantage in agriculture, which causes an *increase* in the country's equilibrium share of the labor force in agriculture. The more open the country's economy is, the stronger the latter effect is relative to the former.

To help illustrate this, in this section we perform a numerical simulation of the model, with $N = 2$ (2 countries). The parameter values we use in our simulation simulation are given in Table 2. The two countries are identical in every way, except for the parameter $T_{iA}$ governing agricultural productivity, which we vary from 5 to 20 for country 1, while holding it fixed at 10 for country 2, and also holding $T_{iM}$ fixed at 10 for both countries.

For simplicity, trade costs here are symmetric. That is, $\tau_{12A} = \tau_{21A} = \tau_{12M} = \tau_{21M} \equiv \tau$.[10] At the same time that we vary $T_{1A}$ from 5 to 20, we also vary $\tau$ from 1 to 3. Note that $\tau = 1$ represents free trade between the two countries, while $\tau = 3$ represents trade costs of 200%.

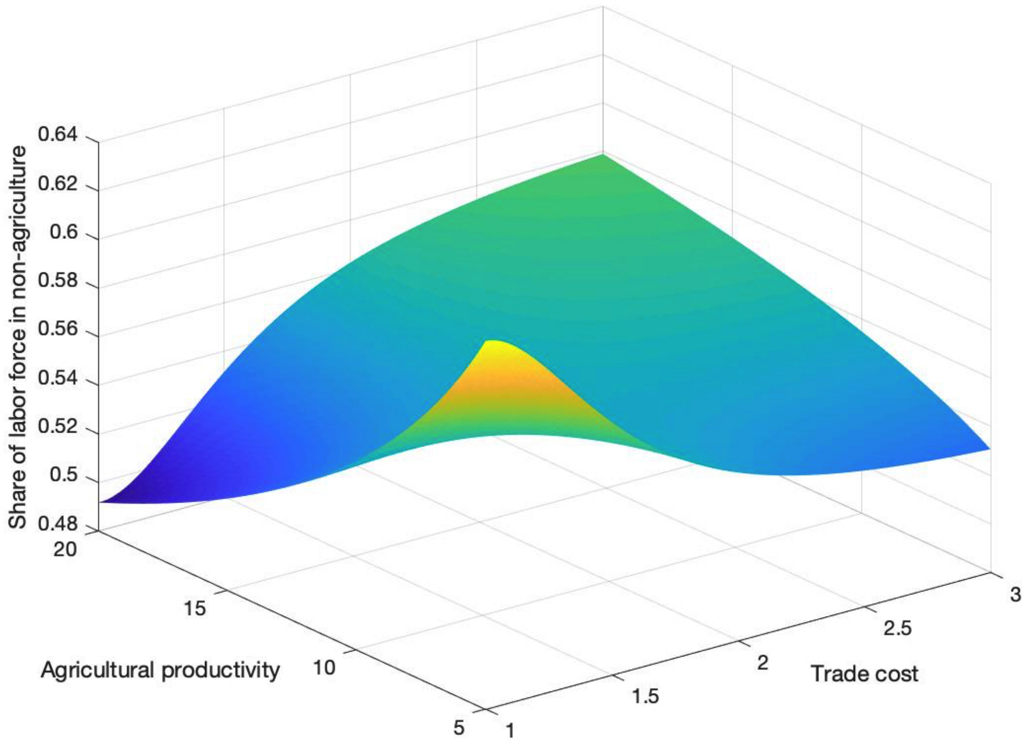
**Table 2:** Parameter values for numerical illustration

| Parameter | Meaning | Value |
|---|---|---|
| $N$ | Number of countries | 2 |
| $L_i$ | Size of labor force in each country | 1 |
| $\theta$ | Within-sector productivity dispersion | 4 |
| $\eta$ | Within-sector elasticity of substitution | 3 |
| $\sigma$ | Cross-sector elasticity of substitution | 0.35 |
| $\Omega_A$ | Weight on ag. relative to non-ag. in utility function | 0.8 |
| $\epsilon_A$ | Income elasticity of demand for ag. relative to non-ag. | 0.9 |
| $T_{iM}$ | Non-ag. productivity in each country | 10 |
| $T_{2A}$ | Agricultural productivity in country 2 | 10 |
| $T_{1A}$ | Agricultural productivity in country 1 | vary from 5 to 20 |
| $\tau$ | Iceberg trade cost | vary from 1 to 3 |

For each combination of $T_{iA}$ and $\tau$, we simulate the model and compute the equilibrium share of country 1's labor force in non-agriculture. The results are shown in Figure 2. The vertical axis is country 1's equilibrium share of its labor force in non-agriculture. The two horizontal axes are $T_{1A}$ and $\tau$. Notice that at high levels of openness (e.g., $\tau = 1$), higher agricultural productivity in country 1 *decreases* country 1's non-agricultural labor share; this is the *comparative advantage effect*. Meanwhile, at low levels of openness (e.g., $\tau = 3$), higher agricultural productivity in country 1 *increases* country 1's non-agricultural labor share; this is the *labor push effect*. One can also see in the figure that, between the two extremes of $\tau = 1$ and $\tau = 3$, the effect varies continuously.

[10] Note, though, that there is free trade within countries, i.e., $\tau_{iiA} = \tau_{iiM} = 1$ for $i = 1, 2$.

**Figure 2:** Numerical illustration of the labor push vs. comparative advantage effect




Matsuyama (1992) analyzed the two extreme cases of a closed economy (which in this model corresponds to $\tau \to \infty$) and a small open economy (which in this model corresponds to $\tau = 1$ and $L_1 \to 0$). What we have shown in this section, using an Eaton-Kortum model of trade with non-homothetic preferences, is that Matsuyama's point holds under cases of intermediate levels of openness as well, with the relative strength of the labor push effect and the comparative advantage effect varying in a continuous way with openness.

This numerical illustration shows this in the simplest, starkest possible way, but given that the parameter values in Table 2 are arbitrary, this raises the question of how strong the labor push and comparative advantage effects actually are. In the next section we take the model of section 3 to data in order to answer this question.

# 5 Quantitative analysis

In this section we examine plausibly exogenous changes in countries' agricultural productivity during the Green Revolution. The previous section showed, through a simple two-country numerical simulation, that whether an increase in agricultural productivity accelerates or retards a country's structural change (more precisely, whether it increases or decreases the share of the country's labor force in agriculture) depends on the level of openness of the country to the rest of the world. During the Green Revolution, when many different countries were simultaneously experiencing increases in agricultural productivity $-$ with the size of this increase varying from country to country $-$ and these countries were trading with each other subject to a complex network of trade costs varying at the country-pair level, the model in section 3 makes a rich set of predictions regarding how the Green Revolution changed the global trading equilibrium, in particular how much each country's sectoral labor shares changed.

In this section we evaluate these predictions. In particular, we calibrate the model from section 3 using 1961 data, then feed into the model the plausibly exogenous changes in agricultural productivity that occurred from 1961 to 1995 during the Green Revolution, and then compute the new equilibrium of the model. The model is able to match much of the observed changes from 1961 to 1995 in countries' sectoral labor shares.

We then use the model to predict the effects of further increases in agricultural productivity post-Green-Revolution, and explore how the predicted effects on structural change vary with countries' openness to trade.

## 5.1 Calibration

The data we use for our structural analysis span from 1961 to 2016 and cover 67 countries. While the raw data includes over 200 countries, we drop those with missing data for 1961 for some of the variables used in this section.

$L_i$ is calibrated for each country $i$ to match the country's 1961 population according to the World Bank's World Development Indicators (WDI).

The parameter $\theta$ that governs the amount of within-country, within-sector productivity dispersion is calibrated to a value of 4, based on estimates from Simonovska and Waugh (2014). The within-sector elasticity of substitution $\eta$ is set to 3.[11] The elasticity of substitution $\sigma$ between agriculture and non-agriculture is set to 0.5, based on estimates from CLM.

For trade costs $\tau_{ijt}$ between each pair of countries, we use a measure of trade costs that is consistent with a broad class of trade models that admit a gravity structure, including our own. In particular, the measure used is what Eaton et al. (2016) call the Head-Ries index, first proposed by Head and Ries (2001). That is, $\tau_{ijt} = (\frac{X_{iit}X_{jjt}}{X_{ijt}X_{jit}})^{\frac{1}{2\theta}}$, where $X_{ijt}$ is the dollar value of exports from country $i$ to $j$ at date $t$, and $X_{iit}$ is the value of intra-national trade in country $i$ at date $t$.[12] The source of data we use is the TRADHIST database from Fouquin and Hugot (2016), which includes data on trade flows, GDP, and other country-level and country-pair-level variables, for many different countries from 1827 to 2014. Note that the data on trade flows are at the country-pair level, rather than sector-specific; in using these data, we are abstracting from differences in trade costs between agriculture and non-agriculture.[13]

$T_{iA}$ is calibrated for each country $i$ based on its 1961 productivity in agriculture. Following Moscona (2018), agricultural productivity is measured in terms of calories per acre, using data from the FAO on each country's production of each crop (rice, wheat, maize, sorghum, potato, groundnut, dry beans, and millet), combined with estimates from the USDA of how many calories per kilogram there are in each of these crops. In our model, the geometric mean of country $i$'s productivity in the infinitely many agricultural goods is $e^{\frac{\gamma}{\theta}}(T_{iA})^{\frac{1}{\theta}}$, where $\gamma$ is Euler's constant ($= 0.577...$).

[11] Recall from footnote 8 that $\eta$ does not actually affect any of the equilibrium objects of interest in the model.

[12] That is, $X_{ii}$ is domestic production in country $i$ that is also consumed in $i$. Technically speaking, this should be measured in gross flows, not value added. However, given the lack of data on gross output for many countries, we follow much of the literature and use a country's GDP, minus exports, as a proxy for $X_{ii}$.

[13] Note that the Head-Ries index is undefined for country-pairs with zero trade flows. For these country-pairs, we set their trade cost equal to 66, which is the maximum estimated trade cost in our sample.

One assumption underlying our usage of Moscona's data to calibrate $\{T_{iA}\}$ is that productivity in the aforementioned eight crops is representative of productivity in agriculture more broadly. Also, given that these productivity data are in units of calories, another assumption is that consumers' utility from agricultural consumption is only a function of calories consumed, with calories consumed from one crop being a perfect substitute for the same number of calories from a different crop (or, if utility is also a function of other aspects of the quality of these crops, then differences across countries in their productivity in generating those qualities mirror the differences in their productivity in generating calories).

Finally, notice that this measure of productivity is in units of land. Our model is Ricardian, i.e., it only has one factor of production. Hence the final assumption is that differences across countries in agricultural land productivity are the same as differences in agricultural labor productivity. We acknowledge that it may be interesting to expand this calibration strategy, in such a way that these assumptions can be relaxed. However, we stress that we are not trying to make any strong claims about explaining the cross-sectional sectoral pattern of trade across countries. Instead, our goal is to capture the effects of the Green Revolution, and predict the effects of post-Green-Revolution improvements in agricultural productivity. Hence the chief concern, in our view, is whether the new technologies introduced by the Green Revolution were factor-neutral or factor-biased, as we discuss in the conclusion.

We set $\epsilon_A = 0.2$, based on estimates from CLM, where $\epsilon_A$ is the income elasticity of demand for agricultural goods, relative to non-agricultural goods. We calibrate $\{\Omega_{Ai}\}$ (the weight on agriculture in country $i$'s utility function, relative to non-agriculture) to match each country's 1961 agricultural labor share, the data for which are taken from Wingender (2014).[14]

Appendix Figure 5 depicts each country's 1961 share of employment in agriculture. The horizontal axis is the share observed in the data, while the vertical axis is the share

[14]By construction, the model matches countries' 1961 sectoral shares more or less perfectly. We abstract from differences across countries in non-agricultural productivity and set $\{T_{iM}\}_i$ to be equal across countries (in particular, equal to the mean of $\{T_{iA}\}_i$).

predicted by the model. Note that these are targeted moments. As one would expect, the model closely matches the data with regard to each of these data points.

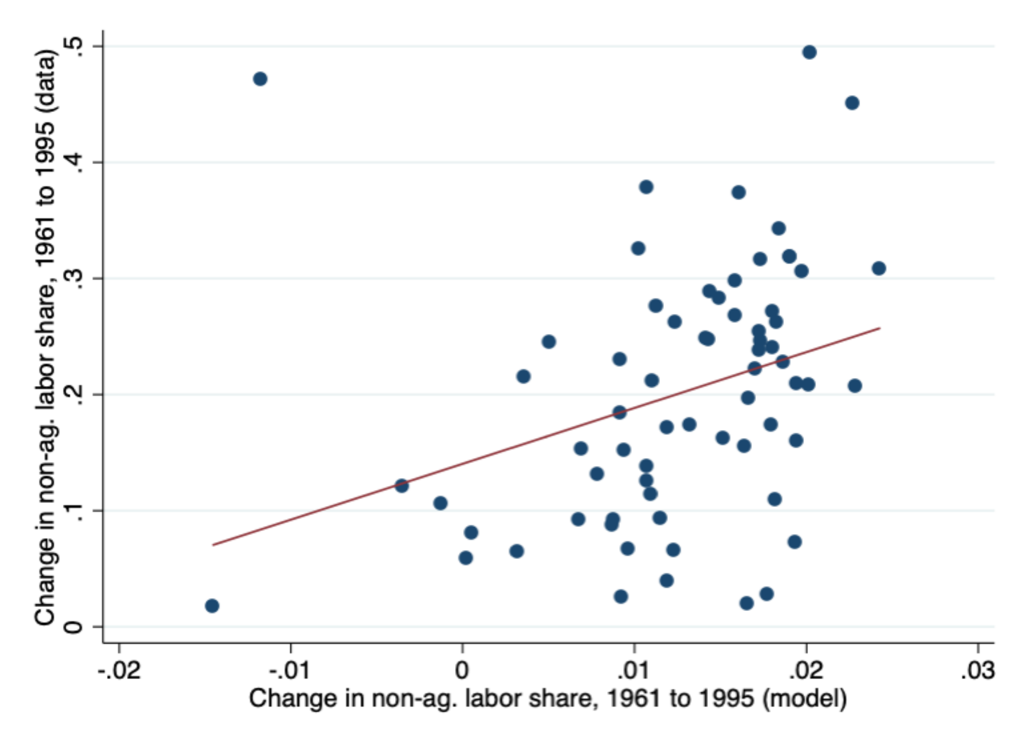
### 5.2 Agricultural productivity growth and structural change (1961-95)

With the model from section 3 calibrated as described in section 5.1, in this section we feed into the model the "Green Revolution shock." That is, we change $T_{iA}$ for each country, based on the plausibly exogenous change from 1961 to 1995 in the Moscona (2018) predicted productivity. Holding all of the other parameters of the model fixed, we then re-compute the equilibrium of the model under these new values of $T_{iA}$. In particular, we calculate the model's prediction for how much each country's agricultural labor share changes from 1961 to 1995, and compare this against the data.

As emphasized throughout our discussion of the model, an important source of expected variation in the effects of agricultural productivity growth on structural change is countries' differing levels of openness to international trade. Consider, for example, the case of two African countries in our sample, Benin and Burundi. In 1961, both of these countries had very large shares of employment in agriculture: 84.5% in Benin, 95% in Burundi. (In our calibrated structural model, these 1961 shares are 84.3% for Benin and 94.4% for Burundi.) Between 1961 and 1995, these two countries experienced similar shocks to their predicted agricultural productivity: an increase of 256% for Benin, 266% for Burundi. However, these two countries had significantly different levels of openness to trade. In 1961, Benin's exports-to-GDP ratio was only 0.046, while Burundi's was 0.13. We should therefore expect Benin's agricultural labor share to decrease significantly more than Burundi's $-$ feeding in the Green Revolution shock and holding all else fixed, our structural model predicts Benin's agricultural labor share to decrease by 1.6 percentage points by 1995, but only decrease by 0.09 percentage points in Burundi. And indeed, in the data, Benin experienced much more rapid structural change than Burundi: from 1961 to 1995 Benin's agricultural labor share decreased by 37 percentage points, while Burundi's only decreased by 2.5 percentage points.

Going beyond the specific example of Benin and Burundi, the results for the full set of 67 countries are shown in Figure 3. The horizontal axis is the change from 1961 to 1995 in countries' non-agricultural share of employment observed in the data. The vertical axis is the change predicted by the model.

**Figure 3:** Changes in non-agricultural labor shares, model vs. data (1961-1995)




Note in Figure 3 that for 5 of the 67 countries (7.5%) (5 countries with high levels of openness), the structural model predicts that their structural change was actually impeded by the Green Revolution. Note that this 7.5% is significantly less than the fraction of countries whose non-agricultural share was predicted to be negatively affected by agricultural productivity growth in our reduced-form analysis (see, for example, Figure 1). This is in part because, during the Green Revolution, many countries were experiencing agricultural productivity growth simultaneously, which attenuates the effect of agricultural productivity growth on any particular country's comparative advantage. In the next section we will quantify the effect of agricultural productivity growth in a particular country, while holding agricultural productivity in other countries constant.

Regressing the data on the model's predictions gives an estimated coefficient of 4.81, with a standard error of 1.74, a p-value of 0.007, and an R-squared of 0.11. This significantly positive fit between the model's predictions and the data is remarkable, given that in this exercise we are using absolutely no information on any changes in any variables between 1961 and 1995 other than the Green-Revolution-induced changes in agricultural productivity. This implies that the Green Revolution was a significant driver of changes in sectoral labor shares during this time period, and that our structural model explains a significant amount of the heterogeneity across countries in the effects of the Green Revolution on structural change.

## 5.3 Agricultural productivity growth and structural change (1995–...)

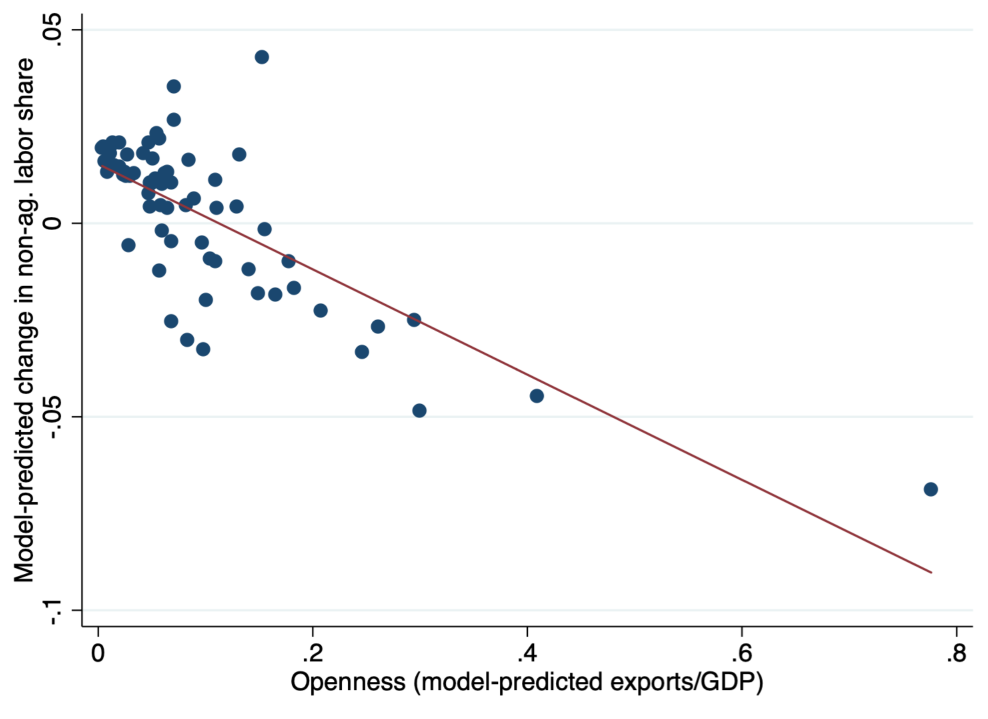
Increasing agricultural productivity remains an important goal of many countries' development policies. Our model can be used to predict the effects of further increases in agricultural productivity, post-Green-Revolution, on structural change, and how this varies with countries' openness to trade. In this section we illustrate this with the following set of counterfactual exercises.

We start from the year 1995, the endpoint of our model validation exercise from the previous section. For each country $i$, $L_i$ is re-calibrated to match the country's 1995 population. The agricultural productivity parameters $T_{iA}$ are re-calibrated to match the 1995 data on agricultural productivity. The agricultural utility weights $\{\Omega_{Ai}\}$ are then re-calibrated to match the 1995 data on agricultural labor shares. Appendix Figure 6 shows how well the model matches agricultural labor shares (the targeted moments). The horizontal axis is the agricultural labor share observed in the 1995 data, while the vertical axis is the share predicted by the model. As was the case for the 1961 data, the model does a good job of matching agricultural labor shares up to a share of roughly 0.7, above which it under-predict the shares.

With the model calibrated to the observed 1995 equilibrium, we then feed into the model a counterfactual 10% increase in country $i$'s agricultural productivity, holding all other parameters of the model fixed (including agricultural productivity in every country besides country $i$). We compute the model's prediction for the change in country $i$'s agricultural labor share. This is done for every country, one country at a time $-$ note that this is 67 separate counterfactual experiments, one for each of the 67 countries in the sample.

The results are shown in Figure 4. Each dot in the figure is a country. The vertical axis is the model-predicted change in that country's non-agricultural labor share. The horizontal axis is the country's openness to trade. The measure of openness used here is the country's equilibrium exports-to-GDP ratio as predicted by the model. As repeatedly highlighted in our discussion of the model, for a given increase in agricultural productivity, countries that are more open to trade will have a smaller increase (or larger decrease) in their non-agricultural labor share. Indeed, there is a negative correlation between these two variables in Figure 4. Regressing the model-predicted change in the non-agricultural labor share on openness gives an estimated coefficient of -0.14, a standard error of 0.018, a p-value of less than 0.001, and an R-squared of 0.57. Note that, for 24 of the 67 countries (36%), the predicted effect on the non-agricultural labor share is negative, which is consistent with our reduced-form results in Figure 1.

**Figure 4:** Effect of 10% increase in agricultural productivity in 1995




# 6 Final comments

Among both academic economists and policymakers, it is often taken as a given that growth in agricultural productivity has purely beneficial effects on structural change and economic growth. Ever since Matsuyama (1992) raised the possibility that the effects could be negative in open economies, this point has been well-appreciated by economists at a theoretical level, but has typically been brushed aside at a practical level, due to his small open economy assumption being so extreme. In this paper we caution against this brushing aside. We show through a two-sector Eaton-Kortum model of trade that the effects can be negative even at intermediate (and realistic) levels of openness. We back this up with reduced-form evidence, exploiting the Green Revolution as a plausibly exogenous source of changes in agricultural productivity.

There is room for future research in several directions. Our analysis is at the country level. Given the recent explosion of research using structural quantitative models in economic geography, our analysis could be carried out within countries. One might expect the comparative advantage effect to dominate even more at the level of localities than it does at the level of countries. This is in line with the findings of Moscona (2018).

One limitation of our analysis is a lack of information on the labor intensity of the new agricultural technologies whose diffusion during the Green Revolution we exploit. Accordingly, in our model we assume for simplicity that labor is the only factor of production. In contrast, Bustos et al. (2016) carefully examine the effects on structural change of the introduction of new agricultural technologies with differing levels of labor intensity, but do not examine how the effects vary with openness. Analyzing both of these dimensions simultaneously would be an interesting extension.

One of the motivations for examining structural change is its implications for economic growth (see, e.g., Matsuyama, 1992; Galor and Mountford, 2008). While our paper, is related to the contributions studying that link, it does not directly address it. We focus on the (heterogeneous) effects of agricultural productivity on structural change, leaving the implications for aggregate productivity growth for future work.

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# 7 Appendix

## 7.1 First stage results

Table 3 gives the first stage results for the IV analysis. While the first stage specification is the same no matter what the outcome variable of the second stage regression, the number of observations is slightly different; we report results for both the first stage corresponding to column 3 of Table 1 (the regression for the non agricultural share of GDP) and to column 4 of Table 1 (the regression for the non agricultural share of employment).

**Table 3:** First stage results

| | Table 1, Column (3) specification | | | Table 1, Column (4) specification | | |
|---|---|---|---|---|---|---|
| | Agri.Productivity | Openness | Agri.Productivity $\times$ Openness | Agri.Productivity | Openness | Agri.Productivity $\times$ Openness |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HYV Agri.Productivity | -0.224 | -1.322*** | -31.94*** | 0.259 | -0.688*** | -8.594 |
| | (0.203) | (0.249) | (10.79) | (0.197) | (0.1773) | (11.17) |
| Market potential | -.0035*** | 0.0013*** | 0.0440 | -0.0024*** | 0.0012*** | 0.043 |
| | (0.0006) | (0.0005) | (0.0395) | (0.0004) | (0.0004) | (0.033) |
| HYV Agri.Productivity | 0.00032*** | 0.00009** | 0.010*** | 0.0003*** | -0.00000 | 0.008*** |
| $\times$ Market potential | (0.00003) | (0.00004) | (0.002) | (0.00003) | (0.0000336) | (0.002) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,124 | 4,124 | 4,124 | 3,979 | 3,979 | 3,979 |

*Notes:* Panel Regression, 1961-2016. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

## 7.2 Agricultural labor shares, model vs data

**Figure 5:** Agricultural labor shares, model vs. data (1961)

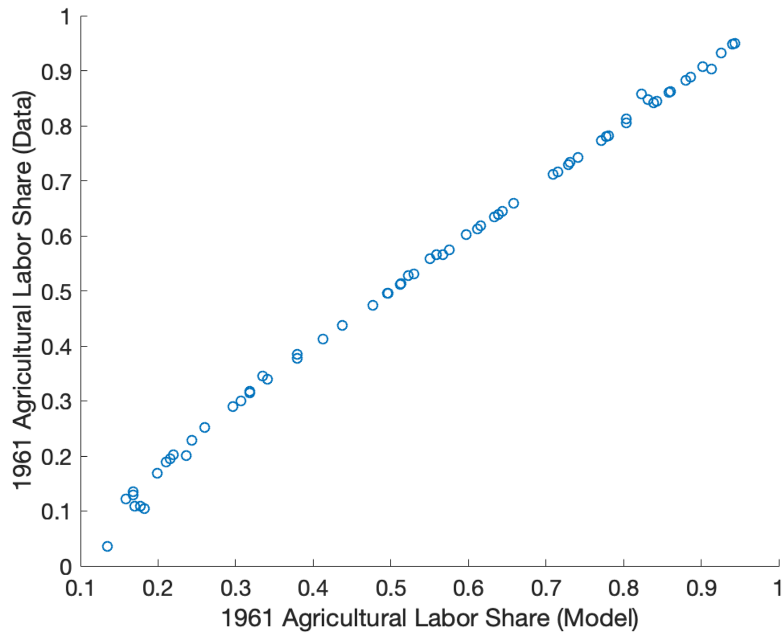


**Figure 6:** Agricultural labor shares, model vs. data (1995)